Forecasting Stock Prices on the Basis of Technical Analysis in the Industrial Sectors of the UK Stock Market

by

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Dedication

I would like to dedicate this thesis to my mom-Aumbia Begum, whose inspiration and supports have made it possible to come to this stage and to my elder brother, Badal and my wife, Peya who have provided me enthusiasm and made me determined to complete my PhD.

Ethical Approval

As this study will collect published secondary data, it will not affect the rights of any person, institution or company. Therefore, it is ethically sound and does not need ethical approval.

As ethical approval is sought before data collection, it is also equally important to assess risks before collecting data. Therefore, the next section assesses research specific risks that may arise while data will be collecting and other associated risks that may arise even after data collection.

Risk Assessment

This research involves published secondary data. Therefore, there is no physical, social, psychological or financial risk or harm involved for the researcher himself, for selected companies, for the project, for the LSC or for Cardiff Metropolitan University. Risks that might arise will be handled with care and confidentiality by:

- keeping all records in a safe place that cannot be accessed by the public;
- protecting data from viruses with regular scans;
- keeping soft copies of data and thesis chapters on a personal hard disk;
- avoiding emailing or uploading information to the internet where there is a possibility of data being hacked.

Abstract

This study aims to evaluate, critically and rigorously the weak-form market efficiency and forecasting power of technical analysis in different industries in the developed market, the London Stock Exchange. For this purpose, weekly data were collected from the FTSE-all share index, FTSE-350 general industrial index and twenty companies of four different industries, for the period between 3 March 1997 and 16 July 2017. Friedman test detects that data do not have any seasonality. It is found that there is a statistically significant impact of structural breakpoints for all selected series. Thus, their impacts have been ignored for the purpose of analysing and forecasting stock prices through identifying the plain data of sub-sample periods where there is no structural break for each series from the application of Bai-Perron's multiple breaks test. The descriptive statistics table, histograms, and kernel density graphs show that the weekly closing prices of all the selected series are not normally distributed. The runs test and variance ratio tests document that the stock prices of all the series do not change erratically and randomly. Furthermore, Ljung-Box's serial autocorrelation test evidences that a few series do not have serial auto-correlation at the first difference. Moreover, the ADF-unit root test demonstrates that there is no unit root at the first difference for all series. Therefore, the statistical inference was made that the market is not weak-form efficient in the period of the tests for all series and their stock prices are predictable. This study extends the current literature by considering the existence of weak-form inefficiency in different industrial sectors. It is found that industrial sectors impact market efficiency. The ARIMA and GARCH (1, 1) models contribute to evidence better short-term predictability of stock prices for all series in the manufacturing industry. Contrary to that, these models argue that most of the series in the service industry are not predictable. Therefore, this study does not find any support for weak-form efficiency over the periods tested in the London Stock Exchange. The ARIMA model shows superior prediction power to the GARCH (1,1) model and exponential smoothing techniques for most of the series. On the other hand, exponential smoothing techniques perform even better than ARIMA and GARCH (1, 1) models for a few series in the manufacturing industry due to series or industry characteristics. It is found that certain econometric models are better in certain industry sectors.

KEYWORDS: Forecasting stock price, technical analysis, Random walk model, structural breakpoint, industrial price behaviour.

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Overview of Chapter One

Weak-form efficiency: A number of studies have been conducted on weak-form market efficiency. However, these studies have not considered the weak-form efficiency of different industrial sectors.

Weak-form efficiency of the London Stock Exchange (LSE): The LSE, a developed stock market which is usually weak-form efficient found from earlier studies, however, testing of weak-form efficiency on different industry sectors in this market may cause the same and/or opposite results.

CHAPTER ONE: INTRODUCTION

The idea of technical analysis is against the efficient-market hypothesis (EMH). The relationship between technical analysis and EMH is so contradictory that technical analysis refutes the existence of market efficiency. More specifically, technical analysts rebut weak-form market efficiency, which is one of the forms of market efficiency. They believe that future performance can be seen as a reflection of past performance. Therefore, the future prices of selected stocks can be estimated from their historical performance.

However, many scholars argue that developed stock markets are usually weak-form efficient. This study believes that a developed market could be weak-form efficient. However, all industries in the developed market could not be sufficiently efficient to embed all relevant new information into stock prices at the same time. The speed in the incorporation of stock price might differ from industry to industry in the same market. Therefore, this study is conducted using a developed stock market, the London Stock Exchange to test this hypothesis. The next section explains the origin of the EMH.

1.1 The Origin of the Efficient-Market Hypothesis

Regnault (1863), a stockbroker, found from his personal experience that stock returns basically depend on holding period, i.e. stock price variation is proportionate to the square root of holding period. However, Gibson (1889) addressed the situation in a different manner in his book 'The Stock Market of London, Paris and New York'. He states in the book that the shares that are publicly well known have more value. He writes that shares are valued by public based on judgement of best intelligence in an open market. Therefore, nobody gets the chance to beat the price and exploit additional returns.

Bachelier (1900) developed Brownian motion through his PhD thesis. He has also evidenced that mathematical speculation is meaningless through his thesis. Samuelson (1965) described market efficiency as a martingale. Bachelier's work of Brownian motion was ignored until Savage (1955) rediscovered it. Einstein (1905) made the equations for Brownian motion without knowing Bachelier's work on it. De Montessus (1908) wrote a book on probability distribution based on Bachelier's thesis specially the idea that closely linked with Brownian motion. Bachelier (1914) had published a book by the name, 'The Game, The Chance and The Hazard' which is basically a probability theory.

Mitchell (1915) claimed that distribution of price changes is very peaked. Keynes (1923), an economist, claimed that investors are rewarded for bearing risks rather than having a better knowledge about the market. This claim later evolved into the EMH. However, MacCauley (1925), an economist, argued that there is a similarity between stock price variations and the probability of getting results from throwing a dice.

Mills (1927) discovered that stock price follows a leptokurtic pattern of returns (large positive returns and smaller standard deviation), which means distribution has fatter tails and there are lesser chances or risks of extreme outcomes compared to a normal distribution. Working (1934) has stated that stock returns behave like a lottery that is unpredictable. Slutzky (1937) found that stock price is the reflection of the sum of independent variables by which stock price could be predicted. Cowles and Jones (1937) claimed stock price could be predicted through a longer time series model as prices are serially correlated. Cowles (1944) again reported that investors cannot beat the market as price behaves randomly. Kendall (1953) has argued that stock prices change randomly and, therefore, are unpredictable.

Harry (1959) has claimed stock prices behave randomly. Osborne (1959) has claimed logarithm of stock prices has long-normal distribution rather than normal distribution, i.e. stock prices change constantly. Larson (1960) applied a new method of time series and found that the central 80% of data plays an important role in changing stock prices. Alexander (1961) has documented that autocorrelation exists in averaging and the random walk model (which has been discussed in detail in section 2.2.3) best fits the data but also found the leptokurtic nature of returns. Granger and Morgenstern (1963) conducted a spectral analysis or time series analysis and claimed that stock prices behave randomly in the short horizon of time, but that they do not in the long horizon of time. They also claimed that a business cycle does not play any significant role in changing prices.

Steiger (1964) has argued that a random walk does not exist in stock market. In contrast to his findings, Fama (1965a) has stated an efficient market in his draft paper and also urged that stock prices move randomly. Samuelson (1965) has documented the theory of efficient market and shown that predicted stock prices move in a martingale rather than randomly. Fama (1965b) has documented that stock prices move randomly and no analysis can predict returns whether it is fundamental analysis or technical analysis.

Mandelbrot (1966) has documented that returns cannot be predicted in a competitive market where rational risk neutral investor trades and prices follow a martingale. This implies that

stock prices change based on historical performance and intrinsic value but are still unpredictable. Roberts (1967) first coined the term efficient-market hypothesis (EMH) and classified it into 2 types: weak and strong-form efficiency. Fama (1970) theoretically and empirically worked with EMH. Ball and Brown (1968) first introduced event study. Afterwards, Fama et al (1969) performed event study and found that the stock market behaves efficiently. Fama (1970) defined EMH after reviewing a body of knowledge on efficient capital markets theory and tested the market empirically.

French and Roll (1986) took data from NYSE and AMEX for the period 1963 to 1982 to investigate the causes and effects of volatility and efficiency. The autocorrelation test indicates that volatility and efficiency are caused for three main reasons. These are a) public information comes very frequently during trading hour which affects and changes prices b) prices are affected by private information that arises during the trading hour c) mispricing causes volatility during business hour. They also documented that private information comes at a higher rate during exchange holidays (e.g. election, Christmas, etc). As a consequence, they concluded that returns vary from time to time and markets are efficient. The following section details EMH and its classification.

1.2 Efficient-Market Hypothesis and its classification

A financial capital market is efficient if the market reacts to all available relevant information entirely and perfectly in estimating security prices. If prices are set on account of rationality, only new information will cause changes in stock prices – which are unpredictable and random. Therefore, new information will reflect the current knowledge and change the prices naturally. The current stock prices are the prices that were already reflected from all available information or knowledge in an efficient-market hypothesis. If stock prices are predictable, the market is inefficient. This is because all information has not yet reflected the current prices (Bodie, et al. 2006).

Fama (1970) claimed that there are three forms of capital market efficiency including strong, semi-strong and weak. These three forms will be discussed broadly in the next chapter named Literature Review. The word 'technical analysis' has come from the first form of capital market efficiency - the weak-form. Weak-form is the assumption that it is impossible to predict future returns based on the analysis of all publicly available historical stock prices and volumes. Metghalchi and Gomez (2013) explain that when financial analysts or investors apply statistical tools and techniques to predict futures prices based on historical prices,

volumes and open interest, the process is known as technical analysis. Technical analysts predict stock returns from the historical trends of prices by drawing graphs and charts. Therefore, they are called chartists. (Bodie et al., 2006). The subsequent section explains how technical analysis is significant to this study.

1.3 Technical analysis and its significance to this research

Technical analysis is conducted to test whether the stock market could be characterised as weak-form or not. No one can estimate future stock prices on the basis of historical prices and volumes in weak-form efficient market. However, technical analysis challenges the theory of weak-form market efficiency. Technical analysis is the analysis of historical prices that identifies trends in prices that are derived from the changing attitudes of investors toward political, psychological and macro-economic factors, market regulation, international news, capital structure and other determinants. Technicians believe that whatever the fundamental, psychological or other reasons for changes in stock prices are, if prices respond slowly, analysts will be able to identify trends to exploit and predict prices (Metghalchi, Hajilee and Hayes, 2013). Thus, it is inevitable and necessary to conduct technical analysis rather than fundamental analysis (the arbitrage pricing theory and capital asset pricing model) and behavioural finance to predict future stock prices.

Existing literature refutes the predictive power of technical analysis. Rao (2007) has stated that technical analysis fails to predict stock returns. In weak-form efficiency, all past prices are already reflected in current prices. Thus, technical analysis cannot predict future price movements (Fama, 1970). In fact, there is no other empirical evidence except efficient-market hypothesis that can predict stock returns (Jensen, 1978). Security market is made up with rational and logical investors who take decisions on the basis of net present value or discounted cash flow/value of future forecasted earnings. Investors can only expect the average expected market returns but not an individual's expected returns (Bromiley and Wade, 2003). Fair price is the outcome of all publicly available information about the company and share prices adjust very quickly to any new relevant information (Parkinson, 1997). In an efficient market, the stock market is information-based efficient and share prices are the reaction of all available information. Therefore, returns and risks are unpredictable (Reilly and Brown, 2003).

Recently, however, a few studies have discovered the predictability of technical analysis. Hsu et al. (2010), Metghalchi et. al. (2013) and Dash and Dash (2016) have claimed that empirical

results strongly support the predictive power of technical analysis. Brock, Lakonishok and LeBaron (1992), Lahmiri (2018) and Maciel (2020) have found that technical analysis can predict stock returns. Steeley (2001) and Jaffe and Westerfield (1985) have claimed that stock markets are not always efficient and prices do not change randomly all the time, and consequently, that trends appear in the form of anomalies and that returns are predictable.

The above discussion confirms that forecasting stock prices based on technical analysis is a controversial issue. Therefore, this research aims to develop a pragmatic model based on an observed sequence of time series data (historical prices) and market regulation of news disclosure to predict future time series values of stock prices of different industries, as well as to simultaneously evaluate the predictability and validity of technical analysis critically in the UK stock market.

This research would perform technical analysis and critically evaluate its performance in predicting stock prices of the London Stock Exchange (LSE). Therefore, a discussion of the history of the LSE is unavoidable.

1.4 History of the London Stock Exchange

The London Stock Exchange (LSE) is more than 300 years old. It first started at a coffee house in the 17th century. It gradually evolved into the number one financial institution in London and was named as the London Stock Exchange. It is now a well-regulated and leading stock market of the world.

At the beginning the LSE was Jonathan's Coffee-House. In 1698, Mr. John Castaing used the place to issue stocks and futures in the form of commodities. Afterwards in 1698, the Royal Exchange moved its operations to the streets and places near Jonathan's Coffee-House due to the rowdiness of stock dealers. In 1748, the coffee house was destroyed in a fire and was afterwards rebuilt by stock dealers. A large number of stock dealers then built a club at the coffee house to buy and sell stocks. In 1773, they built their own building known as the New Jonathan's, the ground floor of which was to be used as an exchange room and the first floor, as a coffee room. Subsequently, they changed the name of New Jonathan's to 'The Stock Exchange'. On 3rd March in 1801, dealers restarted their business under a membership and regulation basis, and the modern stock exchange was born in London. In 1802, the stock exchange shifted into a new building in Capel Court.

In 1812, the first stock market regulation book was published. In 1836, The Stock Exchange opened its branches in Manchester and Liverpool. In 1854, it was rebuilt as both participating members and brokers were taking up so much space that the exchange was uncomfortably crowded. In 1876, a deed for settlement of disputes for the stock exchange was implemented. During the Great War in 1914, the exchange market remained closed. In 1923, the exchange started issuing bonds. In 1939, during World War II, it was closed for six days and reopened on the 7th of September. In 1972, a twenty-six storeyed office block was opened by Queen Elizabeth II. The London Stock Exchange was combined with 11 British and Irish exchanges in 1973. In 1986, market deregulation was performed. In 1991, the trading name of the exchange was decided as 'The London Stock Exchange'. In 1997, the exchange was transformed by electronic service to have faster service and efficiency. International equity derivatives service started in 2003, and in 2004, the headquarters of the exchange moved to Paternoster Square, close to St Paul's Cathedral.

All firms need to be members of the LSE. All member firms are regulated under relevant UK or appropriate overseas legislation. This research will investigate whether there is any relationship between market regulation and stock market efficiency. Therefore, the discussion of the existing stock market regulations regarding disclosure of information and announcements that might impact market efficiency are unavoidable.

1.5 Regulations regarding disclosures and announcements in the UK stock market

This research will observe and analyse the impact of disclosures and announcements as part market regulations on stock price movements. The London Stock Exchange Rule Book (2018) explains that all firms need to be members of LSE. All registered firms are regulated under relevant UK or appropriate overseas legislation. The following regulations have been extracted from the above rule book:

Rule G 1010: All the member firms must always be authorised under relevant United Kingdom, or appropriate overseas legislation, or in the view of the Exchange be otherwise sufficiently regulated, in respect of capital adequacy, and fitness, probity and disclosures. Bailey et al. (2003) claimed that regulation of fair disclosure brings no significant difference in return volatility. As announcements are made on time in a fairly regulated market, stock prices will not move considerably.

Share price manipulation through disclosures [1410]:

G 1410: A member firm trading in a security shall not do any act or engage in any kind of actions or planning including disclosures or announcements for the purpose of moving its price. Gerace et al. (2014) found that stock market becomes inefficient and volatile due to stock price manipulation through misleading disclosures.

Delay in disclosing information:

For a stock market to work efficiently and fairly, two principles must apply: companies need to release relevant information as soon as it is available; and all those who want to deal in shares should have access to the same information at the same time. Any price sensitive information (inside information) must be disclosed as soon as possible. When there is a risk of leak confidential information, a holding announcement should be made. A company must ensure that there is no leaking of information that may give some people an unfair advantage over others. A company should disclose any financial difficulty that it is facing (corporate governance of the Financial Conduct Authority, 2018). Farag and Cressy (2011) detail that when new information leaks out, a stock market becomes more volatile and less efficient. If a company has a legitimate interest to delay disclosure of inside information, it must be evaluated whether the delay is likely to mislead the general investors.

Market rumours:

Stock prices might move in response to unverified rumours. Ahern and Sosyura (2015) found that stock prices of target companies rose sharply on the day of a rumour's publication. Where rumours are false or press speculation is groundless, a company is under no obligation to issue denials. Untruths can’t amount to inside information. But where rumours or speculation are largely correct, the company needs quickly to decide whether it has inside information that should be released. Once any news has leaked, delay can no longer be justified, and directors need to ensure that the market is trading on the basis of accurate information that is available to all (corporate governance of the Financial Conduct Authority, 2018). The spreading of false rumours helps move prices to an artificial level and obtains trading profit (Van Bommel, 2003).

Stock market regulation of fair disclosures and announcements helps promote efficiency in market. Evidences suggest that market regulation regarding announcements and market efficiency are strongly related. Therefore, it is required to discuss whether they are positively

or negatively related. The next section discussses the relationship between market efficiency and market regulation of disclosures and announcements.

1.6 A Link between market efficiency and market regulation of news dissemination

The efficiency of stock markets is crucial for the proper functioning of the economy, and corporate disclosure of financial information has traditionally been viewed as a prominent tool for achieving this result. More information released by firms means more accurate stock pricing, which, in turn, corresponds to a more efficient allocation of financial resources among productive units. Disclosure of information enhances stock market efficiency and leads to equal distribution of financial resources throughout the economic system (Kitch, 1995; Schon, 2006; Gilson and Kraakman, 1984). Every disclosure in the securities market is likely to cause some competitive harm to the firm which provides competitive environment and efficiency and each decision not to disseminate denies investors a further piece of potentially useful information which causes inefficiency Darrough (1993).

However, the association between them is a controversial issue. Some researchers have investigated the link between them and documented that market regulation of news dissemination brings market efficiency (Lee, 2010). On the other hand, other scholars have found a complete opposite picture regarding the relationship between the two. They have claimed that there is a complete inverse relationship between market regulation of news dissemination and market efficiency. Harel, Harpaz and Yagil (2010) argued that if a stock market is well regulated, stock prices are predictable. If there is no strong market regulation, stock prices will not be predictable and there will be abrupt price changes. This is because, when all relevant information is disclosed in a market, investors can easily predict the market. Thus, the market becomes inefficient. However, if market regulation is flexible, firms disclose what they think and it causes market to be unpredictable.

Malcolm et al. (2009) found that there is a strong positive relationship between efficiency and disclosure of information. If regulation regarding dissemination of information is strong, efficiency is strong and if regulation is weak, efficiency is also weak. In contrast to their findings, a contradictory argument can be raised from the findings of Liu (2010) who has claimed that due to deregulation, commission rate falls. Consequently, transaction costs also fall. Lower transaction costs confirm the smooth flow of information. Therefore, the market becomes efficient and prices change randomly.

In an efficient market, all investors have equal opportunity to access to all available information at the same time. Therefore, transaction costs are zero. There is no cost incurred to gather new or insider information. In that situation, no one can beat the market.

But in an inefficient market, there is an informational gap in terms of company disclosures or time gap between insider investors and general investors. So, insider investors invest money for gathering new or insider information, and investors seek chance to gain more substantial returns than general investors as they know better than the general investors. If investors want to predict stock prices, they will incur some transaction costs. Therefore, transaction costs cannot be zero.

In a security market, the buyer and the seller meet to exchange value. There are many counterparties for buyer and seller and a price discovery mechanism in a liquid and efficient market. An efficient market ensures low transaction costs, effective and transparent cleaning and pricing mechanisms, timely transfer of funds and ownership of securities. In an inefficient market, disclosure is limited, insufficient and untimely, and there is uneven distribution of information between insider investors and ordinary investors. Therefore, security market regulation should ensure the following:

- Companies must disclose about businesses, securities and risks associated with investment and provide full, precise financial results.
- Security broker, dealer and exchanges must treat investors fairly and protect investors' interests and rights.

A regulated capital market and regulatory authorities can play a vital role in the effective and efficient functioning of securities market and can affect the market outcome. A sound regulatory framework includes effective enforcement, actions of disclosure and transparency of information, high standard of governance, insider trading laws, etc (Malcolm et al, 2009). However, this study will consider only disclosure and transparency of information. Therefore, it can be mentioned from the above discussion that regulations ensure the smooth flow of market information, help in market efficiency and make sustainable economic development.

It is found from the literature review that regulations based announcements and disclosures influence stock prices significantly. Furthermore, it is also found in the literature that all the research has been performed without considering industrial impacts on price behaviour. Each

industry might have distinct and unique price patterns. The following section addresses research problem that exists in the current literature.

1.7 The rationale for this research

A significant number of studies have shown that stock prices are predictable using technical analysis. Among these studies, special emphasis is given to Brock et al. (1992), Ratner and Leal (1999), Gunasekarage, Power (2001), Lo et al. (2000), Park and Irwin (2007) Wei, Chen, and Ho (2011), Yamamoto (2012), Blume, Easley and O'Hara (1994), Ding, Granger and Engle (1993), Oliveira, Nobre, and Zárate (2013), Zhu & Zhou (2009), Namdari and Li (2018) and Nti et al. (2019). Inconsistent results also obtained from the studies of Bessembinder and Chan (1998), Hong (1977), Chen, Huang and Lai (2011) and Rao (2007) and many more. Therefore, the result from technical analysis is contradictory. However, this study would like to consider the price behaviour of different industrial categories and the impact of market regulations of disclosures and announcements along with technical analysis to see whether stock prices are predictable or not in the UK stock market.

The main assumption of this study is that if the whole stock market is divided into different industrial categories on the basis of their functions, nature, behaviour and attributes; each industrial sector will perform differently in terms of efficiency. As a consequence, the predictability of each sector may differ from the other. Each industrial category might behave differently due to its industry nature. Parwada (2012) showed in the Australian securities exchange that a wide range of industry sectors successfully predict the direction of stock price movements due to their nature. Chen and Lai (2013) found that the biotechnology and medical care industry has significant positive stock returns and they are predictable. They found that the electronic industry provides the complete opposite picture. Sofat (2016) analysed the stock price behaviour of eight companies from the IT industry in the National Stock Exchange (NSE), India, and claimed that they are not weak-form efficient.

Gaganis et. al. (2013) and Onwukwe and Ali (2018) claimed that the returns of the insurance industry are predictable. Kirkwood and Nahm (2005) found that the bank industry in the Australian Stock Exchange has got a significant prediction ability. The findings of Lim et al. (2007), Bashir et al. (2011), and Narayan et al. (2015) evidence that the returns of banking industry are more predictable than other industries. Tsai et al. (2018) claimed that returns of different leading industries are predictable.

All the scholars performed their studies on a specific category of industry. However, this study will divide the London Stock Exchange into four industrial categories based on their functions and nature to investigate the predictability of each sector. For example, this study will keep all service related companies under one category and all production and manufacturing related companies under another category. Their predictability also might differ based on their industry-related announcements and disclosures. Some industries could be weak-form efficient and others may not.

On the other hand, a significant number of research has been conducted on technical analysis and its predictability. In these papers, researchers have shown that most of the stock markets which have been researched in developed markets are efficient. This study assumes that developed markets could be weak-form efficient. However, when disclosure in terms of new information enters a market, even in a developed market, all industries in that market cannot embed them into stock prices at the same time. Dasgupta, Gan, and Gao (2010) found that stock prices do not change significantly when companies make announcements in a transparent environment.

This study assumes that all industries, even in a developed market, are not equally capable of incorporating all relevant information into stock prices at the same time. All industries might not have the same performance level. Some industries could be weaker and other industries could be strong enough to adjust this information into prices. Therefore, all industries in a developed market could not be weak-form efficient.

It has been observed in the existing literature that no scholars have yet come up with this idea. They have only considered a general stock market or specific companies of an industry sector rather than considering the performance of all industrial sectors in a market. This study assumes some industries could be more predictable than others in the same market due to industry-related disclosures and announcements.

The above discussion regarding the predictability of technical analysis and the performance of different industrial sectors in terms of predictability of each sector and research problem has raised the following research questions.

1.8 Research questions

It is often useful to consider research questions in terms of the research's aim and objectives, as they are closely related.

The following research questions were derived for this research after reviewing the existing literature very carefully:

(1) Are stock prices in the industrial sector of the UK stock market weak-form efficient?

(2) What is the forecasting power of different econometric models estimated using the principles of technical analysis (ARIMA, GARCH, exponential smoothing techniques)?

(3) What is the conclusion on the use of technical analysis for estimating econometric models and forecasting stock prices?

Given the above questions, we now consider the research aim that flows from them. More importantly, section 2.4 (figure 2.2) in the second chapter, which contains the literature review, shows how the research's aim and objectives were derived from the review of the literature. The next section explains the aim of this study.

1.9 Aim of the research

After an extensive review of the existing literature on the subjects of technical analysis, market efficiency and a critical analysis of the findings of the review, it was determined that the aim of this research is to fill the gaps in the existing literature. This research assumes that the London Stock Exchange could be efficient, however, all industrial sectors might not be equally capable to incorporate all relevant information into stock prices at the same time. It was observed in the review of literature that no one ever investigated this assumption so far especially in the London Stock Exchange. This research will investigate all industrial sectors to see the predictability of those sectors.

Therefore, the aim of this research is to critically and rigorously evaluate weak-form market efficiency and the forecasting power of technical analysis in different industrial sectors in the UK.

It has been evidenced in many stock markets that technical analysis helps to predict stock prices and gain abnormal profits. At the same time, it has also been documented that technical analysis fails to predict stock prices especially in the developed markets, as prices change randomly and independently in those markets due to different influential factors. Therefore, this research aims to evaluate the predictability of technical analysis in different industrial sectors and the extent to which it can predict stock prices. The research objectives to help achieve the research aim are listed in the next section.

1.10 Objectives of the research

This research has several objectives that help achieve the research aim and answer research questions. The research objectives listed below were designed keeping in mind the famous SMART test recommended by Maylor and Blackmon (2005) – SMART is an acronym where S stands for specific, M for measurable, A for achievable, R for realistic, and T for timely.

The objectives of this study are:

1. To make a critical review of existing literature on weak-form market efficiency and forecasting models using technical analysis.
2. To develop a conceptual framework for simultaneously testing market efficiency and the forecasting power of technical analysis in the industrial sector of the UK stock market.
3. To examine whether stocks in the industrial sectors in the London Stock Exchange are weak-form efficient using a range of econometric tests.
4. To estimate different econometric models using technical analysis (ARIMA; GARCH-1, 1 and exponential smoothing techniques) and test their forecasting power.
5. To compare the results from this study with findings from previous research and synthesize the entire research towards assessing market efficiency and the ability of forecasting models using technical analysis.

These objectives are closely linked with historical data that will be collected through yahoo finance and analysed critically and rigorously through different statistical tools, techniques and models to fulfil the aim of this research. However, historical stock prices in this study do not include any information regarding dividend payment. Therefore, this study will analyse it on the basis of stock market regulation. The impact of announcements will be evaluated through historical price trends and patterns. All the objectives are directly linked with historical prices.

The objectives above will help in achieving the research aim. This is because, the aim has been broken down into several objectives. The combination of all objectives above will help achieve the research aim. Therefore, they are very important to be considered to fulfil the research aim. This research is currently at the end of chapter one. Therefore, the next section provides a road map of how the remaining chapters of the research are designed and laid out in order to achieve the research aim.

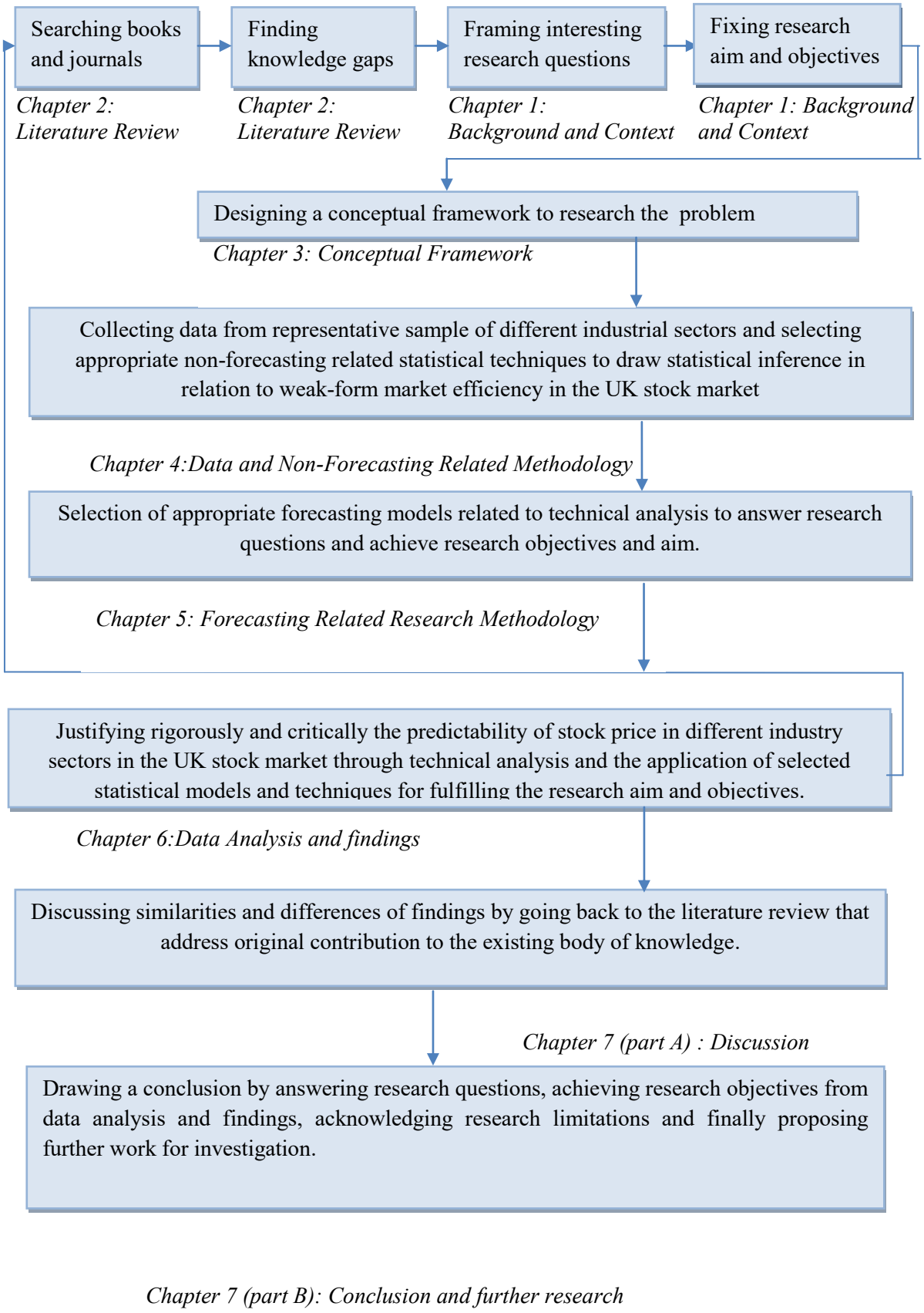
1.11 Thesis road map

The thesis road map explains how entire research will be conducted. First, books and journals were reviewed as part of this research to identify the existing knowledge gaps. This led to some interesting research questions and helped to derive an aim and objectives from the research problem in chapters 1 and 2. A mental diagram is provided in chapter 3 to explain how this research will be conducted. Chapter 4 explains the line graphs, histograms and kernel density graphs from data collected from twenty individual companies listed in FTSE100 in four different industries, FTSE-all share index and FTSE-350 general industrial index to diagnose the impacts of industrial sectors on weak-form market efficiency and stock price movements.

Furthermore, the appropriate non-forecasting related statistical techniques to draw statistical inference in relation to weak-form market efficiency and answer the research questions related to technical analysis are chosen in chapter 4. Then, in chapter 5, this research analyses forecasting related statistical models and techniques. Chapter 6, applies all selected non-forecasting and forecasting related statistical methods and evaluates techniques and models to justify, rigorously and critically, the predictability of different industry sectors and technical analysis. This chapter also explains which model is better than other in terms of forecastability. Chapter 7, interprets and discusses how the findings are different from or similar to others' findings by returning to the literature reviews in chapter 2 and indicates the contribution of the research to the existing body of knowledge.

Furthermore, this chapter draws a conclusion by answering the research questions, fulfilling the research aim and objectives, discussing the limitations of the research and proposing further work that still needs to be undertaken. The road map in figure 1 shows a blueprint of this thesis.

Figure 1: Research Road Map



Source: created by author

This research will be conducted by strictly following the thesis road map shown in section 1.12 (figure 1). The road map addresses how this research will be performed. The next chapter contains the literature review, which presents the existing theory, the findings from early empirical research and a critical argument on the findings.

Overview of chapter two

The concept of behavioural finance contradicts the efficient market hypothesis. Early empirical research shows that announcements and disclosures have a significant impact on price movements and prediction. Furthermore, the early empirical findings detail that a developed market is usually weak-form efficient, which is one of the forms of efficient market hypothesis. However, nobody has ever investigated industrial impacts on weak-form efficiency. A developed market could be weak-form inefficient if a prediction is performed on the basis of different industrial sectors. This study will contribute to the literature by adding the concept of testing the weak-form efficiency on different industrial sectors in the developed market, the London Stock Exchange.

CHAPTER TWO: LITERATURE REVIEW

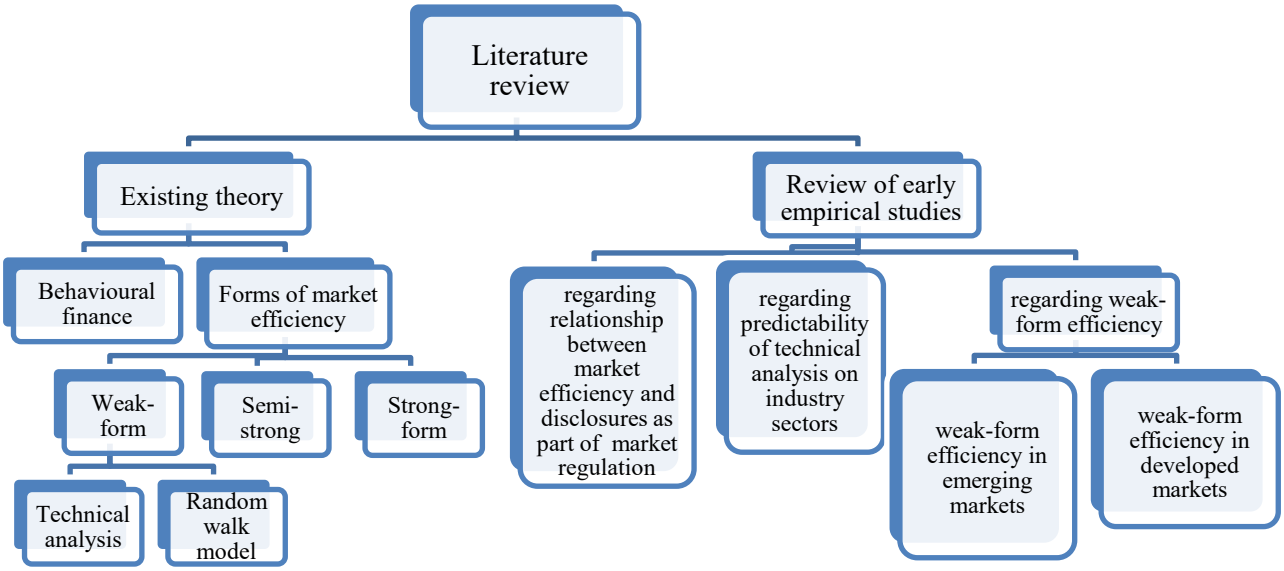
Knowledge evolves through reviewing literature. This literature review explains the existing theory and recently found empirical evidence on technical analysis and performance of different industry sectors in terms of predictability. The chapter is split into two main parts, consisting of the existing theory and early empirical findings. The theory part contains two sections: one explains behavioural finance and other explains forms of market efficiency. Weak-form efficiency is one of the forms of market efficiency and it is closely related with random-walk model.

The section on early empirical findings explains the empirical relationship between company announcements as part of market regulations and efficiency. Furthermore, early empirical research section details predictability of technical analysis on industry sectors. Moreover, it also explains weak-form efficiency in emerging markets and developed markets. The structure of this literature review is shown in the next section.

2.1 The structure of the literature review in this study

This section explains how the review of literature is performed to acquire knowledge regarding technical analysis. The literature review conducted in this research strictly follows the layout shown below in figure 2.1.

Figure 2. 1: Literature review



Source: diagram developed by author.

Following the review, this chapter derives the research aim, objectives, research gap and relevant research questions from the literature review. The next section analyses, evaluates and criticises rigorously the existing theory and empirical findings in the reviewed literature.

2.2 Existing theory

Theory is developed continuously after obtaining appropriate findings from research. The existing theory below explains behavioural finance, market efficiency and its different forms, technical analysis and the random-walk model, which are the implication of many empirical findings so far.

Comparing and contrasting behavioural finance with technical analysis

It is not easy to understand the psychology of market participants. Human beings are fickle-minded. They change their mind without any prior notice. To understand someone, it is required to know sensory reactions and mental activity which are very difficult. Sometimes, people say something but do something else. Behavioural finance is related to finance, economics, psychology and sociology. As the area of behavioural finance is too wide, it is more difficult to predict the actions of market participants and their investment decisions.

Contrary to this, it is much easier to measure the future value of stocks on the basis of their historical values. Stock prices do dot volatile in an equilibrium market and they are correlated. It is very easy to predict future stock prices based on technical models. Technical models deal with statistical tools and techniques. It is simply involved with mathematics. On the other hand, behavioural finance does not deal with any logical and rational calculation. Consequently, the prediction of stock prices is almost impossible or very difficult to measure based on human psychological actions. It does not follow any law or sequence of order.

Therefore, the aim of this study is to measure the predictability of technical analysis rather than behavioural finance. However, this study cannot deny the existence of behavioural finance which helps to understand why stock prices change rapidly in the market. Behavioural finance is a method or science by which price dynamics in the market could be understood.

The scope of behavioural finance:

Behavioural finance is a new idea that emerged in financial markets in response to difficulties faced by the traditional approach which is EMH (Barberis and Thaler, 2002). Behavioural finance draws from different fields and theories, primarily those of psychology, sociology and

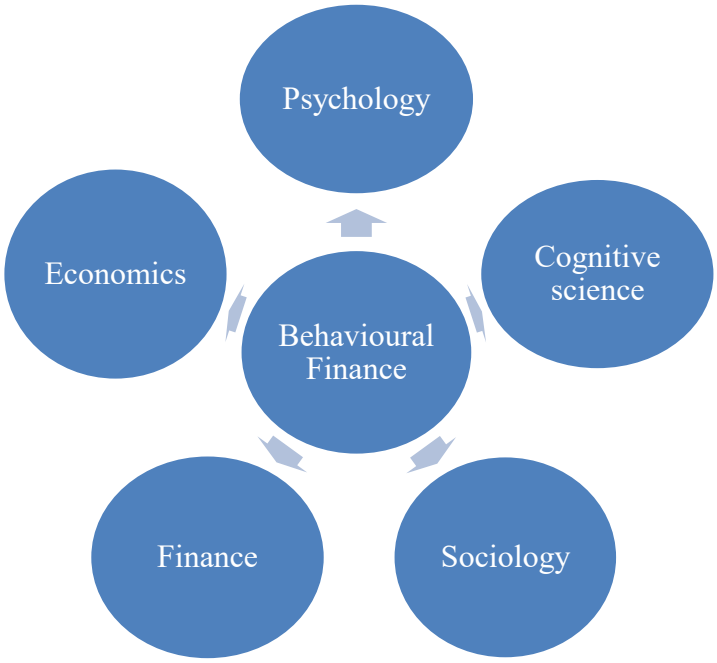
cultural anthropology, cognitive science or neuroscience, economics and finance. Behavioural finance deals with human behaviour as it relates to society, understanding individual and group behavioural dynamics and how people have behaved in the past will help understand how people will behave in the future and the measurement of returns on the basis of rational or irrational calculation to make investment decisions.

Sewell (2010) behavioural finance deals with the psychological factors of individuals who make decisions in the field of finance. Heukelom (2014) offers a comprehensive account of how behavioural economics and finance were founded on the personal level. Hellmann (2016) explains behavioural finance is the combination of behavioural and cognitive psychological theories, conventional economics and finance. This result is in the line with Virigineni and Rao (2017) who claimed that market participants' behaviour is not only associated with finance, but also influenced by a combination of psychological, sociological and financial variables making 'behavioural finance' truly interdisciplinary. Similarly, behavioural finance is a combination of psychology, finance, anthropology, sociology, and economics (Gippel, 2012).

Moreover, behavioural finance is closely related to finance, psychology, and biology or neuroscience (Lo, 2004). A similar finding has also been documented in the study conducted by (Gintis, 2007) that it is an integration of finance, economics, psychology, sociology, and biology. However, Konstantinidis et al. (2012) confined behavioural finance within human behavioural and psychological attitudes. Therefore, it could be concluded that behavioural finance is not limited only to finance and behavioural psychology, but also involved with economics, sociology and biology or cognitive science.

These results suggest that the scope of behavioural finance is very wide and it is very difficult to measure the future movements of stock price on the basis of the behavioural finance. Consequently, behavioural finance is criticized as it lacks a unifying theory (Ball, 2009; Fama, 1998 and Subrahmanyam, 2007). The scope of behavioural finance is shown below in figure 2.2:

Figure 2. 2: The scope of behavioural finance



Source: diagram developed by author

The next section finds out the factors that influence the investors to make investment decisions. The influential factors defer from person to person based on person's personal experience, socio-economical and family background and so on.

The determinants of investment behaviour of investors:

Some factors influence greatly investors to make their investment decisions. These are determinants of investors. Market participants need to understand these determinants well to make predictions which include Personality and motivational processes, social and cultural anthropology, socio-cultural background, macro-economic factors, emotional dynamics, risk attitudes of investors, education, feelings and mentality and cognitive processes (a part of biology).

All people grow in a socio-cultural environment where they build and share their personality, mentality, religion, norms, values, attitudes, and knowledge from. These factors influence significantly to make investment decisions. Culture influences investors to make investment decisions (Statman, 2008). The tendency of people is to be risk-averse for losses rather than gains and loss aversion impacts the investment decisions of professional investors (Coval and Shumway, 2005). Furthermore, Thaler and Johnson (1990) evidenced that investors with prior gains may be more eager to accept a higher risk.

Investors' behaviours are important in deciding. Sociological and demographic factors like age, gender, occupation and personality play an important role in behavioural deviations. An example of this factor is examined by Barber and Odean (2001) who documented that men invest 45 percent more than women due to their overconfidence. Furthermore, Onsomu (2015) found the impact of age on investors' decision at the Nairobi Securities exchange. A similar result was documented in a study conducted by Ansri and Moid (2013) who found that age and risk factor are closely related to investment decisions.

Wright and Bowen (1992) argue that pleasant emotional states result in optimistic choices and judgements in market situations. In a related study, Hirshleifer (2001) documented that mood, emotions and personal preferences affect the tendency to take risk in investment behaviour. These results are consistent with the findings of Anger and Loewenstein (2007) who claimed that emotions and the structure of the mindset of market participants influence the decision-making process in investment. Furthermore, market participants reflect loss aversion when they mentally experience a given loss more drastically than a gain of the same size (Singh, 2012). Moreover, regret aversion exists in the behaviour of investors for which they tend to hold on to investments that deliver negative returns and will try to reduce losses by taking more risks when they realize errors were made in the judgement process (Quiggin, 1994).

As the decision makers' perception is a key factor in the investment decision, their personality is interfering. Persons' opinion, their risk potential, herding behaviour and experience are important in the way of deciding (Khoshnoud, 2004). This result is consistent with the findings of Kannadhasan (2009) and Kumari and Sar (2017) who argued that market participants should have an understanding of their investment attitudes in the context of behavioural finance to enable them to select the most suitable investment based on their risk personality.

Similar findings have also been documented in the studies conducted by Nofsinger and Sias (1999); Bikhchandani and Sharma (2001) who found that market participants have a tendency to ignore their personal information and imitate others as part of social beings which lead them to trade in the same direction and consequently, they move in and out of markets as a group. Thus, Kannadhasan (2009) claims that some investors make their investment decisions on inaccurate market participant perceptions and patterns. Moreover, investors tend to overreact in the market because of the perception of pattern repetition (Singh, 2012).

There is a close relationship between risk and personalities. The amount of risk investors can tolerate depends on their personalities: namely conservative, moderate, growth- or aggressive investors (Mak and Ip, 2017; Pompian, 2016). Conservative investors tend to have a low-risk tolerance and slow in making decisions when they feel uncertain or uncomfortable and like to take care of their family by investing in education and homeownership (APT Wealth Partners, 2014 and Pompian, 2016). Conservative investors seek to minimize investment risk and loss of capital and gain wealth by investing in low-risk investment opportunities (Bourse securities, 2016 and Pompian, 2016). It could be concluded based on the findings that conservative investors are those whose portfolio has greater expected return and less risk.

Moderate investors attempt to reduce risk and increase returns by following the trends set by friends or colleagues (Bourse securities, 2016 and Pompian, 2016). Moderate investors sometimes overestimate their risk tolerance and may even decide to put off their investment decisions without consulting professional advice (APT Wealth Partners, 2014). Consequently, it could be claimed that moderate investors make their investment in the latest and most popular investments. Growth investors are known to have medium to high-risk tolerance levels and their behavioural bias orientation is cognitive (Pompian, 2016). Some growth investors are strong-willed and independent and willing to accept capital gains from irregular sources, although, they are not always competent when doing their research (Dow, 1998).

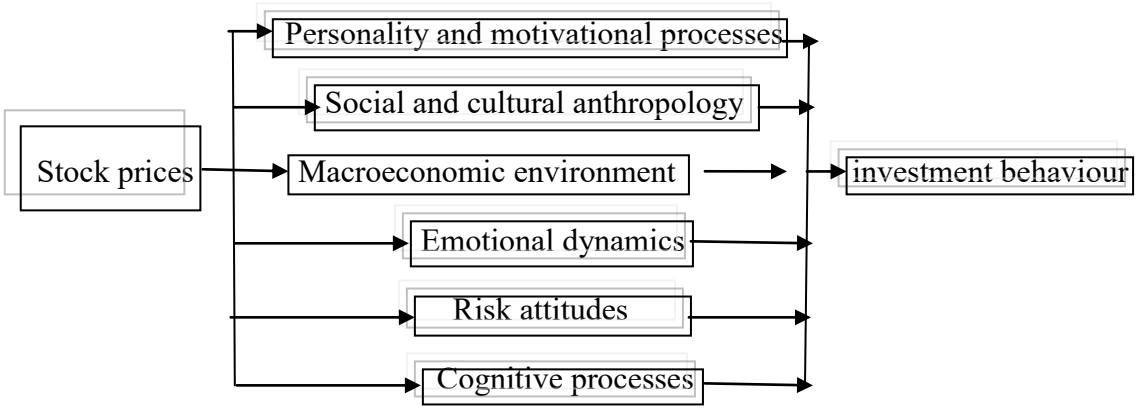
Therefore, it could be concluded that growth investors attempt to outperform the market by taking risks (Oehler et al., 2018). Characteristics associated with aggressive investors are the willingness-to-tolerate high risk and overconfidence in their performance (Bourse securities, 2016). Corter and Chen (2006) claimed that investors with high-risk tolerance scores tend to have higher-risk premium. Thus, a conclusion could be drawn that high-risk investors have either higher risk-premium or greater loss.

Now-a-day, cognitive processes give rise to systematic errors or biases made by investors in the way they think and make decisions about their stock selection (Jain, 2012). Similarly, Kourtidis et al. (2011) disclose that the existence of irrational investors who make random transactions in the market can only be explained by taking into account behavioural factors. Furthermore, noise traders have no sophisticated or statistical knowledge but their emotions play a significant role in their investment decisions (Glaser et al 2009). In a related study, DeLong et al. (1990) revealed that irrational noise traders make fluctuations in the price of an asset with risk-free dividends.

This result is consistent with the findings of Hirshleifer (2001) who claimed that investors make distorted or irrational judgments through mental operations in modern-day fast-moving financial transactions and internet trading due to cognitive biases. Similarly, Todorović (2011) revealed that investors apply neuroscience and cognitive processes based on observation, experience, examination of the conduct of other investors and managers and application of sophisticated mathematical techniques and statistical models.

Macro-economical factors including interest rate or cost of borrowing, economic growth, inflation, technological advancement, infrastructure, government policy and availability of finance from banks impact investors to make investment decisions. Albaity (2011) found that monetary policy and inflation rate affect greatly investment decisions. Similarly, Rashid et al. (2014) evidenced that investor sentiment and macroeconomic variables including inflation rate, money supply, currency index, industrial production and consumer price index have a greater impact on investment decisions in Malaysia. A contradictory result is also found from a study conducted by Majid and Yusof (2009) who evidenced that interest rate is not significant in explaining Islamic stock market volatility. These are summarized below in figure 2.3:

Figure 2. 3: A general model of investment from the perspective of behavioural finance



Source: diagram developed by author

This section explained the factors that persuade to make an investment decision. The next section explains how investors make their minds to make investment decisions.

Pillars of behavioural finance:

Behavioural finance deals with irrational behaviours of market participants in making their investment decisions. The main components by which financial agents form their attitudes and beliefs and make investment decisions, are explained below:

Excessive self-confidence and self-esteem maintenance

There is a lot of evidence that human being show excessive self-confidence while forming their attitudes and decisions. Overconfidence causes market traders to trade more aggressively, which tends to reduce their welfare (Odean, 1998). However, overconfidence reduces the diversification of investment. Moreover, Thaler and shefrin (1981) claimed that investments are subject to temptation and investors look for tools to improve self-control.

Optimism and wishful thinking

Since high skills or abilities lead to a good outcome, overestimation of one's merits makes over-optimism about one's prospects. People tend to be overoptimistic about their life prospects (Weinstein, 1980), which affects their economic and financial decisions (Puri and Robinson, 2007). Moreover, Optimistic investors are viewed as people that have higher risk and return expectations in contrast with people experiencing lower sentiment (Dickason and Ferreira, 2018). These outcomes are very similar to the findings of Heaton (2002) who claims that managers who are excessively optimistic, over-estimate the net present value (NPV) of a company's projects and also believe that a firm's risky securities are undervalued.

Representativeness

Kim and Byun (2011) argue that some market participants select a small sample as representativeness of the whole population ignoring the sample size and ultimately ignoring the law of probability due to representativeness bias. Moreover, traders like to invest in those stocks which yield super abnormal returns most recently and they choose those stocks because of the representativeness bias (Dhar and Kumar 2001). Similarly, Guo (2013) explained that without the existence of noise traders, heuristic traders will be driven out of the market by rational market participants due to their representativeness heuristic.

Sticking to beliefs

Vucinic (2016) claimed that people, once they form their opinion, stick to it persistently. Two effects are concerned. Firstly, people do not agree to seek the evidence contradicting their beliefs. Secondly, when they find such evidence, they are still sceptical. People, usually misinterpret the evidence against their hypothesis, wrongly claiming that the evidence supports it. Within the context of academic finance, sticking to beliefs is manifested simply, i.e., people who believe in EMH will continue to do so long after some evidence against they find.

Affiliation

Ariely (2008) claims that people affiliate the initial value in their mind and give considerable importance to it. Furthermore, Kahneman and Tversky (2000) argue that, once people form their judgments in mind, they often begin the process with some initials, possibly arbitrary number or value, slowly adjust it and adapt the value with the circumstances.

Partiality of availability

While judging the probability of an event, people often search for their memories looking for relevant pieces of information (Vucinic, 2016). Furthermore, Some investors make investment decisions based on only the most recently available information (Kannadhasan, 2009). As these investors make decisions based only on the most recent available information and explain them erroneously, they could impede positive investment returns (Dickason and Ferreira, 2018). Similar findings have also been documented in the study conducted by Sewell (2007) who argued that market participants rely upon the knowledge that is readily available to make financial decisions. These results are consistent with the findings of De Bondt et al. (2008) who claimed that market participants tend to overweight information that is easily accessible.

Herding

Chang et al (2000) examined the investment behaviour of market participants in different international stock markets and found that they tend to herd others. Moreover, Devenow and Welch (1996) explained that irrationality relates to the psychology of investors where some traders neglect their prior beliefs and follow blindly other investors. Similarly, Scharfstein and Stein (1990) revealed that herding may be interpreted as a rational or irrational form of investment behaviour where managers herd others ignoring completely their private information to maintain their reputation in the market. In a related study, Blasco et al. (2012) claimed that herding behaviour among market participants can be driven by rational or irrational motives, which lead to market stress by pushing asset prices away from their fair or fundamental value and consequently, market volatility takes place.

Based on the above analysis, it could be claimed that people make either emotional mistakes or cognitive errors. Emotional mistakes happen from feelings, intuition, and cognitive errors might happen from a misunderstanding of data, making wrong statistical calculations etc. Psychology is made up of personal beliefs, preferences, optimism and wishful thinking.

People make preferences based on emotions. People make unrealistic beliefs about their abilities and prospects. People make ability biases.

This section explained the main components by which financial agents form their attitudes and beliefs to make investment decisions. The next section provides some evidence that show the existence of behavioural finance in real life.

The evidence of the existence of behavioural finance:

The existence of behavioural finance may be ignored. However, there are some incidents that take place often in the markets by which it could be claimed that behavioural finance exists. These incidents could be named market bubbles, anamolies, and volatility. In essence, De Bondt et al. (2008) and Kourtidis et al. (2011) claim that it is essential to understand the psychology of market participants in order to have an explanation of market abnormalities, such as market price bubbles and crashes, market anomalies, volatility and figure out the level of efficiency of the financial markets. This suggests that it is not possible to understand and research the global financial markets without reference to behavioural finance.

Market bubbles

Kindleberger and Aliber (2005) details that some bubbles in the history that took place are the Dutch tulip bubble in the 1630s, the South Sea Company bubble in 1719-1720 and the US stock market bubble in the 1920s, which ended with the Wall Street crash of 29th October 1929. Rehmen (2013) claimed that the idea of behavioural finance emerged due to some of the major global financial and economical crashes.

The efficient market hypothesis explains that when market participants are fully rational and well informed, bubbles cannot exist, Fama (1965). However, Blanchard and Watson (1982) argue that rational behaviour and expectation does not necessarily confirm that prices would follow fundamental values. Furthermore, Abreu and Brunnermeier (2003) claim that some rational arbitrageurs also take the benefits of a bubble and leave the market just before the crash.

De long et al. (1990) claimed that noise traders are liable for the development of bubbles and crash in the financial markets for which asset prices deviate from fundamental value. This result is consistent with the findings of Johansen et al. (1999) and Johansen et al. (2000) who documented that rational bubbles can occur due to noise traders. In a related study, Tirole

(1982) argues that no bubbles would take place when traders have rational expectations and the same information sets.

Market anomalies

Rozeff and Kinney (1976) evidenced a higher average yield in January compared to the other months of the year. Similarly, French (1980) found that returns of stocks tend to be negative on Monday, while on other days of the week tend to be positive. In a related study, Bouman and Jacobsen (2002) evidenced that the summer holidays seem to bring a strong seasonality in yields in the European continent. Consistent results were found in a study conducted by Hensel (2011) who claimed that when cash flow increases just after and before a specific period, it causes higher short-term equity return anomalies. Moreover, Zaremba (2018) claims that the momentum effect is a useful tool for global investors.

Stock market volatility

Volatility in the market takes place due to investors' irrational behaviour. De long et al. (1990) claim that when noise traders over-react or under-react to the available information, stock prices stay away from an equilibrium point. Such unpredictability of investor sentiment, affected by risk-averse behaviour causes price deviation and volatility in the market. Moreover, Huiwen and Sun (2012) argue that noise traders' misperceptions regarding the prices of the assets cause deviation from their fundamental values. Similarly, Lee et al. (1991) argue that individual investor sentiment and stock prices are auto-correlated.

In a related study, Black (1986) and De Long et al. (1990) argued that the irrational behaviour of individual investors changes sentiment fast. Moreover, Froot et al. (1992) concluded that market participants tend to imitate one another, and this emulation drives volatility. This finding is consistent with the finding of Avramov et al. (2006) who revealed that both herding and contrarian trading impact strongly on daily volatility.

Empirical evidence in relation to behavioural finance:

Efficient market hypothesis explains that assets are always fairly priced. However, EMH are based on several assumptions. First, markets have to be large, competent and all relevant information about economy and individual firm is freely available to all investors. Second, all agents have rational expectations. Third, information comes to the market independently and in a random fashion. Fourth, all information has to be incorporated into prices instantly and correctly. Fifth, there is no tax and transaction cost (Chittedi, 2014; Fama, 1970).

All these assumptions jointly take the market to an equilibrium point with fair and competitive under conditions of uncertainty and risk (LeRoy, 1989). However, some market analysts are sceptical about the concept of EMH due to both theoretical and empirical arguments being well documented and claimed in journals. Meanwhile, the behavioural finance paradigm is an alternative to prediction models by which predictions are made based on the multidisciplinary understanding of human actions and behaviour. Fromlet (2001) explains behavioural finance joins together investors' behaviour and market phenomena and applies knowledge taken from both the psychological field and financial theory while making investment decisions.

In behavioural finance, boundedly and adaptively rational behaviour plays a crucial role in making investment decisions. The bounded rational theory explains human beings behave rationally up to a certain limit and add behavioural heuristics and biases on top of that to make final decisions (Simon, 1955). Each and every individual makes decisions through personal preferences, choices, incomplete information, and different learning environment (Brocas & Carrillo, 2000). Further, human decisions are made on the basis of cognitive logic and cognitive heuristics and affective bias (Carmerer, Loewenstein, & Prelec, 2004; Shimp et. al. 2015). On the other hand, adaptive rationale indicates human preferences and expectations change on the basis of environment where they live due to behavioural forces (Tinbergen, 1939).

On asset price behaviour, many scholars documented that asset prices are not rationally related to firm and economic factors (Shiller, 1981; Summers, 1986). Psychological factors influence investment decisions in the stock market. Shleifer and Vishny (1997) claim that arbitrage is costly. Therefore, it could be restricted. Daniel, Hirshleifer and Teoh (2002) claim that arbitrageurs are not able to remove all systematic mispricing of assets due to risk aversion.

Psychological factors including herding and availability bias, overconfidence bias and conservatism bias could possibly affect financial decisions. Qadri and Shabbir (2014), Lim (2012), Qureshi et al. (2012) and Bashir et al. (2013) have claimed that overconfidence help positively while investment decisions are made. On the other hand, Atif (2014) and Kengatharan and Kengatharan (2014) have evidenced that overconfidence influences negatively on investment decisions. Furthermore, Ouni (2015) explored the Tunisian stock

market for the period between January 2000 and December 2010. The scholar evidenced that overconfidence increased the volume of transactions.

Graham, Harvey and Huang (2009) found that rich, highly educated and sophisticated investors are more competent and have more experience in the analysis of stock prices. Therefore, they are not overconfident but rational. Ekholm and Pasternack (2007) found that investors with larger portfolios are less overconfident than investors with smaller portfolios.

Meier (2014) detailed that investors slowly react to the new information and it is adjusted into prices only gradually in conservatism bias. Lim (2012) and Kengatharan and Kengatharan (2014) documented that conservatism influences positively on investment decision making.

Luong and Thu Ha (2011) disclosed that the herding behaviour of investors makes a market inefficient and volatile. Herding behaviour exists significantly with institutional investors rather than retail investors (Hirt and Block, 2012).) Herding behaviour impacts positively on investment decisions (Kengatharan and Kengatharan, 2014; Wamae 2013). Contrary to that Lim (2012) found that herding does not influence investment decision making.

Nofsingera and Varmab (2013) revealed that investors have a strong tendency on recent and easily available information rather than the overall situation in availability bias. Availability bias persuades positively on decision making (Qureshi, Rehman and Hunjra, 2012). Furthermore, Luong and Thu Ha (2011) availability bias has a moderate impact while Nofsingera and Varmab (2013) claims it has a strong impact on investment decision making in United States.

Overreaction hypothesis explains that market participants sometimes react excessively to market information which helps deviate stock prices temporarily from their fundamental value. The stock prices come back to fundamental value within a short period of time De Bondt (2000). The overestimation of information on asset prices during initial public offering cause prices up. When good or bad news come sequentially in the market, overreaction by the market participants takes place assuming the continuation of trend, Barberis et al. (1998). Daniel et al. (1998) claim that market participants are overconfident in their collected private information which lead to an overreaction in the market.

On the other hand, they tend to underreact in public information. Furthermore, Barberis et al. (1998) disclose that some market participants show conservative attitude to updating their model incurring the underreaction hypothesis. Kirchler (2009) claims that market

participants' overreaction or underreaction to information leads to overvaluation or undervaluation during bulls or bears market respectively.

Insider trading, behavioural finance and market regulation:

One form of behavioural finance is preference bias. Insiders show the attitude of preference bias for investing in stocks to exploit abnormal returns. Insiders' trading behaviours are affected greatly by stock market regulation. Insiders have a attitude to purchase stocks on the basis of information they hold. Stock market regulation helps a well-informed insider to disclose information in advance tends to increase welfare to both the insider and less-informed outsiders (Lenkey, 2014).

Irrational agents can earn more expected returns than rational ones. The irrational investors as a group can outperform the rational investors in terms of market returns due to private information (Hirshleifer, Subrahmanyam and Titman, 2006). Similarly, Tamersoy et al. (2014) found that insiders buy stocks when price is low and sell when price is high. They also found that trading behaviours of insiders (officers, directors, beneficial owners) differ based on their roles in the firms. Furthermore, Lo and Cheng (2006) evidenced that insiders strategically disclose bad and good news to benefit themselves. They claimed that when managers want to purchase shares, they disclose more bad news forecasts to reduce share price and good news forecasts when they want to sell the shares.

Some investors buy investment related information from company agents to make their investment decisions. Consequently, market becomes inefficient through misallocation of resources as informed traders earn more positive returns than rational traders and volatile as prices differ greatly from their fundamental values. Stock prices also underreact when announcements and disclosures are made (Daniel and Hirshleifer, 2015).

Contribution of behavioural finance to an understanding of this research

Misra (2017) explains that the two pillars on which the field of behavioural finance is formed are limits to arbitrage and psychology. The main contribution of behavioural finance is it helps to bring economic equilibrium when there is a price difference between two or more markets through limits to arbitrage. Technical analysis helps to predict a market on the basis of the historical trend of stock prices. When stock prices are unusual or differ from fundamental value, behavioural finance brings the prices to in an equilibrium point. It brings

prices to come back to the normal trend and helps technical models to predict prices precisely. Therefore, it is very necessary to consider behavioural finance in this research.

The second pillar on which behavioural finance is structured, is human psychology. Stock prices differ from fundamental value due to human psychology in investment decisions. Structural breakpoints take place due to overreaction of information caused by human psychology in investment decisions. Therefore, human behaviour is a determinant factor, this research should take it into consideration for predicting stock prices accurately. The best way to do that in technical analysis is to consider structural breakpoints into the analysis. Therefore, this study will take breakpoints in time series data into account and check them through Bai-Perron multiple breakpoints test to predict the stock prices in the London Stock Exchange precisely by avoiding their impact.

Overview

From the above analysis, it is found that investment decision is influenced in a large proportion by psychological and emotional factors. It is most likely that risk attitude, panic, anxiety, envy, greed, satisfaction, ambition or vanity play a robust role in making financial investment decisions. Behavioural finance is an alternative solution to the difficulties faced by the classical theory; the efficient market hypothesis. Market anomalies take place due to behavioural finance (BF) whereas efficient market hypothesis fails to defend it.

Behavioural finance is based on the assumptions that investors may be irrational in their reactions to new information and investment decisions. The EMH details that, all investors are rational whereas BF assumes investors could be irrational. Therefore, mispricing takes place in the market and rational investors are powerless to do anything about it. Irrational traders cause price deviations from the intrinsic value of stocks. Therefore, it could be concluded that investment decisions are made on the basis of rational and irrational behaviours of investors. All individuals do not behave rationally.

2.2.1 Market efficiency, Normality and Predictability and their relationships

Market efficiency, normality of distribution and predictability are closely related to each other. A significant number of studies regarding skewness, kurtosis and tail-fatness in the distribution of stock returns evidence that their movements are predictable. However, it is also evidenced that when returns are normally distributed, market is efficient and returns are not

predictable. This section explains regarding stock market efficiency, normal distribution, and predictability of stock returns and their relationships.

Market efficiency

Stock prices are not predictable when a market is efficient. In an efficient market, prices move randomly and independently. There is no correlation between price from earlier days and today. In an efficient market, security (for example, share) prices logically and rationally reflect all relevant new information (Arnold, 2008). Brigham and Ehrhardt (2011) concluded that whenever new information including disclosures and announcements is broadcast to people, stock prices will react only if they are different. If the news is same, stock prices would remain same. However, new information is unpredictable and random. Therefore, stock prices are unpredictable.

The efficient-market hypothesis (EMH) is the concept that no one can beat the market in any situation. The efficient-market hypothesis is closely related to the random walk hypothesis (RWH) and black swan theory. All of these theories claim that stock prices are unpredictable although information is available. However, this study discusses only RWH as it is closely related with weak-form market efficiency.

A random walk happens when new information arrives and reflects in the stock prices. Stock prices may change every moment because new information might arrive every moment, and new prices are set by relevant new information that might be good or bad for investors. News is unpredictable and consequently prices are random (Bodie et al., 2006). The next section talks about the classification of EMH.

Types of market efficiency:

Fama (1970) empirically found that an efficient market could take 3 forms. These are 1) Weak-form market efficiency 2) Semi-strong form market efficiency and 3) Strong-form market efficiency. These are detailed below.

1) Weak-form of market efficiency:

In the weak-form market efficiency, all historical information that can be derived by analysing market trading data such as historical price of stocks and volumes is fully reflected in the actual asset price. Therefore, the analysis of movements of historical stock price and volume is worthless. This is because, no investors can earn excess return from such analysis.

Weak-form market efficiency also details that asset prices follow random walk, which indicate that there is no correlation between subsequent price and previous prices. All prices are random and independent.

2) Semi-strong form of market efficiency:

In the semi-strong form of efficiency, future stock prices cannot be determined based on analysis of all publicly available information. Publicly available information includes annual reports and financial statements of companies, reports in the financial press, and historical data. Based on this kind of information, no one can earn excess returns (Brooks, 2009).

3) Strong-form of market efficiency:

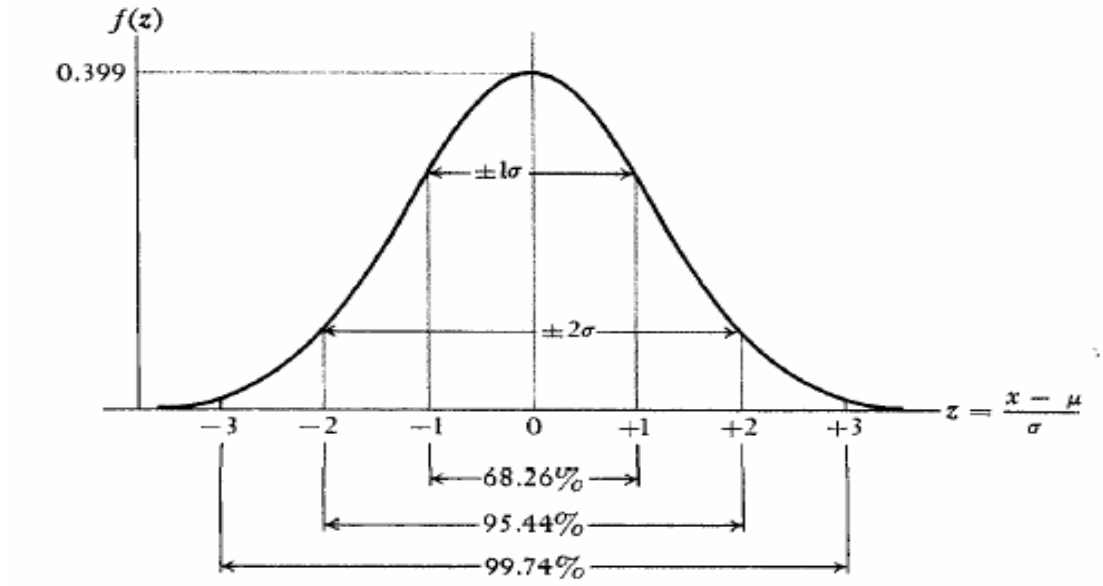
In strong-form market efficiency, future stock prices cannot be predicted based on all kinds of relevant information that are publicly and privately available including historical prices, financial statements, macro-economic factors, announcements, and company's private information; Fama (1970).

Normality/ Normal distribution

When the distribution is normal, stock prices are not predictable. This is because, stock prices change randomly and frequently in normal distribution. It is symmetric and bell shaped. Non-symmetrical distributions are positively skewed or negatively skewed. They could be leptokurtic or platykurtic too. A non-symmetrical distribution occurs when one side of the distribution does not mirror the other.

The normal distribution is symmetric about μ. Therefore, the area to the left of μ is equal to the area to the right of μ (50% each). A normal distribution assumes that all values in the sample will be distributed equally above and below the mean. About 99.74% of all variations falls within three standard deviations of the mean and remaining 0.26% chance of an extreme event occurring. Thus, normal distribution understates risk and volatility (Hayes, 2019). The figure 2.4 below shows normal distribution.

Figure 2. 4: Normal distribution



Source: Fleming and Nellis (2007), p. 127

Predictability

Weekly stock price data will be collected to identify relationships whether the data is correlated and these relationships will be used to make predictions. It is also necessary to measure the strength of relationships. Predictive modelling plays an important role in quantifying the level of predictability of measurable phenomena by creating benchmarks of predictive accuracy (Ehrenberg and Bound, 1993). Predictive modelling is the process of applying a statistical inferences to data for the purpose of predicting future observations (Geisser, 1993). Predictive modelling enables assessing the distance between theory and practice, thereby serving as a reality-check to the relevance of theories.

The relationships between market efficiency, normality and predictability

Predictability relates directly to the market efficiency. If market is efficient, it is not possible to predict the stock prices. If the market is inefficient, stock prices are predictable. When stock returns are mean reverting (prices move around the average price), they are predictable. In an efficient market, returns significantly deviate from the average returns. Therefore, returns are not predictable in an efficient market. When returns are normally distributed, they are not predictable. In normal distribution of stock returns, the standard deviation is very large. Returns deviate greatly from the mean value.

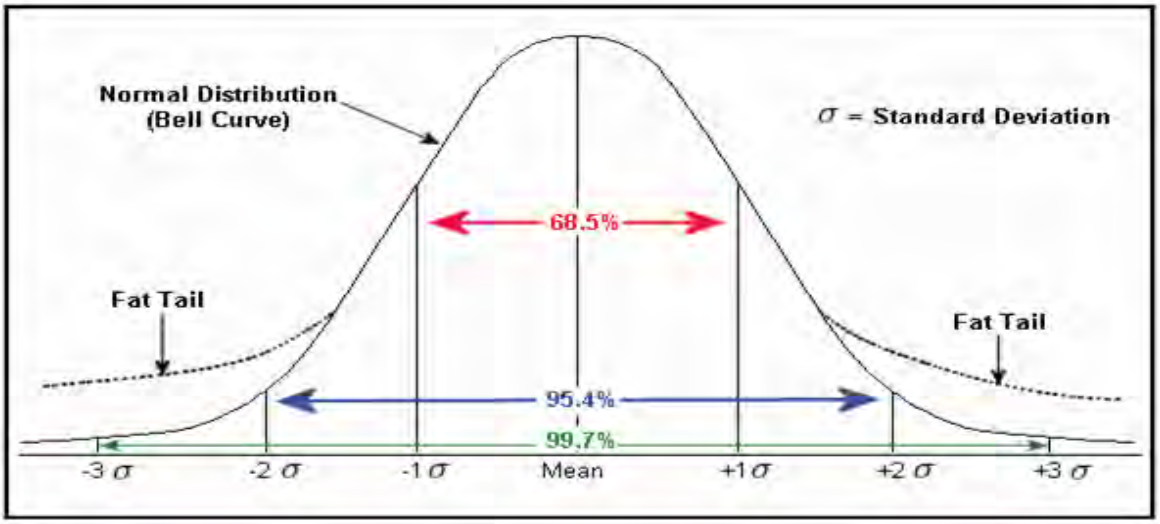
Therefore, prediction errors are very high. Normal distribution of data leads to market

efficiency. There is a positive relationship between normality and market efficiency. When the distribution is normal, market is efficient. When the distribution is not normal, the market is inefficient. However, there is a negative relationship between market efficiency and predictability of that market. When a market is efficient, stock returns are not predictable in this market. When it is inefficient, returns are predictable.

The association between heavy tails and normal distribution

This study will be using different forecasting models which include ARIMA, GARCH, Holt and Winters. The aim of this study was to evaluate the predictability of these models to conclude on the extent of reliability of technical analysis in investment decisions. The first thing every study does after collecting data, is to see whether they are normally distributed or skewed. These distributions of data provide a clue about investments. To perform forecasting through these models, researchers use log return of the raw data. However, log returns usually show heavy tails and skewness in the distributions and these are associated with financial risks and extreme events especially in the emerging and developed countries (Kittiakarasakun and Tse, 2011). Figure 2.5 below shows the association between the normal distribution and fat tail.

Figure 2. 5: Relationship between normal distribution and fat tail distribution



Source: Resnick, 2007, p. 123

The world experienced extreme financial events in 2008 and 2009 due to heavier tails and larger kurtosis (Mohtadi and Ruediger, 2013). Furthermore, the fat-tail property associated with extreme value distributions is more dominant than skewness in the sample (Bali, 2007). Although, tail events have a large impact on market returns and might cause a financial crisis,

the normal distribution shows a 0.26% (100-99.74) chance of an extreme event of risk and volatility occurring (Hayes, 2019). Parallel results were documented by Taleb (2007) who claimed that normal distribution underestimates the probability of extreme events in financial markets. Therefore, any financial model using normal distribution offers a very low chance of events in tail probabilities and thus might cause failures in risk management.

Similarly, Cartea and Figueroa (2005) documented that the existence of heavy tails in energy markets is so apparent and thus, the probability of extreme events is significantly higher than estimated by Gaussian distribution. In a related study, Aloui and Mabrouk (2010) confirm the existence of fat tails and long memory in energy markets. Moreover, Feng and Shi (2017) evidence that tempered stable distribution outperforms normal, Student-t and GED distributions. Similar outcomes were evidenced by Gunay and Khaki (2018) who claimed that capturing conditional distribution, fat tails and price spikes properly is key to the correct measurement of risk.

Contradictory results were obtained from the study conducted by Bali (2007) who disclosed that the Black-Scholes model and models based on the lognormal distribution of stock prices not only account for the negative skewness and the excess kurtosis but also largely influenced by unpredictable human behaviour, which leaves the market with fat tail risks. Similarly, Nirei (2006) found that systematic risks and herding behaviour could produce such events as well. Moreover, Gopikrishnan et. al. (1999) disclosed that systematic or market risk includes the dynamics of entry and exit behaviour of companies that provide short memory in the market could generate heavy tails. Similarly, LeBaron (2001) claimed that different patterns may emerge with different time horizons.

In relation to systematic risk, Banz (1981) included one more factor which is firm size and it has been one of the key factors to explain changes in stock returns. Similarly, Gabaix et. al. (2003, 2006, 2008) find that excess stock market volatility is due to trades by very large institutional investors in relatively illiquid markets. Furthermore, extreme events might take place due to power-law persists in the market, Stanley et. al. (2008).

These results are consistent with the findings of Stoyanov et al. (2011) who claimed that market crashes and volatility clustering may not fully account for the existence of fat tails in return distributions. As a result, neither market crashes nor volatility clustering explains the fat tails completely. On the other hand, Bollerslev (1986, 1987) documented that GARCH model is an extremely useful tool for describing the influence of volatility clustering and its

relationship to fat-tails in return distributions. Consistent results were found from the study conducted by Rachev et al. (2010) who evidenced that the fatness of the tails in return distributions tends to increase during market crashes.

Mantegna and Stanley (1995) and Ponta et al. (2019) evidenced that the fatness of the tails in return distributions is not constant, in accordance with changes in the measurement time interval used to convert price data into return data. Sornette (2008, 2009) argues that financial crashes are interdependent events, following several successive large declines and therefore should not be modelled as independently and identically distributed (iid) events as they are often done in Gaussian models. Similarly, Mohtadi and Ruediger (2012) claimed that Gaussian distributions are unable to explain extreme events because of their assumption that data points are independently and identically distributed (iid).

2.2.2 Theory regarding weak-form efficiency

The hypothesis of weak-form market efficiency claims if publicly accessible historical stock prices would have ever disclosed any credible indications as to upcoming performances, all types of institutional and retail investors would have previously understood to use such indications to gain supplementary income. Actually indications do not add any value to the investment. This is because they become extensively familiar as they generate an indication which would cause an instant price rise. When stocks are bought at a higher price, there is a higher possibility to incur loss from such investment (Bodie et al., 2006). However, in response to this position, an argument emerges that all investors are not statistically certified technicians, and that this does not allow them all to exploit the indications to predict future prices and enjoy abnormal returns.

In the weak-form, current stock prices are determined based on all past or historical stock prices. However, no one can earn an additional return by analysing the historical prices or trends. So, it is useless to predict future returns based on historical information (Glen, 2008). In response to this, an argument arises that although technical analysis is performed based on historical prices, historical prices provide clues about future performance of particular stocks. Therefore, the analysis of historical prices could generate future indication for investment through which abnormal returns could be enjoyed.

The idea that challenges weak-form market efficiency is called technical analysis. The next section clearly explains how technical analysis functions, and how it plays a role in predicting stock prices.

Technical analysis:

In technical analysis, historical data is analysed in a graphical way that shows trends or patterns in stock prices as a means to predict future prices. Technical analysis has evolved extensively from graphical presentations that were used in earlier days to sophisticated statistical methods now-a-days (Metghalchi and Gomez, 2013).

Technical analysis fails to predict future returns in EMH. However, technical analysts do not agree with the concept of EMH. They present trends in a graphical way and forecast future returns. They believe that future returns can be forecasted by drawing a diagram from historical data. The well-known diagrams are Head and Shoulder, line and breakout pattern, and filter approach (Bodie et al. 2006).

Technical analysts are sometimes called chartists, because they study records or charts of past stock prices, hoping to find patterns they can exploit to make profit. The Dow theory named after its creator Charles Dow (who established the Wall Street Journal), is the grandfather of most technical analysis. Dow theory details that there are three types of trends by which investment decisions are made:

i) Long-term trends: They arise when stock prices usually do not move up and down and remain same more than one year.
ii) Medium-term trends: They occur when stock prices move away from the underlying price trend and exist from three weeks to three months. Such deviations of stock prices are corrected by market actions in that time period.
iii) Short-term trends: These trends are seen from more than one day to less than three weeks. When stock prices move very frequently every day, they do not provide any trend or indication by which abnormal returns could be exploited.

EMH is closely related with random walk model (RWM). This model could be in the form of weak-form efficiency. Therefore, this model is required to explain in details. The next section explains RWM.

2.2.3 Theory regarding Random Walk model

The assumption of RWM is stock prices move randomly and abruptly and thus, prices are unpredictable. Random walk theory assumes that the analysis of historical prices will not able to predict the next movement as fluctuations of prices are independent.

Simple random walk:

Gujarati (2004) formulated random walk as follows:

$$VSTK_t = VSTK_{t-1} + \epsilon_t \quad (2.1)$$

Or, $VSTK_t - VSTK_{t-1} = \epsilon_t$

Source: Gujarati (2004)

Where,

$VSTK_t$ = Value of stock (stock price) at time period t (Stock's current period value)

$VSTK_{t-1}$ = Value of stock (stock price) at time period t-1 (one period before or stock value at the end of last period)

ϵ_t = the value of error term or white noise in time period t (a normal variable with zero mean and variance one).

The stock price (VSTK) is random and cannot be predicted. Although the mean of random walk process is constant, variance increases with t. Thus, random walk process is non-stationary where variance extends with time period t (Gujarati, 2004). There is a close relationship between random walk and white noise. White noise helps stock prices be random and therefore unpredictable. A few terms related to random walk are explained below.

White noise:

White noise occurs when variations arise in stock prices and volumes that cannot be accused for changing in macro-economic factors or company performance but due to private information and investors' irrational reaction to that information (Kehinde and James, 2013). Forecasted values from mathematical models can be fitted with time series data. However, residual errors (white noise) can still exist in the forecasted values or models, which are independent and serially uncorrelated. These could be shown through a correlogram. Random walk can be differentiated from white noise that random walk can fit time series data with

stochastic trends but white noise cannot. Gujarati (2004) explained random walk with drift, deterministic trend, and random walk with drift and deterministic trend are given below:

Random walk with drift (non-stationary):

$$VSTK_t = \quad + VSTK_{t-1} + \varepsilon_t \qquad (2.2)$$

Source: Gujarati (2004)

Where, $VSTK_t$ = Value of stock (stock price) at time period t (stock's current period value)

$VSTK_{t-1}$ = Value of stock (stock price) at time period t -1 (one period before or stock value at the end of last period)

ε_t = The value of error term or white noise in time period t (a normal variable with zero mean and variance one).

α = Drift,

For $\alpha > 0$ the process will show an upward trend. It is also known as positive drift or sub-martingale. If $\alpha < 0$, it is called negative drift or super-martingale in random walk. If $\alpha = 0$, it would be a normal random walk (Islam and Watanapalachaikul, 2005). In random walk with drift, the current stock price is equal to last stock price plus a constant or drift ( ) which acts like a trend and a white noise term (ε_t). In another word, the best forecast of tomorrow's price is today's price plus a drift term and a white noise term. It could be made a stationary process by differencing or subtracting $VSTK_{t-1}$ from both sides.

Thus, $VSTK_t - VSTK_{t-1} = \quad + VSTK_{t-1} + \varepsilon_t - VSTK_{t-1}$

Or, $VSTK_t - VSTK_{t-1} = \alpha + \varepsilon_t$

Then the process becomes difference-stationary. The disadvantage of this process is that the process losses one observation each time the difference is taken.

Deterministic trend:

$$VSTK_t = \quad + \beta_t + \varepsilon_t \qquad (2.3)$$

Source: Gujarati (2004)

Where,

$VSTK_t$ = Value of stock (stock price) at time period t (Stock's current period value)

α = Drift,

t = time period

β_t = time trend

ε_t = The value of error term or white noise in time period t.

Deterministic trend is closely related with random walk with drift. Both of them consider a constant and a white noise factor. However, they are different from each other. A random walk with drift considers last period's stock price whereas a deterministic trend takes into account a time trend (β_t) which changes with each period of time. A non-stationary process with a deterministic trend becomes stationary after removing the trend (β_t) or detrending. Thus, $VSTK_t - \beta_t = \quad + \beta_t + \varepsilon_t - \beta_t$ or, $VSTK_t - \beta_t = \quad + \varepsilon_t$, no observation is lost when detrending is used to transform a non-stationary process to a stationary one.

However, a trend stationary series which shows a structural break either in the intercept (level) or the slope of the deterministic trend (growth) cannot easily be differentiated from a non-stationary process. Thus, a unit root test which does not consider breaks in the series has very low power. A equation could be made that considers both random walk with drift and deterministic trend shown as follows:

Random walk with drift and deterministic trend:

$$VSTK_t = \quad + VSTK_{t-1} + \beta_t + \varepsilon_t \qquad (2.4)$$

Source: Gujarati (2004)

Or, $VSTK_t - VSTK_{t-1} = \quad + VSTK_{t-1} + \beta_t + \varepsilon_t - VSTK_{t-1}$

Or, $\Delta VSTK_t = \quad + \beta_t + \varepsilon_t$

Source: Gujarati (2004)

Where, $VSTK_t$ = Value of stock (stock price) at time period t (Stock's current period value)

$VSTK_{t-1}$ = Value of stock at time period t -1 (stock value at the end of last period)

ε_t = The value of error term or white noise in time period t.

It is a non-stationary process that combines a random walk with a drift component ( ) and a deterministic trend (β_t). It specifies the value at time or period 't' by the last period's value, a drift, a trend and a stochastic component. In the case of a random walk with a drift and deterministic trend, detrending can remove the deterministic trend and the drift, but the

variance will continue to go to infinity. As a result, differencing must also be applied to remove the stochastic trend.

As the theoretical part that basically includes the origin of technical analysis and its role to predict stock prices has been discussed, this research will now move to empirical findings about technical analysis and market regulation based announcements already conducted by many scholars to critically evaluate and justify their significance and validity in predicting stock prices. Thus, the next sections will critically assess the empirical findings from early studies on weak-form efficiency and company announcements as part of market regulation.

2.3 Findings from early studies

First, it evaluates, critically and rigorously, the validity and predictability of technical analysis, which may help to predict stock prices in the UK-regulated market. Then, in the subsequent sections, this research measures the empirical implications of company announcements as part of stock market regulations for market efficiency. The following section explains, criticises and evaluates the validity of technical analysis in emerging and developed markets.

2.3.1 Findings from the early literature regarding weak-form efficiency

Many researchers have reported contradictory results about technical analysis. Some have found that technical analysis could predict the future movements of prices. On the other hand, some researchers have found that technical analysis is unable to predict stock prices. Moreover, it involves transaction costs, and a naïve model defeats any of the technical analyses. However, the literature on financial forecasting documented evidence on the predictability of current prices from past prices. Metghalchi, Chang and Marcucci (2012) emphasized that technical analysis works only for underdeveloped or emerging countries and not for developed countries. Mollah (2007) explained that developed markets are usually efficient and that returns are independent and random.

Weak-form efficiency in underdeveloped and emerging markets:

Most of the studies show that stock prices are predictable in the emerging markets. A few studies document that results from developing markets are contradictory. Gilmore and McManus (2003) investigated weak-form efficiency of stock price in three European countries including Czech Republic, Hungary, and Poland and found that all the markets are

not weak-form efficient. Similar results were documented in the study conducted by Smith and Ryoo (2003) who analysed five developing stock markets in Europe including Hungary, Portugal, Poland, Greece, and Turkey. The study evidenced that all the markets are not weak-form efficient except Istanbul market. This may be because, Istanbul is a comparatively large market.

Abrosimova, Dissanaike, and Linowski (2005) tested the weak-form efficiency in the Russian stock market and documented that the market is weak-form efficient when risk and transaction costs are taken into account. On the contrary, Hassan, Haque, and Lawrence (2006) found that the Russian stock market is not weak-form efficient. Hasanov and Omay (2007) examined eight stock markets including Chinese, Bulgarian, Czech Republic, Hungarian, Polish, Romanian, Russian, and Slovakian stock markets. The applied tests provided contradictory results. Mixed results were obtained from different tests in another study conducted by Omay and Karadagli (2012) who examined weak-form efficiency of Bulgarian, Greek, Hungarian, Polish, Romanian, Russian, Slovenian, and Turkish stock markets.

McGowan and Ibrihim (2009) and Rasajski and Rankov (2016) documented that the Russian stock market is not weak-form efficient due to thin trading and lack of transparency and sufficient market regulation. McGowan (2011) re-examined the weak-form efficiency of the Russian stock market and found that the market is efficient after 2000. However, Terence, Cheng, and Wong (2010) claimed that the stock market in Russia is the most inefficient among Brazil, Russia, India, and China (BRIC) and that Brazil is the most efficient market. Similarly, a study conducted by Chen and Metghalchi (2012) found that Brazil is a very efficient market.

Jose and Suresh (2017) explored NSE in India and uncovered that stock prices of NSE are not random and the market is inefficient in the weak-form. However, Gupta and Yang (2011) obtained mixed results for different sub-sample periods in the Bombay Stock Exchange and National Stock Exchange in India. Similarly, Lim, Habibullah and Hinich, (2009) found weak-form efficiency for a few sub-sample periods and weak-form inefficiency for other sub-sample periods in both the Shanghai and Shenzhen Stock Exchanges.

Contrary to the above study, Liu (2011) found that the Chinese stock exchange is not weak-form efficient. Consistent results were documented in another study conducted by Wang, Zhang, and Zhang (2015) for seven Asian stock markets including Hong Kong, Thailand,

China, Japan, South Korea, Malaysia. and Singapore. A similar result was documented in another study conducted by Rahim, Arizan, and Nor (2016). The results provided strong support to earlier evidence that the stock market in Malaysia is not weak-form efficient.

Dhaka Stock Exchange (DSE) is not weak-form efficient and the returns are predictable; Mobarek and Keasey (2000), Mollah, Rahman, and Islam (2005). Contrary to this research, Islam and Khaled (2005) and Ahsan and Sarkar (2013) found that market was predictable prior to the market crash but not predictable after the crash in 1996. However, Khan and Huq (2013), Miah and Banik (2013) claimed that returns of DSE are predictable using ARIMA model. Furthermore, Rehman et al. (2018) found stock markets in the India, Pakistan and Bangladesh are weak-form inefficient. Similarly, Rehman and Qamar (2014) and Khan et al. (2016) documented weak-form inefficiency for the Karachi Stock Exchange (KSE).

Peyavali and Sheefeni (2016) documented that the Namibian Stock Market in Africa is weak-form efficient. However, Appiah-Kusi and Menyah (2003) found mixed results in eleven African emerging stock markets including Ghana, Botswana, Egypt, Ivory Coast, Mauritius, Morocco, Kenya, Nigeria, South Africa, Swaziland, and Zimbabwe.In a similar study, Mollah (2007) documented that returns are predictable in the Botswana Stock Exchange and the market does not follow random-walk behaviour. Contrary to this study, Akinkugbe (2005) showed that the Botswana stock market is informationally weak-form efficient.

Contradictory results were obtained in the stock markets of the Middle Eastern countries. Al-Jafari (2011a) and Al-Jafari (2011b) revealed that both Kuwait and Bahrain stock markets are weak-form inefficient. Maghyereh (2003) and Jaradat and Al- Zeaud (2011) disclosed that the Amman Stock Exchange (ASE) does not follow random walk hypothesis and is inconsistent with weak-form efficiency. This contradicts the findings of Civelek (1991) who claimed that ASE is informationally weak-form efficient. However, Al-Jafari and Altaee (2011) investigated weak-form efficiency in the Egyptian Stock Market. They revealed that the market is not weak-form efficient.

Awad and Daraghma (2009) found that weak-form efficiency does not exist in the Palestinian Securities Market. Consistent results were evidenced by Omran and Farrar (2006) who examined weak-form efficiency for five Middle Eastern countries. They found that none of the markets is weak-form efficient. Similarly, Salameh et al. (2011) tested the weak-form efficiency of twelve Arab stock exchanges. The empirical results showed that all twelve Arab stock markets do not behave randomly under the ADF and PP unit root tests. Contrary to

these studies, Abdmoulah (2010) tested the weak-form efficiency for 11 Arab stock markets using GARCH-M (1, 1) and found that all markets are weak-form efficient.

Marasheh and Shrestha (2008) tested the United Arab Emirates (UAE) Securities Market and documented that stock prices have unit root and they change abruptly and randomly, satisfying the requirements of weak-form efficiency. Parallel results were documented by Mustafa (2004) who claimed that the UAE market is informationally weak-form efficient. Mixed results were documented in a study performed by Butler and Malaikah (1992) who explored market efficiency in Saudi Arabia and Kuwait.

Contrary to this study, Hassan, Al-Sultan, and Al-Saleem (2003) claimed that the Kuwaiti Stock Exchange is not weak-form efficient. Similarly, Abraham, Seyyed, and Alsakran (2002) scrutinized stock market efficiency in Bahrain, Saudi Arabia, and Kuwait. The results showed that all of the markets are not weak-form efficient and they do not follow a random walk model. Similarly, Al-Ahmad (2012) evidenced the Damascus Securities Exchange (DSE) is informationally weak-form inefficient. Abbas (2014) reinvestigated the Damascus Securities Exchange and found similar results.

Ojah and Karemera (1999) found the stock markets of Argentina, Brazil, Chile, and Mexico are consistent with random walk hypothesis and weak-form efficiency. Similar results were obtained by Grieb and Reyes (1999) who conducted a study in Brazil and Mexico and evidenced that stock markets are weak-form efficient. However, Urrutia (1995) found stock markets in Argentina, Brazil, Chile, and Mexico do not follow a random walk hypothesis. Furthermore, Palma and Sartoris (2016) claimed that the Brazilian exchange market is not weak-form efficient.

But the limitation in the above studies is that they have not considered structural breaks that could exist in the time series data which could be resulted from any financial or political crisis. A number of approaches could be applied to test the random walk hypothesis of stock prices (Tiwari and Kyophilavong, 2014). One of them is a unit root test. If a unit root exists in data, it indicates the data series follows the random walk hypothesis. But if data is mean reverting, it indicates that the random walk hypothesis is not accepted (Mishra and Smyth, 2017). In response to limitation of early studies, Ismaiel (2017) considered structural breaks in the stock prices. The results showed that Damascus Securities Exchange (DSE) follows random walk hypothesis. Parab and Reddy (2020) examined the role of Bai-Perron's multiple structural breaks for different time periods in response to dynamic macroeconomic variables.

Summary of findings from emerging and underdeveloped markets:

The results from the application of technical analysis in underdeveloped and emerging markets disclose that most of the markets are predictable. Furthermore, some scholars have found mixed results that a particular market is evidenced as weak-form efficient by the application of a few technical tools, whereas the same market is found as weak-form inefficient when different scholars have tested the market by applying different methods of technical analysis. Therefore, results of technical analysis from underdeveloped and emerging markets are still unresolved. This research has not found any study to be conducted on the basis of industrial sectors explicitly. However, one study is found that considers industrial-sectors partially in the emerging country that Sofat (2016) has analysed the stock prices of eight IT sector companies from the National Stock Exchange (NSE) in India.

Most of the studies have not considered structural breaks in their studies. However, more recent studies have shown their application and, therefore, their results are more reliable. Fama (1970) and Chittedi (2014) disclosed that there are some pre-conditions before testing market efficiency which include markets have to be large and competent, all relevant information about economy and individual firm is freely available to all investors, all investors are rational, information comes to the market independently and in a random fashion, there is no transaction cost and all information has to be incorporated into prices instantly and correctly. However, underdeveloped and developing countries lack these attributes. Therefore, there is no point to test market efficiency in underdeveloped and developing countries.

Early studies of Developed Markets:

Most early research on investigating weak-form efficiency, initiated on the developed stock markets, support the weak-form efficiency of the stock markets taking into account transaction cost and a low degree of auto correlation (Kendall 1953, Cootner 1962, Osborne 1962 and Fama 1965). All of these researchers found that stock prices change randomly, frequently, and independently. Therefore, future prices are not possible to predict on the basis of past performance of stocks especially when transaction costs are considered.

Some researchers found that the forecastability of stock price alters in developed markets, however, they did not conclude regarding profitable trading rules (Fama and French 1988, Poterba and Summers, 1988). Poterba and Summers (1988) claimed that noise trading and

demand for stocks are measured by several factors other than desired returns of investors. They claimed that serial autocorrelation in stock prices take place when researchers try to construct and examine the theory of noise trading. Fama and French (1988) surmised that stock market inefficiency could happen due to serial correlation. However, none of the studies consider serial correlation in stock prices that could take place when a long historical data is taken even in a developed market. Hudson, Dempsey, and Keasey (1996) claimed that the technical analysis could have forecasting power but not adequate to satisfy an additional return in the UK stock market.

Mills (1997) evidenced that technical analysis generated profits in the London Stock Exchange until 1979. However, the application of technical trading rules could not beat the buy-and-hold strategy after 1980. The reason that Mills suggested was that the predictability in the period between 1935 and 1979 was driftless (stationary). Contrary to these findings, Brock et al. (1992) applied the same trading rules to the American stock market and found that they worked successfully throughout the sample period. However, Mills (1997) found a discrepancy in the last sub-sample period, which is doubtable. Furthermore, if the specified period was driftless, the market would have collapsed. Therefore, the findings of the research are confusing and seem to be invalid. Summers, Griffiths, and Hudson (2004) investigated the validity of technical analysis of the London Stock Exchange and confirmed their assumption that returns are predictable.

McMillan, Speight, and Apgwilym (2000) found that the FTSE 100 index and FTA All-Share Index in the UK provide returns. Similarly, Maris et al. (2004) evidenced that the FTSE (UK)/the ASE (Greece) 20 stock index provide prediction more precisely for short-term investment, especially for one week.

Lee (1992) investigated weak-form efficiency in ten developed countries including Japan, Australia, Belgium, France, Italy, Netherlands, Canada, Switzerland, United Kingdom, and West Germany. His applied variance ratio test showed that all markets are weak-form efficient and prices move randomly. Consistent with the study of Lee (1992), Choudhry (1994) found that the stock prices of developed countries including United Kingdom, France, Italy, Japan, German, Canada, and United States of America are not predictable. However, Al-Loughani and Chappel (1997) examined the London Stock Exchange and claimed that stock prices do not behave randomly and they are predictable. Similarly, Du and Wong (2018) found that the forecastability of technical analysis in the Singapore Stock Market.

Groenewold (1997) examined Australia and New Zealand for the periods between 1975 and 1992 and obtained mixed results. Furthermore, Chan et al. (1997) studied eighteen stock markets from developed and developing countries including the UK, the USA, Canada, Germany, France, Italy, Spain, Denmark, Finland, Netherlands, Norway, Sweden, Switzerland, Australia, Belgium, Japan, India, and Pakistan and documented that all the developed markets are weak-form efficient.

Lee et al. (1999) explored the Spanish future market and found that the market is weak-form efficient and prices change very frequently. In relation to the findings of Lee et al. (1999) and Groenewold (1997), Worthington and Higgs (2006) studied sixteen developed and four developing stock markets in Europe. They claimed that only Germany, Ireland, Portugal, Sweden, and the United Kingdom of developed countries strictly follow a random walk hypothesis. Consistent results were found from the study conducted by Andrews and Hellen (2010) who found that the European markets of Germany, Ireland, Portugal, Sweden, and the UK follow a random walk fashion.

Similarly, Adebayo (2013) confirmed the weak-form market efficiency for the UK for the period between 2006 and 2011. Moreover, Konak and Seker (2014) reconfirmed the existence of weak-form efficiency for the UK stock market. The developed markets, such as the US and UK markets, are perceived as being weak-form efficient, but other studies found support for the inefficiency of these markets. For example, Otilia (2011) studied the US, UK, and the Japanese market, Shynkevich (2012), Arevalo et. al. (2017) and Lin (2018) in US market. All the researchers claimed that these markets do not follow a random walk hypothesis over the inquiry period and returns are predictable. Furthermore, Ghimire et al. (2016) investigated the validity of weak-form market efficiency for six developed and underdeveloped agricultural markets. The findings show that all the markets are weak-form inefficient.

Smith (2012) tested martingale behaviour of stock prices for fifteen developing markets in Europe including Croatia, the Czech Republic, Estonia, Hungary, Iceland, Latvia, Lithuania, Malta, Poland, Romania, Russia, the Slovak Republic, Slovenia, Turkey, and the Ukraine, and three developed stock markets including Greece, Portugal, and the UK. The variance ratio tests evidenced the mixed results that developed markets are not always weak-form efficient. The results detail that the Turkish, UK, Hungarian, and Polish stock markets are highly weak-form efficient. The consistent results were documented by Ahmad et al. (2017) who studied the London Stock Exchange and documented that moving average strategy substantially

outperforms a buy-and-hold strategy. However, the market is weak-form efficient as actual transaction costs are considerably lower than breakeven transaction costs. Groenewold (1997) also demanded that long historical prices have forecasting power in the Australian stock market, but the degree of forecastability is not significant.

Gan et al. (2005) claimed stock markets in Japan, New Zealand, Australia, and United States are weak-form efficient. Furthermore, Fang et al. (2014) reconfirmed weak-form efficiency of the US market. Similarly, Torun and Kurt (2008) evidenced that eleven European markets are weak-form efficient. Hasanov (2009) re-investigated the stock markets from Australia and New Zealand using the work of Narayan (2005). The application of unit root test documented that none of the markets are weak-form efficient, opposing the findings of Narayan (2005). Kim and Shamsuddin (2008) claimed that stock prices of highly developed markets move very frequently and randomly. Consequently, stock prices of these markets are unpredictable. Conversely, stock prices of under developing markets are mean reverting and predictable.

Early studies used traditional unit root tests to examine weak-form efficiency. Scholars have not considered structural breaks in the data set even in the developed markets. However, traditional unit root tests (ADF, PP, KPSS and so on) have low power to reject the null hypothesis of series have unit root in the presence of one or multiple structural breaks (Perron, 1989). Wu et al. (2019) found from the from the application of Bai-Perron test that structural breaks take place in stock market due to an event which impact fall on mean or variance or both level. As a consequence, Parab and Reddy (2020) found significant impact of multiple structural breakpoints on returns in the stock market of India caused by macroeconomic variables from the application of Bai-Perron test. Barari et al. (2014) found structural breaks in the housing prices from the application of Bai-Perron's multiple breakpoints test in U.S. Furthermore, Stylianou (2014) found a significant impact of multiple breakpoints in the relationship of growth, foreign direct investment and exports in the U.S.

Narayan and Liu (2013) identified one possible reason for that is not to consider structural breaks of dataset in the analysis. The early studies have largely ignored the presence of heteroskedasticity in the data series. Lim and Brooks (2011) revealed that when return series contains a unit root, they show a random walk and shock in that series and resulted in unpredictability of future return series based on past series. When return series are stationary, they exhibit a mean reverting and make it possible to predict future movement of returns using past data series.

Summary of findings from developed markets

Most of the developed markets (especially the London Stock Exchange in the UK) have documented that technical analysis cannot predict those markets and they are weak-form efficient. In this case, naïve models perform better. Therefore, the application of technical analysis especially in developed markets are worthless. However, the application of methods in technical analysis are evolving day by day. The analysts have been identifying the problems in the applied methods for not generating good results from predictions. For example, some scholars have recently considered structural breaks in the time series data in their analysis rather than applying traditional methods. The consideration of structural breaks may generate better forecasts.

Furthermore, it is observed in the literature review that technical analysis fails to predict stock prices in a developed market. Developed markets are weak-form efficient. Therefore, this study assumes that the consideration of company announcements as part of market regulations will strengthen the predictability of a developed market. No scholars have ever considered whether developed markets are predictable on the basis of industrial sectors. However, one study has considered the efficiency of banking industry in US market performed by Berger (1993). The next section explains the relationship between market efficiency and company announcements as part of stock market regulations.

2.3.2 Review of the early findings regarding the impact of company announcements as part of market regulations on market efficiency

It is a legal requirement to disclose all relevant information to the market participants on time. Announcements and disclosures of as much information as investors need enhance stock market efficiency. It is closely related with news and information being spread instantaneously in the market. One way of transparency is simply that news is announced in a timely manner, so that the surprise component from future events is lower. To formalize this notion of transparency, it is required that at the beginning of every period, there is some disclosure that reduces the variance of the cash-flow shock disclosed to the public at the end of the period. For a more transparent firm, more information is already available to market participants, reducing surprise from future announcements and maintaining market efficiency.

Jin and Myers (2006) claimed that, in a more transparent environment, proportionately more firm-specific information is disclosed to outside investors. Consequently, the overall return

variation is lower and return synchronicity is also lower. In a related study, Shehata (2017) found in the Gulf countries that corporate governance disclosure enhances firm value and capital market efficiency. On the other hand, Durnev et al. (2003) found that there is a strong relationship between higher information content about future earnings of a firm and higher stock price variation of that firm.

Piotroski and Roulstone (2004) documented that return synchronicity rises with analyst coverage. They explained that analysts are specialized in a particular industry. When the number of analysts is higher in different industrial sectors, more industrywide and marketwide information gets incorporated into stock prices. Similarly, Chan and Hameed (2006) found in an emerging market that higher analyst coverage enhances return synchronicity. The idea that a more transparent firm discloses more information in the market, consequently, future events are not new and price volatility is lower. Furthermore, Alfraih (2017) evidenced that intellectual capital disclosure is positively and strongly correlated with market value in the Kuwait Stock Exchange, indicating that higher disclosure of such information in the market helps to achieve higher capital market efficiency.

Disclosure of information to the market participants could be harmful for the companies, as well. Gilotta (2012) found that the requirement of too detailed or early disclosure of information improves market efficiency and protects investors. However, they would ultimately harm the firm's competitive capacity and the firm's capacity to raise finance and make the process of resource allocation less efficient. Therefore, the scholar claimed selective communication of information to the securities market would help markets to be more efficient and raising capital at the least cost.

However, Fishman and Hagerty (1989) developed a model which shows that when firm disclosure increases, the resource allocation efficiency increases. Furthermore, Gelb and Zarowin (2002) found that better disclosure policies are closely related to stock prices that contain more information about future returns changes. Bhattacharya et al. (2000) found that stock prices in the Mexican Stock Exchange respond very little to the company's announcements due to insider trading. In response to this study, Lenkey (2014) documented that advance disclosure requirements increase welfare for both insiders and outsiders.

Lang and Lundholm (1996) found that companies in a particular industry which are more transparent in their disclosure policies have a greater analyst following, more precise analysts' return forecasts, and less volatility between actual price and predicted price. Similarly, Yang

(2015) claimed that transparency enhances traders' participation activity and dynamic interactions and causes higher informational efficiency and greater market predictive accuracy. This view is similar to the study conducted by Rahman and Debreceny (2010) who argued that frequent corporate announcements through stock exchange websites increase market efficiency significantly.

In another study, Dasgupta et al. (2010) found that stock prices do not change significantly when companies make announcements in a transparent environment. In a related study, Odabasi et al. (2004) found that Istanbul Stock Exchange (ISE) is an efficient market due to informativeness of the market and thus, no significant stock return volatility was observed during the sample period.

Tinic (1995) claimed that government regulations do not stop the volatility of stock prices. A competitive environment and private organisational attempts can ensure market efficiency. Contrary to this research, Heflin et al. (2003) claimed that regulations regarding fair disclosures encourage firms to disclose information publicly rather than privately. They also found that fair disclosures reduce stock return volatility around announcements and improve the speed of incorporation of information into stock prices.

Liu (2010) claimed that stock market regulation makes transaction costs higher and more volatility in the market, whereas, deregulation makes transaction costs cheaper and more random, and unpredictable market. In relation to this study, Korsmo (2017) found that a security market would be fairer and more efficient if the Securities and Exchange Commission (SEC) or regulators design disclosure requirements to minimize the costs that sophisticated professionals face. Furthermore, Zhang et al. (2015) evidenced that information disclosure does not reduce market volatility significantly.

Ahmed and Schneible (2007) evidenced that fair disclosure reduces the quality of information that is available to investors prior to announcement in Korea. In a related study, Callen, Livant, and Segal (2006) found that annual reports are more informative than quarterly reports. As a consequence, long-term investors get less value-relevant information than short-term investors at Securities and Exchange Commission (SEC) filling date.

Opong (1996) found that stock prices move significantly in an hour of release of preliminary annual financial reports in the UK. Similarly, Park et al. (2013) claimed that the disclosure of preliminary financial reports prevent insiders to be benefited from insider trading.

Summary from early empirical findings of company announcements:

The relationship between market regulations on fair disclosure of information and market efficiency is a controversial issue. The implementation of market regulations has raised divergent opinions on market efficiency, although the majority of investors believe that regulations have increased fairness regarding the dissemination of information in the markets. There is significant evidence that market regulations have increased the availability and quality of information and thus that markets are efficient. A market regulation makes markets efficient, helps investors to access all the information at the same time, and ensures the availability of information. This section has analysed the relationship between market efficiency and market regulation.

2.3.3 Review of the early findings regarding predictability of technical analysis on industry sectors

The random walk, stationary, and predictability components in stock prices can differ across industries. Firm size and industry are dimensions known to capture differences in return behaviour (King, 1966; Banz, 1981; Huberman and Kandel, 1985). Fama and French (1988) evidenced that size and industry portfolios provide independent evidence on the behaviour of long-horizon returns. Hong, Torous, and Valkanov (2007) found that the US stock market is predictable to a short-horizon under industrial categories. They also found that stock markets react with a delay to the information contained in a particular industry about fundamentals and that information diffuses only gradually across markets. Similarly, Sofat (2016) analysed the stock prices of eight companies from the IT industry in the National Stock Exchange (NSE), India, and claimed that they are not informationally weak-form efficient. This study is motivated by this theory that stock prices could be predictable under different industrial categories, which is meagre but not extensive.

This concludes the literature review. The literature review discussed different technical analytical tools and their performance in predicting stock price. However, this study will not use all the methods that have been discussed. This research will apply simple, easy to understand and widely used but very effective methods for achieving the research aim and objectives. These methods are Holt's double exponential smoothing, Winters' triple exponential smoothing, GARCH model and Box-Jenkins' ARIMA model to achieve the research aim and objectives. The subsequent sections of the study will demonstrate briefly how the research aim, objectives and knowledge gap were derived from the literature review.

2.4 How the research aim and objectives were derived from the literature review

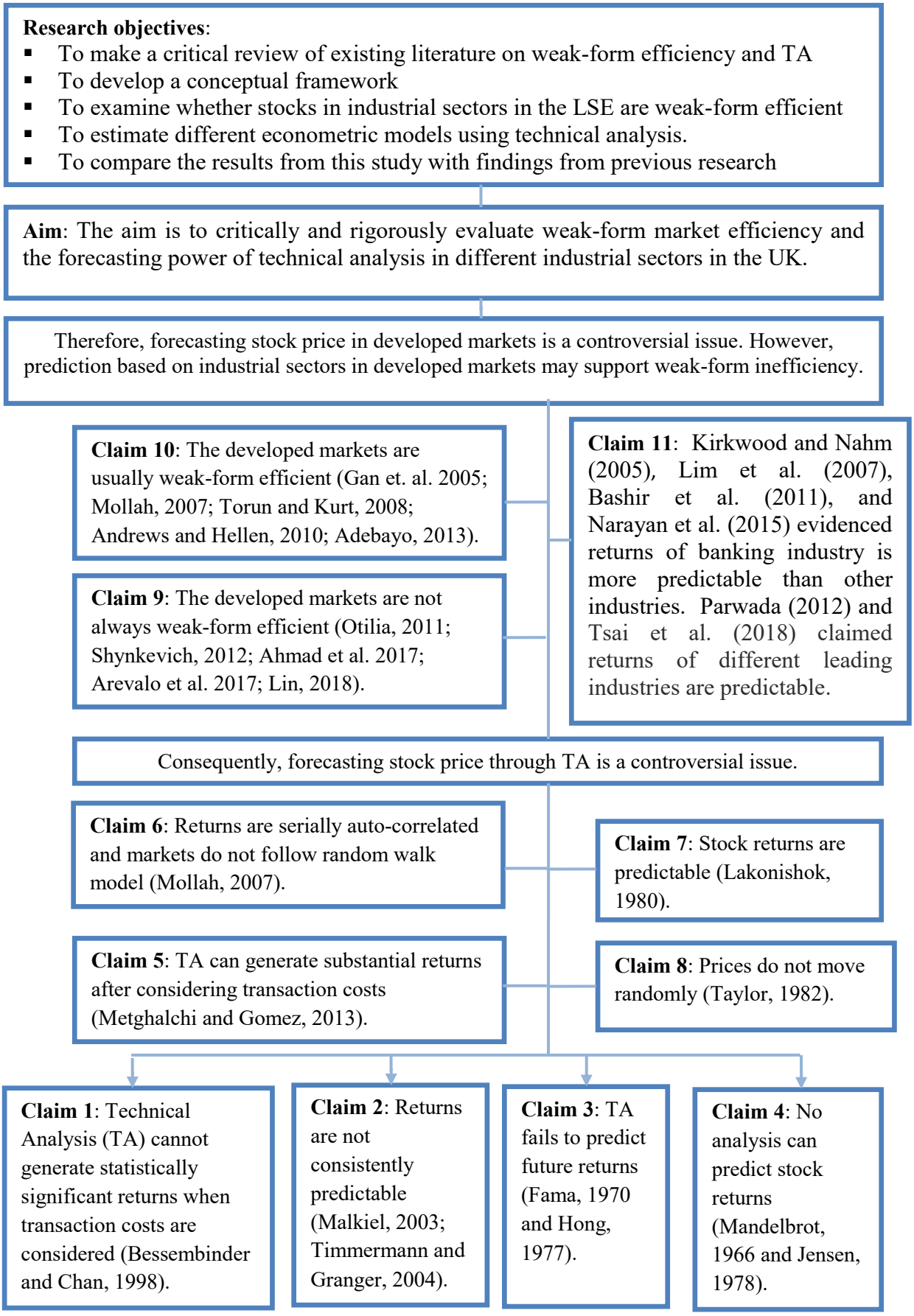
Many scholars have claimed from their findings that stock prices are not predictable. For example, Mandelbrot (1966), Fama (1970), Hong (1977), Jensen (1978), Bessembinder and Chan (1998), Timmermann and Granger (2004) and Malkiel (2003) agreed with similar findings that new information is independent, unpredictable and random. Stock prices incorporate new information very quickly. Prices change very frequently, and all the changed prices are independent, random and uncorrelated. As a consequence, future prices are unpredictable. It might be possible to earn a profit by predicting stock prices, but when transaction costs are considered, the prediction generates negative returns and the returns are lower than returns based on the buy-and-hold strategy, as transaction costs cannot be zero.

On the other hand, many scholars have recently found that stock prices are predictable. For example, Lakonishok (1980), Taylor (1982), Mollah (2007), Metghalchi and Gomez (2013), Shynkevich et al. (2017), Dai and Kang (2021) and many others have agreed with similar outcomes that stock returns are serially autocorrelated. Future prices are the reflection of past performances. Therefore, returns are predictable. Information is not incorporated into stock prices spontaneously, and it allows investors to exploit the time lag and earn abnormal returns even after considering the transaction costs. Therefore, it can be concluded that predicting stock prices through technical analysis is a controversial issue.

Furthermore, Metghalchi, Chang and Marcucci (2012), Mollah (2007) and so on explained that developed markets are usually efficient and that returns are independent and random. Advocates like Kirkwood and Nahm (2005), Lim et al. (2007), Bashir et al. (2011), Narayan et al. (2015), Tsai et al. (2018), Chen and Lai (2013), Sofat (2016), Gaganis et. al. (2013), Onwukwe and Ali (2018) and Parwada (2012) showed that a wide range of industry sectors successfully predict the direction of stock price movements due to their nature regardless the economic situation of a country. Thus, markets are inefficient and offer opportunities to investors to make abnormal returns on the basis of industrial-sectors.

From the literature review, the knowledge gap has been identified and the research aim and objectives have been defined. The following figure 2.6 shows the linkage between the literature review and the research aim and objectives:

Figure 2. 6: Designing reseaech aim and objectives



Source: diagram created by author

This study will assess critically and austerely the predictability of econometric models using technical analysis in the developed stock market, the London Stock Exchange to see whether weak-form efficiency exists in different industrial sectors or not. The next section will determine the knowledge gap from the existing literature to carry out research while addressing this gap and fulfilling the study's research aim and objectives.

2.4 Research Gap

Much research has been undertaken on technical analysis over the decades. However, the review of the existing literature identified a lack of such research in the UK. No studies have yet been carried out in relation to investment on the basis of the performance of a particular industry rather than randomly selected companies. No studies have yet investigated the combination of technical analysis and stock market regulation to forecast the stock prices of the London Stock Exchange (LSE). The research performed so far on forecasting stock prices through technical analysis or market regulation all over the world is listed below briefly in table 2.1:

Table 2. 1: Identifying the research gap

Name (s) of Scholar (s) and publication period	Research title	Name of journal	The applied methods	The name of stock market and sample period	Research findings	Form of efficient market hypothesis
Lo, Mamaysky and Wang (2000)	Foundations of technical analysis: computational algorithms, statistical inference, and empirical implementation	The Journal of Finance	The goodness-of-fit test, Kolmogorov-Smirnov test, descriptive statistics and kernel regression	New York Stock Exchange (NYSE), American Stock Exchange (AMEX) and National Association of Securities Dealers Automated Quotations	Researchers have detected some visual patterns including head and shoulder, rectangles, triangles, double tops and bottoms. They have found that such patterns are very useful in providing incremental information for buying and selling stocks, but that does not necessarily mean that technical analysis can be used to generate excess profits. These patterns add value in	Technical analysis

				System (Nasdaq) for the time span between 1962 and 1996	investment decisions.	
Zhu and Zhou (2009)	Technical analysis: an asset allocation perspective on the use of moving averages	Journal of Financial Economics	Moving Average (MA)	Standard and Poor 500 index from December 1926 to December 2004	When stock returns are predictable, technical analysis plays a substantial role in investment of fixed proportion of wealth in stock, but when uncertainty exists regarding investment in stocks, technical analysis with fixed allocation of asset in stock investment rule play a robust rule to make optimum investment.	Technical analysis
Brown and Jennings (1989)	On technical analysis	Review of Financial Studies	Correlation, variance analysis, covariance	AMEX for the period of 1978	When investors want to apply rational conjectures regarding future stock prices, technical analysis substantially helps make investment decisions.	Technical analysis
Hudson, Dempsey and Keasey (1996)	A note on the weak form efficiency of capital markets: the application of simple technical trading rules to UK stock prices – 1935to 1994	Journal of Banking & Finance	Descriptive statistics, Variable moving average (VMA) rule and Trading-range breakout rule (TRB)	FT30 (London Stock Exchange) from July 1935 to January 1994	The findings of their study are that technical analysis has predictive power only when a long series of data are considered and transaction cost (costly trading environment) is ignored, which confirms weak-form efficiency of the stock market in the UK.	Technical analysis
Ding, Granger and Engle (1993)	A long memory property of stock market returns and a new model	Journal of Empirical Finance	Descriptive statistics, ARCH model, autocorrelati on, GARCH	Daily closing prices of S & P 500 stock market for	If long term returns are considered, a very high autocorrelation exists in the return series although ARCH model denies this return property, but Monte	Technical analysis

			model, A-PARCH model	the period from January 1928 to August 1991.	Carlo study shows high autocorrelation for long lags.	
Jensen and Beningto n (1970)	Random walks and technical theories: some additional evidence	Journal of Finance	Levy's relative strength trading rule or portfolio upgrading rule, portfolio return calculation by considering transaction costs	Monthly closing prices, dividends and commission rates were taken from NYSE for the time span from January 1926 to March 1966	Risk and return have been calculated after deducting transaction costs. Researchers have found market does not follow random walk model, and buy and hold policy based strategy earns better returns than professionally managed portfolio.	Technical analysis
Blume, Easley and O'Hara (1994)	Market statistics and technical analysis: the role of volume	Journal of Finance	Brown and Jennings model, Grundy and McNichols model		Researchers have investigated the role of volume and found that it provides information and signals regarding information quality.	Technical analysis
Brown and Warner (1985)	Using daily stock returns – the case of event studies	Journal of Financial Economics	Skewness, Kurtosis, Ordinary Least Square (OLS) model, variance estimation	Centre for Research in securities prices at the University of Chicago (CRSP) that contains 250 samples of 50 securities for the period from 1962 to 1979	They have used daily data and found that daily data cause difficulties in the case of event studies but they provide serial autocorrelation in the stock returns, which is not available when monthly data are considered.	Technical analysis
Aiolfi and Favero	Model uncertainty,	Journal of	Thick model (multiple	US stock market for	Thick model strategy	Technical

(2005)	thick modelling and predictability of stock returns	forecasting	assets allocation portfolio model)	the time span from 1959 to 1992	outperforms the thin model.	analysis
Al-Jafari (2013)	The random walk behaviour and weak-form efficiency of the Istanbul stock market 1997-2011: Empirical evidence	International Journal of Management	Unit root tests, run tests and the variance ratio test	Istanbul Stock Exchange (ISE) for time span from 1997 to 2011	Stock returns do not change randomly and therefore, returns are predictable.	Technical analysis
Carvalhal and Mendes (2008)	Evaluating the forecast accuracy of emerging market stock returns	Journal of Emerging Markets, Finance & Trade	ARMA, GARCH, TARCH, EGARCH, FIGARCH and TARCH-M	General Index, Ibovespa, IGPA, IPC, Bombay Sensitivity Index, Jakarta Stock Exchange Composite, Seoul Composite, Kuala Lumpur Composite, Manila Composite, Singapore Straits Industrial, Taipei Weighted Price Index, Bangkok SET Index, S&P 500 and the Nikkei Average for the time span from	ARCH, EGARCH and ARMA provide better forecast ability for daily returns for longer period and out-of-sample forecasts respectively.	Technical analysis

				January 1994 to June 2006.		
Mahfoud and Mani (1996)	Financial forecasting using genetic algorithms	Applied Artificial Intelligence	Algorithms and neural networks	S&P 500 index for the period from May to June 1995	Genetic algorithm performs better than neural network system and both systems together perform significantly better than any individual system.	Technical analysis
Rehman and Khidmat (2013)	Technical analysis of efficient market hypothesis in a frontier market		Regression and correlation analysis	Karachi Stock Exchange from 2001 to 2011	Karachi Stock Exchange is weak-form efficient and returns are not predictable.	Technical analysis
Hokroh (2013)	An application of the weak-form of the efficiency hypothesis on the Saudi Arabia Stock Market (SSM) after Tadawul	Asian Journal of Finance & Accounting	Autocorrelation and run test	Saudi Stock Market (SSM) from January 2007 to May 2007	Returns are predictable before Tadawul but afterwards, prices change randomly.	Technical analysis
Bessembinder and Chan (1998)	Market efficiency and the returns to technical analysis	Journal of Financial Management	Variable moving average, fixed moving average and trading range break rules	DJIA US stock market data for the period between1926 and 1991	Market efficiency and statistical evidence of predictive power of technical analysis coexist in a way that simple technical analysis generates very small returns that cannot ignore the phenomenon of market efficiency.	Technical analysis
Grinblatt and Moskowitz (2004)	Predicting stock price movements from past returns: the role of consistency and tax loss selling	Journal of Financial Economics	Cross sectional regression and time series analysis	NYSE, AMEX and NASDAQ-NMS firms from 1963 to 1999	Technical analysis generates statistically significant returns through discovering anomalies including calendar month, size effect etc.	Technical analysis

Higgins (2011)	Forecasting stock price with the residual income model.	The Journal of Review of Quantitative Finance and Accounting	Residual income model (RIM) regression, GARCH model, naïve model and Darbin-Watson test	S & P 500 index for time span from 1982 to 2005	RIM provides better predictability with low mean absolute percentage error.	Technical analysis
Metghalchi and Gomez (2013)	The use of technical trading rules to predict overall stock price movements: A study on share prices on Irish Stock Exchange	International Journal of Management	MA, Relative strength index (RSI), parabolic stop and reverse, directional movement system, stochastic, and MACD	Irish Stock Exchange from March 1988 to October 2010	This study has found that if transaction cost is less than .5%, technical trading rules based strategies can beat buy and hold strategy with low risk and vice versa.	Technical analysis
Harel, Harpaz and Yagil (2010)	A new paradigm for forecasting security returns in a market regulated by price limits.	Review of Quantitative Finance and Accounting	Bayesian forecasting model	Stock market in the USA for the period 2008	They have innovated multi-period prediction model under 'price limit' regulation for US futures markets.	Technical analysis
Milionis and Papanagiotou (2011)	A test of significance of the predictive power of the moving average trading rule of technical analysis based on sensitivity analysis:	Journal of Applied Financial Economics	Moving Average (MA)	New York Stock Exchange (NYSE), Athens Stock Exchange (ASE) and Vienna Stock	Their statistical evidence indicates NYSE is weak-form efficient and ASE and VSE are not weak-form efficient except for some sub-periods.	Technical analysis

	application to the NYSE, the Athens Stock Exchange and the Vienna Stock Exchange, Implications for weak-form market efficiency testing			Exchange (VSE) from 1993 to 2005		
Taylor (1982)	Tests of the random walk hypothesis against a price trend hypothesis	Journal of Financial and Quantitative Analysis	autocorrelati on, spectral and run test	London Stock Exchange (LSE) for the time span 1966 to 1978	Prices do not move randomly and they have positive autocorrelation.	Technical analysis
Chakrabo rty (2006)	On the validity of Random Walk Hypothesis in the Colombo Stock Exchange, Sri Lanka	Decision	Unit root test, serial correlation, run test, variance ratio (VR) test, multiple variance ratio (MVR) test and ARMA model	Colombo Stock Exchange from 1991 to 2001.	Unit root test shows that market is efficient but rest of the tests invalidate random walk hypothesis. Moreover, results are very conflicting for individual company.	Technical analysis
Mishra (2013)	Random walk behaviour: Indian equity market	SCMS Journal of Indian Management	Unit root test and run test	India's equity market S&P CNX Nifty index for the period between January 2008 and March 2013	Stock prices are not random and returns are predictable.	Technical analysis

Chong and Ng (2008)	Technical analysis and the London Stock Exchange: testing the MACD and RSI rules using the FT30	Applied Economics Letters	Moving Average convergence divergence (MACD) and relative strength index (RSI)	London Stock Exchange from 1935 to 1994	They have found technical analysis can earn more returns than buy and hold strategy in maximum cases.	Technical analysis
Merh (2013)	Optimal model design of Artificial Neural Networks for forecasting Indian stock trends: An experimental approach	XIMB Journal of Management	Artificial neural networks (ANN)	Bombay Stock Exchange (BSE) from April 2004 to April 2009	The scholar has developed a model based on ANN that provides better forecasting power.	Technical analysis
Choudhry and WU (2008)	Forecasting ability of GARCH vs Kalman-Filter method: evidence from daily UK time varying Beta	Journal of Forecasting	Bivariate GARCH, BEKK GARCH, GARCH GJR, GARCH-X model and Kalman-Filter approach (KFA)	London Stock Exchange (LSE) from1989 to 2003	KFA provides better forecast accuracy than GARCH model through estimating beta. GARCH-GJR provides more accurate results than other GARCH models.	Technical analysis
Loh (2007)	An alternative test for weak-form efficiency based on technical analysis	Applied Financial Economics	Combinatio n of moving average and stochastic oscillators (MA-SO rules)	Stock markets of Australia, Hong Kong, Japan, South Korea and Singapore from 1990 to 2005	MA-SO provides 25% more predictive power than traditional MA	Technical analysis
Nemes and Butoi	Data mining on Romanian stock market using	Informatica Economica	Matlab, Weka and	Bucharest Stock Exchange	Integrated Matlab, Weka with T-MAS provide better	Technical analysis

(2013)	neural networks for price prediction		T-MAS	(BSE), Romania from 2012 to 2013	predictive power.	
Lee and Tzeng (2013)	Trend oriented training for neural networks to forecast stock markets	Asia Pacific Management Review	Bias, %R and MACD (moving average convergence and divergence) and combination of these.	Taiwan Stock Exchange Corporation (TSEC) from 2001 to 2005	The model provides 70% - 83.1% forecast accuracy based on the selection of single input or multiple inputs indicators.	Technical analysis
Jarrett and Schilling (2008)	Daily variation and predicting stock market returns for the frankfurter borse (stock market)	Journal of Business Economics and Management	Augmented Dickey-Fuller's unit root test and ARIMA model	Frank Stock Exchange and data were collected from stratified random sample	Frank Stock Exchange does not follow random pattern and returns are predictable.	Technical analysis
Jasic and Wood (2004)	The profitability of daily stock market indices trades based on neural network predictions: case study for the S&P 500, the DAX, the TOPIX and the FTSE in the period 1965-1999	Applied Financial Economics	Univariate neural networks	Stock markets of USA (S&P500), Germany (DAX), Japan (TOPIX) and UK (FTSE) from 1965 to 1999	Univariate neural network provides better predictability than conventional technical analysis.	Technical analysis
Liu and Zheng (2011)	Stochastic volatility model and technical analysis of stock price	Acta Mathematica Sinica	Black-Scholes model Bollinger bands, relative	NYSE from 1993 to 2005	Technical analysis indicators and stock price models help generate more profitability by reducing risk.	Technical analysis

			strength indicator (RSI), ROC (rate of change indicator) and rate of convergence			
Hanclova and Rublikova (2006)	Testing the weak-form of efficiency on Czech and Slovak Stock Market	The Journal of Badania Operacyjne i Decyzje	GARCH, EGARCH, TARCH and Martingale model.	Czech and Slovak Stock Market for the period between 2000 and 2004	Czech stock market is weak-form efficient, but the Slovak Stock Market is not weak-form efficient or returns are not normally distributed.	Technical analysis
Kohara et al. (1997)	stock price prediction using prior knowledge and neural networks	Intelligent Systems in Accounting, Finance and Management	Neural networks and multiple regression analysis	Tokyo Stock Exchange from 1989 to 1991	They have used economic indicators, international and political events as prior knowledge and put them together into a neural system that provides better forecast ability than multiple regression with lower errors.	Technical analysis
Balsara, Chen and Zheng (2007)	The Chinese stock market: an examination of the random walk model and technical trading rules	Quarterly Journal of Business & Economics	Naïve forecasting model and ARIMA model	Shanghai and Shenzhen Stock Exchanges from 1995 to 2005	Random walk model is absent and prices are predictable. ARIMA model outperforms naïve model.	Technical analysis
Hong (1977)	Predictability of price trends on stock exchanges: A study of some far eastern countries	The Review of Economics and Statistics	Serial correlation and run tests and Theil Leenders	Stock markets of Japan, Australia, Hong Kong and Singapore from 1973 to 1976	Larger markets and wide range of stocks are more efficient than small market.	Technical analysis

Abedini (2009)	Weak-form efficiency: stock market in the Gulf Co-operation Council countries (GCC)	SCMS Journal of Indian Management	Autocorrelation function (ACF), run test, Augmented Dickey-Fuller's unit root test (ADF) and variance ratio (VR) test.	Bahrain Stock Exchange (BSE), Kuwait Stock Exchange and Dubai Financial Market for the period between 2005 and 2008.	GCC stock markets are generally weak-form efficient.	Technical analysis
Islam and Khaled (2005)	Tests of weak-form efficiency of the Dhaka Stock Exchange	Journal of Business, Finance & Accounting	Augmented Dickey-Fuller's unit root test (ADF) and variance ratio (VR) test and Heteroscedasticity-robust Box-Pierce test	Dhaka Stock Exchange (DSE) for the period between January 1990 and November 2001.	Evidence indicates short-term forecast ability had existed before market crashed in 1996, but afterwards, the market has become efficient as transparency has increased.	Technical analysis
Mollah (2007)	Testing weak-form market efficiency in emerging market: evidence from Botswana Stock Exchange	International Journal of Theoretical and Applied Finance	Multi approaches or triangulation of parametric tests including autocorrelation co-efficient, autoregression, ARIMA model and non-parametric tests including	Botswana Stock Exchange for the period between 1989 and 2005.	The market is not weak-form efficient and returns are predictable as returns are serially auto correlated.	Technical analysis

			run test, Kolmogrov-Smirnov goodness of fit test.			
Chen, Huang and Lai (2011)	Data snooping on technical analysis: evidence from the Taiwan Stock Market	Review of Pacific Basin Financial Markets and Policies	Both bootstrapped tests including White's Reality Check and Hansen's superior predictive ability test	Taiwan Stock Market for the period between 1971 and 2006	Taiwan Stock Market is weak-form efficient.	Technical analysis
Choudhry and Wu (2008)	Forecasting ability of GARCH vs Kalman-Filter method: evidence from daily UK time varying beta	Journal of Forecasting	Four different GARCH model including GARCH, BEKK GARCH, GARCH-GJR and GARH-X model as well as Kalman-Filter approach	UK stock market for the period between 1989 and 2003	Kalman-Filter approach provides overwhelmingly better forecast ability than GARCH model.	Technical analysis
Lee (2010)	The impact of deregulation on stock market efficiency	The International Journal of Business and Finance Research	General variance ratio (VR) test, non-parametric based VR test and a rolling VR	Taiwan Stock Exchange for the period between 1970 and 2008	Researcher has found contradictory results that deregulation enhances efficiency in first and third deregulation period but market is not efficient in second deregulation period.	Technical analysis

			test			
Moustafa (2004)	Testing the weak-form efficiency of the United Arab Emirates Stock Market	International Journal of Business	Autocorrelation test, run test, skewness and kurtosis and lilliefors statistic	The United Arab Emirates (UAE) Stock Market for the period from October 2001 to September 2003	Scholar found that stock prices of UAE Stock Market are not in normal distribution. Run test documented that prices change randomly and the market is weak-form efficient. This is due to recently developed stock market regulations.	Technical analysis
Binder (1985)	Measuring the effects of regulation with stock price data	Rand Journal of Economics	Event studies	New York Stock Exchange (NYSE)	It is possible to predict formal regulatory announcements, but the methods and data (daily and monthly) that the researcher has used have little ability to detect the effects of regulation on price changes.	Technical analysis
Tseng, Kwon and Tjung (2012)	Time series and neural network forecast of daily stock prices	Investment Management and Financial Innovations	Time series decomposition (TSD), Holt-Winters model, ARIMA model and artificial neural network (ANN)	Data have been taken from the world's major stock markets for the period from 1998 to December 2010.	This study has been conducted during world recession and economic crisis. Researchers could not predict the market because of large prediction errors.	Technical analysis

Research Gap:

No one has ever investigated the predictive power of econometric models using technical analysis in the industrial sectors of developed stock market, the London Stock Exchange.

Furthermore, no body has ever examined that certain econometric models are better in certain industry sectors.

Source: table designed by author with research findings from different scholars

The previous sections have shown how the research aim, objectives and gap were derived from the literature review. The next section will identify the problems in the existing body of knowledge and how this study will contribute to this current knowledge.

2.5 Rationale for choosing this topic and expected contributions to the knowledge

Through the identification of the research gap, the reasons behind the choice of this topic are explained below, along with the contribution that is expected to be gained from this study.

Rationality

This study excludes all psychological (behavioural finance) and fundamental factors that help to change weekly stock prices and impact on prediction. Weekly stock prices are the outcomes of all fundamental and psychological factors. Therefore, this study assumes that it is meaningless to analyze fundamental and psychological factors or any type of analysis except technical analysis to predict future prices. This is because whatever fundamental or psychological reasons for a change in stock prices, if stock prices respond slowly enough and trends in the stock prices can be identified, future price movements could be predicted.

However, technical analysis is a controversial issue. A number of scholars have shown that stock prices are forecastable on the strength of historical data, and others have shown that markets are efficient; that is, no one can predict the markets. Some papers have documented that stock prices are predictable at a moderate level, and this is not statistically significant. On the other hand, a few other papers have discovered some anomalies that can be exploited to gain abnormal returns. Thus, theoretical and empirical studies have shown contradictory findings on the usage of technical analysis in terms of profitability.

A few scholars have uncovered that stock prices are predictable in underdeveloped countries, where information is not incorporated instantaneously and thus abnormal returns are achieved. These markets are not weak-form efficient. On the contrary, abnormal returns cannot be gained and stock prices are not predictable in developed countries, where all information is embedded into prices straightway. Therefore, these markets are weak-form efficient. Sometimes prediction provides contradictory results even for the same market when different methods are used. Therefore, the performance of technical analysis is still in dispute.

Many researchers are still exploring how share prices are determined. Various scholars have conducted ample empirical research on technical analysis and stock return predictability in many countries and employed many statistical techniques, but the empirical results are

polemic in that some scholars claim that returns are not predictable while others argue that returns are predictable.

On the basis of the above discussion, it is assumed that performing technical is current, relevant and very important to conduct at the PhD level. This study will look at the real picture of price movements in the stock market and not only employ sophisticated statistical techniques but also see the impacts of industry sectors on prediction to make précised prediction. This is a particularly current topic in the area of finance, which is why this topic was chosen. This study will contribute to the existing body of knowledge in the following way.

Expected contribution

Millions of studies have been conducted on the predictability of technical analysis. Most of them which are conducted on developed markets have documented that developed markets are weak-form efficient. This study believes that a developed market could be weak-form efficient. However, all the industries in a developed market could not be sufficiently efficient in incorporating all relevant new information into stock prices at the same time. This research assumes that some industries might hold weak-form efficiency and some do not. Some industries might be laggard to embed all relevant information into stock prices. Therefore, their stock prices are predictable. However, the existing literature has largely neglected this assumption.

On the basis of the above assumption, this paper will investigate all industrial sectors to see the predictability of those sectors in a developed market, the London Stock Exchange. Institutional investors and retail individual investors even from a developed market will be benefited if they are able to know before they invest which industry or companies in a specific industry provide greater predictability with the smallest forecasting errors to minimise risk and gain profits.

This paper will also contribute to the existing body of knowledge by diagnosing the series or industry-specific performance of econometric models and techniques. Certain econometric models could be better in certain sectors. A well-performed model might fail to predict stock prices for a particular industry or series. However, a less performed model could predict better where the well-performed model fails. This study will investigate the predictability of a model in relation to industrial sectors. Some forecasting models might be better for a specific series

or industry category and some might not be better in relation to some series or industry categories due to their specific characteristics. This indicates that exponential smoothing techniques might perform better in prediction for a series or industry where ARIMA fails. Therefore, this study will contribute by investigating company-specific or industry-specific characteristics that influence a model to perform better or worse.

The research aim and objectives, research gap and research contribution were drawn from the review of the existing literature in this chapter. This chapter also included the previous empirical evidence that documents that predicting stock prices based on technical analysis are a controversial issue.

The next chapter contains the conceptual framework which addresses how this research will be conducted based on the findings from the literature review to achieve the research aim and objectives.

Overview of chapter three

This chapter explains how the research will be conducted. This chapter develops a conceptual framework to planning the whole thesis. This chapter also discusses the statistical models and techniques (Holt and Winters' models, GARCH 1- 1 and ARIMA) that will be applied in chapter six to predict the stock prices of the LSE.

CHAPTER THREE: CONCEPTUAL FRAMEWORK

The term 'conceptual framework' defines how a research is carried out. The conceptual framework for this research has been drawn to provide a mental route map that explains the relationship between technical analysis and its variables. This chapter addresses a causal link between dependent and independent variables and operationalisation of the framework.

3.1 The variables in this study

A general conceptual framework usually consists of dependent and independent variables, which are described below:

Dependent variable:

Future stock prices will be predicted by factors identified through technical analysis. Therefore, stock price prediction is a dependent variable in this research.

Independent variable:

Stock prices have different values at different periods of the week; therefore, the price variables – including weekly closing prices of twenty companies listed on FTSE 100 from 4 different industries, FTSE –all share index and FTSE-350 general industrial index are independent variables in this research.

There are a lot of price influential factors that cause stock prices to change all the time. Therefore, all the factors including macro-economical and psychological factors that affect stock prices will not be used to make the conceptual framework of this research. The technical analysis is only the interest of this study. Furthermore, this research will not consider any sort of stock volume. Trading volume could be in the form of short interest from arbitraging and net open interest from options and future contracts which are closely related to technical analysis. This study will avoid them too due to time constraint.

Long historical price behaviour is analysed through different statistical models and techniques to predict future prices in technical analysis. This study will perform the technical analysis to predict future stock prices of the London Stock Exchange. It is not worth anything to analyze the psychological factors, fundamental factors or indeed any other type of analysis, except technical analysis. This is because, the analysis of historical stock prices provides trends.

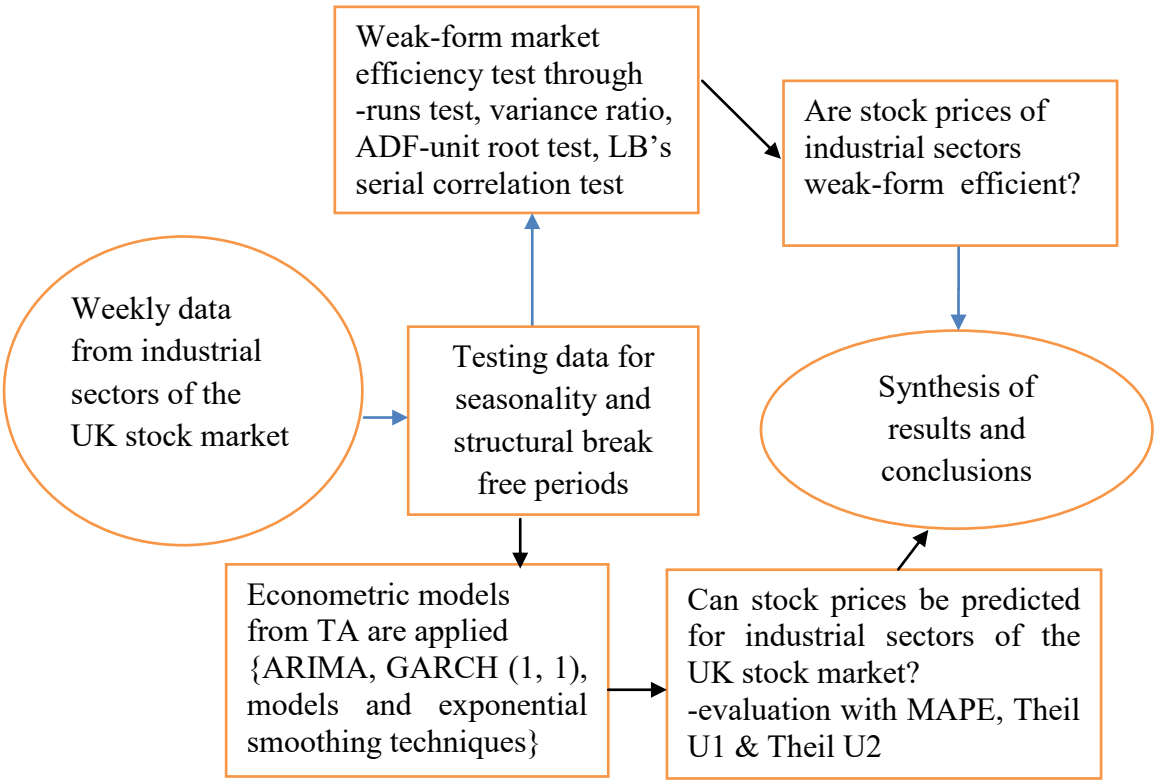
These trends will be exploited to predict future movements of stocks. Profits could be gained and losses could be stopped from the prediction of futures price movements.

This study will not consider all of the factors to design its conceptual framework. However, it will consider something new that has not yet considered in the existing theory. The technical components that the conceptual framework will consider in this study are discussed in the next section.

3.2 Designing and operationalizing the conceptual framework for this study

The present study will take into account the publicly available weekly closing price data of twenty companies listed on the FTSE 100 under four different industries for the period between 3 March 1997 and 16 July 2017, to predict the future stock price in the LSE. Furthermore, this study will include weekly closing prices of the FTSE- all share index and FTSE-350 general industrial index as a proxy to compare the results with those from 20 series from different industrial sectors. The following figure 3.1 shows the conceptual framework of this study:

Figure 3. 1: The conceptual framework of this study



Source: developed by author

This research will perform technical analysis on the basis of industrial sectors to determine the predictability of each sector. Weekly closing price data will be collected from different industrial sectors to evaluate their predictability. Furthermore, this study will collect weekly data from the FTSE-all share index and FTSE-350 general industrial index as a proxy to compare the outcomes with those from industrial sectors. It is assumed that all industrial sectors might not show the same level of efficiency. Some industries could adjust all relevant information into stock prices spontaneously and others might fail. In an efficient market, stock prices are reflected by all available information at the same time (Fama, 1970). The efficient market hypothesis might not work in all industrial sectors at the same time.

This study believes that when new information enters the market, they do not impact on all industries equally. It might not be possible for all industries in a market to embed all information at the same time. Some industries may be very competent and others may be laggard to adjust all relevant information into stock prices. Therefore, the stock prices of some industries may be more predictable than others. Keeping these beliefs in mind, this study will go ahead and evaluate these beliefs through statistical techniques and models to see how they work in reality.

However, in a weak-form efficient market, price movements are independent and random. Price trends and movements of all industrial sectors will be investigated critically through commonly used statistical methods in this study. This paper will apply different non-forecasting related statistical tests to see whether the market is weak-form efficient or not. The runs test, variance ratio tests, ADF-unit root test and Ljung-Box' autocorrelation test will be applied to draw statistical inference regarding weak-form efficiency.

The runs test helps measure the randomness of stock prices. Furthermore, randomness will be checked by running the variance ratio test as well. Stock prices might follow a martingale rather than random walk model. Variance ratio test determines whether stock prices follow a martingale or a random walk model. Ljung-Box's serial correlation will be applied to see any correlation or interdependence of data in a series at first difference. Furthermore, the ADF-unit root test will be applied to check whether any unit root exists in data at first difference. Therefore, the application of runs test, ADF-unit root test, autocorrelation test and variance ratio test is significant to achieve an objective in the list in chapter one.

The first condition of forecasting is data has to be stationary to predict the market. If data is not stationary, data has to be made stationary. Unit root test helps determine whether data is

stationary or not. The Augmented Dickey-Fuller (ADF) unit root test will be applied to measure that. However, it does not consider structural breaks in the time series. Therefore, Bai-Perron's multiple breakpoints test will be performed in this study to see any structural breaks. This study will select the sub-sample period where there is no structural break to ignore its impact on forecasts.

This research will use the line graphs, histogram and Kernel density graphs to analyse trends, patterns, and movements of historical stock prices. The GARCH (1, 1) model will be applied to measure the volatility of different industrial sectors as well as to predict their stock prices. The most common and widely used ARIMA, Holt and Winters' forecasting models will be applied to see their predictability and measure informational efficiency of different industrial sectors.

The forecast errors will be recorded to justify the results through evaluation statistics to meticulously evaluate the forecastability of technical analysis as well as the predictability of different industries. The forecast evaluation statistics including Theil inequality coefficient of U_1 and U_2 and mean absolute percentage error (MAPE) will be measured to measure the forecastability of a model. The forecast encompassing tests of Fair-Shiller and Chong-Hendry will be used to determine the better predictable model in this study.

This study will investigate the predictability of a model in relation to industrial sectors. Some forecasting models might be better for a specific series or industry category and some might not be better in relation to some series or industry categories due to their specific characteristics. This indicates that exponential smoothing techniques might perform better in prediction for a series or industry where ARIMA fails. Therefore, this study will investigate company-specific or industry-specific characteristics that influence a model to perform better or worse.

Furthermore, this study would like to determine the most predictable industry among four different industries using different technical models and techniques to challenge the weak-form market efficiency.

Finally, this study will articulate and synthesize the findings to see similarities between this study and findings from other studies conducted by different scholars. Moreover, A comparison will be made between findings from this study and those from other studies and conclude on contribution in expanding literature through this study.

Four different prediction models and techniques will be applied to determine the most predictable industry or companies in four different industries in the London Stock Exchange. The four models listed below will be applied to see their predictability. The equations from one to four listed below are available in the existing literature too.

(1) Holt' double exponential smoothing technique:

The Holt's double exponential smoothing technique will be applied to see if historical prices could predict stock prices or not. This is a very simple and commonly used forecasting model. Therefore, this model will be applied in this study. The equation for this model is given as follows:

$$L_t = \gamma\ VSTK_t + (1 - \gamma)\ (L_{t-1} + T_{t-1}) \qquad (3.1)$$

$$T_t = \theta\ (L_t - L_{t-1}) + (1 - \theta)\ T_{t-1}$$

$$\widehat{VSTK}_t = L_{t-1} + T_{t-1}$$

Where,

L_t is the level at time t, γ is the weight for the level

T_t is the trend at time t, θ is the weight for the trend

$VSTK_t$ is the value of stock (stock price) at time t,

$\widehat{VSTK}_t$ is the fitted value, or one-step-ahead forecast, at time t

(2) Winters' additive model of triple exponential smoothing technique

Winters' model considers seasonality in the time series data. Although there is no seasonality found in the data, this study apply this technique to see the difference in prediction. The Winters' model will be used to see whether it could predict stock prices better than Holt's model. The test is performed on the basis of the following equations:

$$L_t = \gamma\ (VSTK_t - S_{t-p}) + (1 - \gamma)\ (L_{t-1} + T_{t-1}) \qquad (3.2)$$

$$T_t = \theta\ [L_t - L_{t-1}] + (1 - \theta) T_{t-1}$$

$$S_t = \delta\ (VSTK_t - L_t) + (1 - \delta)\ S_{t-p}$$

$\widehat{VSTK}_t = L_{t-1} + T_{t-1} + S_{t-p}$

Where

L_t is the level at time t, γ is the weight for the level

T_t is the trend at time t, θ is the weight for the trend

S_t is the seasonal component at time t,

δ is the weight for the seasonal component

p is the seasonal period

$VSTK_t$ is the value of stock (stock price) at time t

$\widehat{VSTK}_t$ is the fitted value, or forecasted value (forecasted stock price) at time t

(3) GARCH (1,1) model

The GARCH (1,1) model will be applied to consider the volatility in the prices. Future stock prices will be predicted to see whether it could forecast better than ARIMA model or not. The equation of this model is given below:

$$\sigma_t^2 = \omega + \alpha y_{t-1}^2 + \beta \sigma_{t-1}^2 \quad (3.3)$$

Where $y_t = \sigma_t \epsilon_t$ [ϵ_t is white noise]

The parameter ω is related to the scale of the volatility and α and β to the dependence of the volatility on the past.

(4) ARIMA model

Finally, the ARIMA model will be used to see predictability of each company. The ARIMA model is the most widely used approach to time series forecasting. While exponential smoothing models (for example, Holt and Winters' models) are based on trend and seasonality in the data, ARIMA model aims to consider autocorrelations in the time series data. Therefore, this model will be applied in this study.

This research will be carried out by meticulously following the above-described conceptual framework. The next chapter, Chapter 4, details data and non-forecasting related research methods, providing a detailed explanation of how data and the adopted statistical methods will achieve research aims and objectives.

Overview of chapter four

This chapter explains that this study would take data from 3 March 1997 to 16 July 2017 and apply non-forecasting related methods including the runs test, descriptive statistics, variance ratio test, Augmented Dickey–Fuller (ADF) unit root test, Friedman test, Bai-Perron multiple breakpoints test and the correlogram. This chapter also explores the impacts of announcements and disclosures as part of market regulation on market efficiency through analysing the movements in stock prices in the line graphs, histogram, and kernel density graphs. This chapter finds that announcements and disclosures impact significantly change stock prices.

CHAPTER FOUR: DATA AND NON-FORECASTING RELATED RESEARCH METHODOLOGY

This chapter explains the sampling technique, sample period, sample size, source of the data and industrial classification. It also searches for and adopts an appropriate non-forecasting method and data analysis techniques that will help to achieve the research aim and objectives. The next section discusses and evaluates the sampling technique that will be applied in this study.

4.1 The adopted sampling technique for this study

There are two sampling techniques: probability and non-probability sampling. Non-probability judgemental sampling will be used in this study. This research will select a representative sample size based on judgement and a rational basis. This study will select FTSE-all share index, FTSE-350 general industrial index, five top companies on a specific day from each of four different industries. Therefore, the sampling method used in this study is non-probability judgemental sampling. The next section explains the source of the data and industrial classification.

4.2 Source of data, sample period and industrial classification

For this study 20 years' weekly closing data from 3 March 1997 to 16 July 2017 were collected through London South East (LSE) stock prices. These data include the weekly closing prices of FTSE-all share index, FTSE-350 general industrial index, 20 individual companies from 4 different industries for the purpose of evaluating the discrepancies between the actual price and the predicted price. Thus, there are 22 series, each of which contains 1064 observations except FTSE-350 general industrial index.

This is because, data of FTSE-350 general industrial index is not available for this time span. This series includes period from 07/06/2009 to 16/07/2017, which is 424 observations. However, this study has chosen an estimation period of 204 observations. Hyndman and Athanasopoulos (2018) explain that the number of observations should not be large especially for stock market as most time series do not work for very long time series. The number of observations should be around 200. Therefore, the short period of observations for FTSE-350 general industrial index will not affect significantly.

All the industries were classified into four types based on the functions that they perform. Five top companies from each industry listed on the FTSE 100 on a specific day were chosen for this study. Company related information from different industries has been extracted from London South East stock prices. These are listed below.

1. **The primary industry**

Different prediction models document that stock prices of each company in the primary industry are not predictable. Market news of the following companies are incorporated into prices instantly. Therefore, stock prices move randomly and the applied prediction models failed to predict their future prices.

Companies in primary industry extract and collect natural resources from the land, including oil, gas, gold and platinum. The primary industry also involves in fishing and farming. The five top listed companies in the primary industry on a specific day are Antofagasta plc (ANTO.L), BP plc (BP.L) and Centrica plc (CNA.L), Severn Trent plc (SVT.L) and Johnson Matthey (JMAT.L). Their products and functions that they carry out are provided below:

Antofagasta plc (ANTO.L):

Antofagasta plc explore, develop, and excavate copper properties in Chile. The company extracts from the land and processes molybdenum, gold, silver and copper cathodes. [London South East share price, company profile]

British Petroleum plc (BP.L):

The primary market for BP's ordinary shares is the London Stock Exchange. Ordinary shares are also traded on the Frankfurt Stock Exchange in Germany. BP plc operates as an integrated oil and gas company worldwide. It operates through three segments: upstream, downstream and rosneft. The upstream segment explores oil and natural gas, and develops field. This segment also involves in production, transportation, storage, and processing and marketing. The downstream segment involves in refining, manufacturing, marketing, transporting, supplying, and trading crude oil, petroleum, and petrochemical products and related services to wholesale and retail customers. The rosneft segment does exploration and production of hydrocarbons in different countries and also offers jet fuel, bunkering, bitumen, and lubricants. [London South East share price, company profile]

Centrica plc (CNA.L):

Centrica plc supplies competitive energy and provides services to the customers in United Kingdom, North America, Norway, and some other parts of the world. It operates through three segments including international downstream, international upstream, and Centrica storage segments. The international downstream segment is involved in the supply of gas and electricity. The international upstream segment produces, processes, trades in, and optimizes gas and oil; generates, trades in, and optimizes power from thermal, nuclear, and wind sources. The Centrica storage segment engages in the gas storage business. [London South East share price, company profile]

Severn Trent plc (SVT.L):

Severn Trent Plc was established in 1974. The headquarter of this company is in Coventry, the United Kingdom. Severn Trent Plc works as a water and sewerage company in the United Kingdom, the United States, and some other countries. The company performs activities through two segments, which are regulated water and waste water and business services. The regulated water and waste water segment gives water and sewerage services to approximately 4.5 million households and businesses in the Midlands and mid-Wales of the United Kingdom. The business services segment does contract services to municipal and industrial clients in the UK and the UK Ministry of Defence for designing, building, and operating water and waste water treatment facilities and networks. This segment also provides contract services to community, municipal, and industrial clients for the operation and maintenance of water and waste water treatment facilities and networks in the United States and generates renewable energy from wind turbines, anaerobic digestion, hydropower and solar technology. [London South East share price, company profile]

Johnson Matthey (JMAT.L):

The company was known as Johnson & Cock in the past, however it has changed its name to Johnson Matthey Plc in 1851. Johnson Matthey Plc was established in 1817. The company has got its headquarter in London, the United Kingdom. Johnson Matthey plc works as a specialty chemicals company in North America, Europe, China, rest of Asia, and other parts of the world. It operates through five divisions which are emission control technologies, process technologies, precious metal products, fine chemicals and new businesses. The emission control technologies division produces catalysts which control harmful emissions

from cars and other light duty vehicles powered by various types of fuel, as well as from diesel powered trucks, buses, and non-road machinery.

The Process technologies division produces catalysts, additives and absorbents as well as licenses process technologies and delivers services to the petrochemical, biochemical, syngas, oil refining, and gas processing industries. The Precious metal products division involves in managing, distributing, refining, and recycling precious metals and other special material using precious metals or related materials, platinum group metal catalysts, and platinum group metal chemicals for automotive and chemical markets and develops and manufactures functional coatings and inks.

The fine chemicals division involves in developing and manufacturing active pharmaceutical ingredients for various treatments including pain management and attention deficit hyperactivity disorders and specialty chemical, chiral, and biocatalytic technologies and products, as well as provides custom pharmaceutical research, development, and manufacturing services. The new businesses division performs research, development and manufacture of battery materials; design and supply of battery systems and development and manufacture of catalysts and components for fuel cell markets. [London South East share price, company profile]

2. The secondary or manufacturing industry

The applied prediction models including ARIMA, Holt-Winters cannot forecast stock prices of the following companies in the manufacturing industry. Stock market regulation helps stock prices move very quickly. Company announcements and news are embedded into prices rapidly. Therefore, the applied models are unable to predict their prices. However, GARCH (1,1) model shows that all the companies in manufacturing industry are predictable although forecast encompassing test denies their predictability.

Companies in the secondary industry involve in manufacturing and selling different products on the basis of the customers' needs, wants and demands. The selected companies from this industry are Associated British Foods plc (ABF.L), British American Tobacco plc (BATS.L), Barratt Developments plc (BDEV.L), Berkeley Group Holdings plc (BKG.L) and Diageo plc (DGE.L). Their products, markets and functions that they perform are given below:

Associated British Foods plc (ABF.L):

This company is a multinational company. It manufactures and sells consumer products all over the world. This company has four segments to operate its activities which are grocery, agriculture, ingredients, and retail. The grocery segment does manufacturing and selling different grocery products to final consumers and wholesalers. The agriculture segment involves in producing and selling animal feeds. The ingredients segment does bakers' yeast, bakery ingredients, enzymes, lipids and cereal specialties. The retail segment does buying and merchandising clothing and accessories through the Primark and Penneys retail chains, which provide a wide variety of womenswear, lingerie, childrenwear, menswear, footwear, accessories, hosiery, and homeware to the customers. [London South East share price, company profile]

British American Tobacco plc (BATS.L):

This company provides tobacco and nicotine products to the consumers around the world. It sells its products in more than 200 markets. It involves in selling cigarettes, roll-your-own tobacco, cigars, and snus, as well as other nicotine products, and electronic cigarettes. This company offers its products in the Asia-Pacific, the Americas, Eastern and Western Europe, Africa, and the Middle East. [London South East share price, company profile]

Barratt Developments plc (BDEV.L):

Barratt Developments plc performs the housebuilding and commercial development businesses in Britain. The company buys and develops land; plans, designs, and constructs residential properties including apartments, penthouses, and communities; and develops and sells homes. [London South East share price, company profile]

Berkeley Group Holdings plc (BKG.L):

The Berkeley Group Holdings plc performs the residential-led, mixed-use property development activities in the United Kingdom. The company makes luxury homes, and affordable housing for families, first time buyers, students, and senior people in London and the south of England markets. [London South East share price, company profile]

Diageo plc (DGE.L):

Diageo plc involves in manufacturing, marketing, and selling alcoholic beverages worldwide.

The company manufactures and sells scotch whiskey, gin, vodka, rum, beers, Irish cream liqueurs, wine, Raki, tequila, Canadian and American whiskey, Cachaça, brandy, adult beverages and ready to drink products [London South East share price, company profile].

3. The tertiary or service industry

Stock prices of service industry are not predictable. All applied models and forecast evaluation statistics show a significant difference between actual price and predicted price. Companies in the service industry provides services. The selected companies in this industry are Aberdeen Asset Management plc (ADN.L), Ashtead Group plc (AHT.L), Aviva plc (AV.L), Babcock International Group plc (BAB.L) and Barclays plc (BARC.L). Their services, product range and functions that they perform are given below:

Aberdeen Asset Management plc (ADN.L):

Aberdeen Asset Management plc is engaged in providing services to governments, national pension schemes, listed investment companies, foundations and charities, private banks and discretionary fund managers and retail clients. The company does separate client focused equity, fixed income, and balanced portfolios through its subsidiaries. The firm also involves in managing mutual funds for its clients. The company invests in different sectors including the public equity, fixed interest income, currency, and property markets across the world. The firm invests in real estate in the Nordic growth regions [London South East share price, company profile].

Ashtead Group plc (AHT.L):

This company involves in renting a range of construction and industrial equipment. The company provides equipments that are used to lift, move, dig, scrub, pump, heat and ventilate various works. It has different types of construction equipments for non-residential construction markets; and facilities management equipment for the maintenance and repair of facilities. The company also offers disaster relief equipment, such as pumps and power generation equipments for different types of applications, such as assisting at times of flooding due to weather and burst water supply; power generation, lighting, and other equipments for managing events, including super bowl events, sporting events, music concerts, and festivals; and climate control equipment, including cooling, heating, and dehumidification equipment. Furthermore, it offers scaffolding rental solutions [London South East share price, company profile].

Aviva plc (AV.L):

Aviva plc involves in providing long-term insurance and savings, general and health insurance, and fund management products and services all over the world. The products that the company offers are pensions products including personal and group pensions and stakeholder pensions; annuities; protection products comprising term assurance, mortgage life insurance, and critical illness cover; bonds and savings consisting of single premium investment bonds and regular premium savings plans; and investment products, such as unit trusts, individual savings accounts as well as equity release services. Its general and health insurance products are personal lines of insurance products comprising motor, household, travel, and creditor insurance; health insurance products, including private health, income protection, and personal accident products, as well as various corporate healthcare insurance products. Furthermore, the company provides fund management products and services to its long-term insurance and savings, and general insurance operations. [London South East share price, company profile]

Babcock International Group plc (BAB.L):

The company offers engineering support services for defence, emergency services, transport, and education sectors. It functions through marine and technology, defence and security and support services. The company's defence and security division gives airbase support, military flying training, and engineering support services for jet training aircraft; and life maintenance, repair and upgrade support services for defence equipment, as well as army technical and mechanical trade training, and fleet management services. The support services division is engaged in teaching vital skills, managing critical assets, and delivering complex programs for civil governments and blue-chip commercial organizations. The international division is involved in providing air ambulances, search and rescue and civil protection services; distributes Volvo and DAF equipment; engineering support for power stations; crane hire for infrastructure and construction industries. [London South East share price, company profile]

Barclays plc (BARC.L):

The company was known as Barclays Bank Limited in earlier times. However, it has changed its name to Barclays plc in January 1985. Barclays plc was established in 1896. It has its headquarter in London, the United Kingdom. Barclays plc has various financial products and services that are offered worldwide through its subsidiaries. It provides personal and business

banking services, credit cards, transactional and other lending products and investment products and services. The company also engaged in providing financial advice, primary capital raising and capital markets execution, risk and liquidity management, sales and trading, consumer payments and wealth management services. It works for corporates, financial institutions, institutional investors, governments, consumers, high and ultra-high net worth individuals and family offices. [London South East share price, company profile]

4. The quaternary industry

The stock prices of quaternary industry are highly unpredictable. This is because, stock prices move frequently and unsteadily. Companies in the quaternary industry engaged in research and development of new products and services.

The selected companies are AstraZeneca plc (AZN.L), GlaxoSmithKline plc (GSK.L), Shire plc (SHP.L), Sage Group plc (SGE.L) and Smith & Nephew plc (SN.L) for analysing their stock prices. The nature of the companies and the functions they perform are given below:

AstraZeneca plc (AZN.L):

AstraZeneca plc discovers, develops and commercializes medicines for the treatment of respiratory, inflammation, autoimmune, cardiovascular, metabolic, oncology, infection, neuroscience, and gastrointestinal diseases worldwide. [London South East share price, company profile]

GlaxoSmithKline plc (GSK.L):

GlaxoSmithKline plc is involved in discovery, development, production, and marketing of pharmaceutical products, such as vaccines, over-the-counter medicines, and health-related consumer products worldwide. The company operates through five segments: global pharmaceuticals, HIV, pharmaceuticals R&D, vaccines, and consumer healthcare. [London South East share price, company profile]

Shire plc (SHP.L):

Shire plc is a biotechnology company. It provides solution to rare diseases and other specialized conditions. The product lines it covers are hematology, immunology, neuroscience, ophthalmics, lysosomal storage disorders, gastrointestinal/internal

medicine/endocrine and hereditary angioedema. It also involves in developing a franchise in oncology and a pipeline in ophthalmics. [London South East share price, company profile]

Sage Group plc (SGE.L):

The Sage Group plc was established in 1981. Its headquarter is in Newcastle upon Tyne, the United Kingdom. The Sage Group plc provides business management software and related products and services for small and medium sized businesses. Its softwares are used for accounting and payroll, enterprise resource planning, customer relationship management and payments. The main customers of this company are small business owners, book keepers and finance directors. It serves primarily in Europe, North America, South Africa, Australia, the Middle East and Asia. [London South East share price, company profile]

Smith & Nephew plc (SN.L):

Different forecasting models show that it is not possible to predict the stock prices of this company. This may be because, information of this company is reflected very quickly into stock prices. The is no gap between information release and new or updated stock price. Smith & Nephew plc was established in 1856. Its headquartered is in London, the United Kingdom. Smith & Nephew plc involves in designing, developing and selling medical devices all over the world.

The company is involved in researching and developing sports medicine, joint repair products for surgeons including an array of instruments, technologies and implants necessary to perform minimally invasive surgery of the joints and arthroscopic enabling technologies for healthcare providers, such as fluid management equipment for surgical access, high definition cameras, digital image capture, scopes, light sources and monitors to assist with visualization inside the joints, radio frequency wands, electromechanical and mechanical blades and hand instruments for removing broken tissue.

Furthermore, the company develops and manufactures advanced wound care products for the treatment of acute and chronic wounds including leg, diabetic and pressure ulcers, burns, and post-operative wounds; advanced wound devices, such as traditional and single-use negative pressure wound therapy and hydrosurgery systems and biologics and other bioactive technology products for debridement and dermal repair/regeneration. It also involves in providing medical and surgical treatments and services. [London South East share price, company profile]

4.2.1 Form of data (raw data versus log returns)

This study will not change raw data into log returns. Logarithm returns are usually used to measure changes in values over time. This research considers raw data of weekly closing prices rather than their log returns. Adebiyi, Adewumi and Ayo (2014) used raw data in their research as well. Raw data were chosen in this research because of the following benefits over log return data:

a) The movements, trends and directions of log return data in the graphs are not clear, as they all are close to zero. However, they are apparent and easily identifiable in the graphs constructed from raw data. This is because the figures differ significantly from each other most of the time.

b) The comparison table shows the comparison between the actual price and the predicted price. These prices are easily comparable visually, whereas they are not apparent in figures, as they all are close to zero.

c) The aim of this research is to measure the predictive ability of technical analysis rather than measuring profitability from technical analysis. Therefore, the usage of raw data serves the aim of this research.

d) If log return of an individual stock is used, the study needs to consider dividend payments for that stock. The formula of natural log of individual stock return provided by Mobarek and Keasey (2000, p. 10) is as follows:

$LN[(Pk_{t-1} + Dk_t)/Pk_{t-1}]$

Where, LN = natural log

Pk_{t-1}= daily closing price of an individual stock (k) at period t-1

Dk_t = dividend per share of an individual stock (k) at period t

Pk_{t-1}= daily closing price of an individual stock (k) at period t-1

From the above formula, it is apparent that the measurement of log return of an individual stock involves taking into account dividend payments for that stock. However, this study ignores these dividend payments. Therefore, the usage of raw data rather than log return is appropriate to achieve the aim and objectives of this study.

As the usage of raw data has more benefits than the usage of log returns for achieving the aim and objectives, this study decided to use raw data rather than log return data. The following section analyses the impact of disclosures and announcements on stock price movements.

4.2.2 The analysis of impacts of regulation regarding disclosures and announcements through graphical presentation of the data

The data of all twenty individual companies, are explained in the line graph, histogram and kernel density graphs below to show their ups and downs, trends, movements and skewness by using Eviews, version 8. The reasons for fluctuations were investigated to achieve research objectives listed in chapter one.

George and Hwang (2007) found, in the US market, that long-term return reversal occurs when capital gains are taxed but not due to an irrational overreaction to news, and such a prediction can be made successfully. To criticise their findings, a rational argument arises that when there is long-term momentum in a market, all the investors will follow the trend and invest in particular stocks to exploit the returns. This will cause overreaction to information, which helps return reversals. Therefore, not only capital gains but also overreaction to information is liable to cause long-run return reversal.

The investigation for changing in prices were conducted for each company from a website of http://www.lse.co.uk/ShareNews.asp? and news and information headlines section in yahoo finance. The next section explains how announcements and disclosures affect prices to move up and down of different companies in different industrial sectors.

The primary industry

The primary industry includes five companies. Stock prices change for making different announcements and disclosures at different time. How announcements and disclosures affect prices moving up and down is discussed below.

Antofagasta plc (ANTO.L)

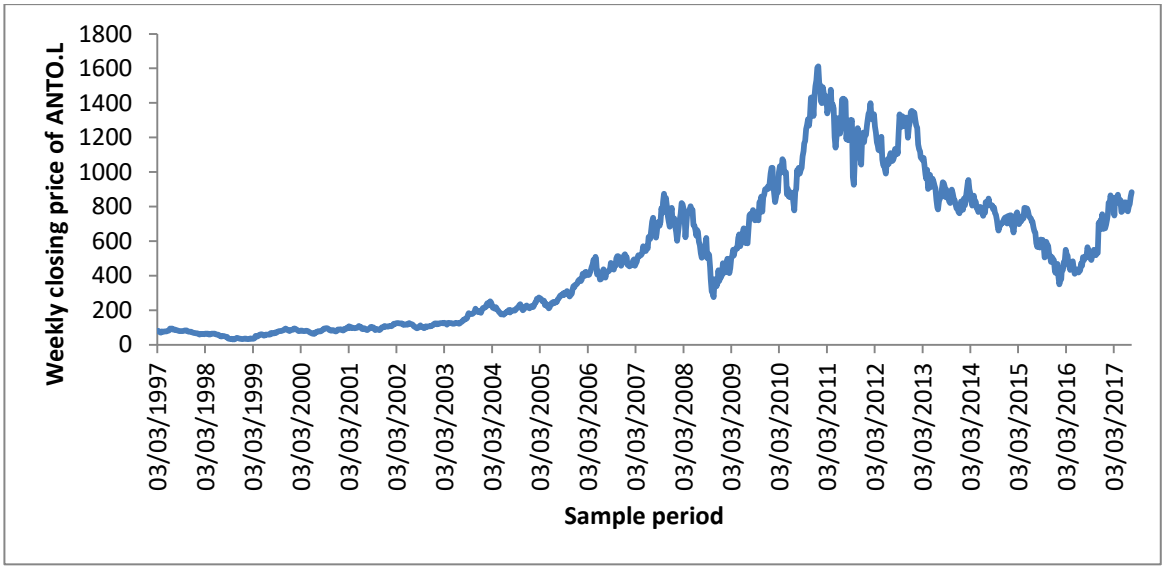
Figure 4.1 presents many ups and downs in the period between March 1997 and July 2017. At the beginning of the sample period, weekly closing prices of Antofagasta plc were very low. They had begun to rise gradually. The structural breakpoint took place in this company on 31 December 2012 as the Antofagasta plc announced the suspension of its Chilean Antucoya copper mine, as it would cost $1.7 billion for development. Stock prices declined on 18

November 2013. This is because the company announced on 14 November 2013 that there would be lower profit as metal price dropped and operational cost increased.

The stock price of this company reached its peak in July 2014, because Antofagasta plc disseminated the news that it had produced a higher quarterly copper output. Subsequently, the price started to decrease continuously until February 2016 due to the impact of inflation in the UK. This result is consistent with the findings of Ansotegui and Esteban (2002). They found in the Spanish share market that an increase in inflation leads to an increase in industrial production and a decrease in the interest rate in the short run; as a consequence, a decrease occurs in the stock price.

However, there was a considerable jump in stock prices on 27 April (Monday) 2015 as the news emerged on 24 April (Friday) 2015 that the supply of iron ore had been recorded as higher. Prices plummeted on 30 August 2015 as the company reported that there were disruptions to its operations and shipment delays on 24 August 2015. Weekly closing price decreased on 11 June 2017 as the company announced on June 7 that mines in northern Chile were suspending key operations after heavy rains lashed the high altitude desert region of Antofagasta overnight. [London South East share price, company finance news]

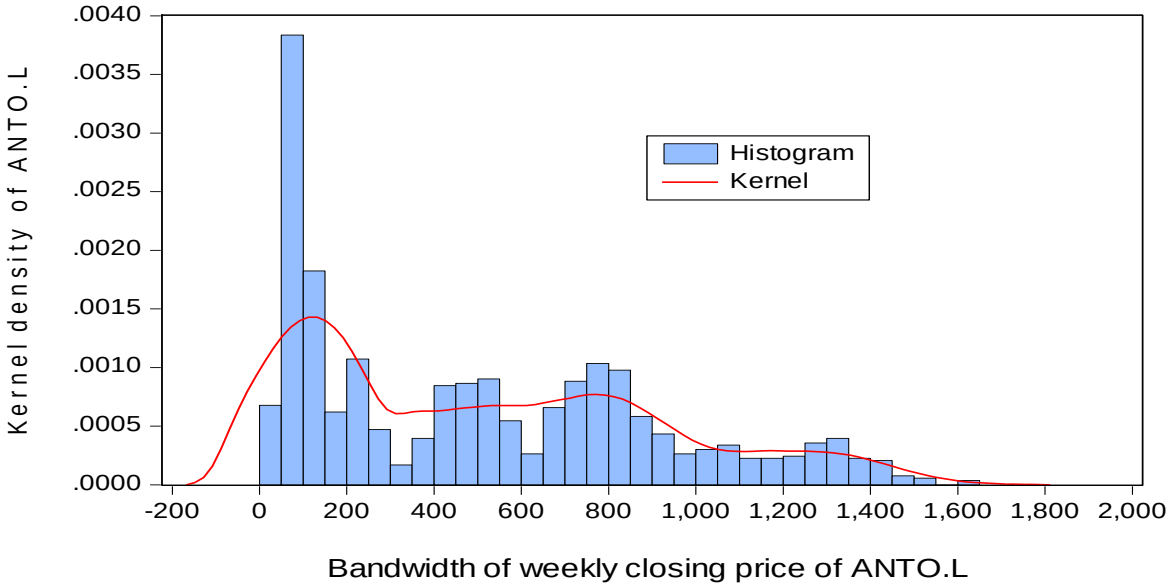
Figure 4. 1: A line graph of Antofagasta plc (ANTO.L) for period from March 1997 to July 2017



Source: Database from March 1997 to July 2017, created through Eviews, v-9

The kernel density graph explains that the histogram below in figure 4.2 is skewed to theright, which is also called a positively skewed distribution. A positively skewed distribution can result in regular small negative returns and a few significant positive returns. Therefore, retail and institutional investors could expect higher returns investing in this company.

Figure 4. 2: Histogram and Kernel Density graph of weekly closing price for Antofagasta plc (ANTO.L) for period from March 1997 to July 2017



Source: Database from March 1997 to July 2017, created through Eviews, v-9

BP plc (BP.L)

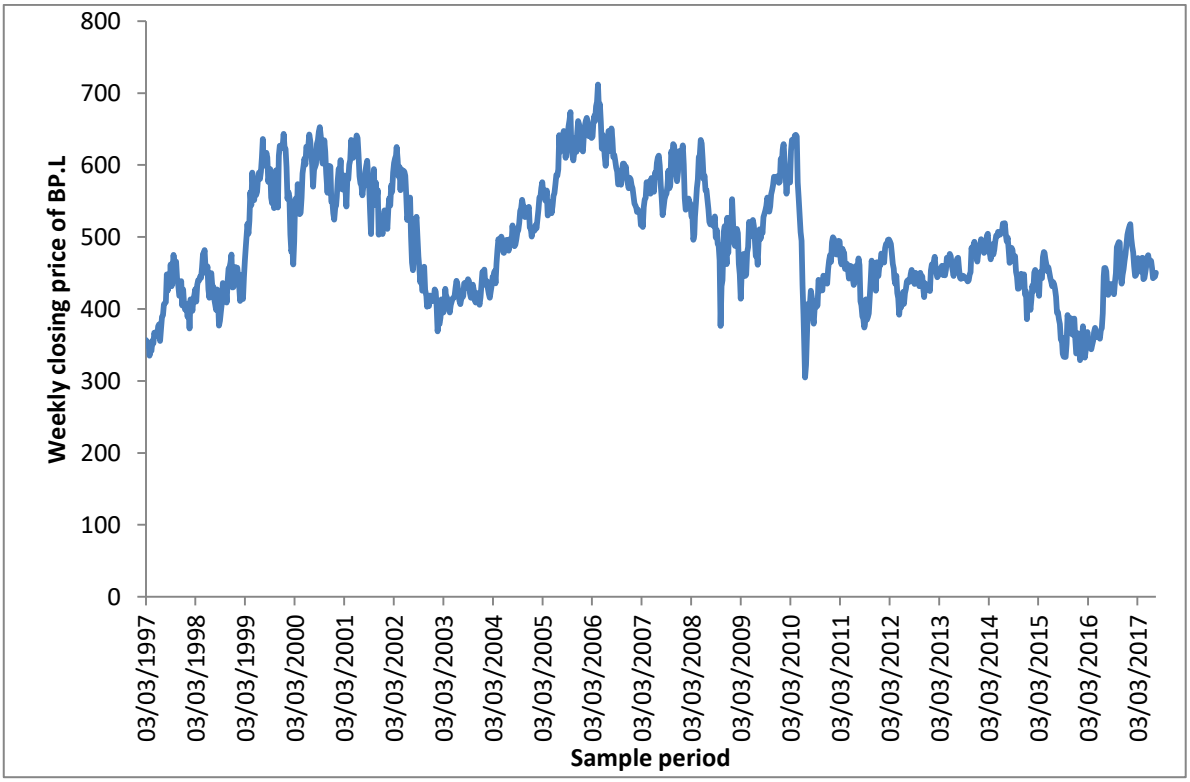
Graph 4.3 below explains that the stock price fluctuates very frequently throughout the whole sample period starting from February 1997 to July 2017. It is also observed in the sample period that there was a structural break on 18 April 2010 as BP plc announced that Chevron Pipe Line Co was almost ready to begin repairing an oil pipeline shut down two weeks prior after leaking into a Louisiana wildlife refuge, a U.S. Coast. As a consequence, the price decreased significantly on 25 April 2010.

It was also reported that natural resources minister, Yuri Trutnev, announced Russian law required TNK-BP to be stripped of its licence for the Kovykta gas field, though a decision had yet to be taken on the fate of the giant eastern Siberian deposit. Russian output was also hit by declining European demand during the economic crisis, as customers switched to cheaper liquefied natural gas.

The price peaked at £523.90 on 24 June 2014 due to a higher oil price. There was a political conflict in Iraq at that time. As a consequence, the oil price rose. Stock price declined on 31 August 2014 due to an accident which happened on 28 August 2014, although production was not stopped. Afterwards, the price started to fall significantly until December 2014, especially 15 December. This is because President Barack Obama did not decide how to respond to a bill authorising new sanctions against Russia over its activities in Ukraine and Russia threatened to cut off the supply of natural gas.

The price rose again on 23 April 2015 as the chief executive of Marathon Petroleum Corporation reported in an interview on 22 April that the company would receive the same kind of domestic oil influx from Texas. The price started to drop on 15 July 2015 when the company agreed to pay to clean up the toxic waste from Monsanto plant in South Wales. There was a soar in the price of BP on 3 November 2015 as the BP Group's Head of Technology announced on 2 November 2015 that the supply of nuclear, wind, and solar energy would be 20 times more than the world would need. The global energy resources would be doubled by 2050. [London South East share price, company finance news]

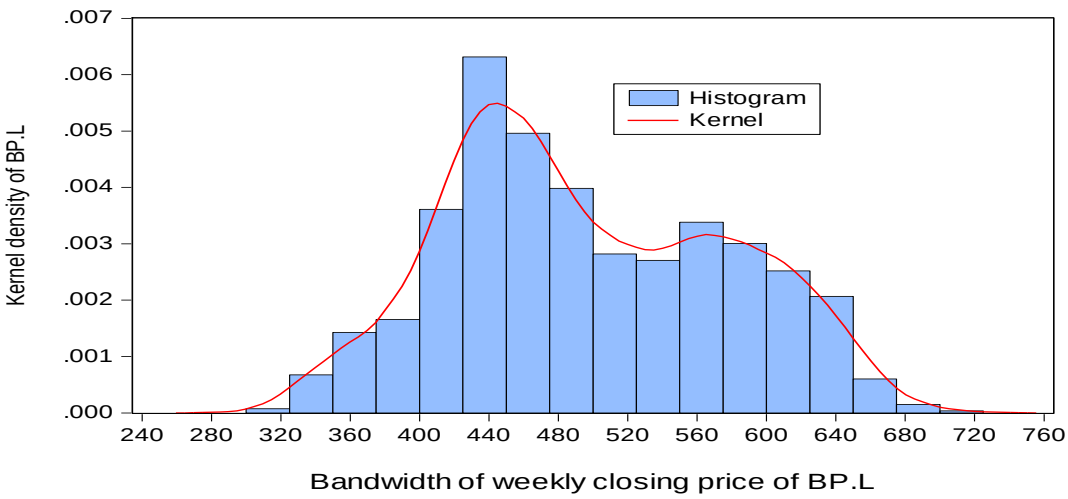
Figure 4. 3: A line graph of weekly closing price for BP plc (BP.L) for period from March 1997 to July 2017



Source: Database from March 1997 to July 2017, created through Eviews, v-9

The histogram and kernel density graph together explain that there is no apparent pattern. This is obviously not normally distributed. The graph has a few peaks and the distribution is random. Therefore, the stock price of BP.L may not be predictable, as it moves up and down randomly.

Figure 4. 4: Histogram and Kernel Density graph of weekly closing price for BP plc (BP.L) for period from March 1997 to July 2017



Source: Database from March 1997 to July 2017, created through Eviews, v-9

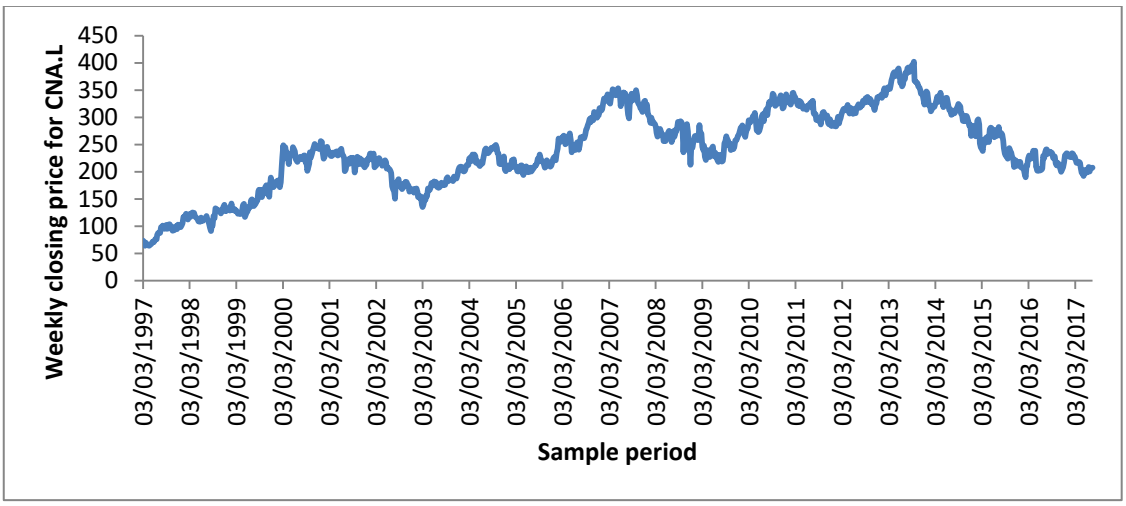
Centrica plc (CNA.L)

The line graph below exhibits the price trend of Centrica plc. The price was at its peak at the beginning of the period. However, it fluctuated at a decreasing rate. It can also be observed from the graph that the fluctuation rate was steady and slow. There was a structural break in stock prices of Centrica plc on 15 September 2013. This is because the environmental group Greenpeace declared on 14 October 2013 to encourage British landowners to join together to enforce a new law opposing fracking, a move that could strengthen the opposition to exploration and development for oil and gas as fracking could pollute water supplies and cause earthquakes. The stock price fell on 4 September 2014 as the company announced that its earnings would be reduced by the shutting down of two power stations operated by its partner Electricite de France (EDF) Energy.

There was a little rise in the price on 6 February 2015 due to the company declaring that it would maintain a high level of gas storage. The price started to decline on 10 September 2015 as the domestic supply continued to be disrupted from 9 September and thus the gas price was lower. There was a sharp decline in price on 24 September 2015 due to new regulations on electricity and gas charges being imposed in the UK. Centrica plc hit its lowest point of

£183.6 on 11 February 2016. This is because British Gas, Scottish, and Southern Energy (SSE), E.ON and EDF announced that they had cut their price by 5.1%, 5.3%, 5.1% and 5%, respectively. As a consequence, the suppliers were bound to reduce their price. The weekly price decreased on 6 March 2017, because the company made a final application on 28 February 2017 to reduce the minimum capacity of the rough gas storage facility to zero. [London South East share price, company finance news]

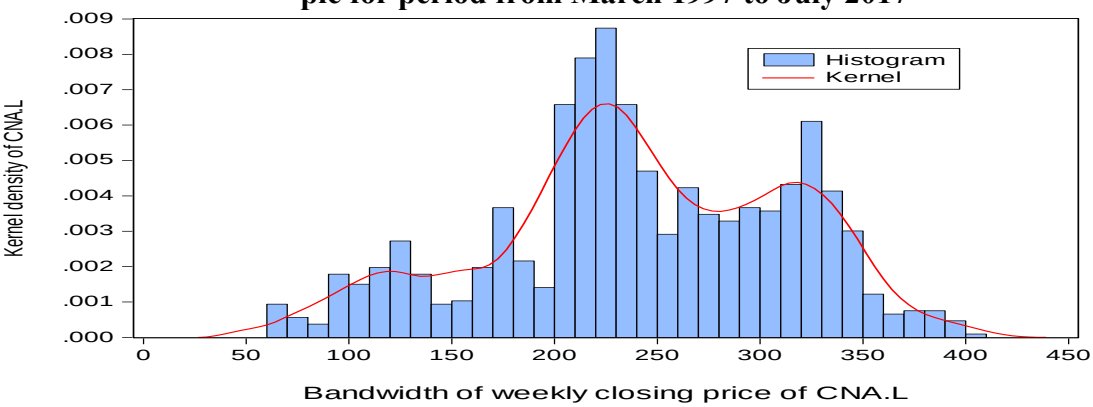
Figure 4. 5: A line graph of weekly closing price for Centrica plc (CNA.L) for period from March 1997 to July 2017



Source: Database from March 1997 to July 2017, created through Eviews, v-9

The graph below shows several peaks, indicating the nature of random distribution. It explains that there are no apparent patterns. Prices are unpredictable in such situations. However, it is a bit skewed to the left which indicates that investors might generate negative returns investing in this company.

Figure 4. 6: Histogram and Kernel Density graph of weekly closing price for Centrica plc for period from March 1997 to July 2017



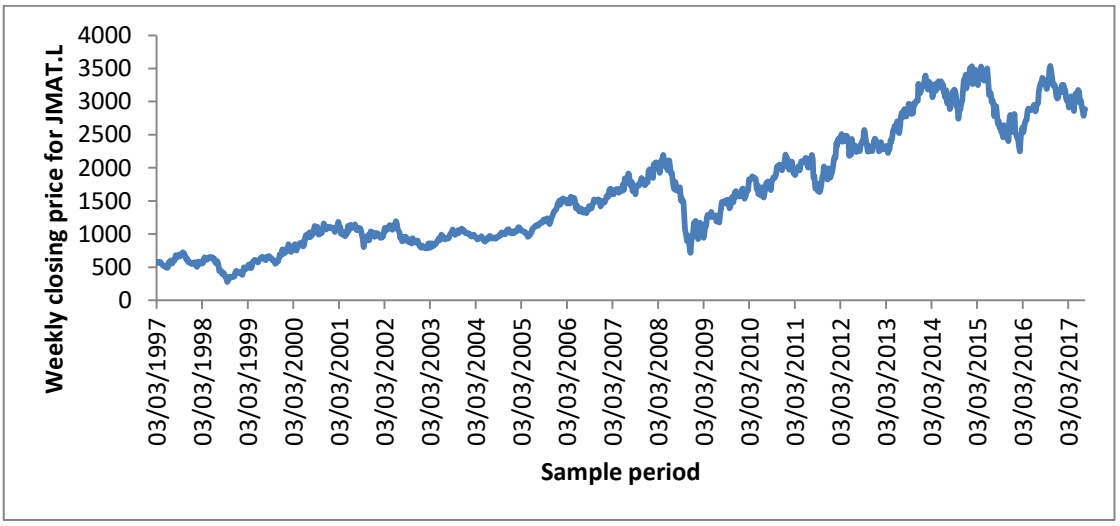
Source: Database from March 1997 to July 2017, created through Eviews, v-9

Johnson Matthey PLC (JMAT.L)

At the beginning of the sample period of Johnson Matthey plc, the stock price was low. It started to rise slowly with little fluctuations. The stock price continued to ascend from the beginning to the end of sample period with many ups and downs. Announcements help price to move up and down. An announcement was made on 14 July 2006 that the fuel cell group Ceres Power Holdings plc was partnering with Rolls Royce and Johnson Matthey as part of a government-backed programme to deliver innovations in sustainable power generation and supply. As a result, price increased of JMAT.L. Johnson Matthey PLC, the UK specialty chemicals group, announced on 10 December 2007 they were to acquire Argillon Group, which makes catalysts and advanced ceramics materials from Ceramics Luxembourg. Therefore, price increased rapidly afterwards.

Stock price decreased significantly on 30 May 2010 as the company declared it would close its Vertec unit in Birmingham and also announced that the company was struggling against stiff competition. An announcement was made on 28 September 2011 that JP Morgan raised Johnson Matthey PLC to overweight from neutral for a summary of rating actions and price target changes on European companies. Consequently, stock prices increased significantly. Stock price increased on 26 December 2016 due to an announcement that new marketing strategies had been adopted to increase sales on 20 December. The company reported on 1 June 2017 that cost was reduced and profit was increased. As a consequence, price rose. [London South East share price, company finance news]

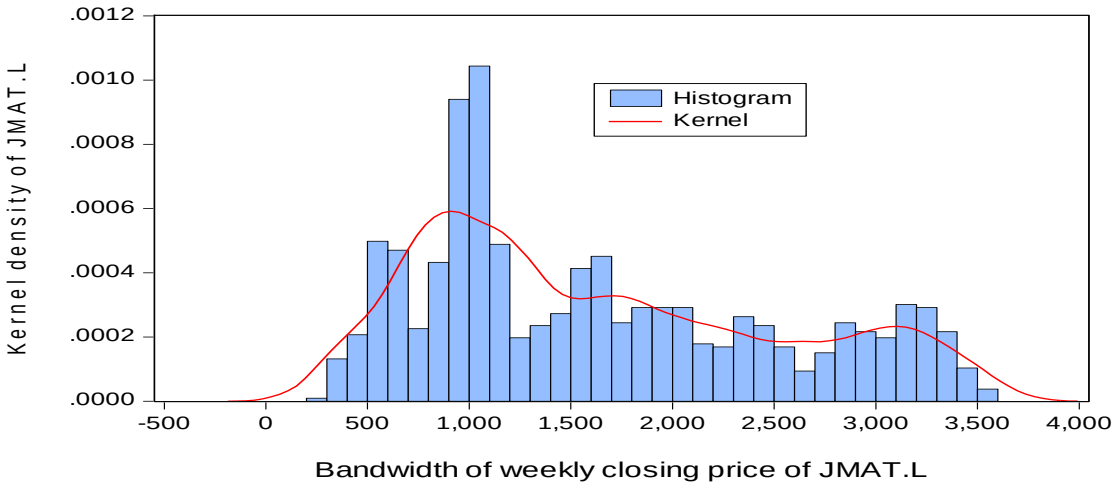
Figure 4. 7: A line graph of weekly closing price for Johnson Matthey PLC (JMAT.L)



Source: Database from March 1997 to July 2017, created through Eviews, v-9

The kernel density graph explains that the histogram below in figure 4.8 is skewed to the right, which is known as a positively skewed distribution. A positively skewed distribution may provide regular small negative returns and a few considerably higher positive returns. Therefore, investors could expect higher returns investing in this company.

Figure 4. 8: Histogram and Kernel Density graph of weekly closing price of Johnson Matthey PLC (JMAT.L) for period from March 1997 to July 2017



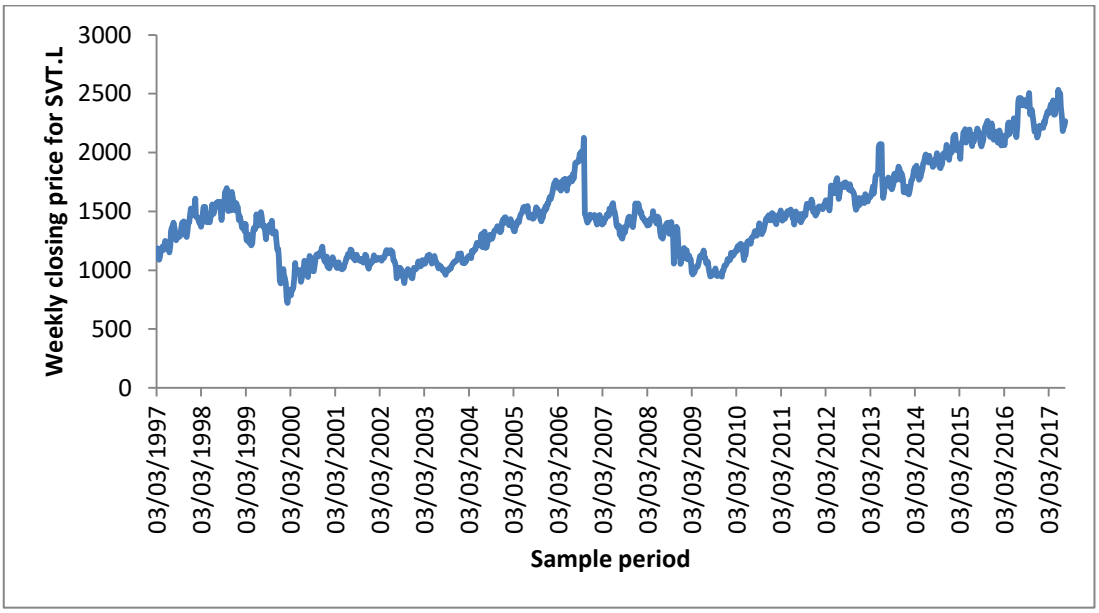
Source: Database from March 1997 to July 2017, created through Eviews, v-9

Severn Trent PLC (SVT.L)

The graph below explains that Severn Trent plc had lower stock price at the beginning of the sample period. Afterwards, stock prices increased and then decreased. This process is seen throughout the whole sample period. There was a structural break in the time series data of this company on 1 October 2006 as Severn Trent PLC announced that H1 revenue would be down by £3.2 million as the company overcharged and now they had to pay back to the customers. Stock price of this company decreased as it was broadcasted on 20 January 2012 that China had bought a minority stake in Thames Water.

Stock price rocketed when the company made an announcement that the company had been taken over from a consortium including Borealis Infrastructure and the Kuwait Investment Office on 14 May 2013. British water company, Severn Trent, publicized on 17 July 2013 that the company had incurred £19 million ($29 million) in legal and advisory costs. Therefore, price decreased afterwards. The company reported on 22 May 2015 a 3.2 % rise in full-year profit due to higher demand, allowing it to pay a dividend of 84.90 pence per share. As a consequence, stock price increased sharply especially on 24 May. [London South East share price, company finance news]

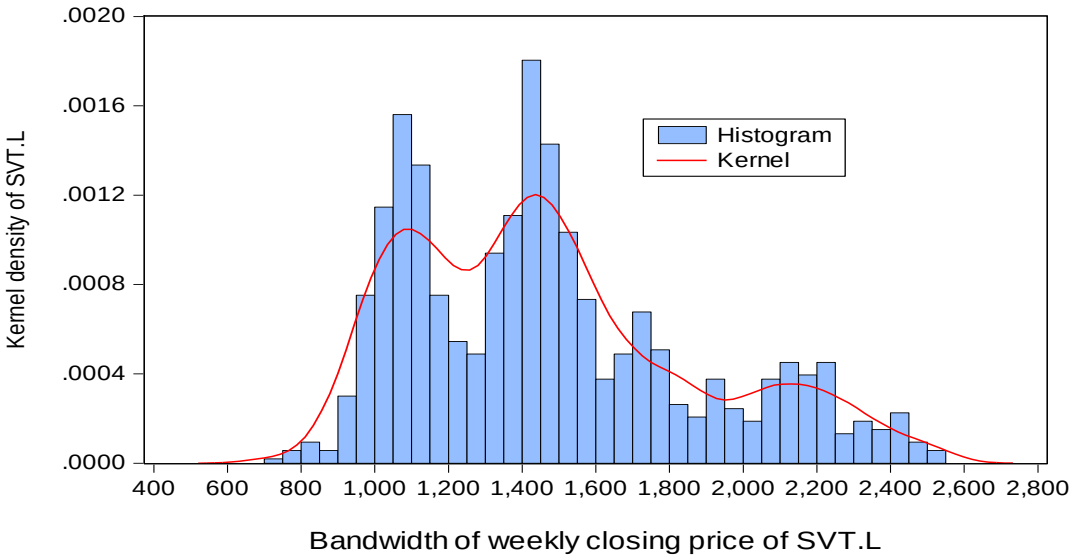
Figure 4. 9: A line graph of weekly closing price for Severn Trent PLC (SVT.L)



Source: Database from March 1997 to July 2017, created through Eviews, v-9

The kernel density graph explains that the histogram below in figure 4.10 has several peaks. Therefore, the stock prices of this company fluctuate frequently and randomly. However, the graph is skewed to the right and it is a positively skewed distribution. A positively skewed distribution explains that investors might experience frequent small negative returns and a few extensively higher positive returns. Therefore, investors could expect infrequent higher positive returns investing in this company.

Figure 4. 10: Histogram and Kernel Density graph of weekly closing price of Severn Trent plc (SVT.L) for period from March 1997 to July 2017



Source: Database from March 1997 to July 2017, created through Eviews, v-9

The manufacturing industry

The manufacturing industry includes five different companies. How disclosures and announcements change prices of different companies in the manufacturing industry are shown below.

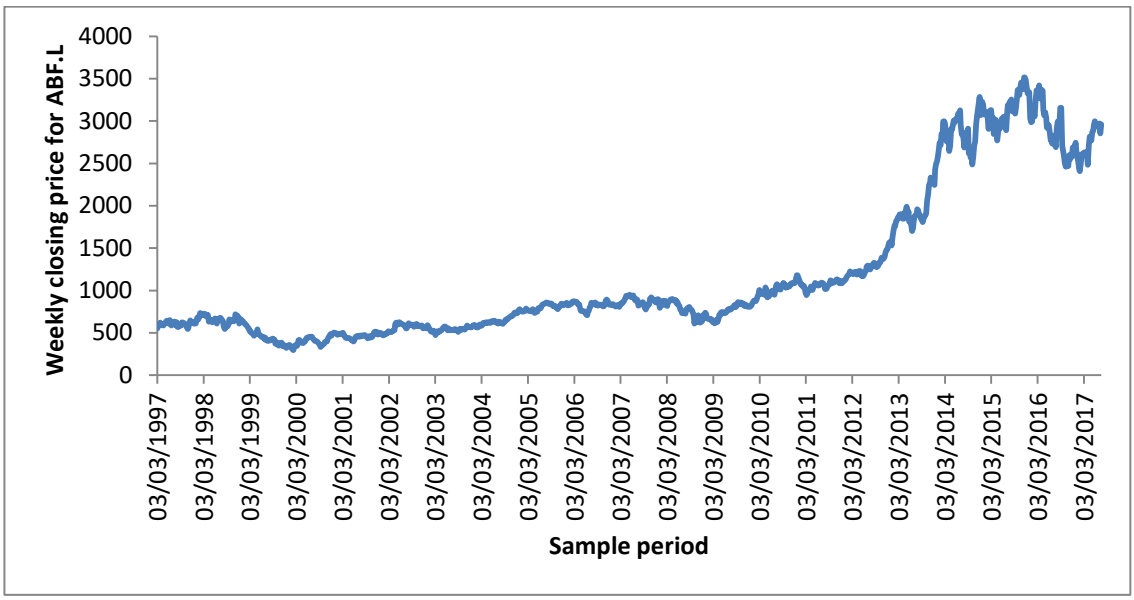
Associated British Foods PLC

The graph below shows several rises and falls. Associated British Foods plc of the manufacturing industry has ascending trends with rapid and random fluctuations. This suggests that investment in this company would be risky, as the trend is unpredictable. New information makes prices change. News comes everyday and change the price. It is not possible to consider all the announcements in the sample period to show their impacts. The following announcements show how they impact on price changes.

Stock price increased slowly and gradually when ABF.L proclaimed on 24 April 2007 that a significant increase in earnings from sugar business and Primark. There was a sharp increase in stock price when an announcement was made on 8 July 2010 that good progress in earnings all over the year. There was a breakpoint on 8 September 2013 that stock prices rocketed due to an announcement made that sales forecast of Primark increased 22% more than last year in Britain and Europe.

The company also reported that consuming power in UK increased significantly. The stock price decreased in October 2014 due to the continued deterioration of the ethanol and sugar markets in Europe. It rose in December 2014 due to an announcement made to reduce costs through lay-off of employees. The stock price increased in November 2015 due to a branch of Primark opening in Boston, USA. The company also announced that it was to open Primark in Italy. The company reported on 4 January 2017 that sales in Primark were not good and shares fell 9%. Therefore, stock prices decreased when the announcement was made and it was continued until 13 February 2017. [London South East share price, company finance news]

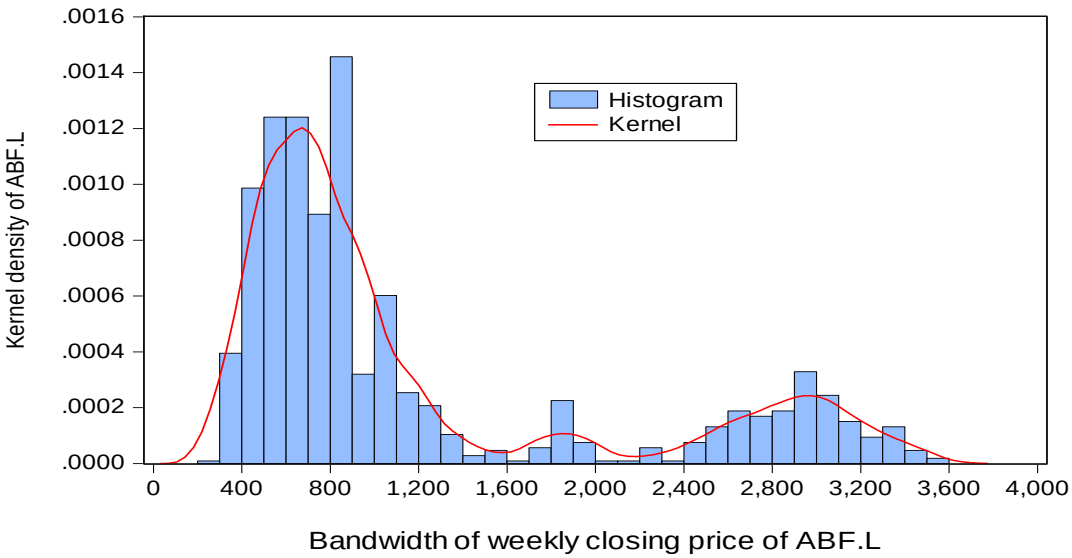
Figure 4. 11: A line graph of weekly closing price for Associated British Foods plc (ABF.L) for periods between March 1997 and July 2017



Source: Diagram created by author with the database from March 1997 to July 2017

The kernel density graph defines the histogram below in figure 4.12 to be positively skewed, which suggests that Associated British Foods plc is not normally distributed. It indicates that positive returns could be generated from investing in this company, as the price shows an upward trend. However, prices move with little fluctuations.

Figure 4. 12: Histogram and Kernel Density graph of weekly closing price of Associated British Foods plc (ABF.L) for period from March 1997 to July 2017



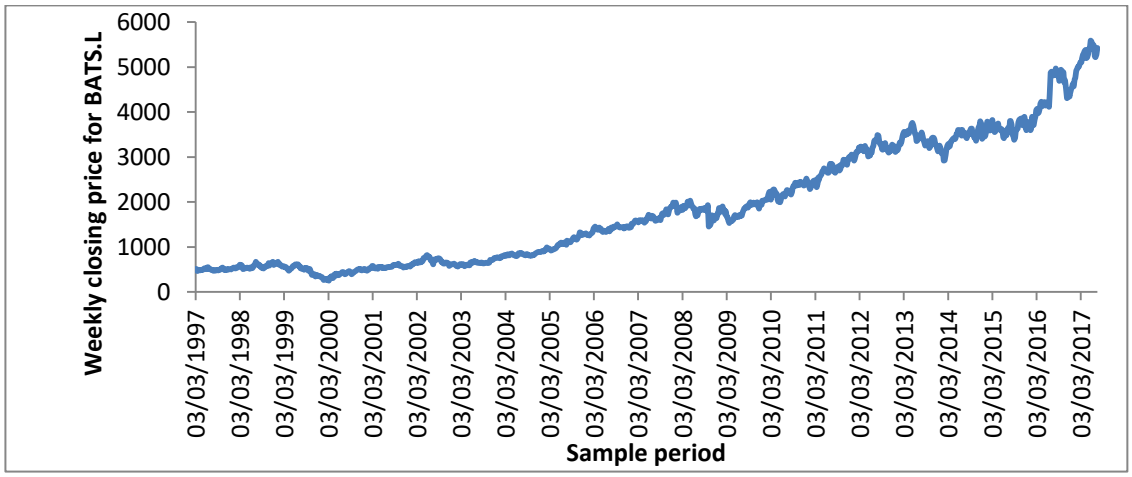
Source: Diagram created by author with the database from March 1997 to July 2017

British American Tobacco plc (BATS.L)

The graph below shows that the trend line of the stock price is upward with frequent fluctuations. At the beginning of the sample period, the stock price was low. The stock price started to increase slowly and gradually from beginning to end of the sample period. There was a sharp increase in price when an announcement was made on 27 July 2006 that 15% rise in first-half profits which was better than expected. There was a steep price decrease due to a report made on 29 July 2011that supreme court in Canada ruled against tobacco companies to bear healthcare costs. The stock price slumped after 10 December 2014 when several tobacco companies pledged to end child labour in their supply chains.

The price fell in January 2015 due to the British Government aiming to pass a new law to force tobacco firms to sell cigarettes in plain packets without branding to improve public health and reduce the number of child smokers. The opposition Labour Party also welcomed their decision. The stock price of BATS.L soared at the end of September 2015 due to the company signing an agreement to buy a Polish e-cigarette company on 22 September 2015. There was a gentle, steady increase in stock price on 4 January 2016 for announcing Britain's drug regulators had given permission to British American Tobacco to sell electronic-cigarette vaping device as a quit smoking medicine. It jumped on 15 March 2016 because BATS.L declared its investment of $11.9 million in a Mali state firm on 14 March 2016. Stock price began to rise slowly and steadily when proclaimed was made on 28 July 2016 that they had gained higher half year sales compared with last six months. [London South East share price, company finance news]

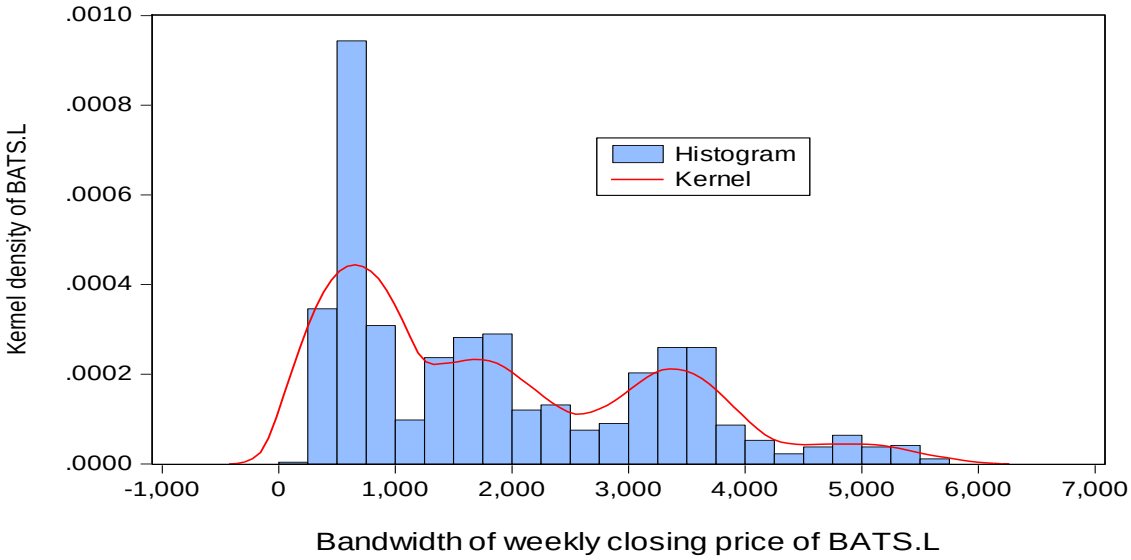
Figure 4. 13: A line graph of weekly closing price for British American Tobacco plc (BATS.L) for periods between March 1997 and July 2017



Source: Diagram created by author with the database from March 1997 to July 2017

The kernel density line explains that the histogram is skewed to the right. Therefore, it is positively skewed, which suggests that British American Tobacco plc has a higher probability of generating a few extreme positive returns and some small negative returns.

Figure 4. 14: Histogram and Kernel Density graph of weekly closing price for British American Tobacco plc (BATS.L) for period from March 1997 to July 2017



Source: Diagram created by author with the database from March 1997 to July 2017

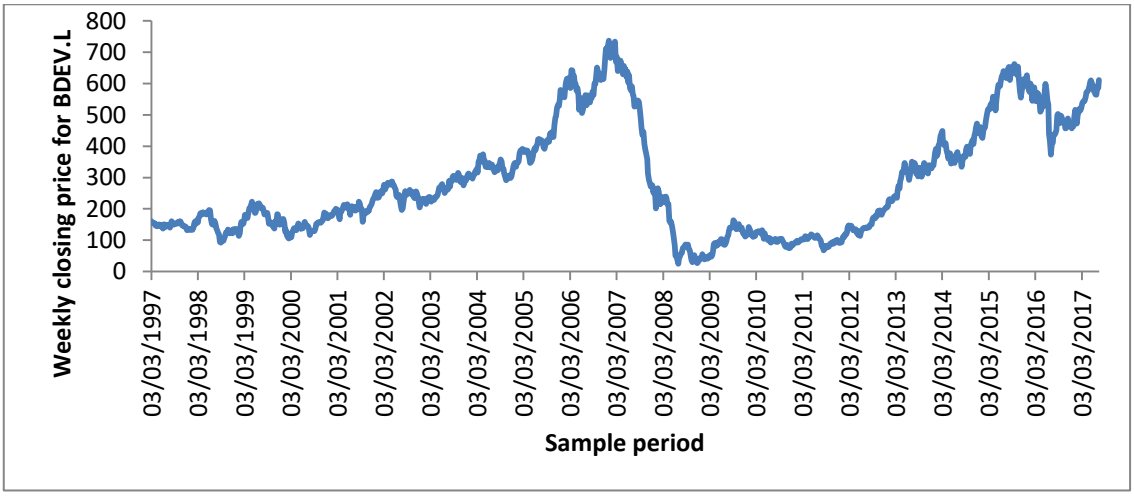
Barratt Developments plc (BDEV.L)

The stock price of Barratt Developments plc (BDEV.L) follows an upward trend. The stock prices increased continuously until 2007. Afterwards, they plummeted and reached a low and started to rise again. It seems as if the company would avoid bankruptcy. Stock prices jumped 20 June 2006 as the company would get £4.37 million to build 153 homes in the West Midlands. Prices plummeted on 8 January 2007 as it was announced that the principal board director Geoff Hester would retire at the end of June. Stock price jumped on 11 September 2013 as it had reported a 74% higher pre-tax return in the full year.

There was a slow and steady increase in the stock price from the beginning of the sample period to October 2015. The British Government announced on 9 July 2015 that it would eliminate hindrances to building new houses in an attempt to tackle the chronic shortage of homes. As a consequence, the stock price rocketed from the next working day. *The Telegraph* reported on 28 November 2015 that share prices had jumped over the last five years due to favourable government policies, low interest rates, and cheaper mortgages for building new houses. *The Telegraph* also reported that stock prices were turbulent a week earlier as a result

of the government disclosure of two unexpected pieces of news, which were the British Government's pledge to provide 400,000 new homes by the end of the decade and the unexpected hike of stamp duty. Subsequently, the price started to decline until March 2016.

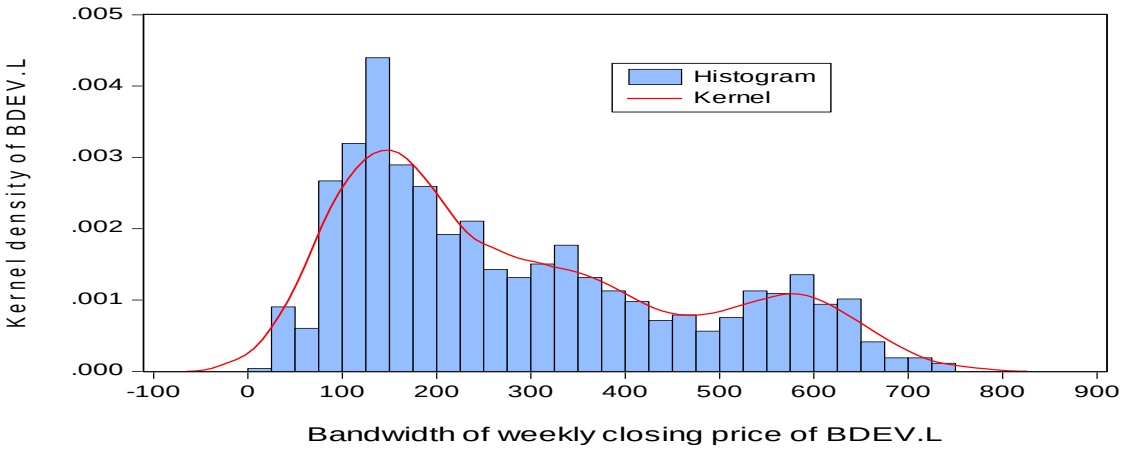
Figure 4. 15: A line graph of weekly closing price for Barratt Developments plc (BDEV.L) for periods between March 1997 and July 2017



Source: Diagram created by author with the database from March 1997 to July 2017

The kernel density graph describes that the histogram below in figure 4.16 is skewed to the right. Therefore, it is a positively skewed distribution. A positively skewed distribution could result in repeated small negative returns and erratic and substantial positive returns. Therefore, retail and institutional investors could expect higher returns with a lower risk investing in this company.

Figure 4. 16: Histogram and Kernel Density graph of weekly closing price of Barratt Developments plc (BDEV.L) for period from March 1997 to July 2017



Source: Diagram created by author with the database from March 1997 to July 2017

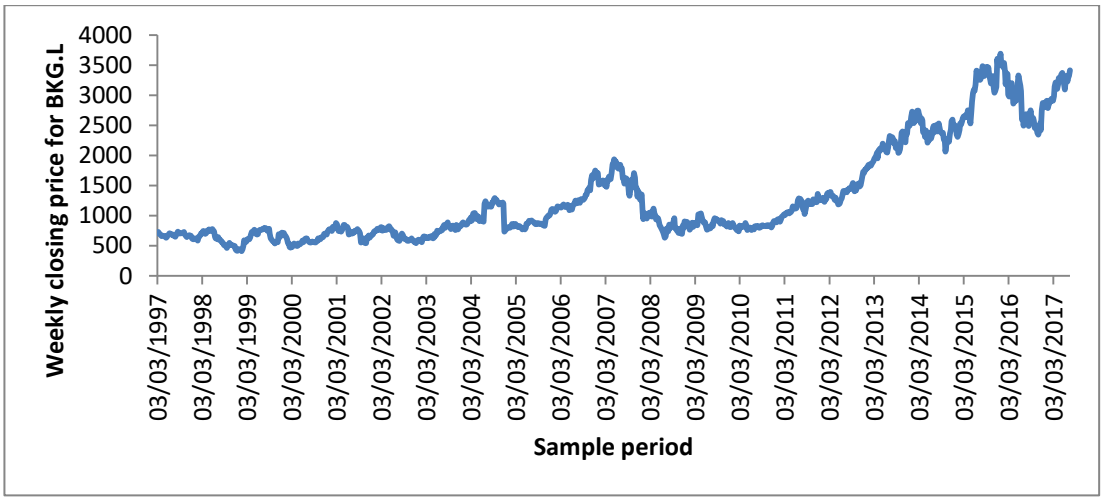
Berkeley Group Holdings plc (BKG.L)

The line graph below shows that the stock price of Berkeley Group Holdings plc (BKG.L) increased to a certain level, then decreased a little and increased again at a higher rate. This process was repeated over the whole sample period. Therefore, the price trends and patterns of this company are identifiable and future prices could be predictable.

Stock prices fall on 12 February 2008. This was due to a deteriorating economic performance. Stock prices went up steeply on 8 December 2008. This is because the company reported that it had gained 3.7% profit. There was a slow and steady increase in price when BKG.L announced on 26 February 2009 that it raised £51 million in placing at 840p per share. The price was low on 28 October 2014 because there was a price correction in the volatile stock market.

There was a significant decrease in the stock price on 12 May 2015 due to Godber, the manager of CF Miton UK Value Opportunities Fund (Miton Asset Management), increasing the exposure to homebuilders after the Conservative Party won the election. The stock price of this company increased on 25 June 2015 as Jefferies announced that the stock returns from the housing market would increase. There was a peak in the stock price of BKG.L of £3700 on 13 January 2016 as it was announced on 12 January 2016 that shares of housebuilding companies would outperform the market in the UK during 2016, since the supply was significantly lower than the demand for houses. [London South East share price, company finance news]

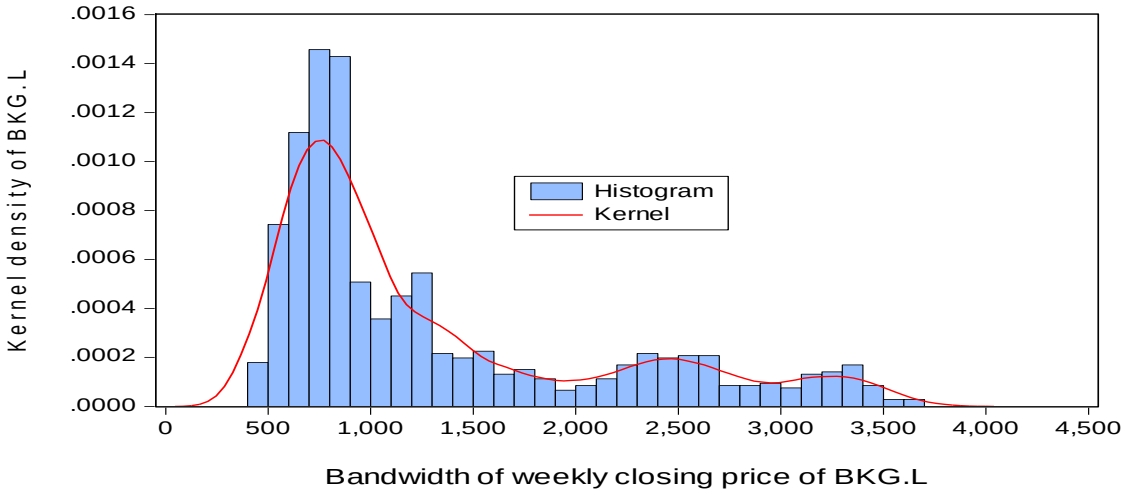
Figure 4. 17: A line graph of weekly closing price for Berkeley Group Holdings plc (BKG.L) for periods between March 1997 and July 2017



Source: Diagram created by author with the database from March 1997 to July 2017

As the price trend of BKG.L was lower from the beginning of sample period to November 2005 and then the stock price increased from the middle of November 2005 to December 2007. Afterwards, the stock price decreased from January 2007 to mid of February 2011. Again the stock prices rise for the periods between April 2013 and March 2016. Therefore, the graph has a few peaks and the distribution takes a multimodal shape. The distribution is also skewed to the right. Therefore, the distribution is positively skewed. It indicates that investment in this company would generate frequent small losses but a few extreme gains.

Figure 4. 18: Histogram and Kernel Density graph of weekly closing price for Berkeley Group Holdings plc (BKG.L) for periods between March 1997 and July 2017



Source: Diagram created by author with the database from March 1997 to July 2017

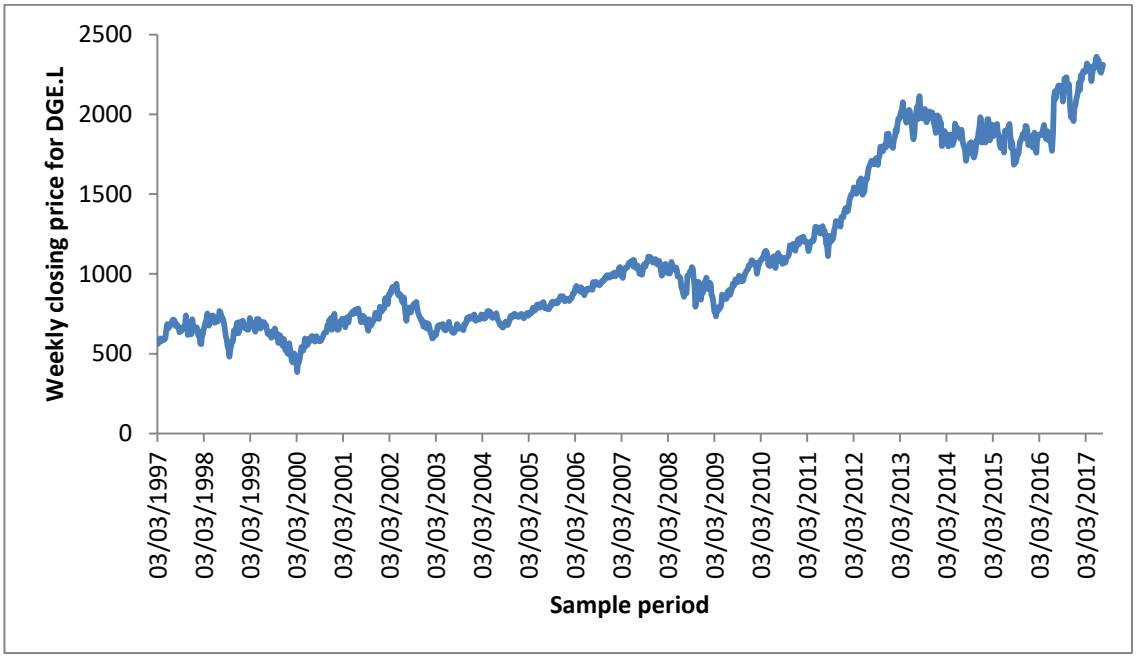
Diageo plc (DGE.L)

The line graph below demonstrates the behaviour of the stock price of Diageo plc. The line in the graph moves up and down very rapidly, erratically and frequently. Therefore, the trend is very difficult to identify and the stock price of this company seems to be unpredictable. Although the trend line changes abruptly, it is upward.

There was an increase in price due to an announcement made by chief the executive of the company on 17 February 2010 that it could raise its dividend increment. Stock prices of this company plummeted after the announcement made on 5 November 2010 that one of the products of Diageo underperformed the market significantly. There was a structural break on 14 August 2011 due to outperformance of Carlsberg in the European markets. Prices increased steeply when the company broadcasted on 9 May 2012 that sales rose significantly in the African market.

Stock prices jumped after the announcement that Diageo would take full control of Tequila Don Julio through a deal with Jose Cuervo. The stock price of this company rose sharply on 27 February 2015 because the former CEO of Diageo, Paul Walsh, was in conversation to be replaced by Sir Mike Rake, who holds one of the most prestigious roles in British business. The stock price of Diageo plc dropped on 24 August 2015 as Heineken, the world's third-largest brewer, was seeking to raise its stake in India's United Breweries Ltd to gain full management control. It increased on 25 February 2016 as Diageo plc declared that it was to take full management ownership of United Spirits, which was owned by Mallya. Stock prices increased on 26 January 2017 as the company reported that half-year sales growth better than expected. [London South East share price, company finance news]

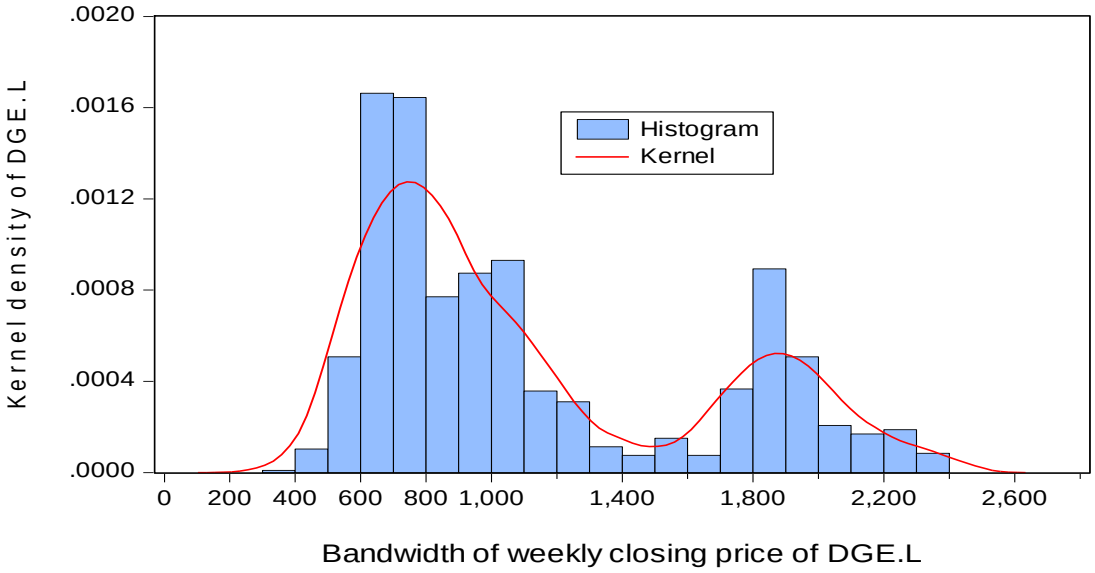
Figure 4. 19: A line graph of weekly closing price for Diageo plc (DGE.L) for period from March 1997 to July 2017



Source: Diagram created by author with the database from March 1997 to July 2017

The kernel density line demonstrates whether the histogram is normally distributed or not. The histogram below is not normally distributed. The graph below appears to have two peaks. As the price repeatedly rises and falls, the graph takes a bimodal shape.

Figure 4. 20: Histogram and Kernel Density graph of weekly closing price for Diageo plc (DGE.L) for period from March 1997 to July 2017



Source: Diagram created by author with the database from March 1997 to July 2017

The service industry

The service industry also explains how different companies fluctuate their prices due to the impacts of their disclosures at different periods of time. The following companies show their movements of prices influenced by different announcements.

Aberdeen Asset Management plc (ADN.L)

When the stock price of Aberdeen Asset Management plc (ADN.L) starts to rise, it continues to rise rapidly until a certain limit. When it begins to fall, it continues to fall speedily up to a certain limit. This market trend is in the process of reversal either from a bullish or bearish trend. Thus, a head two shoulders pattern take place in the price behaviour of ADN.L. There was a steep increase in stock price when a proclamation was made on 23 August 2006 that ADN.L was going to open an office in Tokyo next month to penetrate the Japanese market.

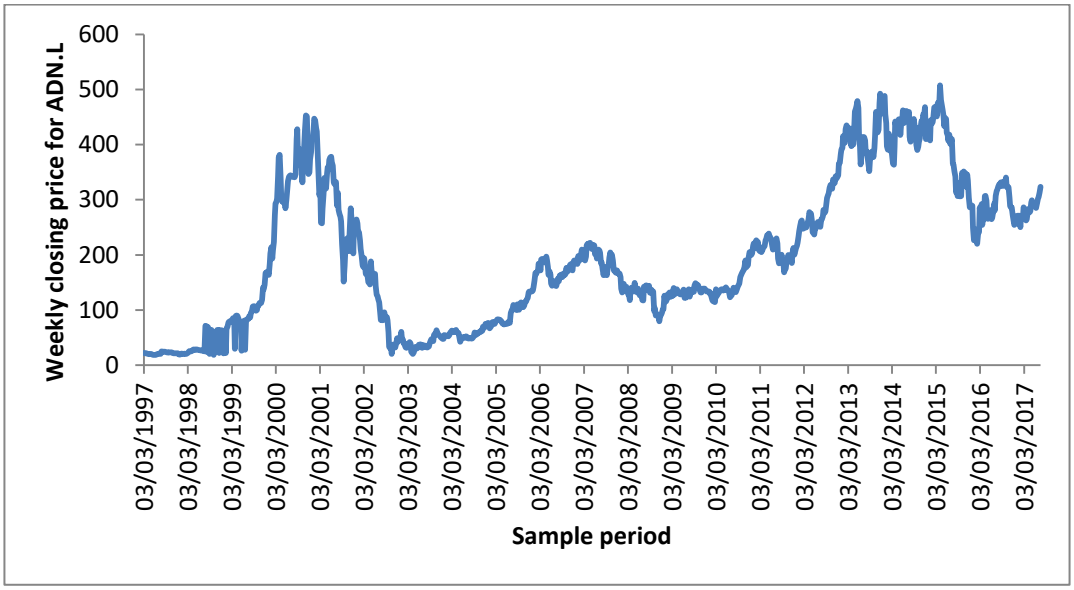
Stock prices increased slowly and steadily after an announcement made on 3 May 2011 that ADN.L posted a 54% rise in pre-tax profit in the six months to end March. Stock prices rose slowly when an announcement made on 24 July 2012 that JP Morgan raises Aberdeen Asset Management price target to 296p from 275p. The stock price of Aberdeen Asset Management plc (ADN.L) oscillated at a constant rate from April 2014 to April 2015. News was released on 9 April 2015 that ADN.L provided financial and technical support to Ashmore Group plc

in its investment to gain higher returns and Ashmore enjoyed positive returns from investments. As a consequence, the stock price of ADN.L reached the high of £507.5 on 10 April 2015. Afterwards, there was a continuous drop in the price until September 2015.

However, the price increased on 28 August 2015 as the company raised a more attractive $500 million hedge fund, which is cheaper, more liquid and transparent. The price again rose from October 2015 to November 2015. It rose on 20 November 2015 as the CEO of the company announced that it was likely to make four or five small acquisitions in 2016. Afterwards, the price started to fall again until the end of February 2016. A message was released on 29 February 2016 that ADN.L would not fall out of the FTSE 100. However, there was a chance that it would leave the FTSE 100 as it was hit by a slowdown in emerging markets. As a consequence, the price started to increase.

The London Stock Exchange regulations explain that if rumours or speculation are largely correct, the company needs quickly to decide whether it has inside information that should be released. Once any news has leaked and directors need to ensure that the market is trading on the basis of accurate information that is available to all. In relation to that, the Aberdeen CEO announced on 6 March 2017 that the merger between Standard Life and Aberdeen Asset Management would lead to some job losses but not the 1,000 figure that had been cited in media reports. [London South East share price, company finance news]

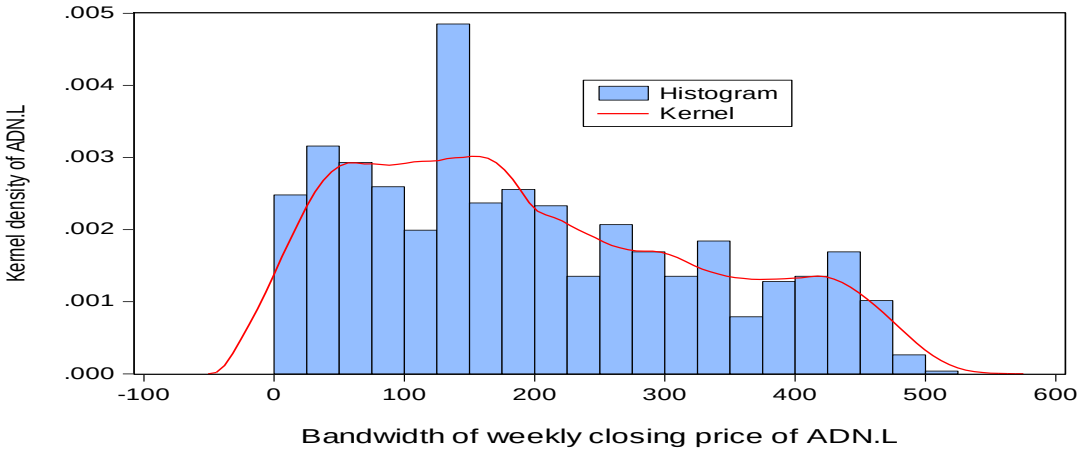
Figure 4. 21: A line graph of weekly closing price for Aberdeen Asset Management plc (ADN.L) for period from March 1997 to July 2017



Source: Diagram created by author with the database from March 1997 to July 2017

The kernel density line documents that the histogram is skewed to the right. A distribution skewed to the right is said to be positively skewed. This skewed distribution can result in regular small losses but significant excessive gains.

Figure 4. 22: Histogram and Kernel Density graph of weekly closing price of Aberdeen Asset Management plc for period from March 1997 to July 2017



Source: Diagram created by author with the database from March 1997 to July 2017

Ashtead Group plc (AHT.L)

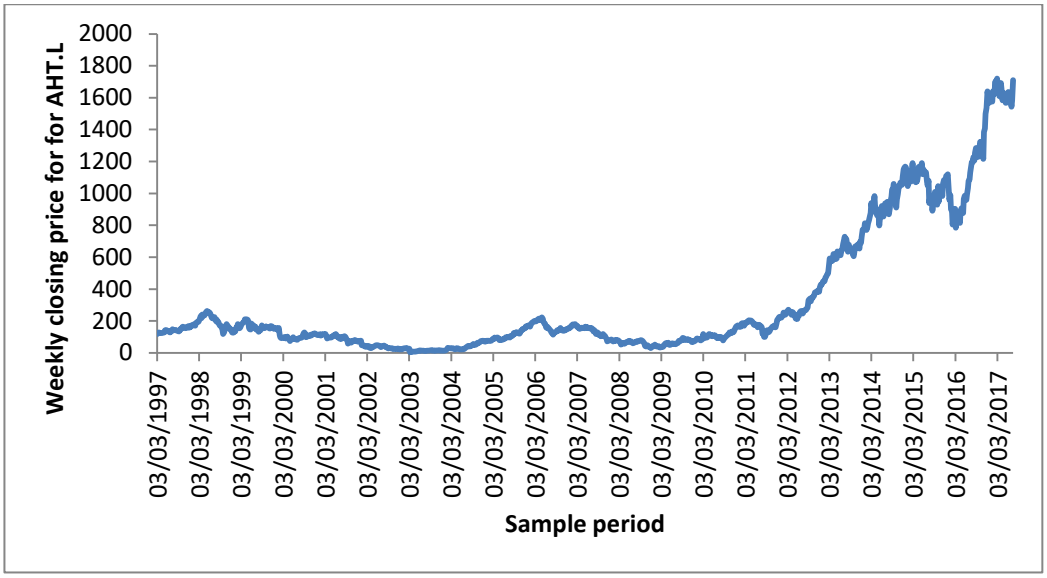
The stock price of Ashtead Group plc (AHT.L) seems levelled off and remained constant from the beginning of sample period to 2011. Stock prices started to ascend very fast from 2012 to 2014. Afterwards, prices began to fall until 2015. Again prices commenced to increase throughout 2016 and 2017.

The graph below discloses that prices fell on 6 March 2007. This is because the company announced that AHT.L posted a lower third-quarter pre-tax profit. The stock price rose from April 2014 to June 2015 with strong oscillations. Since that time, the price declined sharply until September 2015. Stock price increased dramatically when an announcement was made by chief executive Geoff Drabble on 3 September 2014 that AHT.L raised a 33% jump in first-quarter profits on strong demand in the United States and Britain.

The stock price was boosted following 1 June 2015 because of an announcement that the company had achieved profits on equipment disposals above the depreciated book values. The stock price slumped on 16 June 2015 as investors locked in their profits after the results. It again inflated with fluctuations from September 2015 to the end of January 2016. The stock price rocketed on 9 December 2015, caused by the announcement of a 20% jump in profits.

Therefore, the dividend also increased. The price dropped sharply and hit the bottom in February 2016. [London South East share price, company finance news]

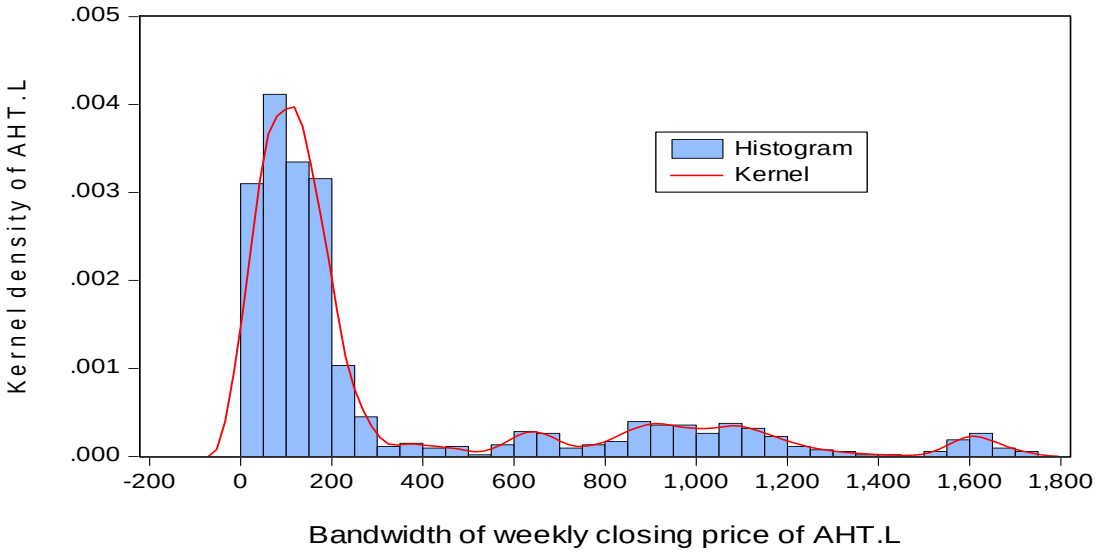
Figure 4. 23: A line graph of weekly closing price for Ashtead Group plc (AHT.L) for period from March 1997 to July 2017



Source: Diagram created by author with the database from March 1997 to July 2017

The graph below appears to have several peaks. As the price repeatedly rises and falls, the graph takes a multimodal shape. As the price trend moves frequently up and down, it could be very difficult to predict future price movements for this company.

Figure 4. 24: Histogram and Kernel Density graph of weekly closing price of Ashtead Group plc (AHT.L) for period from March 1997 to July 2017



Source: Diagram created by author with the database from March 1997 to July 2017

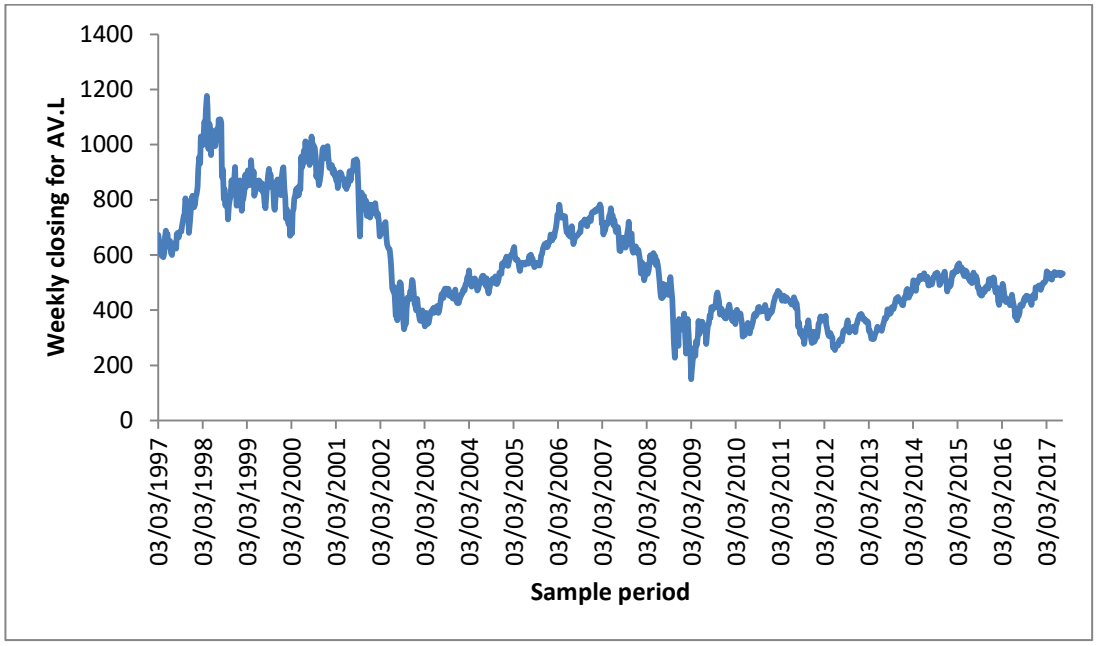
Aviva plc (AV.L)

The graph below discloses that the price moved up and down very frequently throughout the whole sample period. The stock prices hit a low of £4.15 on 10 March 2003. Then prices started to rise until 2007. Afterwards, prices started to fall until 2008. There was a sharp rise in the stock price in March 2015 to reach 569.5, whereas it plummeted in February 2016 at £400. Luckily, the price began to rise again with frequent fluctuations.

There was a rise in stock price when the announcement was made for a special bonus on 6 February 2008. The stock price increased after the announcement was made on 20 November 2012 that Aviva Plc recruited Mark Wilson, a former head of Asian rival AIA Group Ltd, as chief executive. There was a fall in stock price after an announcement made on 7 March 2013 that Aviva slashed its 2012 dividend by more than a quarter to repay debt. The stock price started to decrease from 27 January 2015 due to the asset management arm of Aviva Plc – David Hillier joined the European investment company as a portfolio manager on 26 January 2015. The stock price of Aviva plc increased on 16 March 2016 and afterwards, because EU regulators cleared Aviva's $8.3 billion bid for Friends Life.

It started to drop on 1 February 2016 due to a home insurance policy holder reporting with shock in The Telegraph that an Aviva home insurance policy cost £700 for a one-bedroom house. The news was published in The Telegraph on 19 February 2016 that an insured or policy holder's pension had fallen in value by £6,000 (21.4%) to £22,000 without any explanation being provided by the insurer or Aviva plc. As a consequence, the stock price dropped. The stock price fell when an announcement was made on 23 November 2016 that finance minister Philip Hammond stated in his budget statement that Britain would raise insurance premium tax 2% to 12 percent from June 2017. [London South East share price, company finance news]

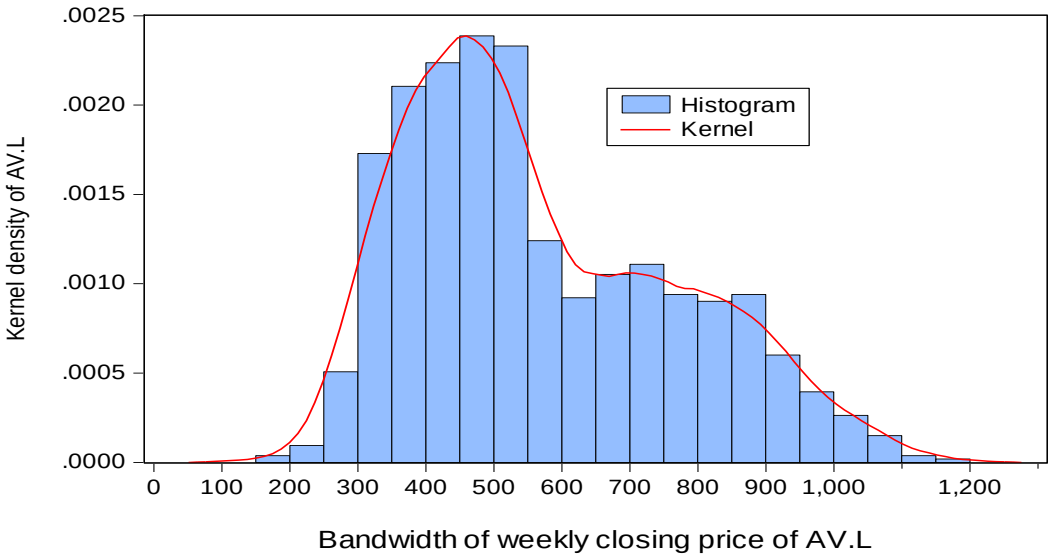
Figure 4. 25: A line graph of weekly closing price for Aviva plc (AV.L) for period from March 1997 to July 2017



Source: Diagram created by author with the database from March 1997 to July 2017

The histogram and Kernel density graph together indicate that it is skewed to the right, which is alternatively called positively skewed distribution. It suggests that there is a higher possibility of making small losses and a few significant gains

Figure 4. 26: Histogram and Kernel Density graph of weekly closing price for Aviva plc (AV.L) for period from March 1997 to July 2017



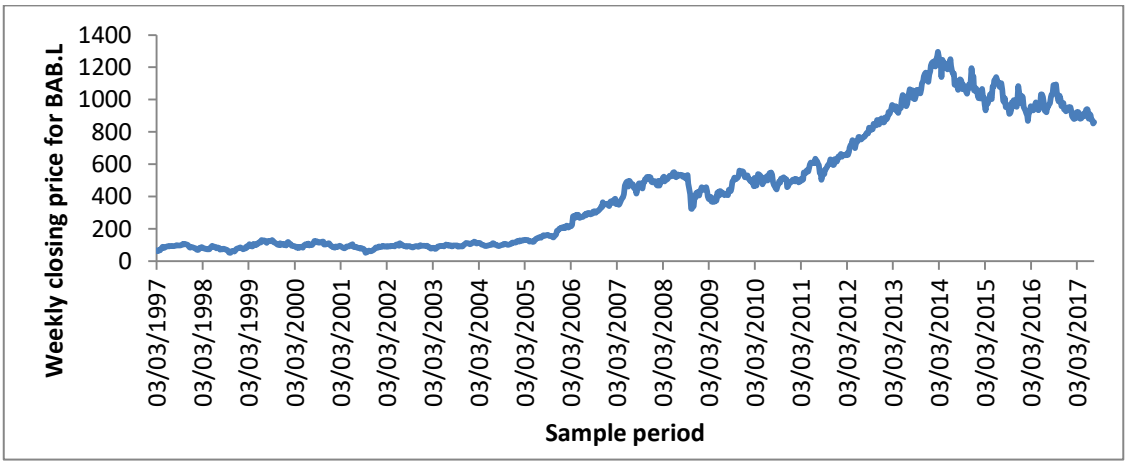
Source: Diagram created by author with the database from March 1997 to July 2017

Babcock International Group plc

The stock price of Babcock International Group plc (BAB.L) was very low at the beginning of the sample period. It seems it levelled off and then remained constant until October 2005. The stock prices rocketed and reached a high of £1250 on 1 July 2014. However, it declined dramatically and reached a low of £854 on 11 February 2016. There were strong undulations throughout the whole sample period. The stock price rocketed after a proclamation was made on 1 September 2008 that BAB.L a 30-year contract with the Royal School of Military Engineering Public Private Partnership worth three billion pounds. There was a rapid price increase on 30 May 2012 as Goldman Sachs raised BAB.L price target to 1036P from 830P. The stock price decreased on 11 March 2015 and afterwards as the British Government declared that it would decrease its spending on defence. As a consequence, the Government would provide less money to the British engineering and support services firm Babcock.

The price increased on 18 May 2015 as the company disclosed its confidence in its long-run profit after earning a 32% rise in its pre-tax profit. The stock price began to increase on 24 November 2015 as the company announced a 7% rise in its pre-tax profit. It dropped on 7 December 2015 due to the announcement of ex dividends. As a consequence, investors would not qualify for the latest dividend payout. The stock price decreased on 28 January 2016, because BAB.L announced that its chief executive officer (CEO), Peter Rogers, would retire in August. The stock price increased rapidly after an announcement made by CEO on 22 November 2016 that Babcock International aimed to expand its foreign business to make up 30 % of sales. [London South East share price, company finance news]

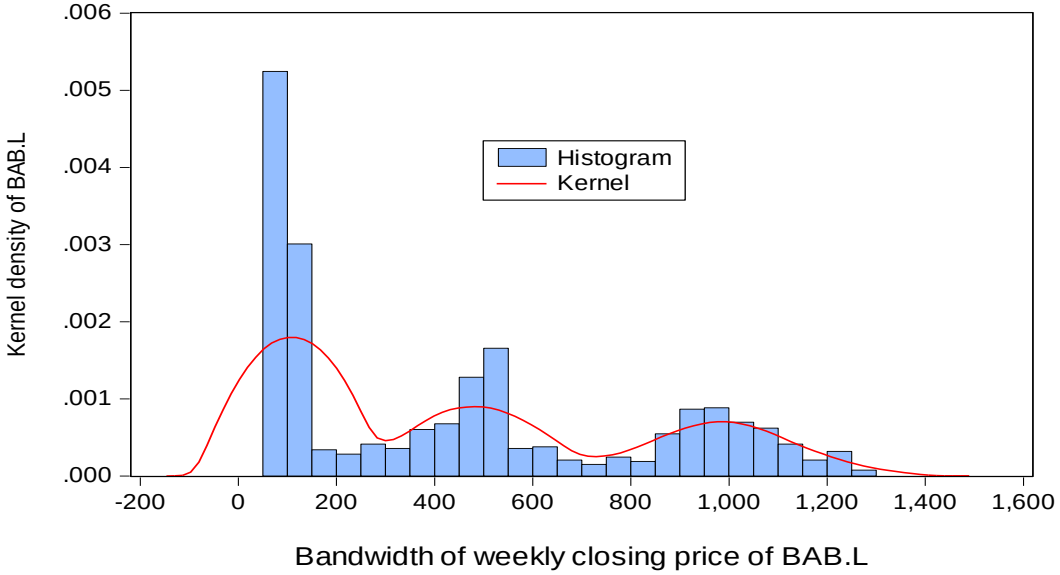
Figure 4. 27: A line graph of weekly closing price for Babcock International Group plc (BAB.L) for period from March 1997 to July 2017



Source: Diagram created by author with the database from March 1997 to July 2017

As the stock price rose and fell frequently with large and small fluctuations, the histogram combined with the kernel density line exhibit that the graph has several peaks. Figure 4.27 also explains that investment in such companies may result in severe losses most of the time. However, sometimes it could generate a few small gains.

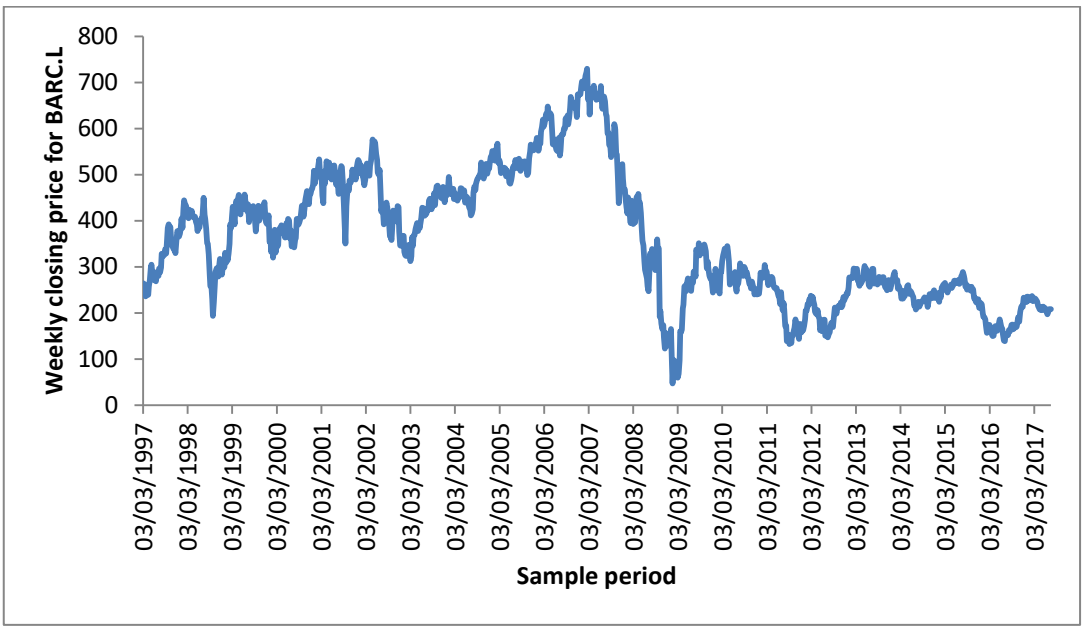
Figure 4. 28: Histogram and Kernel Density graph of weekly closing price of Babcock International Group plc (BAB.L) for period from March 1997 to July 2017



Source: Diagram created by author with the database from March 1997 to July 2017

There were strong fluctuations of stock prices of Barclays plc (BARC.L) from the beginning of the sample period to 2007. There was a peak in price of £729.76 on 19 February 2007. Then stock prices dropped steeply at £47.30 on 19 January 2009. Then stock prices started to rise again with little fluctuations until 2017. The reasons for increasing and decreasing in stock prices were investigated. It was reported on 24 September 2014 that Barclays plc was fined by FCA for breaching client assets and internal compliance procedures. Consequently, stock price dropped. The company announced on 17 March 2015 that it had made a 15% profit during 2014 to just under £1 billion. Therefore, the stock prices jumped the following day. The stock price of Barclays plc increased on 22 June 2015. This is because the company announced the prediction that it would earn an annual yield of 4% by 2016 and the company also announced that it would be able to provide better dividend in 2016. [London South East share price, company finance news]

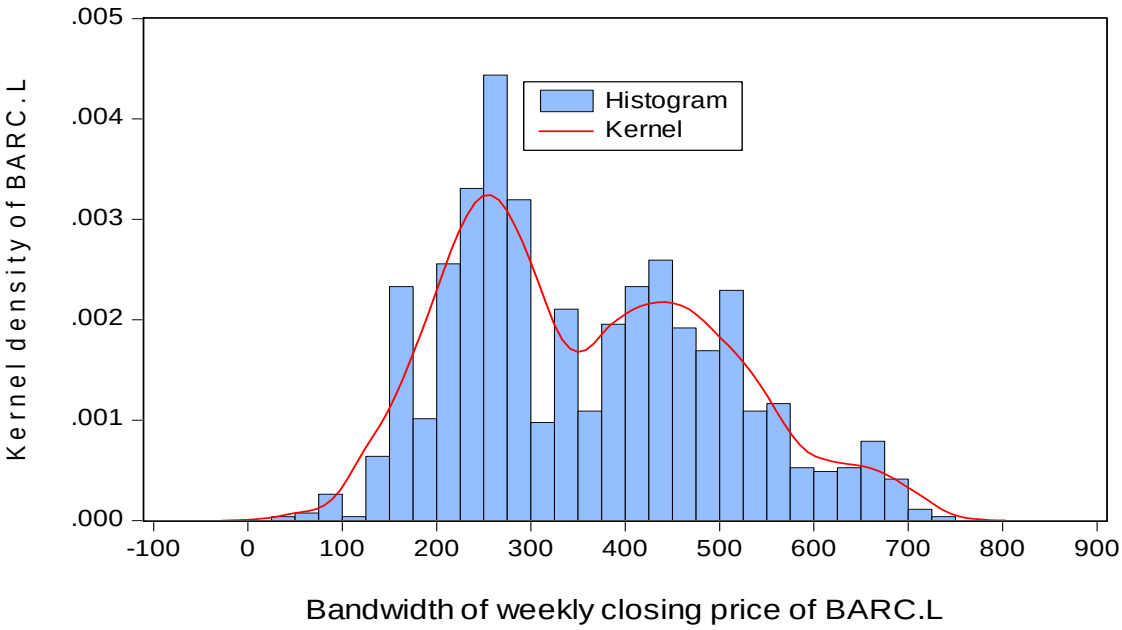
Figure 4. 29: A line graph of weekly closing price for Barclays plc (BARC.L) for period from March 1997 to July 2017



Source: Diagram created by author with the database from March 1997 to July 2017

The graph 4.30 below appears to have two peaks. As the price repeatedly increases and decreases, the graph takes a bimodal shape. It is also a little skewed to the right, which indicates regular small losses and a few excessive gains.

Figure 4. 30: Histogram and Kernel Density graph of weekly closing price of Barclays plc (BARC.L) for period from March 1997 to July 2017



Source: Diagram created by author with the database from March 1997 to July 2017

The quaternary industry

The reasons for fluctuations in prices were detected for the selected companies of the quaternary industry. It was found that announcements and disclosures changed prices significantly up and down.

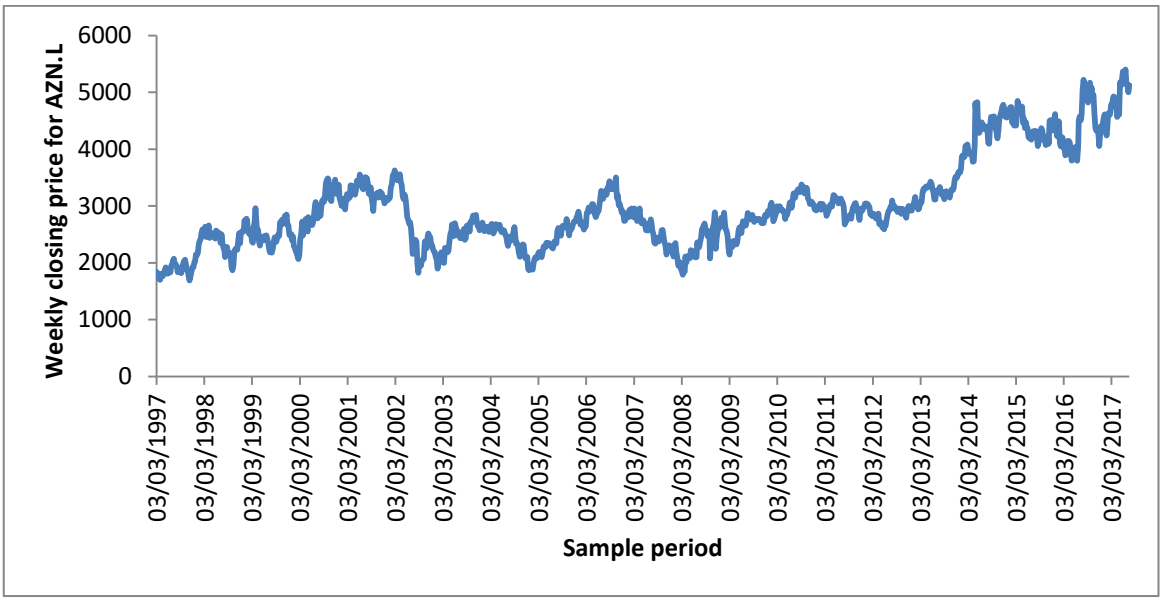
AstraZeneca plc

The graph below delineates the price behaviour of AstraZeneca plc. At the beginning of the sample period, the stock price was £1837.85. However, it jumped to around £5123 from £1837.85 at the end of the sample period. However, the prices fluctuated randomly and frequently throughout the whole sample period. Therefore, the trends and movements of this company seem to be unpredictable.

There was a structural break on 13 October 2013 and the stock price rose sharply the following week. This is because, AstraZeneca announced that the company had signed a deal to co-promote Johnson & Johnson's novel prostate cancer medicine in Japan, giving the British company a new drug revenue stream and bolstering its Japanese presence. The stock price of AstraZeneca rose 0.4% to 48.31 pounds in early trading on 2 May 2014 after Pfizer raised its offer for the British company to 50.00 pounds per share. The price climbed high on 6 May 2014 as the company announced that it was targeting annual revenues of more than $45 billion by 2023 from cancer drugs. The stock price of AZN.L rocketed on 18 March 2016 and afterwards, because the company announced that the lung drug PT003 had proved to be successful in curing chronic lung disease. It jumped on 8 May 2015 due to a public meeting held to relax the guidelines for selling off-label drugs.

The price decreased on 24 August 2015 due to the replacement of the chief medical officer. An announcement was made on 5 February (Friday) 2016 that AZN.L needed a strong performance from a new drug pipeline to cover the loss from the old blockbuster Crestor drug. Therefore, the price slumped on 8 February (Monday) 2016. AstraZeneca unveiled on 2 February 2017 that profit and revenue would fall this year due to cheap generic versions of its cholesterol drug, Crestor. The stock price of AstraZeneca fell more than 5% on 13 July 2017 after the company declined to deny a media report that CEO, Pascal Soriot, was about to defect to Israel-based Teva Pharmaceutical Industries. [London South East share price, company finance news]

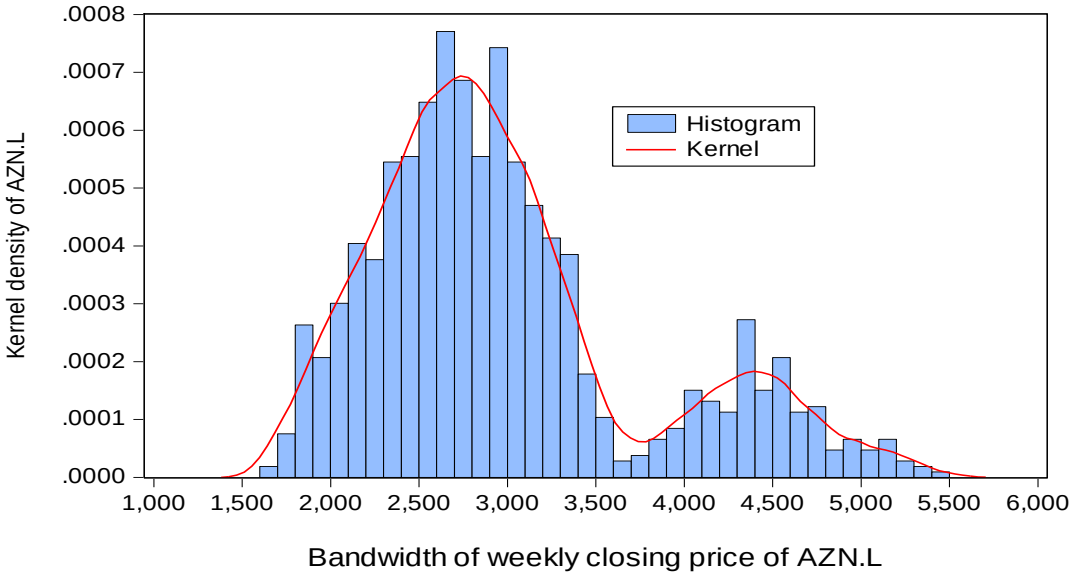
Figure 4. 31: A line graph of weekly closing price of AstraZeneca plc (AZN.L) for period March 1997 to July 2017



Source: Diagram created by author with the database from March 1997 to July 2017

As the price changed from up to down and down to up, the kernel density line creates two peaks in the histogram. The histogram and kernel density line together below shows that the graph is not normally distributed. As the price repeatedly goes up and drops, the graph takes a bimodal shape.

Figure 4. 32: Histogram and Kernel density graph of weekly closing price for AstraZeneca plc (AZN.L) for period March 1997 to July 2017



Source: Diagram created by author with the database from March 1997 to July 2017

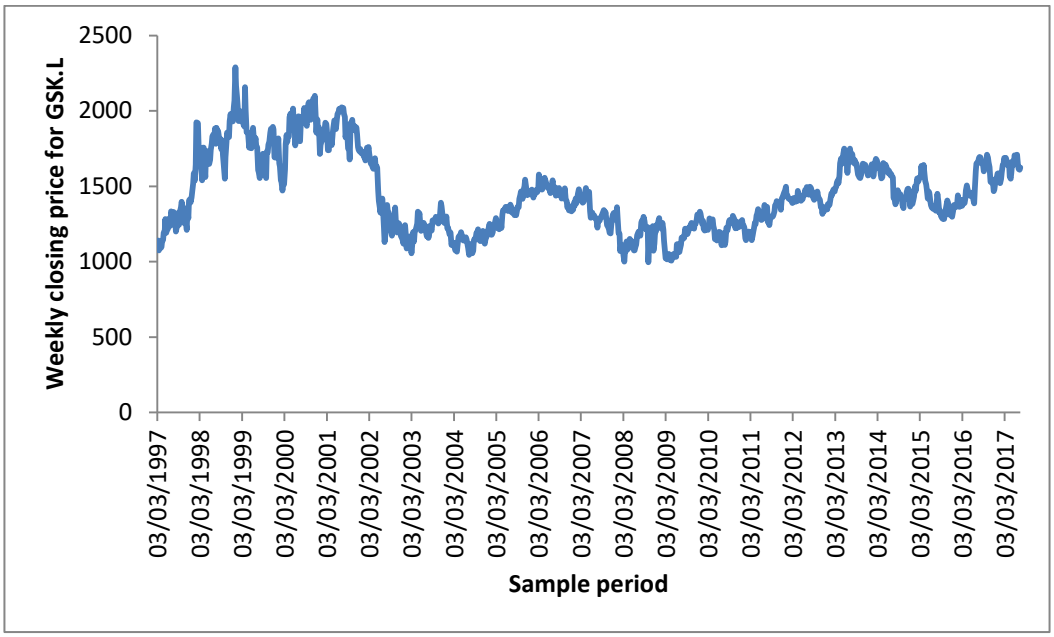
GlaxoSmithKline plc (GSK.L)

The graph below explains that the price was very low at the beginning of the sample period and it ascended steeply at £2288 on 4 January 1999 and then started to fall slowly with fluctuations until July 2004. Afterwards, it repeatedly increased and decreased until July 2017. The price rose sharply from January 2015 to March 2015 then started to decline again with oscillations from April 2015 to July 2015. From August 2015 to July 2017, the stock price moved up and down repeatedly.

The stock prices of GSK.L plummeted with the announcement made on 11 July 2013 that the company was suspected of offering bribes to government officials, medical associations, hospitals, and doctors to enhance sales and prices in China. GSK was also suspected of using fake receipts in unspecified tax law violations in China. The stock prices descended when BBC reported on 14 April 2014 that GlaxoSmithKline Plc was facing a criminal investigation in Poland for allegedly bribing doctors to promote its asthma drug Seretide.

The stock prices went down after the proclamation made on 22 October 2014 that the company would leave the dividend payment unchanged for the third quarter. The stock price fell continuously due an announcement made on 3 December 2014 that the company would shed several hundred U.S. commercial jobs and a similar number of research positions. The stock price of GSK.L rocketed on 10 April 2015 as the company disclosed that Ebola vaccines were being developed by the company. It jumped on 30 September 2015, because the World Health Organization (WHO) made a statement that 37 million people worldwide should be given treatment as soon as HIV is diagnosed to extend their lives and protect their partners from transmission of the virus. The stock price rose on 28 October 2015 due to the announcement that the total number of sales of HIV drugs, vaccines and consumer health care products had increased more than expected. It climbed on 25 January 2016 and afterwards as the company jointly invested £40 million in three British universities for drug research. [London South East share price, company finance news]

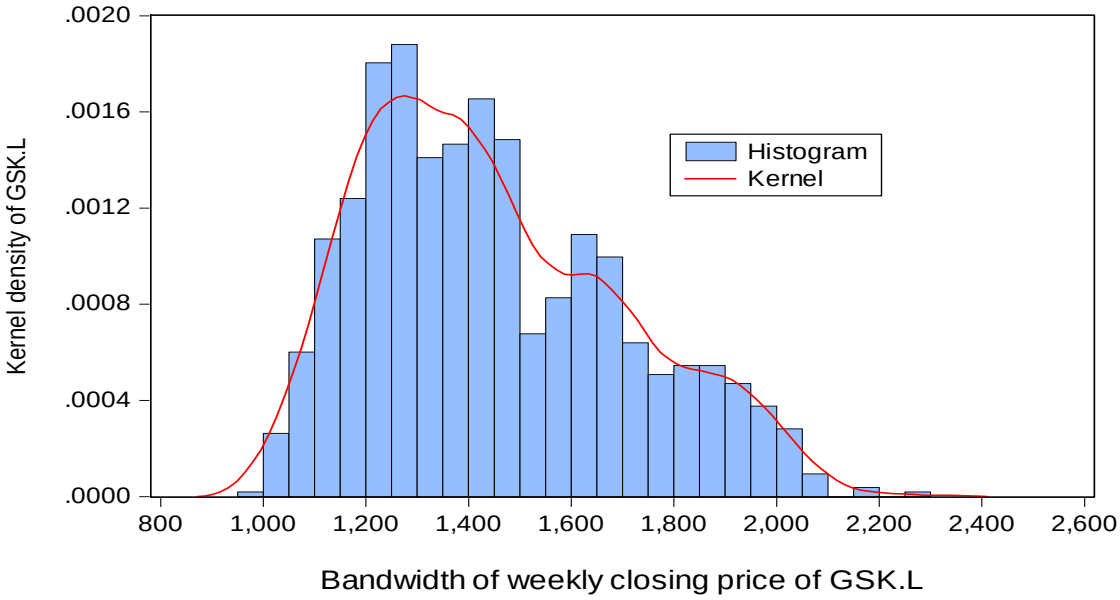
Figure 4. 33: A line graph of weekly closing price for GlaxoSmithKline plc (GSK.L) for period from March 1997 to July 2017



Source: Diagram created by author with the database from March 1997 to July 2017

The graph 4.34 below appears to be skewed to the right, which discloses that there will be a few small losses and several extreme gains from investment in this company. The histogram and kernel density line together also explain that the graph is not normally distributed.

Figure 4. 34: Histogram and Kernel Density graph of weekly closing price of GlaxoSmithKline plc (GSK.L) for period from March 1997 to July 2017



Source: Diagram created by author with the database from March 1997 to July 2017

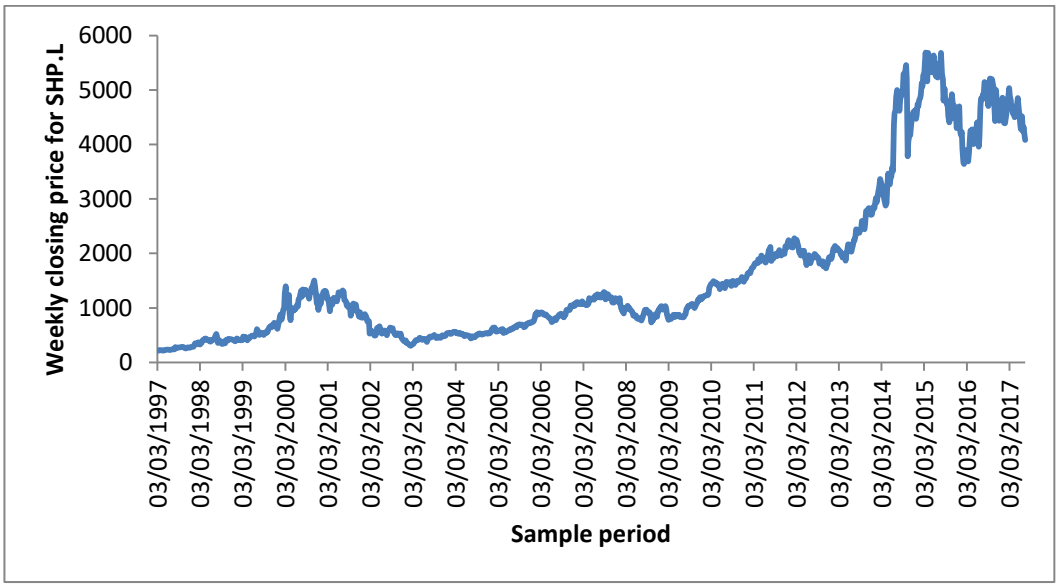
Shire plc (SHP.L)

The graph below explains that the stock price of Shire plc was very low at the beginning of the sample period. It was low until 1998. It commenced rising from 1999 to 2000. It started to decline from 2001 to 2002. The price again began to rise slowly and steadily from 2003 to 2012. The stock prices rocketed from £1978 in March 2013 to £5455 in September 2014. At the end of October 2014, prices fell sharply. At the beginning of November 2014, the prices again rocketed with fluctuations. The prices dropped with random fluctuations from August 2015 to March 2016. The prices increased again with little fluctuations from 31 July 2016 to 9 October 2016. Afterwards, stock prices started to fall until July 2017.

The stock prices rose steeply when the company announced on 26 July 2007 that Shire plc raised 16% growth in second-quarter earnings, driven by strong demand for its top selling medicine Adderall XR. The stock price ascended when the company announced that the forecast showed 12% rise in revenues for the whole year. This is because the company was expecting lower research and development costs. The price dropped steeply on 16 October 2014 as the US pharmaceutical company AbbVie suggested to its shareholders to vote against its $55 billion takeover of Shire in the wake of a US Government move to curb deals designed to evade high taxes.

The price reached its all-time high on 10 April 2015 as the company announced that the Food and Drug Administration in the USA (US FDA regulator) had granted a review of the application for the dry-eye disease treatment lifitegrast. It increased on 12 February 2016 and subsequently. This is because the company announced on 11 February 2016 that it had made a larger profit than expected in the final quarter of 2015. The stock price increased significantly with an announcement made on 2 May 2017 that Pharmaceutical group Shire, which bought haemophilia specialist Baxalta last year, reported a 14% increase in first-quarter earnings, helped by cost savings and higher sales of its rare disease drugs. [London South East share price, company finance news]

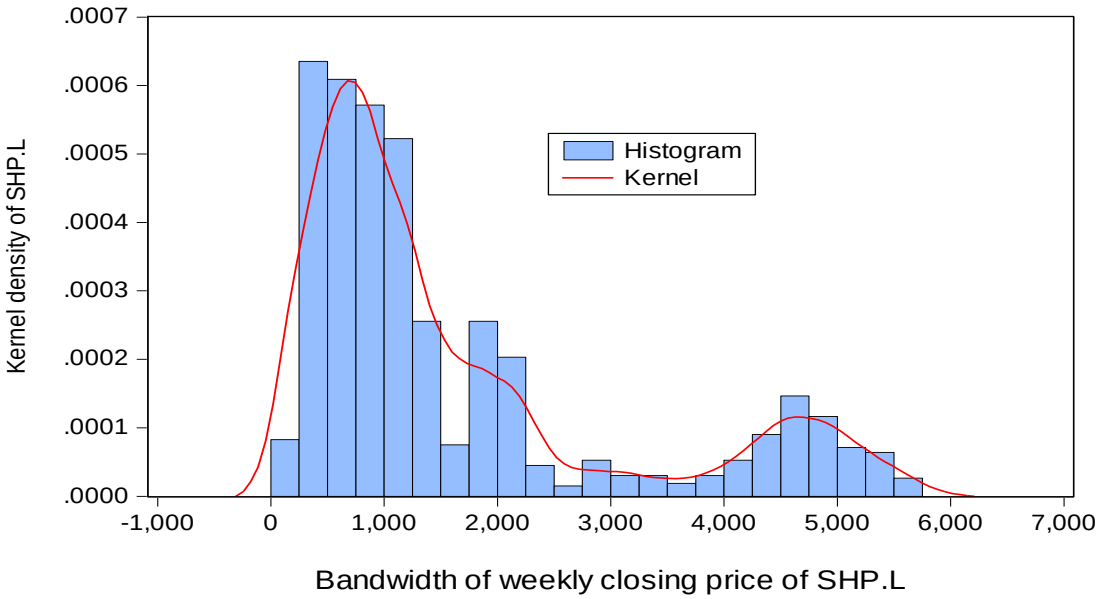
Figure 4. 35: Line graph of weekly closing price of Shire plc (SHP.L) for period from March 1997 to July 2017



Source: Diagram created by author with the database from March 1997 to July 2017

As prices moved from downward trend to uptrend and upward to downward trend, the Kernel density line creates two peaks in the histogram for Shire plc. The graph is skewed to the right which discloses that there is a probability of having a few small losses and several extreme gains from investment in this company. As the price repeatedly goes up and drops, the graph takes a bimodal shape.

Figure 4. 36: Histogram and Kernel Density graph of weekly closing price for Shire plc for period from March 1997 to July 2017



Source: Diagram created by author with the database from March 1997 to July 2017

Sage Group Plc (SGE.L)

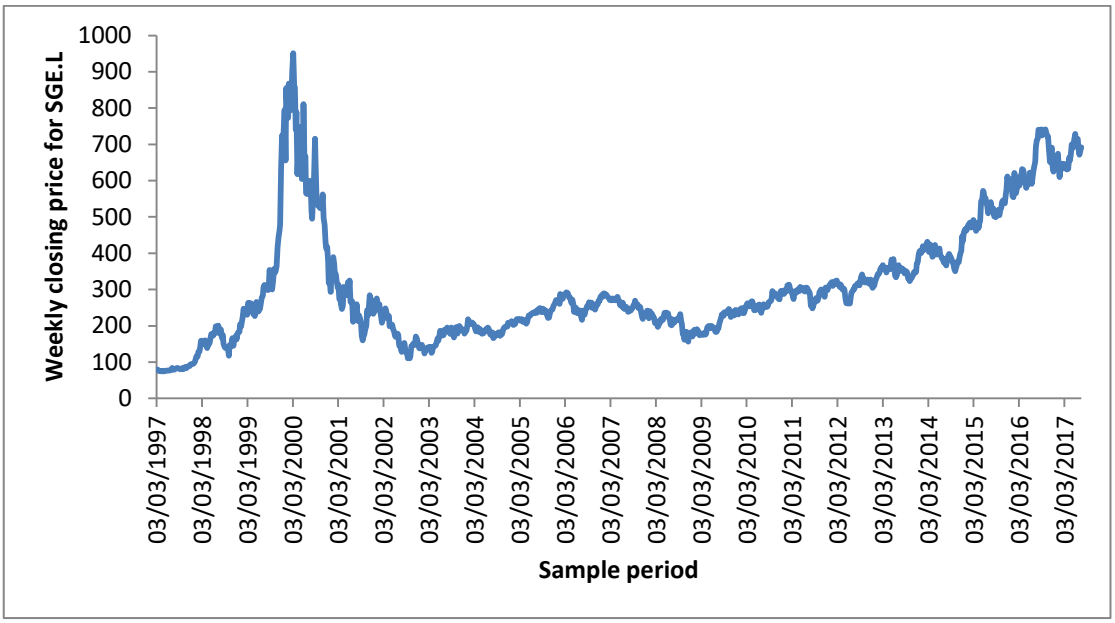
From the beginning of the sample period, there was a steep rise in price to £198.70 on 21 July 1998 from £79.48. There was a small decrease at the beginning of October 1998. Following the effects of announcements from the company and other information, stock price rocketed to a peak of £951.49 from £117.76. Afterwards, the stock prices dropped slowly and steadily and hit a low of £110.45 on 29 September 2002. The stock prices then increased gradually with little fluctuations until the end of the sample period. The reasons for fall and rise of stock prices were explored in this study. The major causes are explained below:

The stock price increased with an announcement made on 24 July 2006 that Software company, Sage Group plc, had bought 51% of French business distribution software company, Elit Group, for £10.8 million in cash. Sage would be able now to make an offer to the remaining Elit shareholders to acquire all outstanding shares. It was announced on 7 December 2010 that JP Morgan raised Sage Group PLC price target to 300P from 248P. Consequently stock prices went up.

British software company Sage unveiled on 23 July 2013 that it was confident of meeting its financial goals after overcoming weak markets in Europe to trade in line with forecasts. The company delivered a resilient performance of accountancy and software service to more than 6 million small companies in France and Spain despite the general weak market conditions across mainland Europe. For this reason, stock prices went up steeply. The company announced on 3 December 2014 a 5 percent rise in revenue and 8 percent rise in earnings. As a consequence, stock prices rose significantly.

The stock price of SGE.L declined by nearly 6 percent on 26 January 2017 after the company's announcement that a disappointing performance by its U.S. payments business hit its first quarter results and that it might sell the division. There was another reason for declining stock price for reporting a reduced income from its software and software-related services (SSRS) division in France in its first quarter. [London South East share price, company finance news]

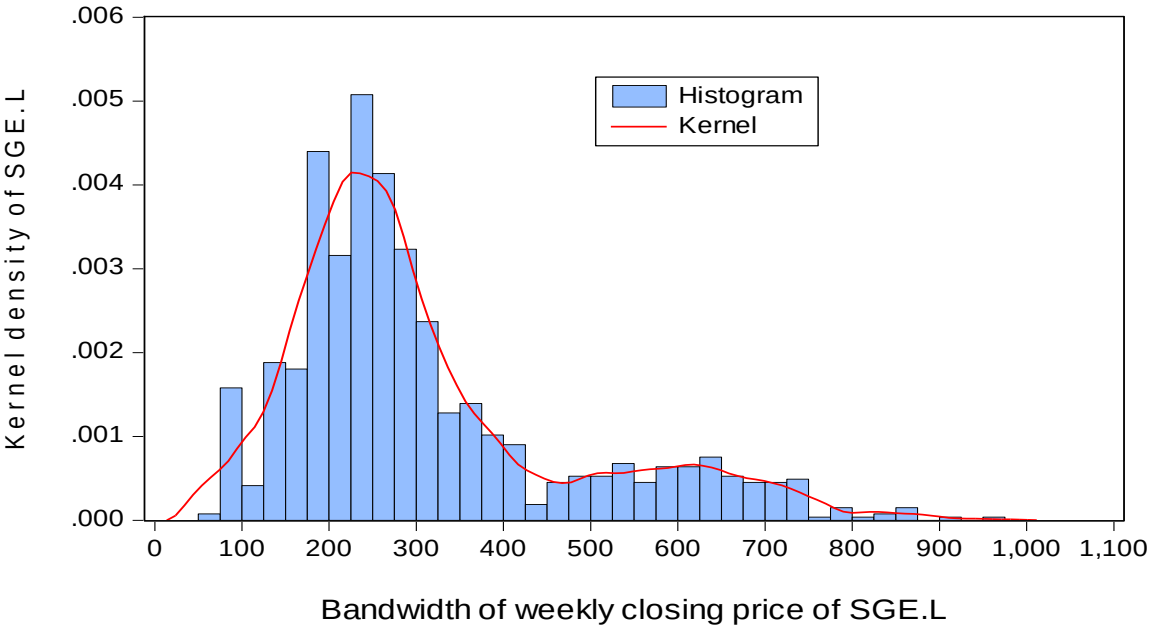
Figure 4. 37: Line graph of weekly closing price of SGE.L for period from March 1997 to July 2017



Source: Diagram created by author with the database from March 1997 to July 2017

The kernel density line explains that the histogram below in figure 4.38 is skewed to the right and it is a positively skewed distribution. A positively skewed distribution may generate frequent small negative returns and a few substantial higher positive returns. Therefore, investors could expect higher returns with lower risk investing in this company.

Figure 4. 38: Histogram and Kernel Density graph of weekly closing price for SGE.L for period from March 1997 to July 2017



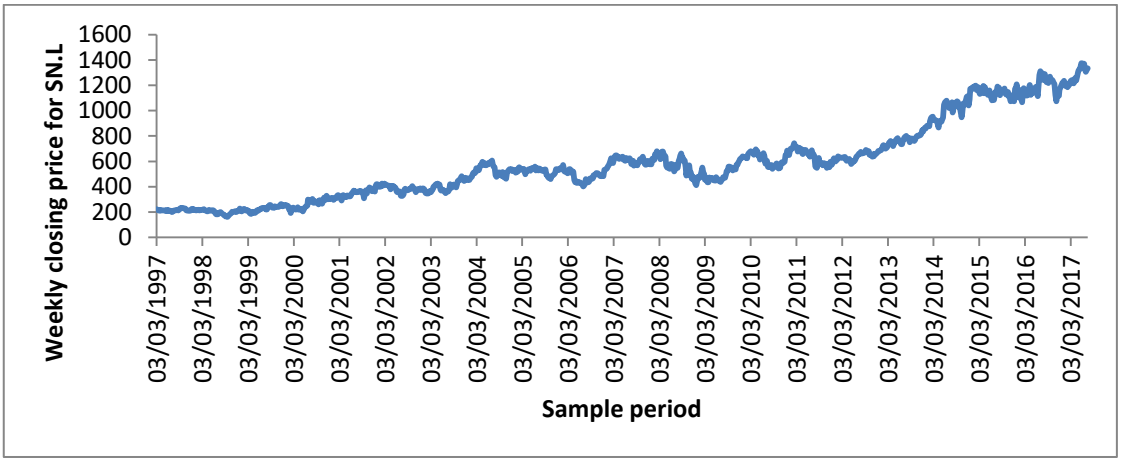
Source: Diagram created by author with the database from March 1997 to July 2017

Smith and Nephew plc (SN.L)

The stock price of Smith and Nephew plc (SN.L) was £218.17 at the beginning of the sample period. Afterwards, the prices levelled off and remained constant until April 1998. There was a small decrease in stock price. Following the company's announcements and other relevant information, stock prices started to ascend until the end of the sample period with frequent and random fluctuations. Therefore, the stock prices of this company may be unpredictable. The stock price fell after the announcement made on 1 May 2008 that the first quarter pre-tax profits decreased to $126 million compared with $131 million last year. Smith & Nephew plc posted on 5 November 2010 a lower third-quarter earnings after it stepped up marketing to consumers in the United States. Consequently, stock prices dropped.

Artificial joints maker Smith & Nephew plc announced on 7 February 2013 a slight dip in trading profit of $272 million in the fourth quarter after it lost market share in its knees implant business. Consequently, stock prices decreased. The stock prices rose after the announcement made on 30 October 2014 that the company would make a 3% rise in three-quarter trading profit fuelled by solid growth in orthopaedic reconstruction. Smith & Nephew Plc announced on 29 October 2015 that the prediction for a higher trading profit margin this year as it had achieved third-quarter revenue higher and also announced the acquisition of a robotics company. Therefore, stock prices rose the following day. The stock price decreased on 5 May 2016 as the company reported a slightly worse-than-expected 3% rise in first-quarter revenue. The stock price in Smith & Nephew plc rose to a nine-month high on 5 May 2017 after the announcement that the company had increased sales significantly in the first quarter in emerging markets. [London South East share price, company finance news]

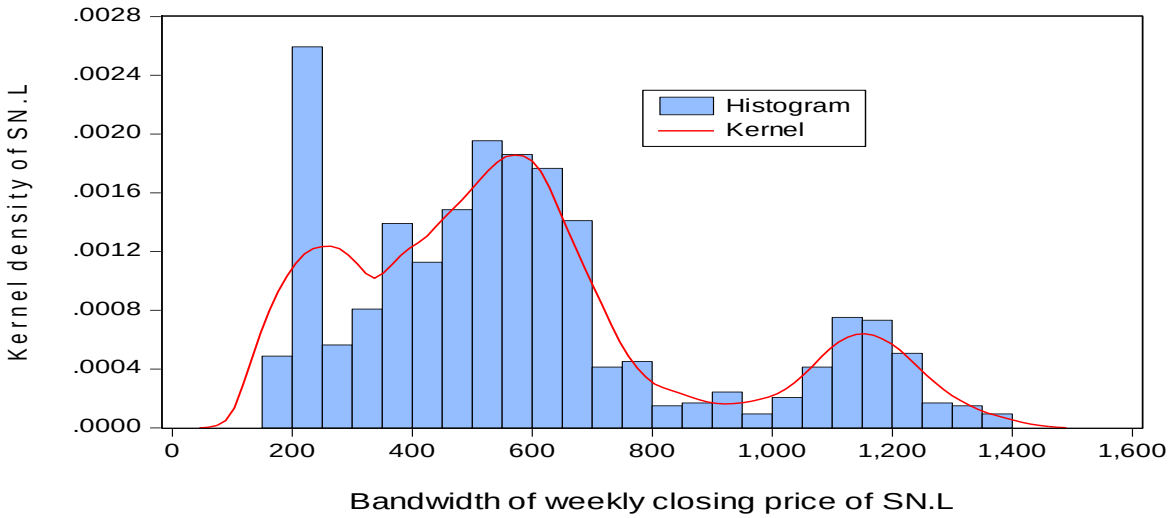
Figure 4. 39: A line graph of weekly closing price of SN.L from 1997 to 2017



Source: Diagram created by author with the database from March 1997 to July 2017

The kernel density line exhibits whether the histogram is normally distributed or not. The histogram below is not normally distributed. The graph is skewed to the right. The kernel density line together with histogram also detail that the distribution has two peaks. Consequently, it is a bimodal distribution. This distribution indicates that both the processes involved in it confirm a normal distribution individually and have different means and standard deviations.

Figure 4. 40: Histogram and Kernel Density graph of weekly closing price for SN.L for period from March 1997 to July 2017



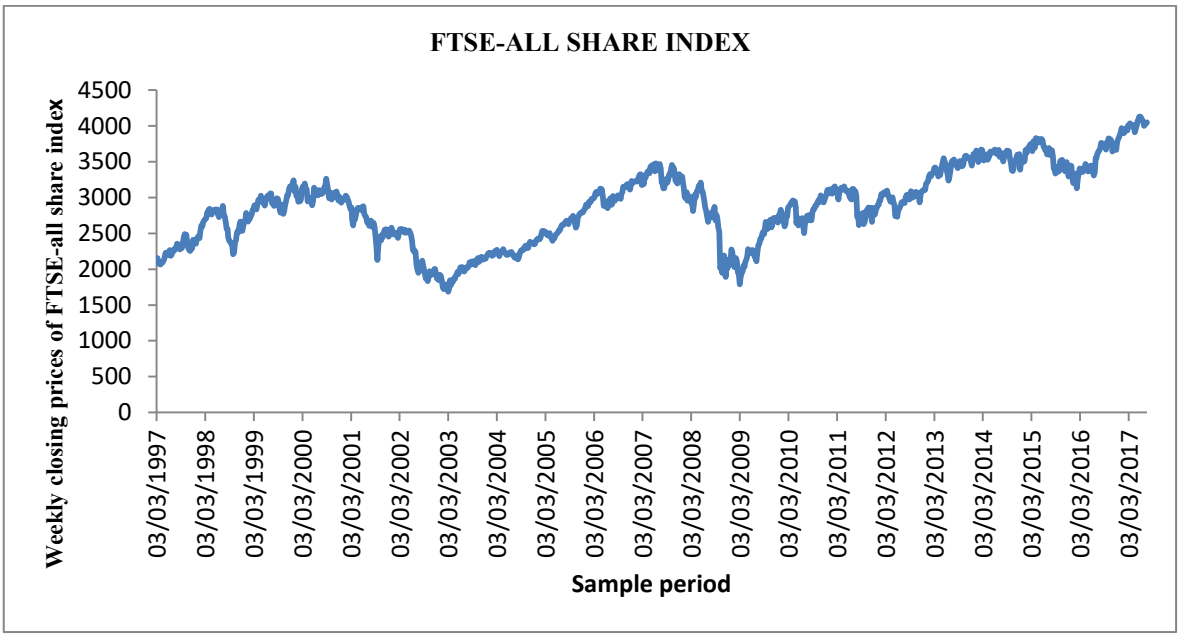
Source: Diagram created by author with the database from March 1997 to July 2017

FTSE-ALL SHARE INDEX

The figure below shows a line graph of weekly closing prices for FTSE-all share index over the periods between 3 March 1997 and 17 July 2017. Overall, the stock price witnessed an upward trend with frequent fluctuations. The stock price was £2153.44 at the beginning of the sample period. Afterwards, the price was decreased to 2092.44 by the period of 14.04.1997.

The stock price started to rise dramatically and peaked at £3118.21 by end of March 2000, but after that the price fell again rapidly and reached £1727.80 in March 2003. The price fluctuated in the same way until 2015. After that, stock prices picked up again and again reached a high of £4048.85 in 2017. It seems that the prediction of stock price for this series is quite impossible due to frequent and random movements of stock prices. For such series, GARCH (1, 1) and ARIMA models might generate better forecasting than exponential smotthing techniques.

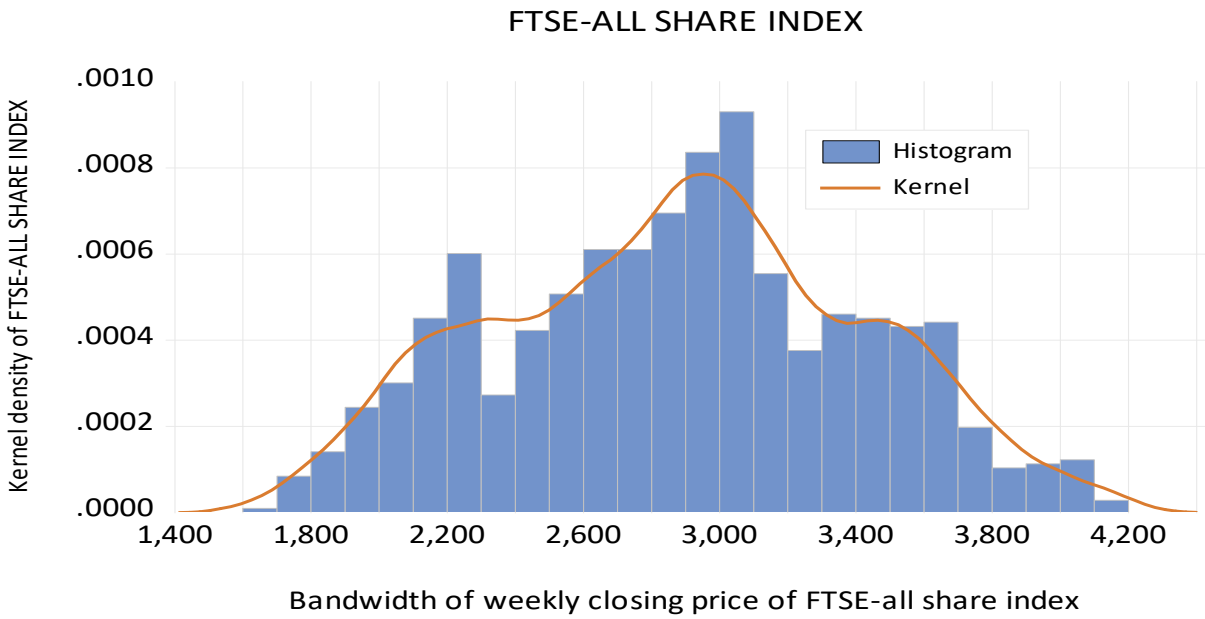
Figure 4.4 1: A line graph of weekly closing price for FTSE-ALL SHARE INDEX from March 1997 to July 2017



Source: Diagram created by author with the database from March 1997 to July 2017

The kernel density line exhibits whether the histogram is normally distributed or not. It shows that the histogram is not normally distributed. However, it looks like mesokurtic. It indicates that stock prices of FTSE-all share index are not predictable as the prices move randomly and erratically for this series.

Figure 4.4 2: Histogram and Kernel Density graph of weekly closing price for FTSE-ALL SHARE INDEX for period from March 1997 to July 2017

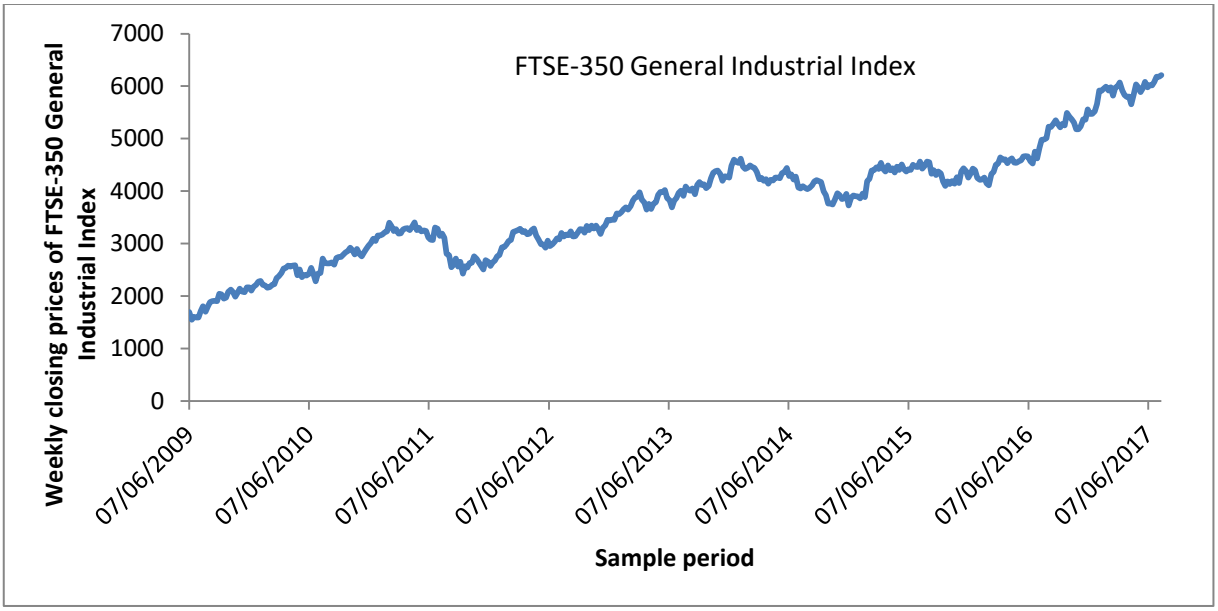


Source: Diagram created by author with the database from March 1997 to July 2017

FTSE-350 General Industrial Index

This series shows information from June 2009 to July 2017 due to unavailability of stock prices in the earlier period. The graph below shows that the trend line of the stock price is upward with frequent fluctuations. At the beginning of the sample period, the stock price was low which is £1696.89. The stock price started to increase slowly and gradually from beginning to end of the sample period. There was a sharp increase in price in £4390.16 in November 2013. After that, there was a gentle, steady decrease in price of this series until middle of 2014. Then, prices again rose erratically over the periods. It seems that stock prices of FTSE-350 are predictable as the price line follows a steady and low upward trend. It also indicates stock prices of industrial sectors are predictable.

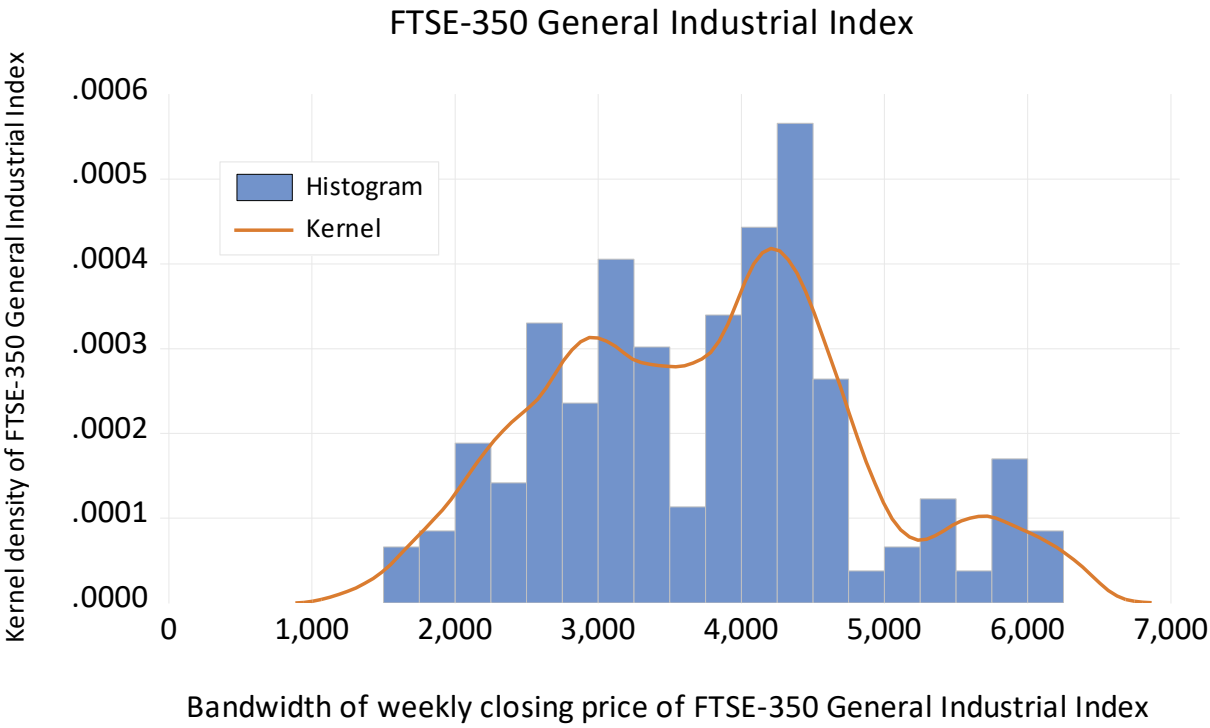
Figure 4.4 3: A line graph of weekly closing price of FTSE-350 General Industrial Index from June 2009 to July 2017



Source: Diagram created by author with the database from June 2009 to July 2017

The kernel density line explains whether the histogram is normally distributed or not. The histogram below is not normally distributed. As prices moved from downward trend to uptrend and upward to downward trend, the Kernel density line creates two peaks in the histogram for FTSE-350 general industrial index. The graph is skewed to the right which discloses that there is a probability of having a few small losses and several extreme gains from investment in this series. As the price repeatedly goes up and drops, the graph takes a bimodal shape.

Figure 4.4 4: Histogram and Kernel Density graph of weekly closing price for FTSE-350 GENERAL INDUSTRIAL INDEX for period from June 2009 to July 2017



Source: Diagram created by author with the database from June 2009 to July 2017

It is found from the graphical analysis and explanation of price movements that most of the companies in the primary industry are positively skewed. This indicates that investment in the primary industry might generate positive returns. It seems that the stock prices of a few companies in the primary industry are traceable and predictable. Most of the series in the manufacturing industry show that stock prices move slowly and there is a upward trend in series. Therefore, stock prices in the manufacturing industry might be predictable.

On the other hand, it is observed that the stock price trends for most of the series in the service industry move randomly and unsteadily. This indicates that the stock prices for most of the series in the service industry might not be predictable. Furthermore, the stock prices for most of the companies in the quaternary industry change abruptly and suddenly. Therefore, their prices are less predictable and they might generate larger forecasting errors. The result also indicates that the stock prices in this industry embed new information promptly.

This section has also analysed the rationality behind any changes in price trends in all the graphs. The next section contains the research methodology and explains all the research methods adopted in this study.

Research Methodology

This part will discuss and formulate the adopted data analysis methods that will be applied in the next chapter to analyse and evaluate the findings from the applied methods. This section explains below how the whole research will be conducted for each of the 22 series.

This study will evaluate 22 series (the FTSE-All share Index, and the FTSE-350 general industrial index and 20 companies from four different industries). At first, all the series will be visually inspected for the whole sample period to see whether there are any seasonality and structural breaks in the data. Furthermore, the Friedman test of Chi-Square statistics will be applied to detect seasonality. Secondly, structural breaks will be investigated if there is any from the application of Bai-Perron's multiple breakpoints test for the whole sample period.

If there are any breakpoints at different point of time, a clean period of data will be selected for each series where there is no any structural breaks for statistical analysis and forecasting purposes. As a consequence, the clean period will be a sub-sample period. However, this sub-sample period might not be the same for all series. This is because, all the series might have specific shocks or events caused by microeconomic factors.

Statistical inferences regarding market efficiency will be made from four different statistical tests (ADF-unit root test at the first difference, runs test at level, Ljung Box's serial autocorrelation at first difference and variance ratio test at level). Weak-form efficiency inference is made if there is no unit root and serial-autocorrelation at the first difference and there is no heteroscedasticity (variance is constant) at the level.

After drawing the statistical inference, statistical models and techniques (ARIMA; GARCH-1, 1; exponential smoothing techniques) will be applied to predict the market for each sub-sample period. This study will choose a sub-sample period of 204 observations for each series to estimate the model. A few observations just before the breakpoint have been excluded from the estimation period to evaluate the forecastability of the model.

The validation period is taken up to 4 observations. This is because, most time series models could not forecast for a very long period or do not provide accurate prediction for multi-step forecasts. There is another reason for considering a short estimation period. The number of observations should not be taken so largely. It should be limited to about 200 (Hyndman and Athanasopoulos, 2018). Afterwards, a conclusion will be drawn on predictability or market efficiency based on evaluation statistics including MAPE, Theil U_1 and U_2 from each model

and technique. The forecast encompassing tests will be applied to determine which model performs better than the other. If the forecast encompassing tests fail to decide a better model, this study will go one step further back and rely on three parameters of forecast benchmarks including MAPE, Theil U_1 and U_2.

The next section explains the adopted research methods and their significance in this study.

4.3 The data analysis techniques adopted and their significance in this study

The forecasting techniques that are applied in this study are the ARIMA model, GARCH (1, 1) model and Holt's and Winters's forecasting models. These models will be discussed in chapter five. In addition to them, a few other statistical tools are used to help the predicting techniques, which include descriptive statistics, the run test, the variance ratio test, the correlogram, ADF-unit root test, Friedman test and Bai-Perron multiple breakpoint test. These non-forecasting related statistical tools will be discussed later in this chapter. All these statistical tools will help to achieve the research objectives and answer the research questions.

There are other time series models, which are the ANN and vector autoregression (VAR). However, this study will apply the above-mentioned four forecasting models instead, because these are highly used and easy to understand models for time series forecasting. The ARIMA model is simpler to apply than the ANN. Many studies have shown that the ARIMA model performs better for linear data than ARMA and ANN models, which were discussed in the literature review chapter. The ARIMA model also performs better than VAR, which was documented by Brandt and Bessler (1984).

The application of exponential smoothing techniques is straightforward. Therefore, investors have benefited from the use of those models for decades. Moreover, Holt's double exponential smoothing technique helps to detect trends and Winters's triple exponential smoothing technique considers seasonality in trends in time series data. Therefore, Holt's and Winters's models are used extensively in predicting future market trends. GARCH (1,1) model helps measuring volatility and making prediction on the basis of volatility. These models play a robust role in making investment decisions.

Non-forecast related research methodology:

This part of the chapter details regarding the application of non-forecast related research methods which include the runs test, descriptive statistics, variance ratio test, ADF-unit root test, autocorrelation: Ljung-Box test, Friedman test and Bai-Perron multiple break-point test. This part of the chapter also explains regarding the application of correlogram and regression analysis.

4.3.1 The runs test

Stock returns may change randomly most of the time but may be serially dependent sometimes and may be argued that returns are serially dependent and therefore, they are predictable which is not right. Correlation coefficient fails to discover such events. Runs test helps to detect such things and plays a vital role to make right decision. Runs test is a non-parametric (non-numerical) test which is used to detect randomness. Runs test eludes the properties of distribution.

It might not be possible to detect randomness by using parametric test including auto-correlation, GARCH model, ARIMA model, Holt-Winter's forecasting model. Runs test is used to test the randomness of weekly returns. This test helps to detect whether stock prices follow random walk model or not. To achieve the research objective three and research question one listed in chapter one that whether the UK stock market is weak-from efficient, runs test will be conducted.

Furthermore, there is an another reason for using runs test in this study. It is because many scholars have used runs test to investigate random walk behaviour of stocks in different stock markets including Al-Jafari (2013) has used runs test in the Istanbul Stock Market, Taylor (1982) in the London Stock Exchange, Chakraborty (2006) in the Colombo Stock Exchange, Mishra (2013) in the India' Equity Market, Hong (1977) in the stock markets of Japan, Australia, Hong Kong and Singapore, Abedini (2009) in Gulf cooperation council countries i.e. the Bahrain Stock Exchange (BSE), Kuwait Stock Exchange (KSE) and Dubai Financial Market (DFM), Mollah (2007) in the Botswana Stock Exchange.

Total number of runs is measured as a sequence of stock price changes of the same sign (for instance ++, 00, --). If there is a significant difference between expected number of runs and actual number of runs, stock returns are random. Poshokwale (1996) explained that when expected number of runs is significantly lower than actual number of runs, it indicates

investors have overreacted to information. In such situation, returns are not predictable and market is weak-form efficient and random walk hypothesis (RWH) is accepted. When expected runs are higher, it indicates investors' lagged response to information and investors can make additional returns. This is because, market is not weak-form efficient. The formula of expected runs (v) is given by Gujarati (2004) as follows:

$$Mean: \mu_v(expected\ runs) = \frac{2M_1M_2}{M} + 1 \quad (4.1)$$

$$Variance: \sigma_v^2 = \frac{2M_1M_2\,(2M_1M_2 - M)}{M^2(M-1)} \quad (4.2)$$

Where, M_1 and M_2 = the number of individual observations above and below the mean,

M = total observations (i.e. $M_1 + M_2$ = M)

v = expected run.

The total number of runs is explained by two tailed Z statistic. Z statistic provides the distinction between expected and observed number of runs. Sharma and Kennedy (1977) detailed that if $Z \geq \pm 1.96$; reject that returns are random (expected runs are higher) at 5% level of significance or if $9 \geq Z \leq 20$; reject that stock prices are random or reject weak-form efficiency (i.e. returns are predictable).

4.3.2 Descriptive statistics

Descriptive statistics helps to measure the normality of distribution. If data are normally distributed, the stock market follows the random-walk model (returns are abrupt) and the market is weak-form efficient. Thus, stock returns are not predictable. If data are not normally distributed, stock prices do not change randomly (returns are serially correlated), the market is not weak-form efficient and stock returns are predictable (Mollah, 2007). Therefore, it is necessary to conduct the descriptive statistics test to achieve the third objective on the list regarding whether the LSE is weak-form efficient or not. In the next chapter, this is measured through Microsoft Excel and Eviews, version 8 in this study.

There is an another reason for applying descriptive statistics in this study: many scholars have applied them in different stock markets to find out whether they are weak-form efficient or not. They are Choudhry and Wu (2008) in the London Stock Exchange, Camelia (2013) in the UE and BRIC countries, Ahsan and Sarkar (2013) in the Dhaka Stock Exchange, Hanclova and Rublikova (2006) in the Czech and Slovak Stock Markets and Pesaran and Timmermann (2000) in the London Stock Exchange, among others.

Descriptive statistics consists of several statistical measures. This study applies descriptive statistics to measure the mean, median, mode, standard error, standard deviation, skewness, kurtosis and a range of sampled data.

At the beginning of this chapter, histograms and kernel density graphs were drawn and explained for the FTSE-all share index, FTSE-350 general industrial index and for all the selected companies from four different industries. This part mainly explained how the data were distributed in the graph and their skewness. A large part of the literature review referred to skewness and kurtosis, which are also discussed in the Jarque–Bera test of normality. Therefore, more importance will be given to the measurement of skewness and kurtosis from the descriptive statistics table.

The formula of the mean has been provided above in regard to the Jarque–Bera test of normality. To find the median, this study follows the guidelines provided by Anderson, Sweeney and Williams (2002) to arrange the values of a sample from the smallest to the largest and pick the middle value in the case of an odd number of observations and measure the average of the two middle values for an even number of observations. To measure the mode of a sample, this study follows the definition provided by Anderson, Sweeney and Williams (2002): the mode is the value that occurs most frequently. The standard error (SE) of the mean is calculated by following the formula provided by Berenson, Levine and Krehbiel (2006), which is as follows:

$$\text{SE of mean} = \frac{SD}{\sqrt{z}} \tag{4.3}$$

Where, SD = standard deviation,

z = sample size

The standard deviation is required to measure due to know how much a particular stock price on a specific date differs from the mean value of that stock prices. The formula of standard deviation for sample is provided by Berenson, Levine and Krehbiel (2006) as follows:

$$SD = \sqrt{\frac{\sum(m-\bar{m})^2}{z-1}} \tag{4.4}$$

Where, m = each value in the sample,

$\bar{m}$ = mean,

z = the number of values or sample size

Higher the range, greater the volatility in the stock market. The range is measured following the formula provided by Anderson, Sweeney and Williams (2002) as follows:

$$\text{Range} = X_{\text{largest value in the sample}} - x_{\text{smallest value in the sample}}$$

There are two types of skewness: positive and negative skewness. If the result of skewness is greater than zero, the distribution is positively skewed. The mean is always larger than the median in positively skewed distribution. If the mean is less than zero, it is negatively skewed, and a mean that is equal to zero means that the distribution is symmetric (Abedini, 2009).

Chakraborty (2006) defined that negatively skewed distribution is called a long left tail and means a greater chance of extremely negative outcomes. The mean is always smaller than the median in negatively skewed distribution. A positive skew means frequent small negative outcomes and extremely bad scenarios are not as likely. Non-symmetrical distributions are described as being either positively skewed (meaning frequent small losses and a few extreme gains) or negatively skewed (meaning frequent small gains and a few extreme losses).

The formula of Pearson's co-efficient of skewness is given by Kazmier (2004) as follows:

$$SK_p \text{ (population skewness)} = \frac{3(Mean - Median)}{Standard\ deviation} = \frac{3(\mu - Median)}{\sigma} \quad (4.5)$$

$$\text{Sample skewness} = \frac{3(Mean - Median)}{Standard\ deviation} = \frac{3(\bar{m} - Median)}{s} \quad (4.6)$$

There are two types of kurtosis including leptokurtic and platykurtic. More peak than normal (leptokurtic) means that a distribution also has fatter tails and that there are lesser chances or risk of extreme outcomes compared to a normal distribution. Platykurtic has a flat centre and heavy shoulder which indicate there are higher chances of negative returns from investment (Chakraborty, 2006). The formula of kurtosis (K) is computed by Gujarati (2004) as follows:

K = fourth moment about mean / square of the second moment.

$$K = m_4 / m_2^2 = m_4 / (\sigma^2)^2 \quad (4.7)$$

This part mainly explained how data distributed in graph and their skewness. A large part of literature review talked about skewness and kurtosis. Therefore, more importance will be given on the measurement of skewness and kurtosis from frequency distribution table. The next part will discuss about the variance ratio test.

4.3.3 Variance ratio test

The question of whether asset prices are predictable has long been the subject of considerable interest. One popular approach to answering this question, the Lo and MacKinlay (1988, 1989) overlapping variance ratio test that examines the predictability of time series data by comparing variances of differences of the data calculated over different intervals. If it is assumed that the data follows a random walk, the variance of a q-period difference should be q times the variance of the one-period difference. Evaluating the empirical evidence for or against this restriction is the basis of the variance ratio test.

Eviews will be used to perform the Lo and MacKinlay variance ratio test for homoskedastic and heteroskedastic random walks, using the asymptotic normal distribution (Lo and MacKinlay, 1988). The variance ratio (VR) is written as follows:

$$VR(q) = \frac{\sigma_q^2}{q * \sigma^2} \tag{4.8}$$

Where,

σ_q^2 = The variance for the qth difference in stock prices

and σ^2 = The variance of the one-period difference in stock prices.

Source: Gujarati (2004)

Abedini (2009) explained that the null hypothesis is that the value of variance ratio equals 1 under the random walk inference. It indicates that there is no correlation in the prices as they change abruptly and randomly. If variance ratio is more than 1, it indicates positive correlation in the stock prices. if it is less than 1, it indicates negative correlation exists in the prices.

The variance ratio test employs z(q) and z*(q) statistics to check null hypothesis of random walk under the assumptions of homoscedasticity and heteroscedasticity, respectively. This study will also apply multiple variance ratio tests developed by Chow and Denning (1993) to detect autocorrelation and heteroskedasticity in stock prices. If p value is achieved more than 5% through Chow-Denning maximum |Z| multiple statistics, it indicates that prices follow a martingale. If p value is less than 5%, it implies prices do not follow a martingale.

Many scholars have used this method to test the randomness and weak-form efficiency of stock prices in many markets. They are Worthington and Higgs (2005) in ten developing markets including China, India, Indonesia, Korea, Malaysia, Pakistan, the Philippines, Sri

Lanka, Taiwan and Thailand and five developed markets including Australia, Hong Kong, Japan, New Zealand and Singapore; Islam and Khaled (2005) in Dhaka Stock Exchange; Enninful and Dowling (2013) in European stock markets; Abedini (2009) in Bahrain, Kuwait and Dubai stock markets; Mobarek and Fiorante (2014) in Brazil, Russia, India and China stock markets. As scholars have tested randomness by employing variance ratio tests, this study will also apply both single and multiple variance ratio tests to detect the randomness of stock prices in the UK stock market.

4.3.4 ADF-unit root test

To apply the augmented Dickey–Fuller (ADF) unit root test, it is assumed that STK is the stock index series. The formula of a random walk model for STK could be written as follows:

$$STK_t = \rho STK_{t-1} + u_t \qquad \text{where } -1 \leq \rho \leq 1 \tag{4.9}$$

If $\rho = 1$, data or STK_t has unit root or random walk model without drift or nonstationarity.

If $|\rho| \leq 1$(ρ is less than 1), time series STK_t is stationary or series does not need to use first or second difference. As u_t is a white noise error term, data are stationary which suggests that first difference of a random walk time series are stationary.

Source: Gujarati (2004)

The above formula can be manipulated by deducting STK_{t-1} from both sides to obtain:

$$STK_t - STK_{t-1} = \rho STK_{t-1} - STK_{t-1} + u_t \tag{4.10}$$

$$= (\rho - 1)STK_{t-1} + u_t \text{ which can be written alternatively as:}$$

$$\Delta STK_t = \delta\, STK_{t-1} + u_t$$

where $\delta = (\rho - 1)$ and Δ, as usual, is the first-difference operator

Source: Gujarati (2004)

In the above formula, it is assumed that the error term u_t is uncorrelated. Dickey and Fuller have developed a test where u_t are correlated which is known as augmented Dickey-Fuller (ADF) test. The ADF test consists of estimating the following regression:

$$\Delta STK_t = \beta_1 + \beta_2 t + \delta\, STK_{t-1} + \sum_{i=1}^{m} \alpha i\, \Delta\, STK_{t-i} + \varepsilon_t \tag{4.11}$$

Where,

ε_t is a pure white noise error term and

$$\Delta STK_{t-1} = (STK_{t-1} - STK_{t-2}), \Delta STK_{t-2} = (STK_{t-2} - STK_{t-3}), \text{etc.}$$

Source: Gujarati (2004)

The presence of unit root in residuals indicates the absence of autocorrelation in errors which confirms non-stationarity and weak-form efficiency of market (Islam and Khaled, 2005).

4.3.5 The correlogram

Correlogram (correlation) has been chosen for this study to find out the values for p and q in ARIMA model. Non -zero auto correlation is related with Ljung – Box Q statistics at 1% level at 22 degrees of freedom (df lags) indicate that stock prices do not follow random walk patterns (Mobarek and Keasey, 2000).

Many researchers have used autocorrelation to predict future stock returns in different stock markets including Rehman and Khidmat (2013) in the Karachi Stock Exchange, Hokroh (2013) in the Saudi Arabia Stock Market, Taylor (1982) in the London Stock Exchange, Chakraborty (2006) in the Colombo Stock Exchange, Hong (1977) in the stock markets of Japan, Australia, Hong Kong and Singapore, Abedini (2009) in the stock markets of Bahrain, Kuwait and Dubai, Mollah (2007) in Botswana Stock Exchange and many more.

Auto-correlation test is a reliable measure for testing of either dependence or independence of random variables in a series. Kendall (1948) computed the price changes at different lag of 1,2,3,4 time periods. Later, the test became very famous and used by different scholars including Laurence (1986); Claessens et al. (1995); Poshokwale (1996); Nicolaas (1997); Nourredine Khaba (1998). The serial correlation coefficient measures the relationship between the values of a random variable at time t and its value in the previous period. Auto correlation test evidences whether the correlation coefficients are significantly different from zero. For a large sample, the Ljung—Box (LB) statistic follows the chi-square distribution with m degrees of freedom. Furthermore, the formula of Box-Pierce statistic will be applied to test whether a time series is white noise. The formula is as follows:

$$Q = n \sum_{k=1}^{m} \rho^2 k \qquad (4.12)$$

Where,

n = sample size

m = lag length

ρ_k = sample autocorrelation co-efficient

Source: Gujarati (2004), p. 813

The formula for the Ljung-Box Q* test is as follows:

$$Q^* = n(n+2)\sum_{k=1}^{m}\frac{\rho^2 K}{n-K} \sim x_m^2 \quad (4.13)$$

Where,

x_m^2= chi-square distribution with m (degree of freedom) df.

ρ_k^2 (Rho squared k) = Auto-correlation coefficients at lag k;

n = sample size

Source: Gujarati (2004, p. 813)

The proforma of identifying market efficiency through autocorrelation provided by Abedini (2009) is given below:

Correlation	If there is no correlation (r = 0) between past prices and current prices	Low correlation between past prices and current prices	High correlation between past prices and current stock prices
Decision	Accept EMH i.e. market is weak-form efficient and accept Random Walk i.e. new information incorporates into stock prices instantly. Consequently, stock returns are not predictable.	Accept EMH i.e. market is weak-form efficient and Reject Random Walk Hypothesis (RWH) i.e. new information does not incorporate into stock prices instantly and there is a time lag.	Reject EMH i.e. market is not weak-form efficient and reject RWH i.e. new information does not incorporate instantly and takes long time to be incorporated into stock prices. Consequently, future stock returns are predictable.

Source: Abedini (2009)

Correlogram has two parts including autocorrelation function (ACF) and partial autocorrelation function (PACF). The formula of ACF and PACF are provided below:

Autocorrelation function (ACF):

The formula of ACF is provided below:

$$r_k = \sum_{t=k+1}^{n-k}(STK_{t-k} - \overline{STK})(STK_t - \overline{STK}) / \sum_{t=1}^{n}(STK_t - \overline{STK})^2 \quad (4.14)$$

Where,

r = correlation, ranging from -1 to +1

k = lag j, k = 1,2,……..

r_k = autocorrelation co-efficient at lag k

STK_t = value of STK (stock) at row t

$\overline{STK}_t$ = mean of stock

n = number of observations in a series

(source: minitab, version-17)

Partial autocorrelation function (PACF):

The PACF is calculated from a recursive algorithm which is provided below:

Let: $N_1(j) = D_1(j) = r_j$, j = 0, 1, 2,...

$$\hat{\emptyset}_k = N_k(1)/D_k(0) \tag{4.15}$$

Let

$$N_k(j) = N_{k-1}(j+1) - \{D_{k-1}(j)(\hat{\emptyset}_{k-1})\}$$

$$D_k(j) = D_{k-1}(j) - \{N_{k-1}(j+1)(\hat{\emptyset}_{k-1})\}$$

Where,

r_j = autocorrelation function for the jth lag and $r_0 = 1$

$\hat{\emptyset}_k$ = partial autocorrelation co-efficient for the kth lag

(source: minitab, version-17)

4.3.6 Bai-Perron multiple break-point test

The unit root test is the representative of current econometrics stationarity test and the basis of subsequent modelling. But in reality, some emergencies such as the introduction of policies, economic crises, and other major social events will cause structural breaks in the data generation process rather than smooth. The main idea of a structural break is that if a process of generating data for an economic variable change, it is considered that a structural break has occurred.

The Bai-Perron test method adds the break factor to the data generation process, overcoming the defect that the traditional unit root test method cannot test the structural break. Bai and Perron (1998, 2001) proposed a method for estimating linear regression models subject to multiple breaks. There are several ways of determining the number of breaks. One approach is to determine the number of breaks sequentially by testing for L + 1 against L breaks. This the *sup FT*(l+1| l) test i.e., a sequential test of the null hypothesis of l breaks versus the alternative of (l+1) breaks. Bai (1997) and Bai and Perron (1998) describe an intuitive approach for detecting more than one break. The procedure involves the sequential application of breakpoint tests.

- It begins with the full sample and perform a test of parameter constancy with unknown break.
- If the test rejects the null hypothesis of constancy, determine break date, divide the sample into two samples and perform single unknown breakpoint tests in each subs-ample. Each of these tests may be viewed as a test of the alternative of versus the null hypothesis of breaks. Add a breakpoint whenever a sub-sample null is rejected. (Alternately, one could test only the single sub-sample which shows the greatest improvement in the sum-of-squared residuals.)
- Repeat the procedure until all of the subsamples do not reject the null hypothesis, or until the maximum number of breakpoints allowed or maximum subsample intervals to test is reached.

Once the sequential breakpoints have been determined, Bai recommends a refinement procedure whereby breakpoints are re-estimated if they are obtained from a subsample containing more than one break. This procedure is required so that the breakpoint estimates have the same limiting distribution as those obtained from the global optimization procedure.

The formula of sequential L+1 breaks vs L is as follows:

$$\text{Sup } F_T(\text{L+1|L}) = \{S_T(\hat{T_1},...,\hat{T_L}) - min\ inf_{1\le i\le L\tau\in^{i},l} S_T(\hat{T_1},...., \hat{T_{i-1}}, \tau, \hat{T_i},...,\hat{T_L})\}/\ \hat{\sigma^2} \quad (4.16)$$

Where, $\hat{}_{i,\eta} = \{\tau\ ;\ \hat{T_{i-1}} + (\hat{T_i},....., \hat{T_{i-1}})\eta \le \tau \le \hat{T_i} - (\hat{T_i},...., \hat{T_{i-1}})\ \eta\}$, $S_T\ (\hat{T_1},...., \hat{T_{i-1}}, \tau, \hat{T_i},..., \hat{T_L})$ is the sum of squared residuals resulting from the least-squares estimation from each m-partition (T_1,.... T_m), and $\hat{\sigma^2}$ is a consistent estimator of σ^2 under the null hypothesis.

Source: Eviews, version-11

4.3.7 Friedman test

The Friedman test is a non-parametric test developed by Milton Friedman in 1937. This test will be applied to detect seasonality in the data in this study. It is because, many scholars have used Friedman test to investigate seasonality in the data of stocks in different stock markets including Berryman et al. (1988) and Nwogu et al. (2016). To calculate the test statistic, S:

1 Ranks the data separately within each block.

2 Sum the ranks for each treatment.

3 If there are no ties in the data, then

$$S = 12\,[nk(k+1)]^{-1}\,[\mathbf{S}_j\,(\,\mathbf{S}\,R_j)^2] - 3n\,(k+1) \quad j = 1,2,\ldots,k \tag{4.17}$$

where,

$j = 1, 2,\ldots,k$

K = The number treatments conditions

n = The number of blocks

R_j = The sum of ranks for treatment j

If there are ties in the data, then

$$S\,(adj) = \frac{S}{C} \tag{4.18}$$

where,

$$C = \text{the correction factor} = 1 - \frac{\Sigma_i\,(t_i^3 - t_i)}{n(k^3 - k)}$$

$i = 1, 2, \ldots, m$

m = number of sets of ties

t_i = the number of tied score in the ith set of ties

The test statistic has an approximately X^2 distribution, with associated degrees of freedom (k - 1). If there are ties within one or more blocks, Minitab uses the average rank and prints a test statistic that has been corrected for ties.

Source: Minitab, version-17

4.3.8 Regression analysis

This study will forecast stock prices based on industrial sectors in the UK stock market using technical analysis. Regression analysis helps detect a relationship or trend in the historical data and predict future values from trend or relationship. Therefore, this study considers regression analysis to predict the market.

In addition to that, there is an another reason for choosing regression analysis for this study that many scholars have used regression analysis to predict future stock returns in different stock markets including Rehman and Khidmat (2013) in the Karachi Stock Exchange, Grinblatt and Moskowitz (2004) and Higgins (2011) in the US stock markets including the New York Stock Exchange (NYSE), American Stock Exchange (AMEX) and National Association of Securities Dealers Automated Quotation (NASDAQ), Kohara et al. (1997) in the Tokyo Stock Exchange, Mollah (2007) in the Botswana Stock Exchange etc.

Nonlinear least squares

This study will apply nonlinear least square method. The formula for nonlinear least square (NLS) is provided below:

Suppose that we have the regression specification,

$$VSTK_t = f(HSTK_t, \beta) + \epsilon_t \tag{4.19}$$

Where, $VSTK_t$ = dependent variable at time t or value of stock (stock price) at time t

$HSTK_t$ = independent variable at time t or historical stock price at time t

f = function of explanatory variable $HSTK_t$

β = parameters

Source: Eviews, version 11

Least squares estimation selects the parameter values that reduce the sum of squared residuals:

$$S(\beta) = \sum\{VSTK_t - f(HSTK_t, \beta)\}^2$$

$$= \{VSTK - f(HSTK, \beta)\}\ \{VSTK - f(HSTK, \beta)\}$$

A model is linear in parameters if the derivatives of *f* with regard to the parameters do not rely on β; if the derivatives are functions of β, the model is nonlinear in parameters.

Source: Eviews, version 11

For instance:

$$VSTK_t = \beta_1 + \beta_2 \log L_t + \beta_3 \log K_t + \epsilon_t \quad (4.20)$$

Source: Eviews, version 11

Each model would usually generate errors from its prediction as predicted values might not be same as actual values.

The non-forecasting related statistical techniques end here. The next chapter shows forecasting related statistical models that will be applied to forecast stock prices to see the predictability of the models and industrial performance in terms of predictability in the subsequent chapter.

Overview of chapter five

Chapter five explains the most commonly and widely used forecast methods including ARIMA, GARCH and double and triple exponential smoothing techniques. This chapter also details forecast errors and other forecast evaluation statistics including MAPE, Theil inequality coefficient ($U_1 \ and \ U_2$) and forecast encompassing tests.

CHAPTER FIVE: FORECASTING RELATED RESEARCH METHODOLOGY

This chapter explains and evaluates different forecasting models that will be applied to predict stock prices in the data analysis chapter. These statistical models will help to achieve the research aim, objectives and answer research questions. The next section discusses about the autoregressive integrated moving average (ARIMA) model and its parameters.

5.1 Autoregressive integrated moving average (ARIMA) model

This method was developed by Box and Jenkins. Therefore, it is known as the Box–Jenkins model as well. In this model previously observed values in the time series are used as the independent variable and predicted values from the past data are used as the dependent variable. AR (autoregressive) stands for p lags, MA (moving average) stands for q lags in the series and I (Integrated) stands for d or differencing. In the ARIMA model, d is used to eliminate the effect of seasonal factors. However, in the ARMA model, it is assumed that the mean is zero and the variance is constant and it is a stationary method. Stationary means that the data (stock prices) do not change over the time period. However, data are not stationary in a real-life situation. They are made stationary by adding I (differencing) to the time series.

The ARIMA model explicitly uses autocorrelation in the time series, which is the correlation between a variable and its lag of one or more periods. The Durbin–Watson test is used to detect the existence of autocorrelated residuals (deviations) or serial correlation in the time series values. A value closes to 2 means that no autocorrelation exists in the time series, a value below 1.4 indicates strong positive serial correlation and a value greater than 2.6 indicates the existence of strong negative serial correlation (Kazmier, 2004).

Gomes et al. (2006) detail that a linear relationship is established between the dependent and the independent variables in the ARIMA model. The assumption of the ARIMA model is that future time series values are linearly autocorrelated with historical time series values. Consequently, future stock prices could be predicted from linearly autocorrelated historical stock prices. The application of this model will help answer second research question that the forecasting power of different econometric models estimated using the principles of technical analysis. This will also help achieve fourth research objective that estimating different econometric models using technical analysis and test their forecasting power.

Furthermore, another reason for using the ARIMA model in this study is that many scholars have used the ARIMA model to predict future stock returns in many different stock markets

around the world and predicted future stock prices successfully, including Schilling and Jarrett (2008) in the German Stock Exchange, Balsara, Chen and Zheng (2007) in the Shanghai and Shenzhen Stock Exchanges and Mollah (2007) in the Botswana Stock Exchange. Gujarati (2004) claims that the Box–Jenkins ARIMA model consists of four steps to perform, which are described below.

First, the model will be defined using data from the FTSE-all share index, FTSE-350 general industrial index, twenty individual companies listed in FTSE100 to determine whether the series is stationary or non-stationary in the graph of the autocorrelation function (ACF). If the data are non-stationary, non-stationary values will be converted into stationary ones by differencing. For this purpose, the Augmented Dickey–Fuller (ADF) unit root test will be used to determine the value of d. The values for p and q will be determined as well through a correlogram. If the values of ACF and PACF are close to 1 at level in the correlogram, the first difference will be applied to determine the values of p and q.

Next, the values of p, d and q will be determined to apply following the ordinary least square (OLS) method to determine the best ARIMA model. The appropriate model should have most significant coefficients, lowest volatility, highest adjusted R square, lowest AIC and SBIC. Furthermore, the normality will be checked of the selected model to review whether the residuals are normally distributed through the serial correlation Lagrange multiplier (LM) test and correlogram Q-statistics. Finally, the future stock prices will be predicted with the parameters if the residuals are considered to be a white noise series.

Rapach and Wohar (2005) explain that stock prices could be predicted using in-sample or out-of-sample data. Prediction is made based on the available data and the prices forecasted based on the model will be compared with the actual prices to check the model's predictability in in-sample forecasting. Out-of-sample forecasting provides further confirmation and a realistic picture of the model's predictability and performance. Out-of-sample refers to making a prediction based on the available data, comparing the predicted prices with the actual prices and recording the forecast errors.

Then a new prediction is made with a rectified model and compared with the actual results recursively until the model provides a sound and reliable prediction power. Therefore, out-of-sample forecasting is more reliable than in-sample forecasting. The next section explains a generalized autoregressive conditional heteroskedasticity (GARCH) (1, 1) model.

5.2 Generalized Autoregressive Conditionally Heteroskedastic (GARCH) (1, 1) model

Since the literature evidences that the simple model GARCH (1, 1) is sufficient to analyze data and produce significant results (Connolly, 1989; Fan and Yao, 2003; Floros, 2007; etc.), this research also uses GARCH (1, 1) model to estimate the volatility of the London Stock Exchange' prices and predict stock prices more precisely considering this volatility.

Therefore, this study will apply GARCH (1, 1) model not only for measuring volatility of stock returns but also to perform multi-period ahead forecasts. Following Zalewska and Hall (1999), Choudhry and Wu (2008), Sharma and Vipul (2016) and Awartani and Corradi (2005) in stock markets of the Budapest, UK, sixteen developed and developing countries and UK respectively. In GARCH (1, 1) model, periods of high volatility are followed by periods of high volatility and periods of low volatility tend to be followed by periods of low volatility. This suggests that residual or error term is conditionally heteroscedastic and it can be represented by ARCH and GARCH model. GARCH (1, 1) model is consist of two following equations:

The conditional mean equation:

The mean equation is written in Eviews-11 as follows

$$Y_t = X_t\ \theta + \varepsilon_t \tag{5.1}$$

The above mean equation is written as a function of exogenous variables with an error term.

Source: Eviews, version-11

The conditional variance equation:

Gujarati (2004) defined the conditional variance equation as follows:

$$\sigma_t^2 = \omega + \alpha y_{t-1}^2 + \beta\sigma_{t-1}^2 \tag{5.2}$$

Where,

ω = constant,

= co-efficient of ARCH term

β = co-efficient of GARCH term

y_{t-1}^2 = ARCH term

σ_{t-1}^2 = GARCH term

$y_t = \sigma_t \epsilon_t$ [ϵ_t is white noise]

Source: Gujarati (2004)

The parameter ω is related to the scale of the volatility and α and β to the dependence of the volatility on the past.

The above equation explains that the conditional variance of y at time t depends on not only on the squared error term in the previous time period but also on its conditional variance in the previous time period. This model can be generalized to a GARCH (p, q) model in which there are p lagged terms of the squared error term and q terms of the lagged conditional variances. The next section details the most common and widely used forecasting techniques, which are double and triple exponential smoothing techniques.

5.3 The Holt–Winters method for trend-fitting and forecasting

This method has not been extensively used in the UK but Tseng, Kwon and Tjung (2012) have applied this method in 26 countries for the period between 1 September, 1998 and 31 December, 2010 that include the London Stock Exchange as well to measure the impact of economic recession and financial crisis on stock markets. The application of exponential smoothing techniques will help obtain objectives in this study. Their application will also help answer research question listed in chapter one.

This study will use Holt's double exponential smoothing and Winters' additive model of triple exponential smoothing techniques to predict the stock prices of the FTSE-all share index, FTSE-350 general industrial index and twenty individual companies from four different industries listed in FTSE-100. For this purpose, future prices will be predicted using Minitab 17. The formulas of exponential smoothing are provided below from Minitab 17:

The double exponential smoothing technique:

The double exponential smoothing employs a level and a trend component at each period. It uses two weights, to update the components at each period. The double exponential smoothing equations are:

$$L_t = \gamma\ VSTK_t + (1 - \gamma)\ (L_{t-1} + T_{t-1})$$

$$T_t = \theta\ (L_t - L_{t-1}) + (1 - \theta)\ T_{t-1}$$

$$\widehat{VSTK}_t = L_{t-1} + T_{t-1} \qquad (5.3)$$

Where,

L_t is the level at time t, γ is the weight for the level

T_t is the trend at time t, θ is the weight for the trend

$VSTK_t$ is the value of stock (stock price) at time t,

$\widehat{VSTK}_t$ is the fitted value, or one-step-ahead forecast, at time t

Source: minitab, version-17

Holt-Winters' triple exponential smoothing technique (additive method):

The triple exponential smoothing employs a level, a trend and seasonality components at each period. It uses three weights, to update the components at each period. The triple exponential smoothing equations (additive method) are:

$$L_t = \gamma\,(VSTK_t - S_{t-p}) + (1-\gamma)\,(L_{t-1} + T_{t-1})$$

$$T_t = \theta\,[L_t - L_{t-1}] + (1-\theta)T_{t-1}$$

$$S_t = \delta\,(VSTK_t - L_t) + (1-\delta)\,S_{t-p}$$

$$\widehat{VSTK}_t = L_{t-1} + T_{t-1} + S_{t-p} \qquad (5.4)$$

Where,

L_t is the level at time t, γ is the weight for the level,

T_t is the trend at time t, θ is the weight for the trend,

S_t is the seasonal component at time t, δ is the weight for the seasonal component,

p is the seasonal period,

$VSTK_t$ is the value of stock (stock price) at time t,

$\widehat{VSTK}_t$ is the fitted value, or forecasted value (forecasted stock price) at time t.

Source: minitab, version-17

5.4 Forecast errors

Wisniewski (2002) detailed that it is required to assess the accuracy of applied forecasting methods. The equation of forecast error is as follows:

$$E_{t+1} = X_{obs\ t+1} - X_{model\ t+1}, \qquad (5.5)$$

Where, E = error,

X_{obs} = observed values ,

X_{model} = model's predicted or fitted values,

t+1 = next time period.

Source: Wisniewski (2002)

Evaluation of forecasting:

The lower the error, better the model. The following methods will be applied in this research for calculating errors from different forecast models. However, the forecastability of models and techniques will be decided based on forecast benchmarks. The forecast benchmarks are MAPE, Theil inequality coefficients of U_1 and U_2 .

Mean absolute percentage error (MAPE):

This study will measure MAPE of the forecasted results obtained from ARIMA model, GARCH (1, 1), Holt's and Winters' model. The question arises in relation to performance of the model that details what percentage is acceptable, a model to be regarded better than a naive method. Gilliland (2010) explains in relation to MAPE that the upper limit of forecast accuracy is much more difficult to determine and it is arbitrary. Furthermore, Gilliland (2010) claims that there is no threshold value for MAPE. Chen (2017) et al. reveal that MAPE is based on arithmetic mean and it does not have any upper bound in case of single error. Makridakis (1993) argued that MAPEs are not comparable directly with naïve models (e.g. random walk). The formula of MAPE is as follows:

$$MAPE = \frac{\sum \left|\frac{X_{obs,t} - X_{model,t}}{X_{obs,t}}\right|}{n} \times 100 \qquad (5.6)$$

Source: minitab, version-17

Mean absolute deviation (MAD):

It is also known as mean absolute error (MAE). Berenson, Levine and Krehbiel (2006) provided the formula of MAD, which is as follows:

$$MAD = \frac{\sum |X_{obs,t} - X_{model,t}|}{n} \qquad (5.7)$$

Source: Berenson, Levine and Krehbiel (2006)

Mean Squared Error or Deviation (MSE or MSD):

Mean squared error measures the average of the squares of the errors or deviations. It does not have any negative values as the differences between actual values and predicted values are squared. The formula is given by Grosan et al. (2010) as follows:

$$\text{MSE} = \frac{\sum_{i=1}^{z}(V_{obs,t} - V_{model,t})^2}{z} \tag{5.8}$$

Where, $V_{obs,t}$ = actually observed values at time t

$V_{model,t}$ = model's predicted values at time t

z = number of observations

Source: Grosan et al. (2010)

Root Mean Square Error (RMSE):

Root mean square error provides large weight to large errors because errors are squared root. Therefore, it is not useful method. The formula is given below by Grosan et al. (2010).

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{z}(V_{obs,t} - V_{model,t})^2}{z}} \tag{5.9}$$

Where, $V_{obs,t}$ = actually observed values at time t

$V_{model,t}$ = model's predicted values at time t

z = number of observations

Source: Grosan et al. (2010)

Theil inequality coefficient U_1:

Theil inequality coefficient U_1 measures a forecast accuracy. The value of Theil coefficient U_1 lies between zero and one. If the value of U_1 is zero, it indicates a perfect fit. The formula of U_1 is provided below:

$$\text{U1} = \frac{[\frac{1}{n}\sum_{i=1}^{n}(O_i - F_i)^2]^{\frac{1}{2}}}{\left[\frac{1}{n}\sum_{i=1}^{n} O_i^2\right]^{1/2} + [\frac{1}{n}\sum_{i=1}^{n} F_i^2]^{1/2}} \tag{5.10}$$

Where, O_i = The observed values and

F_i = The corresponding forecasted values

Source: Omnia (2016)

U_1 has serious defects and is not informative for assessing forecast accuracy. The main defect is that it always provides value close to zero regardless of whether the forecast method led to better or worse performance than the naive no-change model. On the other hand, U_2 has no defects. It provides the correct information about the performance of the applied model. Thus, it works as a benchmark, Bliemel (1973).

Theil inequality coefficient U_2:

Omnia (2016) explains that it is a measure of forecast quality and it compares the measured forecast with the benchmark (naïve) method. Furthermore, Omnia (2016) argues that If U_2 equals one (U_2 =1), the random walk or naïve method (where F_t is equal to the last observation) is as good as the forecasting technique being evaluated. If U_2 is less than one (U_2 <1), the forecasting technique being used is better than the naïve method. When U_2 is greater than one (U_2>1), there is no point using the formal forecasting method. The naïve produces better results. Bliemel (1973) claims that U_2 provides better interpretation of outcomes than U_1. The formula of U_2 is given below:

$$U_2 = \frac{[\sum_{i=1}^{n}(F_i - O_i)^2]^{1/2}}{[\sum_{i=1}^{n} O_i^2]^{1/2}} \tag{5.11}$$

Where, O_i = The observed values and

F_i = The corresponding forecasted values

Source: Omnia (2016)

A number of papers exist that compare and contrast between Theil inequality coefficients of U_1 and U_2. Prominent studies within this literature include Bliemel (1973), Granger and Newbold (1973) and Ahlburg (1984). In these studies, all the scholars provided preference for the use of U_2 over U_1 due to limitations associated with the latter. In contrast to the criticism faced by the U_1 statistic, the U_2 statistic receives support in these studies.

5.5 Forecast encompassing tests

Fair-Shiller (1989) provides forecast encompassing test equation which is as follows:

$$(1)\ y_t = \alpha + \beta_1 f_{1t} + \beta_2 f_{2t} + v_t \tag{5.12}$$

Where,

y = actual price or dependent variable

β_i = coefficients

f_i = forecasted price from different models

Source: Cook (2014)

Forecast encompassing is then explained through the significance of the β_i coefficients. In contrast to the above, the Chong and Hendry (1986) forecast encompassing test is based upon

consideration of the ability of one forecast to explain the error of another. The error (e) is measured as follows:

$e_{it} = y_t - f_{it}$ and the relevant testing equations are then given as:

(2) $e_{1t} = \lambda_2 f_{2t} + \eta_{1t}$ (5.13)

(3) $e_{2t} = \lambda_1 f_{1t} + \eta_{2t}$ (5.14)

where (in)significance of the λ_i coefficient determines whether forecast encompassing occurs.

Source: Cook (2014)

This chapter ends here. This chapter has just analysed the different forecast models. However, the application of these models will be shown and analysed the findings by using the sampled data in the next chapter, data analysis and findings to evaluate the findings critically to answer the research questions and achieve research aim and objectives stated in chapter one.

Overview of chapter six

Chapter six analyses data and explores findings. This chapter has two sections. Section-A details an example of a series to demonstrate how the remaining all series have been analysed. The Section-B explains results from all series. It was found that structural breakpoint has a significant impact on the time series data. Therefore, this study has chosen a sub-sample of 204 observations of clean data through Bai-Perron's multiple breakpoints test where there are no structural breaks. Furthermore, 4 sequential observations of actual values have been chosen for comparing and evaluating the forecasted outcomes from each model. After analysing data, this chapter finds that stock prices of the manufacturing industry are predictable through the application of ARIMA and GARCH (1, 1) models. This has been confirmed from benchmarks of forecast evaluation statistics including MAPE, Theil U_1 and U_2. Therefore, this study supports weak-form inefficiency for the studied period in the London Stock Exchange.

CHAPTER SIX: DATA ANALYSIS AND FINDINGS

Part-A: An illustration of a series

Earlier, it has been explained that the current research is a simultaneous test of weak-form market efficiency and the forecastability of econometric models using technical analysis, specifically the ARIMA model. In the methodology chapter, the methods that will be applied to evaluate all 22 series (the FTSE-All Share Index, FTSE-350 General Industrial Index and 20 individual companies from different industries) were explained. Twenty-two series comprising of two indices and twenty industry sector share prices are analysed in this chapter. The characteristics of the first series are studied (visual inspection, descriptive statistics, test for seasonality, structural breaks) following which clear periods available for analysis are identified.

Next, weak-form market efficiency tests (runs test, unit root tests, correlogram, variance ratio tests), are conducted in a period of clear 204 observations, as required for forecasting using any models (Hyndman and Athanasopoulos, 2018). The ARIMA (p,d,q) models are estimated (after examining the ADF-unit root test, the ACF and PACF). The best ARIMA model is identified and the forecast accuracy is evaluated with a corresponding GARCH(1, 1) model with the same mean equation as the best identified ARIMA model.

In this part of data analysis and findings, as an example, the results for FTSE-All share will first be presented in detail, while the detailed tests following the same sequence for all remaining series are attached in the appendix. The summarised results for all remaining series will be shown in the next section of B.

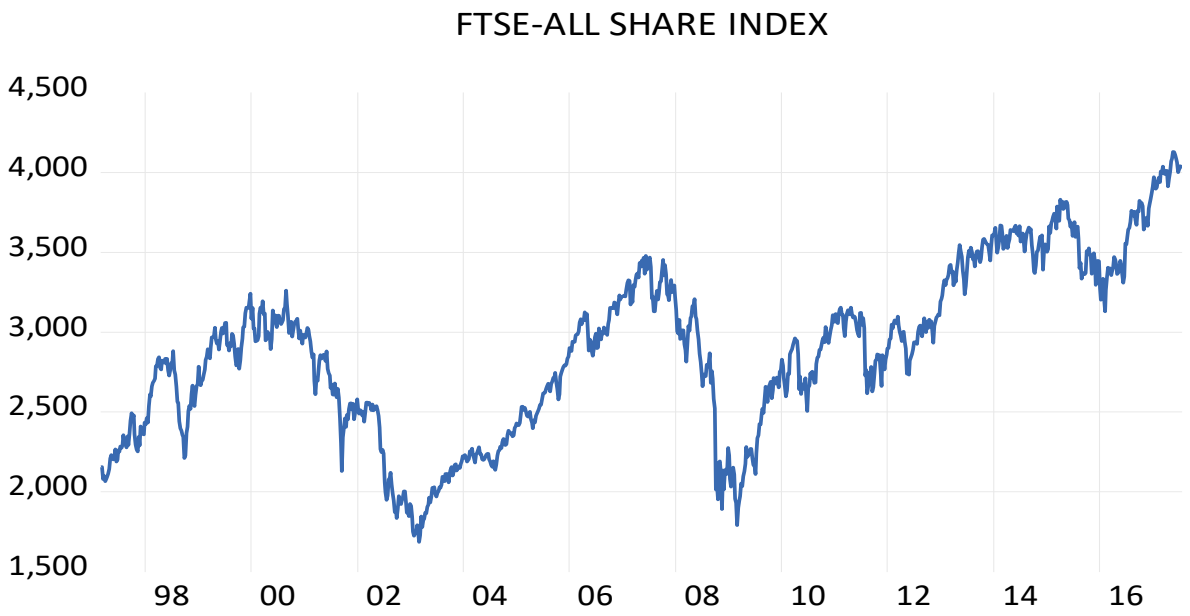
A.6.0: An illustration of FTSE-ALL SHARE INDEX

A.6.1 Series characteristics

Series characteristics include visual inspection, descriptive statistics, test for seasonality and test of structural breaks. These tests are run below one after another.

(i) Visual Inspection of Series:

The figure below shows that FTSE-all share index has several breakpoints. However, it does not show any seasonality.



Source: Figure created by author with the database from 1997 to 2017 using Eviews, V-22

(ii) Descriptive statistics

The descriptive statistics for the periods between 03/03/1997 and 17/07/2017 are as below:

Series	Mean	SE Mean	StDev	Skewness	Range	Kurtosis	Median	Mode
FTSE-ALL SHARE	2879.874	16.299	531.166	0.009	2445.149	-0.666	2915.345	2354.83

Source: Output of descriptive statistics by SPSS, V-22

Statistics

FTSEALLSHAREINDEX

N	Valid	1064
	Missing	0
Mean		2879.873721
Std. Error of Mean		16.2990870
Median		2915.344971
Mode		2354.8301
Std. Deviation		531.6601274
Variance		282662.491
Skewness		.009
Std. Error of Skewness		.075
Kurtosis		-.666
Std. Error of Kurtosis		.150
Range		2445.1499

Source: Output of descriptive statistics by SPSS, V-22

(iii) Testing for Seasonality for the FTSE-All Share Index

The Friedman test is conducted below to detect if there is seasonality in the data. As the mean, standard deviation and mean rank are not same throughout each sub-sample period, the series does not have seasonality and the null hypothesis of seasonality in the data is rejected.

Stock price seasonality on FTSE-All Share Index for the periods between 03/03/1997 and 17/07/2017

Series	Sub-sample 1			Sub-sample 2			Sub-sample 3			Sub-sample 4		
	mean	St dev	rank	mean	St dev	rank	mean	St dev	rank	mean	St dev	rank
FTSE-ALL	2713.54	296.78	2.22	2472.67	453.56	1.59	2802.28	375.85	2.31	3531.00	270.11	3.88

Source: Output of seasonality test using SPSS, V-22.

The table below shows Friedman test of chi-square statistics for detecting seasonality in the data. As the p value of chi-square test statistics is less than 5% and it is statistically significant, the null hypothesis is rejected and alternative hypothesis is accepted.

Hypothesis:
Null hypothesis: Data have seasonality
Alternative hypothesis: Data do not have seasonality

Friedman Test of Chi-Square statistics for detecting seasonality

Series	X^2	P value
FTSE-ALL SHARE INDEX	456.122	0.000***

Note 1: p-value < 1% = *** and P-value < 5% = **

Source: Output from Friedman test of Chi-Square using SPSS, V-22

The full Friedman test:

Descriptive Statistics

	N	Mean	Std. Deviation	Minimum	Maximum
Subsample1	266	2713.538939	296.7839811	2065.0200	3261.5701
Subsample2	266	2472.671283	453.5620288	1685.0000	3433.8601
Subsample3	266	2802.279512	375.8511083	1789.1300	3478.9900
Subsample4	266	3531.005151	270.1107143	2861.5200	4130.1499

Source: output of descriptive statistics using SPSS, V-22

Ranks

	Mean Rank
Subsample1	2.22
Subsample2	1.59
Subsample3	2.31
Subsample4	3.88

Source: output of Rank using SPSS, V-22

Test Statistics[a]

N	266
Chi-Square	456.122
df	3
Asymp. Sig.	.000

a. Friedman Test

Source: Output from Friedman test of Chi-Square using SPSS, V-22

(iv) Testing for structural breaks

The seasonality test earlier showed that the series has no seasonality. However, there might be structural breaks in the series, which will affect estimation and testing. Visual examination details that there could be several breakpoints. The Bai-Perron multiple breakpoint test is used to estimate these. The results are shown below:

The table of the Bai-Perron test and the figure from it below show the clean periods where there are no breaks. The clean period of sub-samples starts from 3/03/1997 to 27/05/2002 which has 274 observations, 17/11/2008 to 24/12/2012 which has 215 observations and 31/12/2012 to 17/07/2017 that has 238 observations. The other period of sub-samples has observations of less than 200. Maximum breaks have been selected five from this test. In the methodology chapter, it was explained that 204 continuous data are sufficient for the estimation of ARIMA models (Hyndman and Athanasopoulos, 2018). The estimation period of the selected sub-sample is chosen from 06/05/2013 to 27/03/2017, which includes 204 observations. The validation period would be 4 more observations after that period, which include from 03/04/2017 to 24/04/2017 for out-of-sample forecasts.

Table: Bai-Perron's multiple breakpoints test for the period from 03/03/1997 to 17/07/2017

Series	Break date	Clean period	Obser.	Co-efficient	Standard error	t-statistic	P value
FTSE-ALL SHARE INDEX	03/06/2002	03/03/1997-27/05/2002	274	2707.82	18.13	149.35	0.00***
	27/06/2005	03/06/2002-20/06/2005	160	2154.07	23.73	90.79	0.00***
	17/11/2008	27/06/2005-10/11/2008	177	3009.60	22.56	133.41	0.00***
	31/12/2012	17/11/2008-24/12/2012	215	2749.68	20.47	134.34	0.00***
		31/12/2012-17/07/2017	238	3591.63	19.45	184.62	0.00***

Note: ***1% level of significance, **5% level of significance, *10% level of significance.

Source: Output from Bai-Perron test using Eviews, SV-11

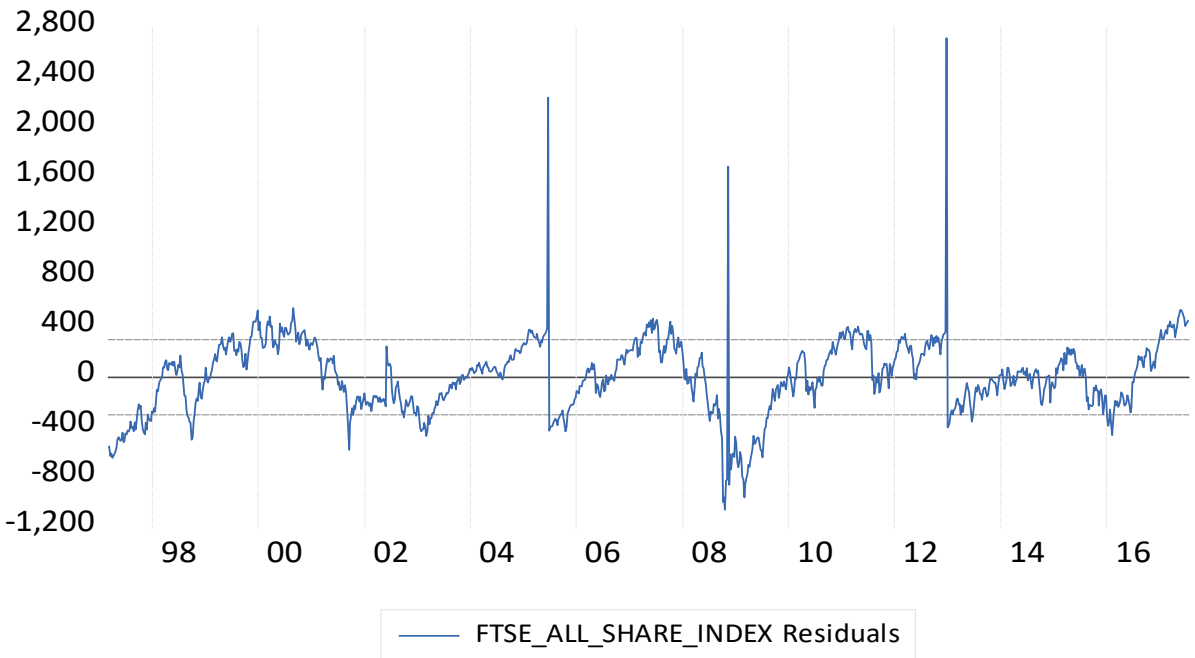
The full Bai-Perron test

Dependent Variable: CLOSE
Method: Least Squares with Breaks
Date: 17/11/20 Time: 21:59
Sample: 3/03/1997 17/07/2017
Included observations: 1064
Break type: Bai-Perron tests of L+1 vs. L sequentially determined breaks

Breaks: 3/06/2002, 27/06/2005, 17/11/2008, 31/12/2012
Selection: Trimming 0.15, Max. breaks 5, Sig. level 0.05

Variable	Coefficient	Std. Error	t-Statistic	Prob.
3/03/1997 - 27/05/2002 -- 274 obs				
C	2707.823	18.13106	149.3472	0.0000
3/06/2002 - 20/06/2005 -- 160 obs				
C	2154.072	23.72677	90.78658	0.0000
27/06/2005 - 10/11/2008 -- 177 obs				
C	3009.600	22.55859	133.4126	0.0000
17/11/2008 - 24/12/2012 -- 215 obs				
C	2749.679	20.46819	134.3392	0.0000
31/12/2012 - 17/07/2017 -- 238 obs				
C	3591.628	19.45405	184.6210	0.0000

R-squared	0.682538	Mean dependent var	2879.874
Adjusted R-squared	0.681339	S.D. dependent var	531.6601
S.E. of regression	300.1225	Akaike info criterion	14.25095
Sum squared resid	95387858	Schwarz criterion	14.27430
Log likelihood	-7576.504	Hannan-Quinn criter.	14.25980
F-statistic	569.2083	Durbin-Watson stat	0.448751
Prob(F-statistic)	0.000000		



Source: Output from Bai-Perron test using Eviews, SV-11

A.6.2 Testing for weak-form market efficiency

(i) Runs test:

Runs test is performed at level. The null hypothesis that prices move randomly is rejected. As the p-value (level of significance) is less than 5% (0.000<0.05), stock prices are not random. Thus, the series does not follow a random-walk model.

Hypothesis:
Null: Prices are random
Alternative Hypothesis: Prices are not random

Runs test on FTSE-ALL SHARE INDEX for the selected sub-sample period of 06/05/2013 to 27/03/2017 (204 observations)

Series	Total number of runs	Z	P value
FTSE-ALL SHARE INDEX	20	-11.65	0.000

Source: Output of runs test using SPSS, V-22

Full runs test:

Descriptive Statistics

	N	Mean	Std. Deviation	Minimum	Maximum
FTSE-All Share Index	204	3579.215588	175.4101190	3129.6299	4038.3799

Source: descriptive statistics from runs test using SPSS, V-22

Runs Test

	FTSE-All Share Index
Test Value[a]	3568.5601
Cases < Test Value	102
Cases >= Test Value	102
Total Cases	204
Number of Runs	20
Z	-11.651
Asymp. Sig. (2-tailed)	.000

a. Median

Source: Full runs test from sub-sample period of FTSE-all share index using SPSS-22.

(ii) Test of unit root

ADF-unit root test is performed under trend and intercept. As test statistics is less than 5% at first difference, there is no unit root at first difference. However, there is unit root at level, as p value is more than 5%. Therefore, d equals to 1 in the ARIMA (p,d,q) model.

Null hypothesis: CLOSE/D(CLOSE) has a unit root
Alternative hypothesis: CLOSE/D(CLOSE) has no unit root

Table: ADF unit root test on FTSE-ALL SHARE INDEX for the selected sub-sample period of 06/05/2013 to 27/03/2017 (204 observations)

Series	t-statistic at level	t-statistic at first difference	Value of d in ARIMA (p,d,q) model
FTSE-All Share Index	-2.425227	-14.81495	d = 1
P value	(0.3654)	(0.0000)***	

Note 1: Their critical values for ADF at 1% level of significance are -4.003902 (at level) and -4.004132 (at first difference). p-value < 1% = ***

Source: Outcome of ADF-unit root test from sub-sample period of FTSE-all share index using Eviews, SV-11

Full ADF-unit root test:

ADF-unit root test at level

Null Hypothesis: FTSE ALL SHARE INDEX has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=14)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.425227	0.3654
Test critical values:	1% level	-4.003902	
	5% level	-3.432115	
	10% level	-3.139793	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(FTSE ALL SHARE INDEX)
Method: Least Squares
Date: 25/03/21 Time: 00:06
Sample (adjusted): 13/05/2013 27/03/2017
Included observations: 203 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
FTSE ALL SHARE INDEX(-1)	-0.065011	0.026806	-2.425227	0.0162
C	223.9058	93.70235	2.389543	0.0178
@TREND("6/05/2013")	0.108971	0.079143	1.376888	0.1701

R-squared	0.030426	Mean dependent var	2.463005
Adjusted R-squared	0.020731	S.D. dependent var	63.20475
S.E. of regression	62.54617	Akaike info criterion	11.12436
Sum squared resid	782404.8	Schwarz criterion	11.17332
Log likelihood	-1126.122	Hannan-Quinn criter.	11.14416
F-statistic	3.138127	Durbin-Watson stat	2.014654
Prob(F-statistic)	0.045507		

ADF-unit root test at first difference

Null Hypothesis: D(FTSE ALL SHARE INDEX) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=14)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-14.81495	0.0000
Test critical values:	1% level	-4.004132	
	5% level	-3.432226	
	10% level	-3.139858	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(FTSE ALL SHARE INDEX,2)
Method: Least Squares
Date: 25/03/21 Time: 00:10
Sample (adjusted): 20/05/2013 27/03/2017
Included observations: 202 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(FTSE ALL SHARE INDEX(-1))	-1.046781	0.070657	-14.81495	0.0000
C	-3.652794	9.023727	-0.404799	0.6861
@TREND("6/05/2013")	0.058156	0.076583	0.759374	0.4485

R-squared	0.524482	Mean dependent var	-0.308910
Adjusted R-squared	0.519703	S.D. dependent var	91.48910
S.E. of regression	63.40512	Akaike info criterion	11.15171
Sum squared resid	800021.7	Schwarz criterion	11.20084
Log likelihood	-1123.322	Hannan-Quinn criter.	11.17159
F-statistic	109.7455	Durbin-Watson stat	2.002097
Prob(F-statistic)	0.000000		

Source: Full ADF-unit root test using Eviews, SV-11

(iii) Autocorrelation : Ljung-Box test

As p value is more than 5%, the null hypothesis is accepted that the series does not have any serial autocorrelation. The test shows that there is no serial autocorrelation at first difference at the 5% level for the selected sub-sample period. Furthermore, the ACF and PACF are quite significant at lags 3 and 6.

Null hypothesis: Time series is not auto-correlated (no serial auto-correlation)
Alternative hypothesis: Time series is auto-correlated

Table: Test of autocorrelation at first difference on FTSE-ALL SHARE INDEX for the selected sub-sample period of 06/05/2013 to 27/03/2017 (204 observations)

Series	P value
FTSE-ALL SHARE INDEX	More than 5% for all 24 lags

Source: output of autocorrelation test for sub-sample period of FTSE-all share index in Eviews, SV-11

Date: 18/11/20 Time: 13:11
Sample (adjusted): 13/05/2013 27/03/2017
Included observations: 203 after adjustments

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
.|. |	.|. |	1	-0.044	-0.044	0.4054	0.524
*|. |	*|. |	2	-0.092	-0.094	2.1687	0.338
*|. |	*|. |	3	-0.155	-0.166	7.1841	0.066
.|* |	.|. |	4	0.079	0.054	8.4921	0.075
.|. |	.|. |	5	-0.012	-0.036	8.5199	0.130
*|. |	*|. |	6	-0.117	-0.138	11.436	0.076
*|. |	*|. |	7	-0.074	-0.076	12.603	0.082
.|. |	.|. |	8	-0.012	-0.062	12.635	0.125
.|* |	.|. |	9	0.123	0.069	15.903	0.069
.|. |	.|. |	10	-0.005	-0.012	15.908	0.102
.|. |	.|. |	11	0.041	0.051	16.273	0.131
.|. |	.|. |	12	0.035	0.061	16.548	0.167
.|. |	.|. |	13	0.037	0.023	16.853	0.206
.|. |	.|. |	14	-0.064	-0.043	17.751	0.218
.|. |	.|. |	15	-0.038	-0.009	18.064	0.259
.|. |	.|. |	16	0.053	0.065	18.684	0.285
.|. |	.|. |	17	-0.009	-0.006	18.702	0.346
.|. |	.|. |	18	-0.060	-0.047	19.511	0.361
.|. |	.|. |	19	-0.046	-0.023	19.996	0.395
.|. |	.|. |	20	0.042	0.001	20.394	0.434
.|. |	.|. |	21	0.003	-0.039	20.396	0.496
.|* |	.|* |	22	0.076	0.075	21.728	0.476
.|. |	.|. |	23	0.027	0.056	21.891	0.527
.|. |	.|. |	24	0.002	0.002	21.892	0.586

Source: Full autocorrelation test for sub-sample period of FTSE-all share index using Eviews, SV-11

(iv) Single and multiple variance ratio (VR) tests at level:

As p value is more than 5%, for both individual tests and Chow-Denning maximum |Z| multiple statistics, it details that weekly closing price follows a martingale and null hypothesis is accepted. Therefore, stock prices do not follow a random walk model. Furthermore, VRs are less than 1 for individual test, which indicate, it does not follow a random walk model and there is a negative or mean reverting relationship in the prices of this series.

Hypotheses for variance ratio test:
Null hypothesis: PRICE is a martingale
Alternative hypothesis: PRICE is not a martingale

Table: Variance ratio tests on FTSE-ALL SHARE INDEX for the selected sub-sample period of 06/05/2013 to 27/03/2017 (204 observations)

Series		q = 2	q = 4	q = 8	q = 16	Chow-Denning joint test and p value
FTSE-ALL	VR	0.9632	0.7845	0.5970	0.5645	Max|z|(q=8)

Z	-0.5078	-1.6188	-1.9131	-1.3840	1.913084
Z*	0.0724	0.1331	0.2106	0.3146	P value =
P value	0.6111	0.1055	0.0557	0.1664	0.25

Source: Table of variance ratio test for sub-sample period of FTSE-all share index in Eviews, SV-11

Full variance ratio test:

Null Hypothesis: CLOSE is a martingale
Date: 18/11/20 Time: 13:16
Sample: 6/05/2013 27/03/2017
Included observations: 203 (after adjustments)
Heteroskedasticity robust standard error estimates
User-specified lags: 2 4 8 16 32

Joint Tests	Value	df	Probability
Max |z| (at period 8)*	1.913084	203	0.2493

Individual Tests

Period	Var. Ratio	Std. Error	z-Statistic	Probability
2	0.963225	0.072407	-0.507890	0.6115
4	0.784510	0.133109	-1.618899	0.1055
8	0.597077	0.210614	-1.913084	0.0557
16	0.564584	0.314602	-1.384019	0.1664
32	0.628634	0.454360	-0.817338	0.4137

*Probability approximation using studentized maximum modulus with parameter value 5 and infinite degrees of freedom

Test Details (Mean = 2.46300487685)

Period	Variance	Var. Ratio	Obs.
1	3994.84	--	203
2	3847.93	0.96323	202
4	3133.99	0.78451	200
8	2385.23	0.59708	196
16	2255.42	0.56458	188
32	2511.29	0.62863	172

Source: Full variance ratio test in Eviews, SV-11

Inference on Weak-form efficiency:

On the basis of the tests conducted, the inference is that the series is not weak-form efficient in the period of the tests. The level data has a unit root, but the number of runs is not random although the data shows that there is no autocorrelation and heteroscedasticity at the first difference (at the 5% level). Furthermore, variance ratio tests at level explain that stock prices do not move randomly. Therefore, results support the inference of weak-form inefficiency over the period tested.

A.6.3 Forecasting

(i) ARIMA model estimation:

For ARIMA model testing, the series must not have a unit root. The Lyung-Box test is done at the first difference of the series, which showed that series does not have a unit root and from the correlogram, the following possible ARIMA models were estimated through the PACF, ACF.

Criteria	ARIMA(6,1,3)	ARIMA(3,1,3)	ARIMA(3,1,6)	ARIMA(6,1,6)
Coefficient-AR term	-0.1029	0.1592	-0.1617	-0.8405
P value	(0.123)	(0.6678)	(0.0177)	(0.0001)
Coefficient –MA term	-0.1616	-0.3403	-0.1216	0.7611
P value	(0.017)	(0.3244)	(0.0564)	(0.0021)
σ^2(volatility)	3813.091	3843.315	3816.752	3889.752
P value	(0.000)	(0.0000)	(0.000)	(0.0000)
Adj. R^2	0.0263	0.0185	0.0254	0.0067
AIC	11.1243	11.1319	11.1252	11.1449
SBIC	11.1895	11.1972	11.1905	11.2101

Source: Table of estimated ARIMA models for sub-sample period of FTSE-all share index in Eviews, SV-11

The appropriate model should have the most significant coefficients, the lowest volatility, highest adjusted R-square and lowest AIC and SBIC. In two of the models, ARIMA (6,1,6) and ARIMA (3,1,6); the three coefficients (AR, MA and volatility) are significant. However, ARIMA (3,1,6) is marginal. Then looking at volatility value, adjusted R^2, AIC, SBIC, the better model is ARIMA (3,1,6). This model has lower volatility, higher adjusted R^2, lower AIC, lower SBIC. However, the residuals also need to be tested for a final decision on which ARIMA model is the best.

The full output for ARIMA (3,1,6) and test of correlogram of the residuals is as below:

Dependent Variable:
D(FTSE_ALL_SHARE_INDEX)
Method: ARMA Maximum Likelihood (OPG - BHHH)
Date: 18/11/20 Time: 23:40
Sample: 13/05/2013 27/03/2017
Included observations: 203
Convergence achieved after 8 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	2.598269	3.356910	0.774006	0.4398
AR(3)	-0.161703	0.067617	-2.391456	0.0177
MA(6)	-0.121647	0.063381	-1.919288	0.0564
SIGMASQ	3816.752	325.2734	11.73398	0.0000

R-squared	0.039850	Mean dependent var	2.463005
Adjusted R-squared	0.025375	S.D. dependent var	63.20475
S.E. of regression	62.39768	Akaike info criterion	11.12518
Sum squared resid	774800.6	Schwarz criterion	11.19046
Log likelihood	-1125.206	Hannan-Quinn criter.	11.15159
F-statistic	2.753071	Durbin-Watson stat	2.118853
Prob(F-statistic)	0.043740		

Inverted AR Roots	.27+.47i	.27-.47i	-.54	
Inverted MA Roots	.70	.35-.61i	.35+.61i	-.35+.61i
	-.35-.61i	-.70		

Date: 21/11/20 Time: 23:52
Sample (adjusted): 13/05/2013 27/03/2017
Included observations: 203 after adjustments

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
.|. |	.|. |	1	0.037	0.037	0.2764	0.599
.|. |	.|. |	2	-0.013	-0.014	0.3106	0.856
.|. |	.|. |	3	0.030	0.031	0.5022	0.918
.|. |	.|. |	4	0.025	0.023	0.6348	0.959
.|. |	.|. |	5	0.001	0.001	0.6353	0.986
.|* |	.|* |	6	0.083	0.083	2.0943	0.911
.|. |	.|. |	7	-0.006	-0.014	2.1024	0.954
.|. |	.|. |	8	0.029	0.032	2.2838	0.971
.|. |	.|. |	9	-0.035	-0.043	2.5477	0.980
*|. |	*|. |	10	-0.067	-0.067	3.5197	0.966
.|* |	.|* |	11	0.080	0.084	4.8962	0.936
.|. |	.|. |	12	0.005	-0.011	4.9011	0.961
.|. |	.|* |	13	0.062	0.074	5.7312	0.955
.|. |	.|. |	14	0.063	0.052	6.6038	0.949
*|. |	*|. |	15	-0.086	-0.089	8.2333	0.914
.|. |	.|. |	16	-0.036	-0.020	8.5172	0.932
.|* |	.|* |	17	0.109	0.091	11.198	0.846
.|* |	.|* |	18	0.115	0.119	14.190	0.717
.|. |	.|. |	19	0.067	0.051	15.208	0.709
.|. |	.|. |	20	0.013	-0.001	15.248	0.762
.|. |	.|. |	21	0.039	0.050	15.589	0.792
.|. |	.|. |	22	0.008	-0.007	15.604	0.835
.|. |	.|. |	23	0.044	0.050	16.062	0.853
.|. |	.|. |	24	0.070	0.048	17.192	0.840

Source: The full output for ARIMA (3,1,6) and the test of correlogram of the residuals in Eviews, 11

In addition to the various criteria applied, ARIMA (3,1,6) does not have autocorrelation in the residuals. So, this is the preferred model and the forecast from this model will be generated for the out-of-sample period. The out-of-sample forecast for ARIMA (3,1,6) is given below:

Model	Series	RMSE	MAE	MAPE	Theil U1	Theil U2
ARIMA (3,1,6)	FTSE-ALL SHARE INDEX	60.0459	45.1256	1.1456	0.0075	1.0604

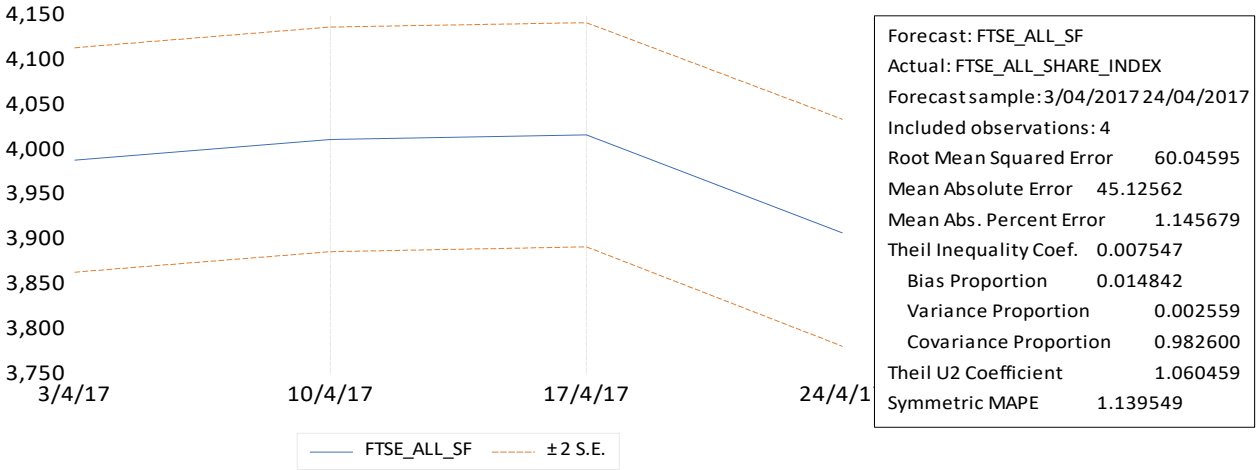
Source: Table Of output from ARIMA (3,1,6) model for sub-sample period of FTSE-all share index in Eviews

The comparison between actual prices and their forecasted prices of stock

Date	close	forecast
3/04/2017	4010.280	3989.244
10/04/2017	4012.300	4012.300
17/04/2017	3912.580	4017.461
24/04/2017	3962.490	3907.905

Source: forecasted outcome from ARIMA (3,1,6) model using Eviews. SV-11

Forecasting and evaluation of the model:



Source: Forecasting errors estimated from sub-sample of FTSE-all share index using ARIMA (3,1,6) model in Eviews, 11.

(ii) GARCH (1,1) model

Next, a GARCH(1,1) model will be estimated with ARIMA (3,1,6) in the mean equation, the results of which are as below:

Series	Mean equation:				Variance equation:				SIC	DW stat
	AR term coefficient	P value	MA term coefficient	P value		P value	β	P value		
FTSE-All share	-0.18116	0.0144	-0.13698	0.0439	0.03618	0.43	0.874480	0.00	11.24	2.12

Source: outcome from GARCH(1,1) model estimated with ARIMA (3,1,6) in mean equation using Eviews, 11

Dependent Variable: D(FTSE_ALL_SHARE_INDEX)
Method: ML ARCH - Normal distribution (BFGS / Marquardt steps)
Date: 09/12/20 Time: 11:20
Sample (adjusted): 3/06/2013 27/03/2017
Included observations: 200 after adjustments
Convergence achieved after 33 iterations
Coefficient covariance computed using outer product of gradients
MA Backcast: 22/04/2013 27/05/2013
Presample variance: backcast (parameter = 0.7)
GARCH = C(4) + C(5)*RESID(-1)^2 + C(6)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	2.889312	3.355857	0.860976	0.3893
AR(3)	-0.181161	0.074019	-2.447478	0.0144
MA(6)	-0.136982	0.067969	-2.015356	0.0439
Variance Equation				
C	340.2897	671.0394	0.507108	0.6121
RESID(-1)^2	0.036186	0.045850	0.789235	0.4300
GARCH(-1)	0.874480	0.206235	4.240209	0.0000

R-squared	0.039195	Mean dependent var	2.580900
Adjusted R-squared	0.029440	S.D. dependent var	63.43704
S.E. of regression	62.49626	Akaike info criterion	11.14669
Sum squared resid	769439.2	Schwarz criterion	11.24564
Log likelihood	-1108.669	Hannan-Quinn criter.	11.18674
Durbin-Watson stat	2.122419		

Inverted AR Roots	.28+.49i	.28-.49i	-.57	
Inverted MA Roots	.72	.36+.62i	.36-.62i	-.36+.62i
	-.36-.62i	-.72		

Source: outcome from full test of GARCH(1,1) model using Eviews, 11

The AR and MA terms are significant in the mean equation, the sum of the coefficients of the GARCH term and the ARCH term are <1; and this model is satisfactory. As a matter of interest, the residuals of ARIMA-GARCH is tested for serial correlation and heteroscedasticity. The null hypothesis of no heteroscedasticity in the residuals is accepted as the p-values of the F statistic is above 0.05. The results are shown below:

Table: Residual diagnostics test for GARCH (1,1) model

Series	P values from correlogram squared residuals under Q- statistic	ARCH-LM test (p values)	Normality test: p value from JB test
FTSE-ALL SHARE	All are more than 0.05	0.9170	0.0000

Source: Table of output from residual diagnostic test of GARCH (1,1) model in Eviews, SV-11

Correlogram of residuals for GARCH (1, 1):

The null hypothesis of no autocorrelation in the residuals is accepted as the p-values of the Q-statistic are all above 0.05.

Full test for correlogram of residuals:

Date: 09/12/20 Time: 11:22
Sample (adjusted): 3/06/2013 27/03/2017
Q-statistic probabilities adjusted for 2 ARMA terms

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob*
.|. |	.|. |	1	-0.065	-0.065	0.8488	
*|. |	*|. |	2	-0.105	-0.110	3.1054	
.|. |	.|. |	3	0.014	-0.001	3.1430	0.076
.|. |	.|. |	4	0.036	0.026	3.4155	0.181
.|. |	.|. |	5	-0.030	-0.025	3.6021	0.308
.|. |	.|. |	6	0.012	0.015	3.6318	0.458
.|. |	.|. |	7	-0.055	-0.060	4.2652	0.512
.|. |	.|. |	8	-0.039	-0.046	4.5851	0.598
.|* |	.|* |	9	0.113	0.099	7.2923	0.399
.|. |	.|. |	10	0.003	0.009	7.2945	0.505
.|. |	.|. |	11	0.032	0.061	7.5102	0.584
.|. |	.|. |	12	0.043	0.051	7.9134	0.637
.|. |	.|. |	13	0.045	0.055	8.3550	0.681
.|. |	.|. |	14	-0.064	-0.046	9.2586	0.681
.|. |	.|. |	15	-0.026	-0.035	9.4067	0.742
.|. |	.|. |	16	0.052	0.047	10.006	0.762
.|. |	.|. |	17	-0.010	-0.001	10.026	0.818
*|. |	.|. |	18	-0.072	-0.065	11.175	0.799
.|. |	.|. |	19	-0.014	-0.022	11.222	0.845
.|. |	.|. |	20	0.043	0.021	11.628	0.866
.|. |	.|. |	21	-0.012	-0.022	11.662	0.900
.|. |	.|. |	22	0.072	0.061	12.828	0.885
.|. |	.|. |	23	0.031	0.047	13.048	0.907
.|. |	.|. |	24	-0.012	0.009	13.083	0.931

*Probabilities may not be valid for this equation specification.

Source: Full test of residual diagnostic of GARCH (1,1) model in Eviews, SV-11

Heteroskedasticity Test:

Heteroskedasticity Test: ARCH

F-statistic	0.010745	Prob. F(1,197)	0.9175
Obs*R-squared	0.010854	Prob. Chi-Square(1)	0.9170

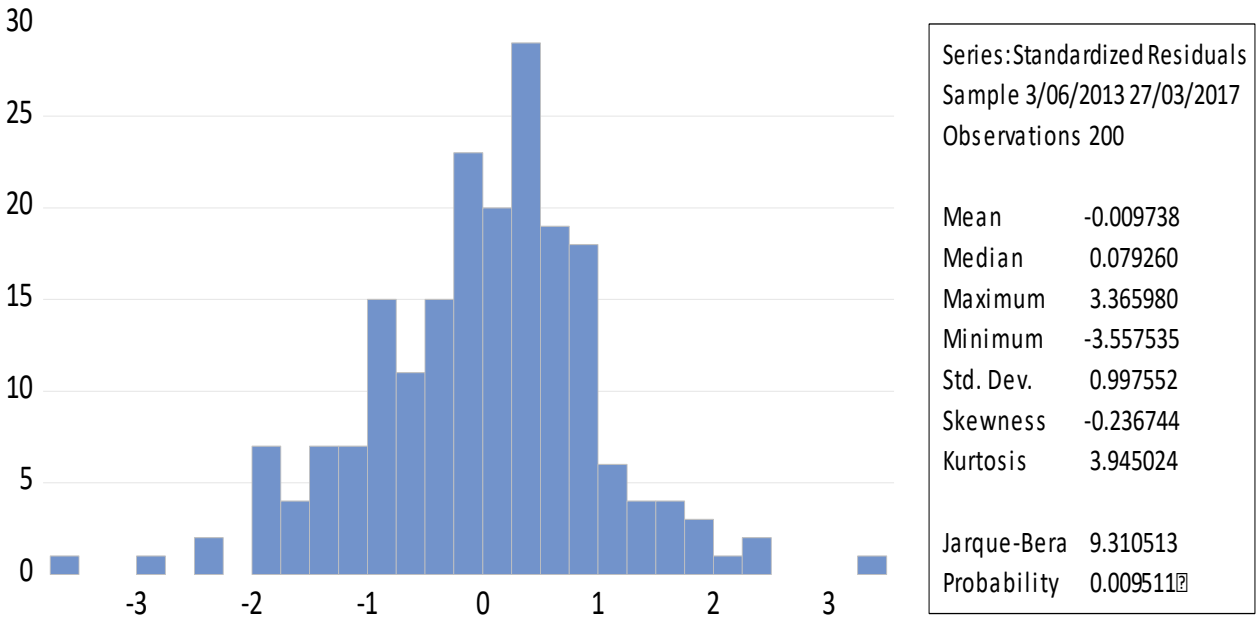
Test Equation:
Dependent Variable: WGT_RESID^2
Method: Least Squares
Date: 09/12/20 Time: 11:23
Sample (adjusted): 10/06/2013 27/03/2017
Included observations: 199 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.981438	0.140743	6.973240	0.0000
WGT_RESID^2(-1)	0.007391	0.071298	0.103659	0.9175

R-squared	0.000055	Mean dependent var	0.988793
Adjusted R-squared	-0.005021	S.D. dependent var	1.710410
S.E. of regression	1.714699	Akaike info criterion	3.926352
Sum squared resid	579.2180	Schwarz criterion	3.959450
Log likelihood	-388.6720	Hannan-Quinn criter.	3.939748
F-statistic	0.010745	Durbin-Watson stat	1.997361
Prob(F-statistic)	0.917546		

Source: Full test of Heteroskedasticity for GARCH (1,1) model in Eviews, SV-11

Normality test:



Source: Full test for normality of GARCH (1,1) model in Eviews, SV-11

Comparative forecast evaluation between ARIMA and GARCH (1, 1) models:

The comparative evaluations of forecasts for ARIMA (3,1,6) and ARIMA (3,1,6) GARCH (1, 1) models, below show that ARIMA (3,1,6) model is better of the two models on all the evaluation measures.

Model	Series	RMSE	MAE	MAPE	Theil U1	Theil U2
ARIMA (3,1,6)	FTSE-ALL SHARE INDEX	60.0459	45.1256	1.1456	0.0075	1.0604
ARIMA(3,1,6) GARCH (1,1)	FTSE-ALL SHARE INDEX	60.45311	45.49908	1.155130	0.007598	1.067716

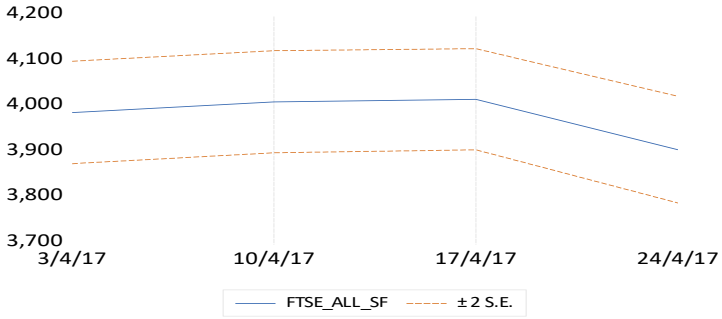
Source: Table of comparison of outcomes from ARIMA and GARCH (1,1) model in Eviews, SV-11

Results of out-of-sample forecast of the series using the ARIMA-GARCH model

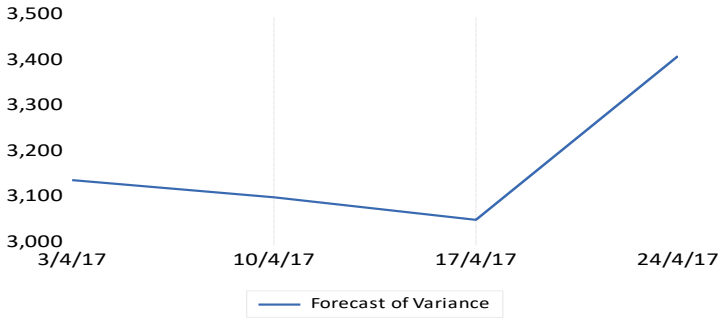
Date	FTSE-ALL	Forecast
03/04/2017	4010.28	3989.129
10/04/2017	4012.3	4012.54
17/04/2017	3912.58	4018.12
24/04/2017	3962.49	3907.425

Source: Forecasted results from ARIMA (3,1,6) –GARCH (1, 1) model using Eviews, 11.

Forecasted errors from ARIMA (3,1,6) GARCH (1, 1) model



Forecast: FTSE_ALL_SF
Actual: FTSE_ALL_SHARE_INDEX
Forecast sample: 3/04/2017 24/04/2017
Included observations: 4
Root Mean Squared Error 60.45311
Mean Absolute Error 45.49908
Mean Abs. Percent Error 1.155130
Theil Inequality Coef. 0.007598
Bias Proportion 0.014948
Variance Proportion 0.003183
Covariance Proportion 0.981869
Theil U2 Coefficient 1.067716
Symmetric MAPE 1.148935



Source: Forecasting errors and forcast comparison graph estimated from sub-sample of FTSE-all share index using ARIMA (3,1,6) GARCH (1,1) model in Eviews, 11.

(iii) Double exponential smoothing technique

The application of double exponential smoothing technique for FTSE-all share index produces the following outcomes. The table details that there is a significant gap between actual prices and forecasted prices compare to that from ARIMA and GARCH (1, 1) models.

Date	FTSE-All	Smooth	Level	Trend	Fits	Residuals	Forecast	Upper	Lower
03/04/2017	4010.28	4045.68	4045.68	12.87	4054.53	-44.2495	4054.53	4227.892	3881.167
10/04/2017	4012.3	4049.3	4049.3	11.02002	4058.55	-46.2496	4069.17	4246.144	3892.195
17/04/2017	3912.58	4030.772	4030.772	5.110435	4060.32	-147.74	4083.809	4264.674	3902.945
24/04/2017	3962.49	4021.204	4021.204	2.174745	4035.882	-73.3922	4098.449	4283.464	3913.435

Source: outputs from double exponential smoothing technique using minitab, V-17.

Forecast evaluation statistics:

The following table details that naive method performs better than double exponential smoothing technique as MAPE and Theil $U_1$are significantly higher. Furthermore, Theil U_2 explains that it is not worth to apply this technique as the value of Theil U_2 is greater than one (U_2>1), Omnia (2016), Bliemel (1973), Granger and Newbold (1973) and Ahlburg (1984).

RMSE	MAE	MAPE	Theil U1	Theil U2
115.1050	102.0770	2.582081	0.014297	2.034027

Source: Forecast errors from double exponential smoothing technique using minitab, V-17.

(iii) Triple exponential smoothing technique

The following table explains the results from triple exponential smoothing technique. It shows that there is a significant gap between actual prices and forecasted prices from this technique compare to those from ARIMA and GARCH (1, 1) models. This method includes seasonality component in analysis in addition to double exponential smoothing. This series explains that triple exponential smoothing performs better than double exponential smoothing technique.

Date	FTSE-All	Smooth	Level	Trend	Seasonal	Fits	Residuals	Forecast	Upper	Lower
03/04/2017	4010.28	4030.19	4007.13	11.26	23.93	4042.75	-32.47	4042.75	4213.55	3871.95
10/04/2017	4012.30	4038.25	4010.95	9.77	25.16	4049.51	-37.21	4057.30	4230.77	3883.82
17/04/2017	3912.58	4036.68	3993.95	4.42	4.31	4046.45	-133.87	4064.47	4240.93	3888.01
24/04/2017	3962.49	4017.88	3986.40	2.02	14.36	4022.29	-59.80	4080.43	4260.16	3900.69

Source: outputs from triple exponential smoothing technique using minitab, V-17.

Forecast evaluation statistics:

The forecast benchmarks detail that there is no point to apply this technique. Omnia (2016), Bliemel (1973), Granger and Newbold (1973) and Ahlburg (1984) claimed that U_2 provides better interpretation of outcomes than U_1. As Theil U_2 is greater than one (U_2>1), random walk or naïve method produces better results (Omnia, 2016; Bliemel, 1973; Granger and Newbold, 1973 and Ahlburg, 1984).

RMSE	MAE	MAPE	Theil U1	Theil U2
100.0719	86.82244	2.197367	0.012453	1.777845

Source: Forecast errors from triple exponential smoothing technique using minitab, V-17.

A comparison table of forecast evaluation statistics among all applied models:

As RMSE and MAE do not work as benchmarks, they have been ignored from the following table. The comparison documents that ARIMA model is the best predictor for this series among 4 forecasting models based on MAPE, Theil U_1 and U_2 as they are the lowest from this model. Furthermore, the benchmark parameters disclose that GARCH (1, 1) is the second-best predictor for the same series. Therefore, the forecast encompassing tests will be performed between ARIMA and GARCH (1, 1) models in the next section.

Series	Forecasting models and techniques	MAPE	Theil U1	Theil U2
FTSE-all share index	ARIMA (3,1,6)	1.145679	0.007547	1.060459
	ARIMA(3,1,6) GARCH(1,1)	1.155130	0.007598	1.067716
	Double exponential smoothing technique	2.582081	0.014297	2.034027
	Triple exponential smoothing technique	2.197367	0.012453	1.777845

Source: Forecast errors from all applied models using Eviews, V-11 and minitab, V-17.

(iv) Forecast encompassing tests between 2 best models out of 4

The table of actual values and forecasted values from ARIMA (F1) and GARCH- 1, 1 (F2) models for performing encompassing test:

Date	FTSE-all share-actual price	ARIMA (F1)-forecast	GARCH (F2)-forecast
03/04/2017	4010.28	3989.244	3989.129
10/04/2017	4012.3	4012.3	4012.54
17/04/2017	3912.58	4017.461	4018.12
24/04/2017	3962.49	3907.905	3907.425

Source: Table of actual values and forecasted values from 2 best models using Eviews, V-11.

Forecast encompassing test of Fair-Shiller:

Forecast encompassing is then examined via the significance of the β_i coefficients. For example, should $H_0 : \beta_{1=0}$ be rejected, but $H_0 : \beta_2 = 0$ not, this indicates the redundancy of f_{2t}. Obviously the switching of the β_i in the above indicates forecast encompassing in the other direction, Cook (2014). The formula for encompassing test of Fair-Shiller is as follows:

(1) $y_t = \alpha + \beta_1 f_{1t} + \beta_2 f_{2t} + v_t$

Hypothesis:
Null hypothesis: model 1 encompasses model 2.
Alternative hypothesis: forecast from model 2 contains more information than that from model 1

The results detail that neither forecast is better than other, indicating that ARIMA and GARCH (1, 1) models do not encompass each other as their p values are more than 5%.

Table: Forecast encompassing test of Fair-Shiller

Series	Coefficient from ARIMA (f1)	P value of f1	Coefficient from GARCH-1,1 (f2)	P value of f2
FTSE-All share	198.1257	0.1965	-196.4468	0.1966

Source: Output from encompassing test of Fair-Shiller between 2 best models using Eviews, V-11.

Full encompassing test of Fair-Shiller:

Dependent Variable: FTSE_ALL
Method: Least Squares
Date: 25/01/21 Time: 22:17
Sample: 3/04/2017 24/04/2017
Included observations: 4

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-2695.466	2392.696	-1.126539	0.4622
ARIMA	198.1257	63.18721	3.135534	0.1965

GARCH01	-196.4468	62.65519	-3.135363	0.1966

R-squared	0.907686	Mean dependent var	3974.413
Adjusted R-squared	0.723057	S.D. dependent var	47.21350
S.E. of regression	24.84629	Akaike info criterion	9.377000
Sum squared resid	617.3384	Schwarz criterion	8.916721
Log likelihood	-15.75400	Hannan-Quinn criter.	8.366951
F-statistic	4.916271	Durbin-Watson stat	3.035486
Prob(F-statistic)	0.303833		

Source: Full encompassing test of Fair-Shiller between 2 best models using Eviews, V-11.

Forecast encompassing test of Chong and Hendry (1986):

(2) $e_{1t} = \lambda_2 f_{2t} + \eta_{1t}$

3) $e_{2t} = \lambda_1 f_{1t} + \eta_{2t}$

The results show that neither forecast is better than the other, indicating that ARIMA and GARCH (1, 1) models do not encompass each other as their p values are more than 5%. Therefore, it might be claimed that the forecast encompassing test is not applicable for stock prices, i. e. FTSE-all share index. This might be because, the forecast encompassing tests need a long period of data. However, a long period of forecasted data is inappropriate in the case of stock prices as the prices move randomly and frequently in the stock market.

Hypothesis:

Null hypothesis: model 1 encompasses model 2.
Alternative hypothesis: forecast from model 2 contains more information than that from model 1

Table: Forecast encompassing test of Chong and Hendry

Series	Coefficient from ARIMA (f1)	P value of f1	Coefficient from GARCH (f2)	P value of f2
FTSE-All share	-0.001977	0.8347	-0.001959	0.8351

Source: Output from encompassing test of Chong-Hendry between 2 best models using Eviews, V-11.

Full encompassing test of Chong and Hendry:

Dependent Variable: E1
Method: Least Squares
Date: 19/01/21 Time: 21:04
Sample: 3/04/2017 24/04/2017
Included observations: 4

Variable	Coefficient	Std. Error	t-Statistic	Prob.
GARCH01	-0.001959	0.008632	-0.226884	0.8351

R-squared	0.002059	Mean dependent var	-7.315000

Adjusted R-squared	0.002059	S.D. dependent var	68.81866
S.E. of regression	68.74777	Akaike info criterion	11.51108
Sum squared resid	14178.77	Schwarz criterion	11.35766
Log likelihood	-22.02217	Hannan-Quinn criter.	11.17440
Durbin-Watson stat	2.595333		

Dependent Variable: E2
Method: Least Squares
Date: 19/01/21 Time: 21:17
Sample: 3/04/2017 24/04/2017
Included observations: 4

Variable	Coefficient	Std. Error	t-Statistic	Prob.
ARIMA	-0.001977	0.008691	-0.227509	0.8347

R-squared	0.002044	Mean dependent var	-7.391000
Adjusted R-squared	0.002044	S.D. dependent var	69.28146
S.E. of regression	69.21062	Akaike info criterion	11.52450
Sum squared resid	14370.33	Schwarz criterion	11.37108
Log likelihood	-22.04901	Hannan-Quinn criter.	11.18782
Durbin-Watson stat	2.593260		

Source: Full encompassing test of Chong and Hendry between 2 best models using Eviews, V-11.

CHAPTER SIX: DATA ANALYSIS AND FINDINGS

Part-B: Summarised analysis of all series and their findings

This part of chapter six will apply non-forecasting related and forecasting related methods that have been discussed in the earlier chapters for all 22 series, summarise and compare the results in a table and analyse the findings, following the same steps as performed in the earlier part of chapter six. The next section will analyse series characteristics for all series.

B.6.1 Series characteristics for all 22 series

(i) The Descriptive statistics

Table 6.1 below shows the results from the descriptive statistics. There are 1064 weekly observations for FTSE-all share index and each selected company (n=1064) in different industries. However, there are only 424 weekly observations for FTSE-350 general industrial index due to unavailability. In the table below, FTSE-350 general industrial index has the highest mean of 3751.74, indicating stock price is 3751.74 on average. Astrazeneca plc of the quaternary industry has the second highest mean of 2992.9. It indicates that the stock price is 2992.9 on average for Astrazeneca plc. However, the weekly closing price of Astrazeneca plc could be higher or lower than 2992.9. Aberdeen Asset Management plc (ADN.L) from the service industry has the lowest mean, which is 197.70. Therefore, the weekly closing price of ADN.L is around that level at the bottom compared with all the selected companies.

FTSE-350 general industrial index has the highest standard error of mean. The standard deviation (SD) is the highest for Shire plc (SHP.L) in the quaternary industry and the lowest for Centrica plc (CNA.L) in the primary industry. CNA.L has got the lowest standard error of mean. The highest standard error indicates that FTSE-350 general industrial index has the lowest representative sample size among all the selected series. On the other hand, Centrica plc has the highest representative sample size. As Centrica plc has the highest representative sample size and the sample deviation is the lowest, the results obtained from this company are more reliable than those from any other company or variable. The second lowest SE and SD are found from BP plc of the primary industry. Therefore, stock prices of that company should be predictable as well.

FTSE-all share index and FTSE-350 general industrial index have kurtosis less than 3. Furthermore, all the selected companies in the primary industry have kurtosis less than 3. Moreover, the other companies in different industries have kurtosis less than 3 apart from

Associated British Foods plc and Berkeley Group Holdings plc, which are from the manufacturing industry, and Ashtead Group plc, which is from the service industry and Astrazeneca plc, Shire plc and Sage Group plc which are from quaternary industry. Therefore, the distribution of these six companies (kurtosis more than 3) are peaked (leptokurtic) relative to the normal and the distribution of remaining fourteen companies in different industries, FTSE-all share index and FTSE-350 general industrial index are flat or platykurtic (Eviews, version 8). Carmody (2013) explains that platykurtic distribution indicates that there is a greater chance of extreme outcomes; therefore, investing in those companies could be risky.

Leptokurtic distribution indicates that there is a lesser risk of extreme outcomes and investors could invest in these assets to avoid risks but with a minimum expectation of higher returns. These leptokurtic and platykurtic distributions also confirm that the prices are not normally distributed (Killam, 2014). All the series have positive skewness apart from Centrica plc of the primary industry, which indicates higher chances of positive returns from investing in those companies. The skewness of Centrica plc is found to be negative, indicating a greater probability of negative returns.

Carmody (2013) argues that a negatively skewed distribution has frequent small gains and a few extreme losses while a positively skewed distribution indicates frequent small losses and a few extreme gains. Therefore, the negatively skewed distribution of weekly closing prices could frequently generate a small amount of positive returns as well. Killam (2014) claims that negative and positive skewness does not confirm that the data are normally distributed while a non-normal frequency distribution of the stock price confirms that the market does not follow the random-walk model.

The greatest range is achieved by Shire plc from the quaternary industry 5468.0. This reveals that the price fluctuation is very high in this company and therefore prices may be unpredictable and the SD is the highest. There is a greater chance of extreme outcomes from the investment in this company. The lowest range is 338.12 for Centrica plc (CNA.L), also from the primary industry. This indicates that the price is stable and less volatile for this company than other companies in different industries. This result also indicates that prices are more predictable for this company than other companies. However, it does not reveal that positive returns will be gained by investing in this company. It also indicates that this company could generate positive returns but not significantly. The second lowest range is achieved from BP plc of the primary industry as well. This result indicates prices are

predictable significantly for this company as fluctuation is low. The table of descriptive statistics for the periods between 03/03/1997 and 17/07/2017 are as below:

Table 6. 1: Descriptive statistics on 22 series for the periods between 03/03/1997 and 17/07/2017

Series	Mean	SE Mean	StDev	Range	skewness	Kurtosis	Median	Mode
FTSE-All								
Share	2879.87	16.30	531.17	2445.15	0.009	2.33	2915.34	2354.83
FTSE-350								
General								
Industrial								
Index	3751.74	51.78	1066.33	4663.93	0.219	2.54	3865.28	1548.76
The primary industry								
ANTO.L	506.1	12.4	404.7	1580.0	0.60	2.30	457.88	124
BP.L	495.98	2.48	80.88	407.40	0.23	2.18	482.03	567.5
CNA.L	240.84	2.21	71.95	338.12	-0.26	2.53	235.42	222.56
SVT.L	1473.2	12.0	390.5	1812.5	0.70	2.74	1426	1102.5
JMAT.L	1637.5	26.8	872.9	3262.4	0.57	2.12	1463	942.86
The manufacturing industry								
ABF.L	1176.8	27.1	884.5	3221.5	1.33	3.28	818.75	830
BATS.L	1875.1	41.5	1353.4	5341.8	0.72	2.43	1584.5	580
BDEV.L	286.46	5.45	177.83	712.48	0.69	2.29	233.76	151.96
BKG.L	1309.9	25.1	819.8	3280.0	1.23	3.29	907.25	782.5
DGE.L	1122.5	15.8	516.1	1977.5	0.83	2.25	925.50	695
The service industry								
ADN.L	197.70	4.01	130.93	488.68	0.48	2.13	172	190
AHT.L	319.8	12.6	410.2	1716.8	1.74	4.93	142.13	154.97
AV.L	568.04	6.11	199.38	1026.78	0.63	2.51	515.60	532
BAB.L	443.7	11.4	370.3	1245.3	0.63	1.98	371.64	93.90
BARC.L	358.80	4.31	140.64	682.46	0.40	2.34	338.78	404.14
The Quaternary industry								
AZN.L	2992.9	24.1	786.3	3714.9	0.96	3.32	2827.9	3380

GSK.L	1448.6	7.73	252.1	1293.0	0.57	2.55	1409.8	1289
SHP.L	1623.9	44.9	1463.9	5468.0	1.38	3.63	1049	1072
SGE.L	309.39	5.07	165.54	877.27	1.28	4.08	259.8	299.80
SN.L	584.77	9.19	299.82	1212.06	0.83	2.90	540.5	213.89

Note: The above table analyses the weekly closing price of the following companies. ANTO.L (Antofagasta PLC), BP.L (BP PLC), CNA.L (Centrica PLC), SVT.L (Severn Trent PLC), JMAT.L (Johnson Matthey), ABF.L Associated British Foods PLC), BATS.L (British American Tobacco PLC), BDEV.L (Barratt Developments PLC), BKG.L (Berkeley Group Holdings PLC), DGE.L (Diageo PLC), ADN.L (Aberdeen Asset Management PLC), AHT.L (Ashtead Group PLC), AV.L (Aviva PLC), BAB.L (Babcock International Group PLC), BARC.L (Barclays PLC), AZN.L (Astrazeneca PLC), GSK.L (GlaxoSmithkline PLC), SHP.L (Shire PLC), SGE.L (Sage Group PLC), SN.L (Smith & Nephew PLC).

Source: Output of descriptive statistics using SPSS, v-22.

(ii) The seasonality test

To check seasonality, Friedman chi-square test statistics has been applied. To check seasonality in different periods, each of 22 series have been divided into 4 sub-sample periods. The following table shows mean, standard deviation and mean rank below for each sub-sample period. They document that they are not same throughout each period. They all are different in value from each other and consequently, they do not have seasonality (Boschetti et. al. 2006). The null hypothesis of the Friedman test, that there is seasonality in the data is rejected.

Hypothesis:
Null hypothesis: Data have seasonality
Alternative hypothesis: Data do not have seasonality
Friedman test:

Table 6. 2: Stock price seasonality on 22 series for the periods between 03/03/1997 and 17/07/2017

Series	Sub-sample 1			Sub-sample 2			Sub-sample 3			Sub-sample 4		
	mean	St dev	rank	mean	St dev	rank	mean	St dev	rank	mean	St dev	rank
FTSE-ALL SHARE	2713.54	296.78	2.22	2472.67	453.56	1.59	2802.28	375.85	2.31	3531.00	270.11	3.88
FTSE-350 Gen. Indus. Index	2550.78	510.79	1.00	3210.21	414.12	2.00	4208.10	224.87	3.14	5037.86	682.34	3.86
The primary industry												
ANTO.L	76.03	21.8	1	262.08	133.28	2.03	905.26	322.38	3.56	781.02	231.33	3.42
BP.L	514.39	86.60	2.69	525.97	85.25	2.63	503.51	70.98	2.77	440.04	44.5	1.91
CNA.L	165.56	57.89	1.39	222.44	47.77	2.30	291.91	33.86	3.40	283.44	59.29	2.91
SVT.L	1229.25	210.32	1.85	1326.66	272.55	2.06	1330.20	194.65	2.09	2006.76	259.95	4.00
JMAT.L	750.73	240.39	1	1138.28	249.26	2.05	1756.07	368.73	2.95	2904.99	366.12	4.00
The manufacturing industry												
ABF.L	512.00	108.04	1.36	696.34	125.79	1.67	925.07	161.68	2.97	2573.67	622.26	4.00
BATS.L	513.15	87.96	1.02	986.22	322.25	1.98	2172.33	479.04	3.00	3828.62	657.35	4.00
BDEV.L	167.88	36.58	1.82	398.86	150.38	3.26	151.53	133.16	1.50	427.56	141.80	3.42
BKG.L	655.73	100.77	1.19	979.21	305.48	2.44	1042.17	278.30	2.44	2562.39	573.66	3.93
DGE.L	658.83	86.20	1.14	795.51	113.07	1.86	1100.50	184.60	3.00	1935.07	166.27	4.00
The service industry												
ADN.L	164.07	138.55	2.27	98.64	57.60	1.34	166.51	44.57	2.60	361.56	73.12	3.79

AHT.L	134.91	48.30	2.18	80.86	62.72	1.51	116.02	59.97	2.32	947.21	369.52	4.00
AV.L	842.40	116.97	3.85	557.30	119.81	2.63	422.61	122.17	1.68	449.85	74.55	1.83
BAB.L	91.70	16.57	1.20	164.80	94.98	1.80	516.25	82.95	3.00	1002.02	114.82	4.00
BARC.L	400.61	76.43	2.89	508.38	94.52	3.69	296.88	134.53	2.09	229.32	39.69	1.33
The quaternary industry												
AZN.L	2636.79	519.53	2.06	2580.70	364.52	1.86	2709.33	341.62	2.11	4044.62	686.81	3.97
GSK.L	1729.80	248.47	3.64	1308.07	140.22	1.92	1240.03	108.99	1.40	1516.44	119.38	3.04
SHP.L	692.22	371.78	1.50	640.70	208.04	1.50	1358.91	438.74	3.00	3803.87	1240.92	4.00
SGE.L	297.19	208.38	2.15	209.09	46.57	1.58	248.00	41.09	2.41	483.28	135.11	3.85
SN.L	259.76	66.04	1.00	477.86	77.77	2.17	589.58	70.00	2.84	1011.88	211.29	4.00

Note: The above table analyses the weekly closing price of the following companies. ANTO.L (Antofagasta PLC), BP.L (BP PLC), CNA.L (Centrica PLC), SVT.L (Severn Trent PLC), JMAT.L (Johnson Matthey), ABF.L Associated British Foods PLC), BATS.L (British American Tobacco PLC), BDEV.L (Barratt Developments PLC), BKG.L (Berkeley Group Holdings PLC), DGE.L (Diageo PLC), ADN.L (Aberdeen Asset Management PLC), AHT.L (Ashtead Group PLC), AV.L (Aviva PLC), BAB.L (Babcock International Group PLC), BARC.L (Barclays PLC), AZN.L (Astrazeneca PLC), GSK.L (GlaxoSmithkline PLC), SHP.L (Shire PLC), SGE.L (Sage Group PLC), SN.L (Smith & Nephew PLC).

Source: Output of seasonality test using SPSS, v-22

The following table explains chi-square test statistics and corresponding p values from Friedman test for each of 22 series derived from 4 different sub-sample periods. The table evidences that all the p values for each series are less than 5% and they are statistically significant. Therefore, null hypothesis is rejected and alternative hypothesis is accepted. This result explains that their medians are different from each other and data do not have seasonality. However, it is not required to know where the differences exist. The purpose is served that they do not have seasonality. Thus, it is not required to run post hoc tests.

Null hypothesis: Data have seasonality
Alternative hypothesis: Data do not have seasonality

Table 6. 3: Friedman Test of Chi-Square statistics for detecting seasonality

Series	X^2	p value	Variable	X^2	p value
FTSE-ALL SHARE	456.122	0.000***	FTSE-350 general industrial index	302.55	0.000***
The primary industry			The service industry		
ANTO.L	707.310	0.000***	ADN.L	492.21	0.000***
BP.L	76.862	0.000***	AHT.L	538.40	0.000***
CNA.L	356.46	0.000***	AV.L	471.82	0.000***
SVT.L	482.07	0.000***	BAB.L	747.80	0.000***
JMAT.L	783.16	0.000***	BARC.L	496.48	0.000***
The manufacturing industry			The quaternary industry		
ABF.L	709.67	0.000***	AZN.L	465.60	0.000***
BATS.L	793.27	0.000***	GSK.L	498.19	0.000***
BDEV.L	461.13	0.000***	SHP.L	716.40	0.000***
BKG.L	603.33	0.000***	SGE.L	447.32	0.000***
DGE.L	760.65	0.000***	SN.L	752.54	0.000***

Note 1: The above table analyses the weekly closing price of the following companies. ANTO.L (Antofagasta PLC), BP.L (BP PLC), CNA.L (Centrica PLC), SVT.L (Severn Trent PLC), JMAT.L (Johnson Matthey), ABF.L Associated British Foods PLC), BATS.L (British American Tobacco PLC), BDEV.L (Barratt Developments PLC), BKG.L (Berkeley Group Holdings PLC), DGE.L (Diageo PLC), ADN.L (Aberdeen Asset Management PLC), AHT.L (Ashtead Group PLC), AV.L (Aviva PLC), BAB.L (Babcock International Group PLC), BARC.L (Barclays PLC), AZN.L (Astrazeneca PLC), GSK.L (GlaxoSmithkline PLC), SHP.L (Shire PLC), SGE.L (Sage Group PLC), SN.L (Smith & Nephew PLC).
Note 2: p-value < 1% = *** and P-value < 5% = **

Source: Output from Friedman test of Chi-Square using SPSS, v-22

(iii) **Testing for structural breaks and Potential causes of breaks**

While the seasonality test shows that the series has no seasonality, there might be structural breaks, which will affect proper estimation and testing. Visual examination shows that there could be a several breakpoints for each series. Therefore, the Bai-Perron test is used to estimate these. Sequential L+1 breaks vs. L is applied to determine the optimal breaks in each series. All the p values are significant at 1% level. The table of Bai-Perron test below and figure from it (which is shown in appendix) shows clean periods where there are no breaks. However, each series shows a several breakpoints at different point of time. Therefore, it could be argued that structural breaks took place due to company or series or industry specific reason.

For estimation of ARIMA models, in the methodology chapter, it was explained that 204 continuous data are sufficient. The estimation period has been chosen where more than 204 observations are available. Furthermore, the estimation period has been chosen from the latest sub-sample period. The sub-sample periods which show observations less than 204, have been ignored from consideration of estimation period. Data from gray area in clean period has been chosen as estimation period for each series. The results are shown below:

Table 6. 4: Bai-Perron multiple breakpoints test for the period from 03/03/1997 to 17/07/2017

Series	Break date	Clean period	Obser.	Coefficient	Stand. error	t-statistic	P value
FTSE-		03/03/1997-27/05/2002	274	2707.82	18.13	149.35	0.00**
ALL	03/06/2002	03/06/2002-20/06/2005	160	2154.07	23.73	90.79	0.00**
SHARE	27/06/2005	27/06/2005-10/11/2008	177	3009.60	22.56	133.41	0.00**
INDEX	17/11/2008	17/11/2008-24/12/2012	215	2749.68	20.47	134.34	0.00**
	31/12/2012	31/12/2012-17/07/2017	238	3591.63	19.45	184.62	0.00**
FTSE-350		31/05/2009-20/01/2013	191	2766.34	43.32	63.86	0.00**
Gen Indus.	27/01/2013	27/01/2013-16/07/2017	234	4547.29	39.14	116.18	0.00**
The primary industry							
ANTO.L		03/03/1997-15/12/2003	355	90.01	6.74	13.35	0.00**
	22/12/2003	22/12/2003-12/03/2007	169	318.06	9.77	32.55	0.00**
	19/03/2007	19/03/2007-28/03/2010	159	664.82	10.07	65.99	0.00**
	04/04/2010	04/04/2010-15/04/2013	159	1201.90	10.07	119.31	0.00**
	22/04/2013	22/04/2013-17/07/2017	222	702.58	8.52	82.41	0.00**
BP.L		03/03/1997-13/03/2000	159	469.45	4.88	96.13	0.00**
	20/03/2000	20/03/2000-31/01/2005	255	513.83	3.85	133.25	0.00**
	07/02/2005	07/02/2005-09/05/2010	275	570.50	3.71	153.64	0.00**
	16/05/2010	16/05/2010-29/06/2014	216	451.43	4.19	107.75	0.00**
	06/07/2014	06/07/2014-16/07/2017	159	425.50	4.88	87.13	0.00**
CNA.L		03/03/1997-13/03/2000	159	123.89	2.42	51.08	0.00**
	20/03/2000	20/03/2000-23/01/2006	306	209.64	1.75	119.93	0.00**
	30/01/2006	30/01/2006-27/06/2010	231	280.97	2.01	139.65	0.00**
	04/07/2010	04/07/2010-29/06/2014	209	330.17	2.11	156.09	0.00**
	06/07/2014	06/07/2014-16/07/2017	159	242.12	2.42	99.84	0.00**
SVT.L		03/03/1997-13/03/200	159	1340.60	14.97	89.56	0.00**

	20/03/2000	20/03/2000-12/09/2004	235	1076.93	12.31	87.47	0.00**
	19/09/2004	19/09/2004-28/01/2008	176	1522.99	14.23	107.05	0.00**
	04/02/2008	04/02/2008-07/04/2013	271	1366.13	11.46	119.15	0.00**
	14/04/2013	14/04/2013-16/07/2017	223	2076.25	12.64	164.27	0.00**
JMAT.L		03/03/1997-26/03/2000	161	576.88	17.98	32.08	0.00**
	02/04/2000	02/04/2000-7/11/2005	293	1001.78	13.33	75.16	0.00**
	14/11/2005	14/11/2005-03/10/2010	256	1564.25	14.26	109.70	0.00**
	10/10/2010	10/10/2010-20/10/2013	159	2262.91	18.09	125.07	0.00**
	28/10/2013	28/10/2013-16/07/2017	195	3054.72	16.34	186.97	0.00**
The manufacturing industry							
ABF.L		03/03/1997-19/09/2004	395	533.07	10.03	53.15	0.00**
	26/09/2004	26/09/2004-04/01/2010	276	801.53	11.99	66.80	0.00**
	11/01/2010	11/01/2010-13/10/2013	197	1274.07	14.20	89.71	0.00**
	20/10/2013	20/10/2013-16/07/2017	196	2904.65	14.24	204.01	0.00**
BATS.L		03/03/1997-04/02/2002	258	508.68	20.93	24.30	0.00**
	11/02/2002	11/02/2002-23/10/2005	194	793.30	24.13	32.87	0.00**
	31/10/2005	31/10/2005-21/03/2011	282	1794.35	20.01	89.65	0.00**
	27/03/2011	27/03/2011-29/06/2014	171	3175.73	25.70	123.55	0.00**
	06/07/2014	06/07/2014-16/07/2017	159	4156.55	26.65	155.94	0.00**
BDEV.L		03/03/1997-26/11/2001	248	161.78	4.94	32.75	0.00**
	03/12/2001	03/12/2001-14/03/2005	172	285.99	5.93	48.22	0.00**
	21/03/2005	21/03/2005-11/02/2008	152	515.70	6.31	81.73	0.00**
	18/02/2008	18/02/2008-07/04/2013	269	117.91	4.74	24.86	0.00**
	14/04/2013	14/04/2013-16/07/2017	223	472.53	5.21	90.71	0.00**
BKG.L		03/03/1997-08/03/2004	367	673.25	15.21	44.25	0.00**
	15/03/2004	15/03/2004-24/12/2007	198	1213.87	20.71	58.61	0.00**
	31/12/2007	31/12/2007-11/02/2013	268	1043.21	17.80	58.59	0.00**
	18/02/2013	18/02/2013-16/07/2017	231	2712.97	19.17	141.48	0.00**
DGE.L		03/03/1997-29/01/2001	205	631.54	9.22	68.51	0.00**
	05/02/2001	05/02/2001-20/02/2006	264	746.09	8.12	91.84	0.00**
	27/02/2006	27/02/2006-30/01/2012	310	1045.25	7.50	139.43	0.00**
	06/02/2012	06/02/2012-16/07/2017	285	1908.27	7.82	244.07	0.00**
The service industry							
ADN.L		03/03/1997-13/03/2000	159	64.64	5.69	11.37	0.00**
	20/03/2000	20/03/2000-30/03/2003	159	235.38	5.69	41.39	0.00**
	06/04/2003	06/04/2003-16/04/2006	159	77.26	5.69	13.59	0.00**
	23/04/2006	23/04/2006-29/07/2012	328	170.73	3.96	43.12	0.00**
	05/08/2012	05/08/2012-16/07/2017	259	364.34	4.45	81.78	0.00**
AHT.L		03/03/1997-26/08/2001	235	144.65	9.45	15.29	0.00**
	02/09/2001	02/09/2001-14/02/2005	181	36.71	10.77	3.40	0.00**
	21/02/2005	21/02/2005-15/03/2010	265	107.01	8.90	12.01	0.00**
	22/03/2010	22/03/2010-02/12/2013	194	301.21	10.41	28.94	0.00**
	09/12/2013	09/12/2013-16/07/2017	189	1125.85	10.54	106.76	0.00**
AV.L		03/03/1997-21/04/2002	269	840.79	4.83	174.17	0.00**
	28/04/2002	28/04/2002-08/05/2005	159	477.39	6.28	76.03	0.00**
	15/05/2005	15/05/2005-08/06/2008	161	556.28	6.24	105.17	0.00**
	15/06/2008	15/06/2008-29/09/2013	277	362.34	4.75	76.16	0.00**
	06/10/2013	06/10/2013-16/07/2017	198	486.29	5.63	86.42	0.00**
BAB.L		03/03/1997-15/06/2003	329	91.87	4.43	20.73	0.00**
	22/06/2003	22/06/2003-08/10/2006	173	156.56	6.11	25.62	0.00**
	15/10/2006	15/10/2006-13/05/2012	292	497.33	4.70	105.75	0.00**
	20/05/2012	20/05/2012-16/07/2017	270	998.39	4.89	204.13	0.00**
BARC.L		03/03/1997-10/09/2000	185	363.81	4.35	83.52	0.00**
	17/09/2000	17/09/2000-24/10/2004	215	454.67	4.04	112.53	0.00**
	01/11/2004	01/11/2004-04/05/2008	184	564.83	4.37	129.32	0.00**
	11/05/2008	11/05/2008-05/06/2011	161	260.21	4.67	55.73	0.00**
	12/06/2011	12/06/2011-16/07/2017	319	222.20	3.32	66.99	0.00**
The quaternary industry							
AZN.L		03/03/1997-13/03/2000	159	2280.70	26.79	85.12	0.00**
	20/03/2000	20/03/2000-30/03/2003	159	2914.24	26.79	108.76	0.00**
	06/04/2003	06/04/2003-23/11/2009	347	2558.23	18.14	141.04	0.00**

	30/11/2009	30/11/2009-06/01/2014	215	3035.20	23.04	131.72	0.00**
	13/01/2014	13/01/2014-16/07/2017	184	4446.41	24.90	178.51	0.00**
GSK.L		03/03/1997-12/05/2002	272	1727.76	9.61	179.82	0.00**
	19/05/2002	19/05/2002-14/01/2008	296	1299.08	9.21	141.04	0.00**
	21/01/2008	21/01/2008-25/09/2011	193	1197.08	11.41	104.95	0.00**
	02/10/2011	02/10/2011-16/07/2017	303	1504.24	9.10	165.24	0.00**
SHP.L		03/03/1997-13/03/2000	159	437.18	26.79	16.32	0.00**
	20/03/2000	20/03/2000-17/09/2006	340	736.50	18.32	40.20	0.00**
	24/09/2006	24/09/2006-26/09/2010	210	1083.05	23.31	46.46	0.00**
	03/10/2010	03/10/2010-20/04/2014	186	2110.80	24.77	85.21	0.00**
	27/04/2014	27/04/2014-16/07/2017	169	4662.07	25.99	179.40	0.00**
SGE.L		03/03/1997-24/06/2001	226	308.99	7.64	40.43	0.00**
	01/07/2001	01/07/2001-24/01/2005	187	186.03	8.40	22.14	0.00**
	31/01/2005	31/01/2005-22/11/2010	304	237.43	6.59	36.03	0.00**
	29/11/2010	29/11/2010-29/06/2014	188	330.01	8.38	39.39	0.00**
	06/07/2014	06/07/2014-16/07/2017	159	568.23	9.11	62.37	0.00**
SN.L		03/03/1997-10/09/2000	185	221.42	4.93	44.94	0.00**
	17/09/2000	17/09/2000-28/09/2003	159	363.39	5.31	68.37	0.00**
	05/10/2003	05/10/2003-06/11/2006	162	508.78	5.26	96.62	0.00**
	13/11/2006	13/11/2006-30/11/2009	160	556.98	5.29	105.12	0.00**
	07/12/2009	07/12/2009-27/01/2014	217	670.25	4.55	147.32	0.00**
	03/02/2014	03/02/2014-16/07/2017	181	1140.73	4.98	228.99	0.00**

Note 1: The symbols ** and * indicate statistical significance level at 1 % and 5% level, respectively.
Note 2: Green area of clean period indicates selected area of 204 observations for data analysis

Source: Output of Bai-Perron multiple breakpoints test using Eviews, SV-11

Potential causes of breaks at different point of time:

This section explains why structural breakpoints have taken place at different point of time, of time series data. For this purpose, the events that influenced to cause structural breakpoints on that day are discussed below. The following news has been extracted from London South East, share news headlines (Thomson Reuters). There are several breaks for each series. The explanation is given only for the most significant break.

The economic crisis was taken place in December, 2012 and raised fears of a worldwide economic meltdown due to financial contagion all over the different industries. There was a breakpoint on 27 January 2013 on FTSE-350 general industrial index as a few companies in different industries declared their target price to go up (source: industry news, Thomson Reuters).

The primary industry

The structural breakpoint took place in Antofagasta plc on 31 December 2012 as the company announced the suspension of its Chilean Antucoya copper mine, as it would cost $1.7 billion for development. Consequently, the price dropped dramatically and a structural break happened. (source: Thomson Reuters)

It is observed in the sample period of BP plc that there was a structural break on 18 April 2010 as BP plc announced that Chevron Pipe Line Co was almost ready to begin repairing an oil pipeline shut down two weeks prior after leaking into a Louisiana wildlife refuge, a U.S. Coast. (source: Thomson Reuters)

There was a structural break in stock prices of Centrica plc on 15 September 2013. This is because the environmental group Greenpeace declared on 14 October 2013 to encourage British landowners to join together to enforce a new law opposing fracking, a move that could strengthen the opposition to exploration and development for oil and gas as fracking could pollute water supplies and cause earthquakes. (source: Thomson Reuters)

There was a structural break in the time series data of Severn Trent plc on 1 October 2006 as the company announced that H1 revenue would be down by £3.2 million as the company overcharged and now they had to pay back to the customers. Therefore, the stock price plummeted very rapidly and erratically. (source: Thomson Reuters)

The stock prices of Johnson Matthey reduced sharply on 18 September, 2011 which caused a structural breakpoint. This is because, the directors of the company bought about 0.73% of the total shares. When the news was disclosed, the share price went down. (source: Thomson Reuters).

The manufacturing industry

There was a breakpoint of Associated British Foods plc (ABF.L) on 8 September 2013 that stock prices rocketed due to an announcement made that sales forecast of Primark increased 22% more than last year in Britain and Europe (source: Thomson Reuters).

There was a breakpoint of Barratt Developments plc in February, 2007. This is because, Bank of England raised interest rates and it was very difficult for many people to buy properties. Consequently, the stock price dropped significantly. After being bearish on the housebuilding sector since the second half of 2007, the UK housing market has improved economically and attractive valuations for many housebuilding stocks have prompted the Swiss bank. Therefore, the stock price of Barratt Developments plc has increased. (source: Thomson Reuters)

The stock price of British American Tobacco plc (BATS) increased dramatically on 18 January, 2016 and thus, there was breakpoint on that day. This is because, JPMorgan helped meet the price target. (source: Thomson Reuters) The structural breakpoint of Berkeley Group

Holdings plc (BKG.L) took place on 12 November 2012. A significant price increased due to raising the target price from 365p to 375p. There was a structural break of Diageo plc on 14 August 2011 due to the outperformance of Carlsberg in the European markets (source: Thomson Reuters).

Switzerland based trading company Glencore International has been one of the more high profile new issues of the year. Consequently, the share price of Diageo plc dropped from 530p to 390p and structural breakpoint took place. (source: Thomson Reuters).

The service industry

The CEO of Aberdeen Asset Management plc (ADN.L) announced that the company might have to report a loss in the interim statement this year. Therefore, the stock price plummeted considerably on 28 April, 2002. (source: Thomson Reuters)

The stock price of Ashtead Group plc (AHT.L) dropped sharply and hit the bottom in March 2016 due to co issues cautious guide (source: Thomson Reuters). There was a structural breakpoint of Babcock International plc (BAB.L) in August, 2011. This was because, the company announced that it would reduce its dept at the half-year stage. 560 jobs were cut at Aviva plc and thus, stock prices plummeted on 19 August, 2001. (source: Thomson Reuters)

The finance minister announced that the pensions industry would have to give retirees greater access to their savings that shook the share value of British insurers. This would include outlines for new annuity products tailor for early lump-sum withdrawals and regular payments that vary over the lifetime of the product to meet the demand of retirement expenses such as care costs. Annuities would also be allowed to provide a guaranteed payout, even if the recipient dies. Consequently, a structural breakpoint took place on Aviva plc on 19 August, 2001. There was a breakpoint of Barclays plc in September 2007. This was because, the company announced an interim pre-tax profit of £103m (source: Thomson Reuters).

The quaternary industry

A structural break took place on 13 October 2013 and the stock price rose sharply the following week.

This is because, AstraZeneca announced that the company had signed a deal to co-promote Johnson & Johnson's novel prostate cancer medicine in Japan, giving the British company a new drug revenue stream and bolstering its Japanese presence. (source: Thomson Reuters)

The stock prices of Shire plc (SHP.L) rose on 6 October, 2013 when the company announced that the forecast showed a 15% rise in revenues for the whole year. This is because, the company was expecting lower research and development costs. (source: Thomson Reuters)

The stock price of Sage Group plc (SGE.L) decreased dramatically which caused a structural break on 27 August 2000. When news was announced that non-executive chairman Colin Goodall and non-executive director Thomas Cross both bought 10m shares at 1p each, stock prices decreased sharply. (source: Thomson Reuters)

The structural breakpoint of Smith & Nephew plc (SN.L) took place in October, 2013 as European Parliament tighten EU rules on medical devices that stopped short of a U.S. style pre-marketing (source: Thomson Reuters).

The stock price of GlaxoSmithKline plc (GSK.L) decreased when it announced that the performance of that company is lower in relation to the share price performance of its European peers, reckons Morgan Stanley. (source: Thomson Reuters)

Application of forecasting principles:

The forecasting principles detail that the number of observations for a series should not be larger. They should be around 200 as most time series do not work for very long time series (Hyndman and Athanasopoulos, 2018). Furthermore, stock prices move very frequently and randomly in stock markets. A long period data will not provide accuracy of measurements as stock markets are usually volatile. Therefore, the estimation period for this study includes 204 observations. The validation period would be 4 more observations after that period for out-of-sample forecasts. The table below shows the selected period of 204 observations for estimation from the clean period where there is no breakpoint and 4 more observations after the estimation period to evaluate forecast.

Table 6. 5: selection of sub-sample period for data analysis and forecasting based on forecasting principles

Series	Selected period of	Forecasted/	series	Selected period of	Forecasted/

	204 observations from clean period for analysis	evaluation period		204 observations from clean period for analysis	evaluation period
FTSE-ALL SHARE	06/05/2013-27/03/2017	03/04/2017-24/04/2017	FTSE-Industry index	05/05/2013-26/03/2017	02/04/2017-23/04/2017
The primary industry			The service industry		
ANTO.L	06/05/2013-27/03/2017	03/04/2017-24/04/2017	ADN.L	12/05/2013-02/04/2017	09/04/2017-30/04/2017
BP.L	02/04/2006-22/02/2010	01/03/2010-22/03/2010	AHT.L	01/06/1997-22/04/2001	29/04/2001-20/05/2001
CNA.L	11/07/2010-01/06/2014	08/06/2014-29/06/2014	AV.L	01/06/1997-22/04/2001	29/04/2001-20/05/2001
SVT.L	12/05/2013-02/04/2017	09/04/2017-30/04/2017	BAB.L	12/05/2013-02/04/2017	09/04/2017-30/04/2017
JMAT.L	02/04/2006-22/02/2010	01/03/2010-22/03/2010	BARC.L	01/10/2000-22/08/2004	29/08/2004-19/09/2004
The manufacturing industry			The quaternary industry		
ABF.L	02/01/2006-23/11/2009	30/11/2009-21/12/2009	AZN.L	04/01/2010-25/11/2013	02/12/2013-23/12/2013
BATS.L	02/04/2006-22/02/2010	01/03/2010-22/03/2010	GSK.L	01/06/1997-22/04/2001	29/04/2001-20/05/2001
BDEV.L	12/05/2013-02/04/2017	09/04/2017-30/04/2017	SHP.L	01/10/2006-22/08/2010	29/08/2010-19/09/2010
BKG.L	12/05/2013-02/04/2017	09/04/2017-30/04/2017	SGE.L	01/06/1997-22/04/2001	29/04/2001-20/05/2001
DGE.L	12/05/2013-02/04/2017	09/04/2017-30/04/2017	SN.L	04/01/2010-25/11/2013	02/12/2013-23/12/2013

Source: Created by author based on forecasting principle

B.6.2. Testing for weak-form market efficiency

i. Runs test: Runs test on 204 Observations at level

Results of runs test on 22 series for the selected sub-sample period are shown below. The run test in the table below shows that the p-value (level of significance) is less than 5% (0.000<0.05), indicating the weekly closing prices of FTSE-all share index, FTSE-350 general industrial index and all 20 selected companies from four different industries are not random. Thus, the London Stock Exchange does not follow a random-walk model. Furthermore, it can be explained in another way using the Z value. Sharma and Kennedy

(1977) explained that if the Z value is more than or equal to 1.96 ($Z > \pm 1.96$), the null hypothesis of a random walk at the 5% level of significance is rejected.

As the Z values of all 22 series are negative and greater than 1.96, they suggest that the expected number of runs are more than the actual number of runs. Mollah (2007) explained that if the actual number of runs is less than the expected number of runs, the null hypothesis of a random walk can be rejected at the 5% level of significance. These results from the run tests indicate that the stock prices are not random and do not change very frequently. As the prices do not change randomly, future prices could be predicted. The null hypothesis of the runs test is that prices move randomly. The results show that the null hypothesis is rejected. The weekly closing price does not move randomly.

Hypothesis:
Null: Prices are random
Alternative Hypothesis: Prices are not random

Table 6. 6: Runs test on 22 series for the selected sub-sample period (204 observations)

Series	Total number of runs	Z	P value
FTSE-ALL SHARE INDEX	20	-11.651	0.000
FTSE-350 General Industrial Index	22	-11.370	0.000
The primary industry			
ANTO.L	13	-12.634	0.000
BP.L	9	-13.195	0.000
CNA.L	30	-10.247	0.000
SVT.L	16	-12.213	0.000
JMAT.L	9	-13.195	0.000
The manufacturing industry			
ABF.L	28	-10.528	0.000
BATS.L	18	-11.932	0.000
BDEV.L	10	-13.055	0.000
BKG.L	20	-11.651	0.000
DGE.L	37	-9.265	0.000
The service industry			
ADN.L	26	-31.071	0.000
AHT.L	2	-32.562	0.000
AV.L	26	-31.047	0.000
BAB.L	12	-31.95	0.000
BARC.L	25	-31.154	0.000
The quaternary industry			
AZN.L	28	-10.528	0.000
GSK.L	34	-9.686	0.000
SHP.L	10	-13.055	0.000
SGE.L	8	-13.336	0.000
SN.L	18	-11.932	0.000

Note: The above table analyses the weekly closing price of the following companies. ANTO.L (Antofagasta PLC), BP.L (BP PLC), CNA.L (Centrica PLC), SVT.L (Severn Trent PLC), JMAT.L (Johnson Matthey), ABF.L Associated British Foods PLC), BATS.L (British American Tobacco PLC), BDEV.L (Barratt Developments PLC), BKG.L (Berkeley Group Holdings PLC), DGE.L (Diageo PLC), ADN.L (Aberdeen Asset Management PLC), AHT.L (Ashtead Group PLC), AV.L (Aviva PLC), BAB.L (Babcock International Group PLC), BARC.L (Barclays PLC), AZN.L (Astrazeneca PLC), GSK.L (GlaxoSmithkline PLC), SHP.L (Shire PLC), SGE.L (Sage Group PLC), SN.L (Smith & Nephew PLC).

Source: Output of runs test using SPSS, V-22

ii. Test of unit root

Lag length for ADF unit root test is chosen automatically through software using Schwarz Information Criterion (SIC). It is found at level that all time series data from ADF have unit root. This is because, critical values are bigger than test statistic. Furthermore, their p values are bigger than 0.05. Therefore, first difference has been applied for all selected time series data in ADF unit root test. It is found that test statistic is significantly bigger than critical values. Furthermore, all the p-values from ADF test for all 22 series are found to be 0.000 at the 1% level of significance.

Therefore, the null hypothesis of data has a unit root can be rejected at first difference and it can be concluded that the weekly closing price of all series is stationary at first difference except SVT.L plc in the primary industry. The results from all the series reveal that the data have no unit root and are stationary at first difference under a trend and constant. Therefore, the first difference of price (d) = 1 for all series except SVT.L plc. The result from the test indicates SVT.L plc is stationary and it does not have any unit root at level. Therefore, d = 0 for SVT.L plc. It could be concluded that the selected time series data for each series has unit root or non-stationary at level except SVT.L plc under ADF unit root test.

Null hypothesis: CLOSE/D(CLOSE) has a unit root
Alternative hypothesis: CLOSE/D(CLOSE) has no unit root

Table 6. 7: ADF unit root test on 22 series

Series	t-statistic at level	t-statistic at first difference	Value of d in ARIMA (p,d,q) model
FTSE-All Share Index	-2.425227	-14.8149	d=1
P value	(0.3654)	(0.0000)	
FTSE-350 General Industrial Index	-1.514486	-16.31693	d=1
P value	(0.8217)	(0.0000)	
The primary industry			
ANTO.L	-1.247710	-15.79736	d=1
P value	(0.8972)	(0.0000)	
BP.L	-3.113588	-15.41136	d=1
P value	(0.1059)	(0.0000)	
CNA.L	-2.361581	-16.41782	d=1
P value	(0.3986)	(0.0000)	
SVT.L	-5.050698	-14.21170	d=0
P value	(0.0002)	(0.0000)	
JMAT.L	-1.663551	-14.99730	d=1
P value	(0.7638)	(0.0000)	
The manufacturing industry			
ABF.L	-2.405900	-14.29350	d=1
P value	(0.3754)	(0.0000)	
BATS.L	-2.118867	-20.04564	d=1

P value	(0.5318)	(0.0000)	
BDEV.L	-1.795830	-13.83110	d=1
P value	(0.7034)	(0.0000)	
BKG.L	-2.294933	-13.94703	d=1
P value	(0.4344)	(0.0000)	
DGE.L	-2.586729	-11.70100	d=1
P value	(0.2869)	(0.0000)	
The service industry			
ADN.L	-2.635057	-14.40116	d=1
P value	(0.2653)	(0.0000)	
AHT.L	-2.538644	-13.34513	d=1
P value	(0.3093)	(0.0000)	
AV.L	-3.128487	-17.43646	d=1
P value	(0.1025)	(0.0000)	
BAB.L	-3.320788	-15.37969	d=1
P value	(0.0658)	(0.0000)	
BARC.L	-2.758690	-14.70388	d=1
P value	(0.2145)	(0.0000)	
The quaternary industry			
AZN.L	-2.338111	-14.21078	d=1
P value	(0.4111)	(0.0000)	
GSK.L	-3.316251	-15.52889	d=1
P value	(0.0665)	(0.0000)	
SHP.L	-1.383367	-15.84551	d=1
P value	(0.8632)	(0.0000)	
SGE.L	-0.839777	-17.78564	d=1
P value	(0.9593)	(0.0000)	
SN.L	-2.260882	-15.65664	d=1
P value	(0.4530)	(0.0000)	

Note 1: Their critical values for ADF at 1% level of significance are -4.003902 (at level) and -4.004132 (at first difference).

Note2: The above table analyses the weekly closing price of the following companies.

ANTO.L (Antofagasta PLC), BP.L (BP PLC), CNA.L (Centrica PLC), SVT.L (Severn Trent PLC), JMAT.L (Johnson Matthey), ABF.L Associated British Foods PLC), BATS.L (British American Tobacco PLC), BDEV.L (Barratt Developments PLC), BKG.L (Berkeley Group Holdings PLC), DGE.L (Diageo PLC), ADN.L (Aberdeen Asset Management PLC), AHT.L (Ashtead Group PLC), AV.L (Aviva PLC), BAB.L (Babcock International Group PLC), BARC.L (Barclays PLC), AZN.L (Astrazeneca PLC), GSK.L (GlaxoSmithkline PLC), SHP.L (Shire PLC), SGE.L (Sage Group PLC), SN.L (Smith & Nephew PLC).

Source: Output of ADF-unit root test using Eviews, SV-11

iii. Autocorrelation : Ljung-Box test

The Ljung-Box's serial autocorrelation is applied at the first difference to diagnose whether the time series data is auto-correlated or not. It is computed up to 24 lags and shown in the appendix. The first series of the FTSE-all share index shows p value is more than 5% for all 24 lags. It indicates the time series data of the FTSE-all share index is not autocorrelated at all. The alternative hypothesis of serial auto-correlation is rejected. This suggests that the series follows a random walk model at first difference. They also reveal that their future prices are not predictable. Similar results have been obtained from JMAT.L in the primary industry, ABF.L and BKG.L in the manufacturing industry, ADN.L and BAB.L in the service

industry and AZN.L and GSK.L in the quaternary industry. Contrary to that, BATS.L in the manufacturing industry, AV.L in the service industry and SGE.L in the quaternary industry show that p-value is less than 5% for all 24 lags. This evidences that they are strongly auto-correlated. This also documents that they do not follow a random walk model. Their future values are predictable. The remaining series shows they are not serially autocorrelated at different lags.

Null hypothesis: Time series is not auto-correlated (no serial auto-correlation)
Alternative hypothesis: Time series is auto-correlated

Table 6. 8: Test of autocorrelation at first difference on 22 series for the selected sub-sample period of 06/05/2013 to 27/03/2017 (204 observations)

Series	P value
FTSE-ALL SHARE INDEX	More than 5% for all 24 lags
FTSE-350 GENERAL INDUSTRIAL INDEX	Less than 5% for the first 2 lags
The primary industry	
ANTO.L	More than 5% for first 2 lags
BP.L	More than 5% for first 6 lags
CNA.L	Less than 5% for the first lag
SVT.L	More than 5% for first 5 lags
JMAT.L	More than 5% for all 24 lags
The manufacturing industry	
ABF.L	More than 5% for all 24 lags
BATS.L	Less than 5% for all 24 lags
BDEV.L	More than 5% for first 3 lags
BKG.L	More than 5% for all 24 lags
DGE.L	More than 5% for first 9 lags
The service industry	
ADN.L	More than 5% for all 24 lags
AHT.L	More than 5% for first 15 lags
AV.L	Less than 5% for all 24 lags
BAB.L	More than 5% for all 24 lags
BARC.L	More than 5% for first 5 lags
The quaternary industry	
AZN.L	More than 5% for all 24 lags
GSK.L	More than 5% for all 24 lags
SHP.L	More than 5% for first 13 lags
SGE.L	Less than 5% for all 24 lags
SN.L	More than 5% for first 3 lags

Note: The above table analyses the weekly closing price of the following companies. ANTO.L (Antofagasta PLC), BP.L (BP PLC), CNA.L (Centrica PLC), SVT.L (Severn Trent PLC), JMAT.L (Johnson Matthey), ABF.L Associated British Foods PLC), BATS.L (British American Tobacco PLC), BDEV.L (Barratt Developments PLC), BKG.L (Berkeley Group Holdings PLC), DGE.L (Diageo PLC), ADN.L (Aberdeen Asset Management PLC), AHT.L (Ashtead Group PLC), AV.L (Aviva PLC), BAB.L (Babcock International Group PLC), BARC.L (Barclays PLC), AZN.L (Astrazeneca PLC), GSK.L (GlaxoSmithkline PLC), SHP.L (Shire PLC), SGE.L (Sage Group PLC), SN.L (Smith & Nephew PLC).

Source: Output of autocorrelation test using Eviews, SV-11

iv. Heteroscedasticity test through Single and multiple variance ratio (VR) tests at level:

The tests consider variance ratio test, homoscedasticity test statistic Z(q), heteroscedasticity test statistic Z*(q) and joint test for weekly observations for FTSE- ALL SHARE INDEX, FTSE-350 GENERAL INDUSTRIAL INDEX and 20 companies in different industrial sectors. The table below shows two sets of test results. One of them includes Lo and MacKinlay (1988) and the other one is the Chow and Denning (1993) multiple VR tests that examines the maximum absolute value of a set of multiple variance ratio statistics. Since it has been specified more than one test period, there are two sets of test results. The "Joint Tests" are the tests of the joint null hypothesis for all periods, while the "Individual Tests" are the variance ratio tests applied to individual periods. The results from the Chow-Denning maximum |Z| statistics are associated with different periods at individual tests.

The joint test of Chow-Denning maximum |Z| statistic explains that the FTSE-All Share Index and FTSE-350 General Industrial Index follow a martingale as their p values are more than 5%. Furthermore, the individual test of FTSE-All Share Index reveals that it also follows a martingale as p values are more than 5%. However, the p value is at marginal level in test period 8. Moreover, Individual test of variance ratio statistics for FTSE-350 General Industrial Idex are less than 1, indicating it does not follow a random walk model and there is a negative or mean reverting relationship in the prices.

In the Chow-Denning joint test, the obtained p values are significantly higher than 5% for all companies in the primary industry, which indicate the acceptance of null hypothesis that weekly closing prices of these companies in the primary industry follow a martingale.

However, the results from VR of individual tests indicate that prices of all companies in the primary industry except SVT.L in period 2 and JMAT.L in period 16 do not follow random walk and there is a negative or mean reverting relationship in the prices as VR is less than 1. Therefore, it could be concluded from VR individual test that primary industry except SVT.L and JMAT.L follows a martingale rather than random walk and null hypothesis is accepted. As VR equals to 1 in period 2 for SVT.L, it could be claimed that it follows a random walk model. On the other hand, JMAT.L gains p value more than 1 in period 16. Thus, it could be concluded that there is a positive relationship in the prices of JMAT.L.

The manufacturing industry claims that p values of all companies have achieved more than 5% through the Chow-Denning maximum |Z| statistic. Therefore, it could be stated that these

companies in the manufacturing industry follow a martingale. Therefore, the manufacturing industry accepts the null hypothesis.

Individual test of variance ratio statistics in the manufacturing industry show that VRs are less than 1 for ABF.L and BATS.L, indicating negative correlation in the prices. However, VR statistics for BDEV.L, BKG.L and DGE.L are more than 1 in test period 2, indicating positive relationship in the prices for these companies. These results evidence that weekly closing prices of the manufacturing industry do not follow a random walk model as variance ratio statistic equals 1 to be randomly distributed.

The service industry details that p values of all companies except AV.L are more than 5% which are achieved through Chow-Denning maximum |Z| statistic. Thus, all companies except AV.L in the service industry follow a martingale and null hypothesis is accepted. However, the values of individual VRs are less than 1 for all companies in the service industry except Ashtead Group plc (AHT.L), which indicate negative or mean reverting relationship exists in this industry. Conversely, Ashtead Group plc shows VR is more than 1 in all periods including 2,4,8 and 16, indicating a strong positive relationship in the prices. The individual test explains that weekly closing price of the service industry do not follow random walk.

All companies in the quaternary industry including the Astrazeneca plc, GlaxoSmithKline plc, Shire plc, Sage Group plc, and Smith &Nephew plc provide p values more than 5% through Chow-Denning maximum |Z| multiple statistics, which detail that weekly closing price of these companies follow a martingale and null hypothesis is accepted for them. Conversely, variance ratio statistics from single variance ratio tests show that their values are less than 1 except AZN.L in period 2 and SGE.L in period 16. The results document that their prices have negative relationship and they do not move randomly. AZN.L shows VR is 1 in period 2, indicating it follows a random walk model. Furthermore, VR is more than 1 in period 16 for SGE.L, indicating positive correlation in the prices.

The conclusion could be drawn from multiple variance ratio tests that all the series except AV.L in the service industry follow a martingale model. However, the single variance ratio test documents that all the series except SVT.L in the primary industry and AZN.L in the quaternary industry do not follow a random walk model. Both SVT.L and AZN.L show that they follow a random walk model in period 2. Therefore, it could be claimed that weekly closing prices of all series do not move randomly, however, some of them follow a martingale.

Hypotheses for variance ratio test:
Null hypothesis: PRICE is a martingale
Alternative hypothesis: PRICE is not a martingale

Table 6. 9: Variance ratio tests on (204 observations)

Series		q = 2	q = 4	q = 8	q = 16	Chow-Denning joint test and p value
FTSE-ALL SHARE	VR	0.9632	0.7845	0.5970	0.5645	Max|z|(q=8) 1.913084 P value = 0.2050
	Z	-0.5078	-1.6188	-1.9131	-1.3840	
	Z*	0.0724	0.1331	0.2106	0.3146	
	P value	0.6115	0.1055	0.0557	0.1664	
FTSE-350 General Industrial Index	VR	0.866883	0.881349	0.833632	0.790008	Max|z|(q=2) 2.043209 P value = 0.1543
	Z	-2.043209	-0.972251	-0.860263	-0.718075	
	Z*	0.065151	0.122038	0.193392	0.292437	
	P value	0.0410	0.3309	0.3896	0.4727	
The primary industry						
ANTO.L	VR	0.9063	0.9145	0.7504	0.6932	Max|z|(q = 2) 1.351129 P value = 0.5405
	Z	-1.3511	-0.6409	-1.1516	-0.9644	
	Z*	0.0693	0.1334	0.2167	0.3180	
	P value	0.1767	0.5216	0.2495	0.3348	
BP.L	VR	0.9255	0.8975	0.7170	0.5343	Max|z| (q=16) 1.154561 P value = 0.6807
	Z	-0.7577	-0.5755	-1.0196	-1.1545	
	Z*	0.0982	0.1781	0.2775	0.4033	
	P value	0.4486	0.5649	0.3079	0.2483	
CNA.L	VR	0.8580	0.7448	0.6416	0.5945	Max|z| (q= 2) 2.074847 P value = 0.1436
	Z	-2.0748	-1.9933	-1.7996	-1.3812	
	Z*	0.0684	0.1279	0.1991	0.2935	
	P value	0.0683	0.0253	0.0027	0.0153	
SVT.L	VR	1.0048	0.8173	0.5639	0.4321	Max|z| (q= 8) 1.907670 P value = 0.2073
	Z	0.0505	-1.1169	-1.9076	-1.8406	
	Z*	0.0967	0.1635	0.2286	0.3085	
	P value	0.9597	0.2640	0.0564	0.0657	
JMAT.L	VR	0.9482	0.9379	0.9791	1.1091	Max|z| (q = 2) 0.639336 P value = 0.9481
	Z	-0.6393	-0.4177	-0.0880	0.3046	
	Z*	0.0809	0.1484	0.2367	0.3583	
	P value	0.5226	0.6762	0.9298	0.7606	
The manufacturing industry						
ABF.L	VR	0.9933	0.9787	0.9731	0.7433	Max|z| (q =16) 0.685922 P value = 0.9338
	Z	-0.0762	-0.1269	-0.1028	-0.6859	
	Z*	0.0872	0.1676	0.2613	0.3743	
	P value	0.9393	0.8990	0.9181	0.4928	
BATS.L	VR	0.6699	0.5878	0.5347	0.3452	Max|z| (q = 2)

	Z	-2.1599	-1.5004	-1.1905	-1.3186	2.1599
	Z*	0.1528	0.2747	0.3908	0.4965	P value =
	P value	0.0308	0.1335	0.2338	0.1873	0.1176
BDEV.L	VR	1.0287	0.9509	0.8805	0.7976	Max|z| (q=
	Z	0.3787	-0.3268	-0.5017	-0.5875	16)
	Z*	0.0760	0.1501	0.2382	0.3445	0.587464
	P value	0.7049	0.7438	0.6159	0.5569	P value =
						0.9614
BKG.L	VR	1.0166	0.9229	0.8374	0.7327	Max|z| (q= 16)
	Z	0.2643	-0.6119	-0.7708	-0.8275	0.827549
	Z*	0.0628	0.1259	0.2108	0.3229	P value =
	P value	0.7915	0.5405	0.4408	0.4079	0.8771
DGE.L	VR	1.0285	0.8626	0.6986	0.5000	Max|z| (q= 16
	Z	0.3676	-0.9833	-1.4368	-1.6555	)
	Z*	0.0777	0.1397	0.2097	0.3019	1.655575
	P value	0.7132	0.3254	0.1508	0.0978	P value =
						0.3375
The service industry						
ADN.L	VR	0.9858	0.8465	0.8358	0.7263	Max|z| (q= 4)
	Z	-0.2138	-1.2197	-0.8150	-0.8998	1.219777
	Z*	0.0660	0.1258	0.2014	0.3042	P value =
	P value	0.8307	0.2225	0.4150	0.3682	0.6347
AHT.L	VR	1.0686	1.0897	1.0123	1.2288	Max|z| (q= 2)
	Z	0.9708	0.6739	0.0553	0.7026	0.970797
	Z*	0.0706	0.1332	0.2224	0.3257	P value =
	P value	0.3316	0.5003	0.9559	0.4823	0.8005
AV.L	VR	0.8006	0.7582	0.6897	0.6165	Max|z| (q= 2)
	Z	-2.7270	-1.6417	-1.3104	-1.118	2.727086
	Z*	0.0731	0.1472	0.2367	0.3428	P value =
	P value	0.0064	0.1006	0.1900	0.2635	0.0253
BAB.L	VR	0.9254	0.8391	0.7337	0.6406	Max|z| (q= 16
	Z	-0.9528	-1.1344	-1.2186	-1.1407	)
	Z*	0.0782	0.1417	0.2185	0.3150	1.218662
	P value	0.3407	0.2566	0.2230	0.2540	P value =
						0.6355
BARC.L	VR	0.9659	0.9168	0.6718	0.6043	Max|z| (q = 8)
	Z	-0.3632	-0.4926	-1.2994	-1.1214	1.299479
	Z*	0.0937	0.1687	0.2525	0.3528	P value =
	P value	0.7165	0.6223	0.1938	0.2621	0.5775
The quaternary industry						
AZN.L	VR	1.0015	0.9500	0.8372	0.6829	Max|z| (q =

	Z	0.0197	-0.3677	-0.8119	-1.1002	16)
	Z*	0.0788	0.1357	0.2004	0.2881	1.100206
	P value	0.9842	0.7131	0.4168	0.2712	P value = 0.7179
GSK.L	VR	0.9107	0.7748	0.6351	0.5186	Max|z| (q = 8)
	Z	-1.2441	-1.6903	-1.7560	-1.5703	1.7560
	Z*	0.0717	0.1332	0.2077	0.3065	P value =
	P value	0.2134	0.0910	0.0791	0.1163	0.2807
SHP.L	VR	0.8938	0.9078	0.9585	0.8322	Max|z| (q = 2)
	Z	-1.4657	-0.7083	-0.2053	-0.5467	1.4657
	Z*	0.0724	0.1300	0.2022	0.3069	P value =
	P value	0.1427	0.4787	0.8373	0.5845	0.4599
SGE.L	VR	0.7833	0.7149	0.7737	1.0618	Max|z| (q = 2)
	Z	-1.4995	-1.1289	-0.6137	0.1166	1.4995
	Z*	0.1444	0.2525	0.3686	0.5304	P value =
	P value	0.1337	0.2589	0.5393	0.9072	0.4369
SN.L	VR	0.9075	0.8544	0.6982	0.8380	Max|z| (q = 8)
	Z	-1.3306	-1.1107	-1.3579	-0.4842	1.3579
	Z*	0.0694	0.1311	0.2222	0.3344	P value =
	P value	0.1833	0.2667	0.1745	0.6283	0.5356

Note: The above table analyses the weekly closing price of the following companies. ANTO.L (Antofagasta PLC), BP.L (BP PLC), CNA.L (Centrica PLC), SVT.L (Severn Trent PLC), JMAT.L (Johnson Matthey), ABF.L Associated British Foods PLC), BATS.L (British American Tobacco PLC), BDEV.L (Barratt Developments PLC), BKG.L (Berkeley Group Holdings PLC), DGE.L (Diageo PLC), ADN.L (Aberdeen Asset Management PLC), AHT.L (Ashtead Group PLC), AV.L (Aviva PLC), BAB.L (Babcock International Group PLC), BARC.L (Barclays PLC), AZN.L (Astrazeneca PLC), GSK.L (GlaxoSmithkline PLC), SHP.L (Shire PLC), SGE.L (Sage Group PLC), SN.L (Smith & Nephew PLC).

Source: Output of variance ratio test using Eviews, SV-11

B.6.3: Statistical inference on market efficiency:

A market is weak-form efficient if the series follows a random walk (that is, returns cannot be predicted). The definition of a random walk is that the first differences are stationary (independent and identically distributed, random variables-i.i.d). It explains that it does not have a unit root (at first difference) or serial correlation (at first difference) or heteroscedasticity (at level).

Tests for market efficiency are conducted on the FTSE-all share index, FTSE-350 general industrial index and 20 companies from four different industries in the period where there are no structural breaks and 204 clear observations are available to later estimate ARIMA and GARCH (1, 1) models. The aim is to simultaneously test for weak-form market efficiency and also to estimate ARIMA and GARCH (1, 1) models over the same data and assess their forecasting power. To test for market efficiency, a range of tests are applied.

They are

(1) Runs test at level
(2) ADF test for Unit Root at first difference
(3) LB test for Autocorrelation at the first difference
(4) Variance ratio tests at level

In the literature, the ADF and LB tests are applied at the first difference to ascertain weak-form efficiency from a parametric point of view; in essence, at the first difference, the null hypothesis of a unit root must be rejected, and the q statistic should show no autocorrelation up to say, 24 lags (Wooldridge, 2019).

An alternative test for weak-form market efficiency is the Variance ratio test of Lo and Mackinlay (1988) which postulates that if the data follows a random walk, the variance of a q period difference should be q times the variance of a one-period difference. The results from all the above tests are compared to infer whether the series follows a random walk, ie returns cannot be predicted and the market is weak-form efficient.

The runs test shows that all the series including FTSE-all share index, FTSE-350 general industrial index and 20 companies from four different industries do not follow a random walk model as the p values are less than 5%. The ADF unit root tests show that all the series do not have unit root at first difference. The results of the Ljung-Box's autocorrelation test are mixed: it seems some of the series do have autocorrelations up to 24 lags and others do not. The Chow Denning statistic joint test shows that the variance is constant at different lags.

In summary, except for the Variance ratio test, none of the series, in a period without a structural break (where ARIMA models will be estimated) robustly passes the criteria required for weak-form market efficiency. Four tests are applied and the results are as below:

Table 6. 10: The tests of weak-form efficiency on 204 observations from each of 22 series

Series	Runs test at level	ADF-unit root test at first difference	LB's Serial autocorrelation at first difference	Variance ratio test at level	Statistical inference
FTSE-ALL SHARE INDEX	Not consistent with random walk	rejects the null of a unit root	Rejects presence of autocorrelation for all 24 lags	The joint test of constant variance accepts the null of martingale	weak-form inefficient
FTSE-	Not consistent	rejects the	Supports presence	The joint test of constant	weak-form

350 General Industrial Index	with random walk	null of a unit root	of autocorrelation up to first 2 lags	variance accepts the null of martingale	inefficient
The primary industry					
ANTO.L	Not consistent with random walk	rejects the null of a unit root	Rejects presence of autocorrelation up to first 2 lags	The joint test of constant variance accepts the null of martingale	weak-form inefficient
BP.L	Not consistent with random walk	rejects the null of a unit root	Rejects presence of autocorrelation up to first 6 lags	The joint test of constant variance accepts the null of martingale	weak-form inefficient
CNA.L	Not consistent with random walk	rejects the null of a unit root	Supports presence of autocorrelation up to first lag	The joint test of constant variance accepts the null of martingale	weak-form inefficient
SVT.L	Not consistent with random walk	rejects the null of a unit root	Rejects presence of autocorrelation up to first 5 lags	The joint test of constant variance accepts the null of martingale	weak-form inefficient
JMAT.L	Not consistent with random walk	rejects the null of a unit root	Rejects presence of autocorrelation up to 24 lags	The joint test of constant variance accepts the null of martingale	weak-form inefficient
The manufacturing industry					
ABF.L	Not consistent with random walk	rejects the null of a unit root	Rejects presence of autocorrelation up to 24 lags	The joint test of constant variance accepts the null of martingale	weak-form inefficient
BATS.L	Not consistent with random walk	rejects the null of a unit root	Supports presence of autocorrelation for all 24 lags	The joint test of constant variance accepts the null of martingale	weak-form inefficient
BDEV.L	Not consistent with random walk	rejects the null of a unit root	Rejects presence of autocorrelation up to first 3 lags	The joint test of constant variance accepts the null of martingale	weak-form inefficient
BKG.L	Not consistent with random walk	rejects the null of a unit root	Rejects presence of autocorrelation for all 24 lags	The joint test of constant variance accepts the null of martingale	weak-form inefficient
DGE.L	Not consistent with random walk	rejects the null of a unit root	Rejects presence of autocorrelation up to 9 lags	The joint test of constant variance accepts the null of martingale	weak-form inefficient

The service industry					
ADN.L	Not consistent with random walk	rejects the null of a unit root	Rejects presence of autocorrelation for all 24 lags	The joint test of constant variance accepts the null of martingale	weak-form inefficient
AHT.L	Not consistent with random walk	rejects the null of a unit root	Rejects presence of autocorrelation up to 15 lags	The joint test of constant variance accepts the null of martingale	weak-form inefficient
AV.L	Not consistent with random walk	rejects the null of a unit root	Supports presence of autocorrelation for all 24 lags	The joint test of constant variance rejects the null of martingale	weak-form inefficient
BAB.L	Not consistent with random walk	rejects the null of a unit root	Rejects presence of autocorrelation for all 24 lags	The joint test of constants variance accept the null of martingale	weak-form inefficient
BARC.L	Not consistent with random walk	rejects the null of a unit root	Rejects presence of autocorrelation up to first 5 lags	The joint test of constant variance accepts the null of martingale	weak-form inefficient
The quaternary industry					
AZN.L	Not consistent with random walk	rejects the null of a unit root	Rejects presence of autocorrelation for all 24 lags	The joint test of constant variance accepts the null of martingale	weak-form inefficient
GSK.L	Not consistent with random walk	rejects the null of a unit root	Rejects presence of autocorrelation for all 24 lags	The joint test of constant variance accepts the null of martingale	weak-form inefficient
SHP.L	Not consistent with random walk	rejects the null of a unit root	Rejects presence of autocorrelation up to first 13 lags	The joint test of constant variance accepts the null of martingale	weak-form inefficient
SGE.L	Not consistent with random walk	rejects the null of a unit root	Supports presence of autocorrelation for all 24 lags	The joint test of constant variance accepts the null of martingale	weak-form inefficient
SN.L	Not consistent with random walk	rejects the null of a unit root	Rejects presence of autocorrelation up to first 3 lags	The joint test of constant variance accepts the null of martingale	weak-form inefficient

Note: The above table analyses the weekly closing price of the following companies. ANTO.L (Antofagasta PLC), BP.L (BP PLC), CNA.L (Centrica PLC), SVT.L (Severn Trent PLC), JMAT.L (Johnson Matthey), ABF.L Associated British Foods PLC), BATS.L (British American Tobacco PLC), BDEV.L (Barratt Developments PLC), BKG.L (Berkeley Group Holdings PLC), DGE.L (Diageo PLC), ADN.L (Aberdeen Asset Management PLC), AHT.L (Ashtead Group PLC), AV.L (Aviva PLC), BAB.L (Babcock International Group PLC), BARC.L (Barclays PLC), AZN.L (Astrazeneca PLC), GSK.L (GlaxoSmithkline PLC), SHP.L (Shire PLC), SGE.L (Sage Group PLC), SN.L (Smith & Nephew PLC).

Source: Output of weak-form efficiency test using Eviews, SV-11

B.6.4: Application of forecasting models and techniques

This study will apply now all the forecasting models and techniques that have been discussed in chapter five. These are ARIMA and GARCH (1, 1) models, Holt's double exponential smoothing and Holt-Winters' triple exponential smoothing techniques. The next section applies ARIMA model.

B.6.4.1: ARIMA model estimation

For the purpose of constructing the best ARIMA model, the autoregressive (p) and moving average (q) parameters have to be determined efficiently for that model. The values for p and q are determined through a correlogram. ARMA (p,q) process is detected by plotting correlogram of auto correlation function (ACF) and partial auto Correlation function (PACF) against lags.

Correlogram in this study discloses that the values of ACF and PACF are very high and close to one at level. The pattern explains that they follow a random walk model and white noise process. Thus, it could be concluded that all these time series are non-stationary. They may be non-stationary in mean or variance or both. Therefore, the first difference of the closing price [D (price)] has been plotted for all the series where ACF and PACF are closed to zero.

The values of ACF tail off and never become zero, though they may be very close to zero. In such cases, PACF helps determine the value. The autocorrelation is not zero, because Xt depends on Xt−2 through Xt−1. The values for p and q have been determined by identifying the biggest difference in ACF and PACF at different lags. The lag length to compute ACF and PACF are chosen up to 24 (Wooldridge, 2019). The appendix shows the table of ACF and PACF for more details. Furthermore, OLS and diagnostic tests have been run to evaluate the values for p and q.

On the basis of the outcome from OLS and diagnostic checking, the parsimonious model has been chosen for better forecasting.

The role of ACF, PACF, AIC and DW statistic in ARIMA model:

To determine the best ARIMA model, a few criteria are set and maintained, which include a relatively small Akaike Information Criterion (AIC) and Schwarz Information Criterion, low volatility and a relatively high adjusted R^2. Lower the AIC, better the model. When DW statistic close to 2, it indicates there is no serial auto-correlation in the residuals. To determine

ARIMA specification in ARIMA forecasting, the value of differencing (d) has been taken 1 for all series except SVT.L in the primary industry as it was found from ADF unit root test. The next step is to find the values of p and q through ACF and PACF in correlogram. The value for the ACF and PACF at the first lag are the same, because both measure the correlation between data points at time t with data points at time t-1.

1) **FTSE-350 General Industrial Index**

The correlogram in the appendix shows the highest values of ACF and PACF are at lags 1, 11 and 22. Therefore, these values of ARMA specification have been inserted in the OLS regression model to derive the optimal ARIMA model. The appendix shows the result of an optimal model from OLS. The table below shows that ARIMA (1,1,22) is the best model among all models. ARIMA (22,1,1) and ARIMA (22,1,22) have also been checked. However, the following table does not show them and their outcomes are insignificant.

The p values of coefficient AR term are significant for ARIMA (1,1,11) and ARIMA (1,1,22). However, adjusted R^2 is relatively higher, AIC, SBIC are lower and DW statistic is closer to 2 for ARIMA (1,1,22). Therefore, ARIMA (1,1,22) is the optimal model among all models. Furthermore, the residual diagnostic through correlogram of residuals squared has been checked later in this chapter for the optimal model. The tentative models are as follows:

Criterion	ARIMA (1,1,11)	ARIMA (11,1,1)	ARIMA (1,1,1)	ARIMA(11,1,11)	ARIMA(1,1,22)
Coefficient AR term P value	-0.149629 (0.0473)	-0.078996 (0.2532)	-0.611241 (0.0642)	-0.412531 (0.6032)	-0.146730 (0.0504)
Coefficient MA P value	-0.068402 (0.3141)	-0.126753 (0.1026)	0.477252 (0.1949)	0.339176 (0.6755)	0.110744 (0.1700)
^{2}(volatility) P value	8929.270 (0.0000)	8953.216 (0.0000)	8900.033 (0.0000)	9101.045 (0.0000)	8863.912 (0.0000)
Adj. R^2	0.010307	0.007653	0.013548	-0.008732	0.017551
AIC	11.97474	11.97747	11.97128	11.99383	11.96847
SBIC	12.04003	12.04276	12.03656	12.05911	12.03376
DW-statistic	1.96	2.02	1.97	2.30	1.97

Source: Output of ARIMA models for FTSE-350 industrial index with different parameters using Eviews, SV-11

The primary industry

2) **ANTO.L**

ACF and PACF are significant at lags 2 and 3 out of 24 lags. The following table shows that ARIMA (3,1,2) is the optimal model among all models for ANTO.L. Coefficient for both AR term, MA term and volatility are significant for ARIMA (3,1,2). The adjusted R-squared is relatively higher, AIC and SBIC are lower and DW-statistic is closer to 2 for ARIMA (3,1,2).

Therefore, ARIMA (3,1,2) is the optimal model for ANTO.L. The tentative ARIMA models are as below:

Criteria	ARIMA (2,1,3)	ARIMA (2,1,2)	ARIMA (3,1,3)	ARIMA (3,1,2)
Coefficient AR term P value	0.113899 (0.0936)	-0.351914 (0.3260)	-0.059490 (0.8916)	-0.155627 (0.0538)
Coefficient MA P value	-0.154851 (0.0575)	0.500895 (0.1315)	-0.115552 (0.7911)	0.136707 (0.0374)
^{2}(volatility) P value	1159.252 (0.0000)	1179.250 (0.0000)	1174.030 (0.0000)	1156.312 (0.0000)
Adj. R^2	0.026978	0.010193	0.014575	0.029447
AIC	9.933304	9.950248	9.945937	9.930825
SBIC	9.998588	10.01553	10.01122	9.996110
DW-statistic	2.16	2.15	2.18	2.16

Source: Output of ARIMA models for ANTO.L with different parameters using Eviews, SV-11

3) BP.L

The BP.L in the primary industry shows that ACF and PACF are higher at lags 4 and 7. The best ARIMA (p,d,q) model for BP plc is (4,1,7). The ARIMA (4,1,7) below shows that coefficient of AR, MA and sigma squared are significant as their p values are lower than 5%. The adjusted R-squared is relatively higher than that from other models. Furthermore, AIC and SBIC are also comparatively lower than those from other models. Therefore, it could be concluded that ARIMA (4,1,7) is the best predictive model for BP plc.

Criteria	ARIMA (4,1,7)	ARIMA (4,1,4)	ARIMA (7,1,4)	ARIMA (7,1,7)
Coefficient AR term P value	-0.182926 (0.0057)	-0.672754 (0.0030)	-0.198217 (0.0014)	0.252584 (0.4316)
Coefficient MA P value	-0.226023 (0.0002)	0.530454 (0.0362)	-0.171916 (0.0146)	-0.450132 (0.1387)
^{2}(volatility) P value	378.2420 (0.0000)	392.1052 (0.0000)	381.2687 (0.0000)	390.4647 (0.0000)
Adj. R^2	0.055794	0.021186	0.048238	0.025282
AIC	8.815299	8.849806	8.822764	8.846381
SBIC	8.880584	8.915091	8.888048	8.911666
DW-statistic	2.15	2.13	2.16	2.11

Source: Output of ARIMA models for BP.L with different parameters using Eviews, SV-11

4) CNA.L

ACF and PACF are largest in the correlogram at lags 1 and 8 for Centrica plc (CNA.L). The ARIMA (8,1,8) is found to be the most appropriate model among four following models. This is due to its highest adjusted R-squared and lower sigma square or volatility and AIC and SBIC. Furthermore, co-efficient of AR, MA and sigma square are highly significant.

Criteria	ARIMA (1,1,8)	ARIMA(1,1,1)	ARIMA (8,1,1)	ARIMA (8,1,8)
Coefficient AR term	-0.149045 (0.0346)	0.411611 (0.2115)	0.127645 (0.0887)	0.870110 (0.0000)

P value				
Coefficient MA P value	0.087071 (0.2367)	-0.563972 (0.0608)	-0.157306 (0.0319)	-0.754188 (0.0000)
^{2}(volatility) P value	56.61281 (0.0000)	56.94147 (0.0000)	56.24651 (0.0000)	55.53298 (0.0000)
Adj. R^2	0.018432	0.012734	0.024783	0.037155
AIC	6.913932	6.919508	6.907801	6.899020
SBIC	6.979217	6.984793	6.973086	6.964305
DW-statistic	2.00	2.01	1.99	2.32

Source: Output of ARIMA models for CNA.L with different parameters using Eviews, SV-11

5) SVT.L

The significantly higher ACF and PACF are found at lags 2 and 3 for SVT.L. The ARIMA (2,0,2) has been chosen as the most appropriate model. The OLS explains that DW statistic is 0.94, indicating that there is strong positive serial correlation in the residuals. A stock price displaying positive autocorrelation would indicate that the price yesterday has a positive correlation on the price today and thus, if the stock fell yesterday, it is also likely that it falls today. It seems that the ARIMA model is not applicable for this series. However, the selected model has highly significant adjusted R-squared. Furthermore, coefficient from AR term, MA term and volatility are quite significant.

Criteria	ARIMA (2,0,3)	ARIMA (2,0,2)	ARIMA (3,0.3)	ARIMA (3,0,2)
Coefficient AR term P value	0.952671 (0.0000)	0.957506 (0.0000)	0.949661 (0.0000)	0.869839 (0.0000)
Coefficient MA P value	-0.152782 (0.0910)	-0.186027 (0.0179)	-0.240292 (0.0111)	0.247089 (0.0000)
^{2}(volatility) P value	5868.582 (0.0000)	5790.537 (0.0000)	7809.371 (0.0000)	7630.335 (0.0000)
Adj. R^2	0.869980	0.871709	0.826981	0.830947
AIC	11.57796	11.56195	11.86757	11.83849
SBIC	11.64302	11.62701	11.93263	11.90355
DW-statistic	1.12	0.94	0.66	0.90

Source: Output of ARIMA models for SVT.L with different parameters using Eviews, SV-11

6) JMAT.L

The correlogram in the appendix explains that the ACF and PACF are significant at lags 5 and 11. The optimal model has been selected as ARIMA (11,1,11). Coefficients from this model are quite significant as p values are lower than 5%. This model has got comparatively higher adjusted R-square, although AIC is not lower.

Criteria	ARIMA (5,1,11)	ARIMA (5,1,5)	ARIMA (11,1,5)	ARIMA (11,1,11)
Coefficient AR term P value	0.106883 (0.0790)	-0.626781 (0.0293)	-0.124096 (0.0451)	0.749223 (0.0005)
Coefficient MA	-0.137506	0.708681	0.116461	-0.853746

P value	(0.0281)	(0.0062)	(0.0643)	(0.0000)
^{2}(volatility) P value	4954.736 (0.0000)	5026.651 (0.0000)	4960.034 (0.0000)	4949.904 (0.0000)
Adj. R^2	0.011093	-0.003261	0.010035	0.012057
AIC	11.38670	11.40034	11.38763	11.38916
SBIC	11.45199	11.46562	11.45292	11.45444
DW-statistic	2.15	2.14	2.14	2.17

Source: Output of ARIMA models for JMAT.L with different parameters using Eviews, SV-11

The manufacturing industry

7) ABF.L

The ACF and PACF are found to be significant at lags 8 and 10. The parameters of ARIMA (p,d,q) model shows that ARIMA(10,1,10) seems to provide better forecasted results. This is because, this model generates significant coefficients. However, AIC and SBIC are not reasonably lower from this model.

Criteria	ARIMA (8,1,10)	ARIMA (10,1,8)	ARIMA (10,1,10)	ARIMA (8,1,8)
Coefficient AR term P value	0.125195 (0.1110)	-0.147141 (0.0347)	-0.675649 (0.0038)	0.720235 (0.0034)
Coefficient MA P value	-0.129931 (0.0520)	0.113695 (0.1358)	0.547890 (0.0408)	-0.613891 (0.0302)
^{2}(volatility) P value	568.8372 (0.0000)	568.2094 (0.0000)	570.0740 (0.0000)	573.6990 (0.0000)
Adj. R^2	0.019071	0.020154	0.016938	0.010687
AIC	9.222341	9.221367	9.225122	9.230850
SBIC	9.287626	9.286652	9.290407	9.296134
DW-statistic	2.02	2.03	2.08	1.98

Source: Output of ARIMA models for ABF.L with different parameters using Eviews, SV-11

8) BATS.L

The ACF and PACF have been found significant at lags 1 and 12 for BATS.L. The following table shows that ARIMA (1,1,12) and ARIMA (12,1,1) produce highly significant coefficients. However, the ARIMA (1,1,12) has been selected as parsimonious model as it provides higher adjusted R^2, lower AIC , SBIC and σ^2. Furthermore, the DW-statistic is 2.02 which indicates it is a good model.

Criteria	ARIMA (1,1,12)	ARIMA (1,1,1)	ARIMA(12,1,12)	ARIMA (12,1,1)
Coefficient AR term P value	-0.338322 (0.0000)	-0.311851 (0.0301)	-0.663857 (0.0285)	-0.173236 (0.0178)
Coefficient MA P value	-0.146584 (0.0453)	-0.026099 (0.8765)	0.533057 (0.1102)	-0.327903 (0.0000)
^{2}(volatility) P value	3383.784 (0.0000)	3470.767 (0.0000)	3783.381 (0.0000)	3392.798 (0.0000)
Adj. R^2	0.122579	0.100024	0.018963	0.120242
AIC	11.00592	11.03000	11.11813	11.00906
SBIC	11.07120	11.09529	11.18342	11.07434
DW-statistic	2.02	2.00	2.66	2.05

Source: Output of ARIMA models for BATS.L with different parameters using Eviews, SV-11

9) BDEV.L

ACF and PACF have been found significant at lags 3 and 4 for BDEV.L. The ARIMA (4,1,3) has been chosen as the best model. The OLS shows p values from coefficients of AR term, MA term and σ^2 are significant at 5% level. The OLS also details that the adjusted R^2 is higher than that from other ARIMA models, the AIC and SBIC are comparatively lower. The DW statistic is 1.86, which is character of a good model.

Criteria	ARIMA (3,1,4)	ARIMA (3,1,3)	ARIMA(4,1,4)	ARIMA (4,1,3)
Coefficient AR term P value	-0.119470 (0.0877)	0.221452 (0.6304)	-0.133455 (0.7383)	0.166290 (0.0261)
Coefficient MA P value	0.180742 (0.0142)	-0.370202 (0.3916)	0.318887 (0.4038)	-0.136737 (0.0575)
^{2}(volatility) P value	358.5040 (0.0000)	367.9292 (0.0000)	363.5482 (0.0000)	358.3731 (0.0000)
Adj. R^2	0.033831	0.008430	0.020237	0.034183
AIC	8.760093	8.785570	8.773951	.8.759692
SBIC	8.825378	8.850855	8.839236	8.824977
DW-statistic	1.86	1.93	1.87	1.86

Source: Output of ARIMA models for BDEV.L with different parameters using Eviews, SV-11

10) BKG.L

The ACF and PACF are found to be significantly large at lags 10, 17, and 24. The following table does not show the models of ARIMA (10,1,24); ARIMA (24,1,10); ARIMA (17,1,10); ARIMA (10,1,17). However, they have checked and are found not significant. The table below shows that ARIMA (17,1,24) generates significant coefficients from MA term and σ^2 (volatility). However, its coefficient from AR-term is not significant. The adjusted R^2 is also higher than that from other ARIMA models. Furthermore, the AIC and SBIC are lower than those from any other models. Therefore, ARIMA (17,1,24) has been chosen as the best model among all following models.

Criteria	ARIMA (17,1,24)	ARIMA (24,1,17)	ARIMA(17,1,17)	ARIMA (24,1,24)	ARIMA (10,1,10)
Coefficient AR term P value	0.090334 (0.2586)	0.119038 (0.0507)	0.502593 (0.4963)	-0.101441 (0.8877)	-0.744042 (0.0512)
Coefficient MA P value	0.126826 (0.0426)	0.084590 (0.3068)	-0.419892 (0.5900)	0.221352 (0.7585)	0.817643 (0.0207)
^{2}(volatility) P value	11333.48 (0.0000)	11353.19 (0.0000)	11489.42 (0.0000)	11433.75 (0.0000)	11457.39 (0.0000)
Adj. R^2	0.008843	0.007119	-0.004794	0.000074	-0.001993
AIC	12.21541	12.21683	12.22739	12.22340	12.22545
SBIC	12.28069	12.28211	12.29268	12.28869	12.29073
DW-statistic	1.97	1.97	1.99	1.95	1.98

Source: Output of ARIMA models for BKG.L with different parameters using Eviews, SV-11

11) DGE.L

The correlogram in the appendix shows that ACF and PACF are statistically significant at lags 2 and 6. It is found in the following table by comparing with each other that ARIMA (2,1,2) is the parsimonious model among all models. All the coefficients from this model are statistically significant. Furthermore, the adjusted R^2 is the largest for this model among all models. Moreover, the ACF and PACF are lowest from this model. The DW-statistic is also close to 2, indicating there is no serial correlation.

Criteria	ARIMA (2,1,6)	ARIMA (2,1,2)	ARIMA(6,1,2)	ARIMA (6,1,6)
Coefficient AR term P value	-0.172326 (0.0212)	0.610638 (0.0001)	-0.187368 (0.0143)	-0.513693 (0.1024)
Coefficient MA P value	-0.167960 (0.0269)	-0.814035 (0.0000)	-0.192862 (0.0054)	0.360211 (0.3185)
^{2}(volatility) P value	2287.366 (0.0000)	2272.318 (0.0000)	2273.060 (0.0000)	2345.118 (0.0000)
Adj. R^2	0.041404	0.047710	0.047399	0.017201
AIC	10.61360	10.60760	10.60762	10.63844
SBIC	10.67889	10.67289	10.67291	10.70373
DW-statistic	1.97	1.97	1.98	1.98

Source: Output of ARIMA models for DGE.L with different parameters using Eviews, SV-11

The service industry

12) ADN.L

The ACF and PACF are higher at lags 3 and 18. Therefore, the parameters of ARIMA model have been formed with these lags. The following table documents that ARIMA (3,1,18) is the most economical model among all models. This is because, this model meets all the criteria of a parsimonious model. The coefficients of AR, MA and σ^2 (volatility) are significant at 5% level. The ARIMA (18,1,18) also produces similar outcomes. However, the adjusted R^2 is larger, the values of AIC and PACF are smaller for ARIMA (3,1,18) model. Furthermore, DW-statistic is close to 2, which indicates there is no serial auto-correlation in the residuals. Therefore, this model could generate better forecasting compare to others.

Criterion	ARIMA (3,1,18)	ARIMA (18,1,3)	ARIMA(3,1,3)	ARIMA (18,1,18)
Coefficient AR term P value	-0.153445 (0.0389)	-0.109209 (0.0924)	-0.208890 (0.5911)	0.566832 (0.0462)
Coefficient MA P value	-0.131089 (0.0376)	-0.155385 (0.0348)	0.039122 (0.9222)	-0.722749 (0.0069)
^{2}(volatility) P value	308.4526 (0.0000)	309.3777 (0.0000)	312.9273 (0.0000)	310.3711 (0.0000)
Adj. R^2	0.028240	0.025325	0.014143	0.022196
AIC	8.610743	8.613274	8.623696	8.621462
SBIC	8.676028	8.678559	8.688981	8.686747
DW-statistic	2.03	2.03	2.02	2.04

Source: Output of ARIMA models for ADN.L with different parameters using Eviews, SV-11

13) AHT.L

The ACF and PACF are higher at lags 13 and 16 for AHT.L in the correlogram out of 24 lags. Therefore, they have been exercised to produce a parsimonious model. The following table shows that ARIMA (13,1,16) is the best model for AHT.L. It is documented that the coefficients obtained from this model are statistically significant and they are not from other models. The adjusted R^2 is larger and the values of AIC and PACF are smaller for this model. However, ARIMA (16,1,16) generates the highest adjusted R-squared value. On the other hand, ARIMA (16,1,13) obtains the lowest AIC and SBIC. Overall, ARIMA ((13,1,16) performs better than other models.

Criteria	ARIMA (13,1,16)	ARIMA (13,1,13)	ARIMA(16,1,13)	ARIMA (16,1,16)
Coefficient AR term P value	0.150194 (0.0361)	0.479976 (0.1301)	-0.225043 (0.0008)	-0.590639 (0.0045)
Coefficient MA P value	-0.174854 (0.0349)	-0.301646 (0.3740)	0.118607 (0.1047)	0.372677 (0.1242)
^{2}(volatility) P value	96.32052 (0.0000)	99.63663 (0.0000)	95.53206 (0.0000)	96.08922 (0.0000)
Adj. R^2	0.061264	0.028946	0.068949	0.063519
AIC	7.448876	7.481663	7.441751	7.448973
SBIC	7.514161	7.546947	7.507036	7.514258
DW-statistic	1.91	1.88	1.92	1.93

Source: Output of ARIMA models for AHT.L with different parameters using Eviews, SV-11

14) AV.L

The ACF and PACF are significant at lags 1 and 4 for AV.L. The ARIMA (1,1,4) is found to be the most appropriate model among them. This is due to its highest adjusted R-squared coefficient and lower σ^2 or volatility, AIC and SBIC. Moreover, coefficients of AR and MA terms are significant at 5% level. Furthermore, DW statistic is 2.01, which indicates there is no serial correlation in the residuals. Guidelines say that a good model should not have any serial correlation. The other models do not satisfy all the requirements of a good model.

Criteria	ARIMA (1,1,4)	ARIMA (4,1,1)	ARIMA(1,1,1)	ARIMA (4,1,4)
Coefficient AR term P value	-0.194501 (0.0156)	-0.134805 (0.0289)	-0.124804 (0.6398)	0.286572 (0.3814)
Coefficient MA P value	-0.160080 (0.0124)	-0.192993 (0.0207)	-0.085351 (0.7529)	-0.455319 (0.1487)
^{2}(volatility) P value	1789.209 (0.0000)	1796.192 (0.0000)	1828.770 (0.0000)	1852.198 (0.0000)
Adj. R^2	0.049918	0.046210	0.028911	0.016471
AIC	10.36751	10.37126	10.38890	10.40217
SBIC	10.43280	10.43655	10.45419	10.46746
DW-statistic	2.01	2.01	2.00	2.39

Source: Output of ARIMA models for AV.L with different parameters using Eviews, SV-11

15) BAB.L

The correlogram evidences that ACF and PACF are higher at lags 10 and 15 out of 24 and thus, the best ARIMA model for BAB.L is (10,1,15). This is because, the values of AIC and SBIC are the lowest from this model. The DW statistic is close to 2, indicating there is no serial correlation in the residuals and they are normally distributed. Furthermore, this model creates the highest adjusted R^2. More significantly, coefficients of AR and MA term and σ^2(volatility) are highly significant as their p values are less than 5%.

Criteria	ARIMA (10,1,15)	ARIMA (10,1,10)	ARIMA(15,1,10)	ARIMA (15,1,15)
Coefficient AR term P value	-0.142331 (0.0436)	-0.667870 (0.0625)	0.119527 (0.0769)	-0.499508 (0.1283)
Coefficient MA P value	0.165271 (0.0188)	0.558768 (0.1510)	-0.141589 (0.0464)	0.657407 (0.0322)
^{2}(volatility) P value	929.3382 (0.0000)	943.7253 (0.0000)	935.6071 (0.0000)	932.6946 (0.0000)
Adj. R^2	0.023904	0.008793	0.017320	0.020379
AIC	9.714817	9.728637	9.720540	9.719565
SBIC	9.780102	9.793921	9.785825	9.784850
DW-statistic	2.17	2.18	2.18	2.13

Source: Output of ARIMA models for BAB.L with different parameters using Eviews, SV-11

16) BARC.L

The correlogram of BARC.L explains that ACF and PACF are significant at lags 4, 6 and 22. Thus, the best ARIMA (p,d,q) model is ARIMA (4,1,22) for this company. The ARIMA specifications with ARIMA (22,1,4); ARIMA (22,1,22); ARIMA (22,1,6) and ARIMA (6,1,22) have been analyzed and verified that their criteria do not meet the requirements of a good model. ARIMA (4,1,22) model evidences that it generates the highest adjusted R-squared value, the lowest AIC and SBIC. The DW statistic from this model is also close to 2, indicating there is no serial correlation and residuals are normally distributed. Furthermore, the coefficients of AR and MA terms and σ^2(volatility) are highly significant at 5% level.

Criteria	ARIMA (4,1,6)	ARIMA (6,1,4)	ARIMA(4,1,4)	ARIMA (6,1,6)	ARIMA (4,1,22)
Coefficient AR P value	-0.187710 (0.0023)	0.135239 (0.0749)	-0.223832 (0.5294)	0.793230 (0.0001)	-0.215201 (0.0002)
Coefficient MA P value	0.116894 (0.1223)	-0.164481 (0.0105)	0.041655 (0.9110)	-0.688888 (0.0033)	0.172835 (0.0227)
^{2}(volatility) P value	370.7662 (0.0000)	371.2337 (0.0000)	376.9516 (0.0000)	377.8971 (0.0000)	366.7388 (0.0000)
Adj. R^2	0.035263	0.034047	0.019169	0.016709	0.045743
AIC	8.793973	8.795202	8.810081	8.813515	8.786157
SBIC	8.859258	8.860487	8.875365	8.878800	8.851442
DW-statistic	2.08	2.07	2.12	2.01	2.10

Source: Output of ARIMA models for BARC.L with different parameters using Eviews, SV-11

The quaternary industry

17) AZN.L

The parsimonious ARIMA model for AZN.L has been derived from different ARMA specifications which is ARIMA(12,1,12). The correlogram explains that the ACF and PACF are significant at lags 12 and 22. All other models claim that their coefficients of AR and MA terms are not statistically significant. However, ARIMA (12,1,12) details that its coefficient of AR term is not significant as its p value is more than 5% and the value of AIC is not lowest. In case of DW-statistic, it is in optimum level. This model is been selected as the best model among all applied models. This is due to its residual diagnostic obtained through correlogram of residuals squared supports this model significantly.

Criteria	ARIMA (12,1,22)	ARIMA (22,1,12)	ARIMA(12,1,12)	ARIMA (22,1,22)
Coefficient AR term P value	-0.112310 (0.1983)	-0.132773 (0.0825)	0.614034 (0.0812)	-0.538221 (0.2311)
Coefficient MA P value	-0.127818 (0.1018)	-0.122448 (0.1426)	-0.725463 (0.0156)	415514 (0.3969)
^{2}(volatility) P value	4677.931 (0.0000)	4668.650 (0.0000)	4716.655 (0.0000)	4716.507 (0.0000)
Adj. R^2	0.012367	0.014326	0.004191	0.004222
AIC	11.33043	11.32873	11.33858	11.33885
SBIC	11.39572	11.39402	11.40386	11.40414
DW-statistic	2.02	2.02	1.99	2.00

Source: Output of ARIMA models for AZN.L with different parameters using Eviews, SV-11

18) GSK.L

The ACF and PACF have been found significant at lags 1 and 3 for GSK.L. The OLS regression of different ARMA specifications shows that ARIMA (1,1,1) model would provide better prediction than any other models. This model explains that its coefficients of AR, MA and σ^2(volatility) are highly significant as their p values are 0.0000. The adjusted R^2 is the highest from this model compare to that from all other models. Furthermore, this model provides the lower AIC and SBIC in contrast to those from other models. More importantly, DW statistic is exactly 2.00, which is positive signal, the model to be good.

Criteria	ARIMA (1,1,1)	ARIMA (1,1,3)	ARIMA(3,1,1)	ARIMA (3,1,3)
Coefficient AR term P value	0.782065 (0.0000)	-0.104461 (0.1362)	-0.139960 (0.0461)	-0.067510 (0.9168)
Coefficient MA P value	-0.900019 (0.0000)	-0.139375 (0.0413)	-0.117515 (0.0993)	-0.066393 (0.9171)
^{2}(volatility) P value	5968.542 (0.0000)	6010.282 (0.0000)	6002.476 (0.0000)	6075.585 (0.0000)
Adj. R^2	0.020767	0.013918	0.015199	0.003205
AIC	11.57239	11.57886	11.57758	11.58958
SBIC	11.63768	11.64414	11.64286	11.65487

DW-statistic	2.00	2.00	1.98	2.20

Source: Output of ARIMA models for GSK.L with different parameters using Eviews, SV-11

19) SHP.L

The significantly higher ACF and PACF are found at lags 8 and14 for SHP.L. This study has chosen ARIMA (8,1,14) as the most appropriate model. The reasons for choosing this model are, this model generates significant coefficients for AR, MA and ^{2}(volatility) at 5% level. Furthermore, it provides higher adjusted R^2 and lower AIC and SBIC. Moreover, DW-statistic is reasonable. On the other hand, ARIMA (14,1,8) also provides significant coefficients for AR, MA and ^{2}(volatility) at 5% level. However, its adjusted R^2 is lower than that from chosen one. Furthermore, AIC and SBIC are higher from ARIMA (14,1,8).

Criteria	ARIMA (8,1,14)	ARIMA (14,1,8)	ARIMA(14,1,14)	ARIMA (8,1,8)
Coefficient AR term P value	-0.141579 (0.0144)	0.210173 (0.0033)	1.000000 (0.0000)	-0.626104 (0.0255)
Coefficient MA P value	0.199888 (0.0107)	-0.117453 (0.0424)	-1.000000 (0.0000)	0.480413 (0.1101)
^{2}(volatility) P value	1595.180 (0.0000)	1596.635 (0.0000)	1432.315 (0.0824)	1644.856 (0.0000)
Adj. R^2	0.048772	0.047904	0.145891	0.019149
AIC	10.25564	10.25660	10.23519	10.28444
SBIC	10.32092	10.32189	10.30048	10.34973
DW-statistic	2.17	2.16	2.05	2.16

Source: Output of ARIMA models for SHP.L with different parameters using Eviews, SV-11

20) SGE.L

The correlogram of SGE.L explains that ACF and PACF are significant at lags 1 and 15. Thus, the best ARIMA model for SGE.L is (1,1,15). This model meets all the criteria of a better model compare to other models listed below. The least square regression shows that this model produces lower volatility, AIC and SBIC. In case of adjusted R^2, it provides higher value and non auto-correlated DW statistic which is exactly 2.00, indicating residuals are normally distributed. More importantly, the coefficients of AR and MA terms are highly significant.

Criteria	ARIMA (1,1,15)	ARIMA (15,1,1)	ARIMA(1,1,1)	ARIMA (15,1,15)
Coefficient AR term P value	-0.219753 (0.0000)	-0.195902 (0.0001)	-0.184032 (0.3245)	-0.336191 (0.3456)
Coefficient MA P value	-0.191772 (0.0002)	-0.200433 (0.0000)	-0.040961 (0.8289)	0.133898 (0.7181)
^{2}(volatility) P value	1594.398 (0.0000)	1596.105 (0.0000)	1664.952 (0.0000)	1665.228 (0.0000)
Adj. R^2	0.076766	0.075777	0.035912	0.035752
AIC	10.25455	10.25570	10.29509	10.29840

SBIC	10.31983	10.32099	10.36037	10.36368
DW-statistic	2.00	2.02	2.00	2.41

Source: Output of ARIMA models for SGE.L with different parameters using Eviews, SV-11

21) SN.L

The correlogram table evidences that the ACF and PACF are significant at lags 4 and 18 for SN.L. Thus, the parsimonious model is selected as ARIMA (4,1,4) from different ARMA specifications. In relation to that, the least square regression table suggests that volatility, AIC and SBIC are reasonably lower compare to those from other models. The higher adjusted R^2 is also reported from this model. Furthermore, its coefficients of AR and MA terms are significant at 5% level. However, p value from coefficient AR term is at the marginal level. Moreover, DW-statistic is competitive.

Criteria	ARIMA (4,1,18)	ARIMA (18,1,4)	ARIMA(4,1,4)	ARIMA (18,1,18)
Coefficient AR term P value	-0.193532 (0.0035)	-0.123317 (0.1177)	-0.645700 (0.0037)	0.019651 (0.9708)
Coefficient MA P value	-0.122343 (0.1338)	-0.172954 (0.0092)	0.471422 (0.0591)	-0.156693 (0.7690)
^{2}(volatility) P value	317.9457 (0.0000)	319.6164 (0.0000)	319.5609 (0.0000)	330.5747 (0.0000)
Adj. R^2	0.042593	0.037563	0.037703	0.004565
AIC	8.641256	8.646365	8.645511	8.679810
SBIC	8.706541	8.711649	8.710796	8.745095
DW-statistic	2.23	2.22	2.22	2.23

Source: Output of ARIMA models for SN.L with different parameters using Eviews, SV-11

Residual Diagnostic through Correlogram of Residuals Squared

The best ARIMA models have been chosen based on higher ACF and PACF and selection criteria in the previous section. However, their residuals diagnostic have not been checked up. The following table explains the selected ARIMA model for each series and their p values from residual diagnostics of correlogram squared residuals. 24 lags in the correlogram have been chosen for each selected model (Wooldridge, 2019). They have been shown in the appendix.

When p values from correlogram squared residuals are more than 5%, it indicates the selected model has no serial autocorrelation and the model is good enough to apply. Most of the series explain that ARIMA model is good and applicable. However, a few series show that their p values are less than 5% for all 24 lags. It indicates the ARIMA models are not applicable for those series. These series include BP.L, SVT.L in the primary industry; ABF.L in the manufacturing industry; BARC.L in the service industry and SGE.L in the quaternary industry. Forecasting from these series might not generate better forecasting. In such a case,

the naïve method might generate a better prediction. This method explains all forecasts would be the value of the last observation (Hyndman and Athanasopoulos, 2018).

Table 6. 11: Residual diagnostics for selected ARIMA model

Series	Best ARIMA (p,d,q) model	P values (Residual diagnostics- correlogram Squared residuals)
FTSE-ALL SHARE INDEX	ARIMA(3,1,6)	more than 5% for all 24 lags
FTSE-350 General Industrial Index	ARIMA(1,1,22)	more than 5% for all 24 lags
The primary industry		
ANTO.L	ARIMA (3,1,2)	more than 5% for all 24 lags
BP.L	ARIMA(4,1,7)	LESS than 5% for all 24 lags
CNA.L	ARIMA(8,1,8)	more than 5% for all 24 lags
SVT.L	ARIMA(2,0,2)	LESS than 5% for all 24 lags
JMAT.L	ARIMA (11,1,11)	more than 5% for first 4 lags
The manufacturing industry		
ABF.L	ARIMA(10,1,10)	LESS than 5% for all 24 lags
BATS.L	ARIMA(1,1,12)	more than 5% for all 24 lags
BDEV.L	ARIMA (4,1,3)	more than 5% for first 4 lags
BKG.L	ARIMA (17,1,24)	more than 5% for all 24 lags
DGE.L	ARIMA(2,1,2)	more than 5% for all 24 lags
The service industry		
ADN.L	ARIMA (3,1,18)	more than 5% for all 24 lags
AHT.L	ARIMA(13,1,16)	more than 5% for all 24 lags
AV.L	ARIMA(1,1,4)	more than 5% for first 15 lags
BAB.L	ARIMA (10,1,15)	more than 5% for all 24 lags
BARC.L	ARIMA(4,1,22)	LESS than 5% for first 18 lags
The quaternary industry		
AZN.L	ARIMA(12,1,12)	more than 5% for all 24 lags
GSK.L	ARIMA(1,1,1)	more than 5% for all 24 lags
SHP.L	ARIMA(8,1,14)	more than 5% for all 24 lags
SGE.L	ARIMA(1,1,15)	LESS than 5% for all 24 lags
SN.L	ARIMA(4,1,4)	more than 5% for first 4 lags

Source: Output of residual diagnostics test for the selected ARIMA model using Eviews, SV-11

There cannot be a perfect ARIMA model. It is because, it is an art but not science. As all the criteria for a good model have been satisfied, prediction will be performed using the appropriate values of the parameters for all 22 series that include 204 observations for estimation period and the validation period would be 4 more observations after that period. For the ARIMA model, a static forecast is used rather than dynamic forecasting. Dynamic forecasting is used when changes take place in original prices and volumes, when forecasting is made from previously forecasted data. As data have not changed and are original in nature, static forecast is applied in this research. The forecast errors and evaluation statistics from ARIMA model are shown in the next section.

Forecasting and evaluation of the model

Omnia (2016) explains that the value of Theil inequality coefficient U_1 lies between zero and one. The value of zero indicates a perfect fit. If U_2 equals one (U_2 =1), the random walk or naïve method (where F_t is equal to the last observation) is as good as the forecasting technique being evaluated. If U_2 is less than one (U_2 <1), the forecasting technique being used is better than the naïve method. When U_2 is greater than one (U_2>1), there is no point in using the formal forecasting method. The naïve produces better results. A value of 0 for both U_1 and U_2 indicates a perfect prediction (Leuthold, 1997).

However, Bliemel (1973), Granger and Newbold (1973) and Ahlburg (1984) claim that U2 provides a better interpretation of outcomes than U1. Leuthold (1997) explains that "If one is to select a Theil inequality coefficient as a means for comparing forecasting accuracy among various models, U_2 appears more flexible, more appropriate in a wider range of circumstances, and easier to understand and interpret than U_1." Furthermore, Leuthold (1997) claims that Theil U_2 has some problems as well and no single statistic can capture all the qualities of an estimated model.

Table 6.12 below shows evaluation statistics of forecasted values from ARIMA model. The lower the error, the better the model. The lowest root mean squared error (RMSE) which is 3.976416, observed in the ARIMA model from Ashtead Group plc (AHT.L) in the service industry, whereas the highest RMSE is 111.1220 obtained from FTSE-350 General Industrial Index. The second highest RMSE is 109.4557, shown for BATS.L in the manufacturing industry. Therefore, it could be claimed that the manufacturing industry represents the general industrial index. However, RMSE cannot measure the prediction accuracy of a company. This is because; the stock prices of some companies could be significantly higher than other companies in different industries. Consequently, higher RMSE will be measured for the company which has got higher stock prices and lower RMSE will be measured for the company which has got lower stock prices. Therefore, it is not possible to measure the prediction accuracy on the basis of RMSE.

The smallest mean absolute error (MAE) is 3.051042, which is achieved through the ARIMA model from Ashtead Group plc (AHT.L) in the service industry. It might be claimed that AHT.L provides better forecastability, especially in the service industry. The largest MAE is 97.42271, which is produced from BATS.L plc in the manufacturing industry. Consequently, it could be claimed that BATS.L provides the worst predictability in that industry. It is also

observed that the highest and lowest RMSE and MAE are obtained from the same company in the same industry. However, MAE also does not provide prediction accuracy of a company, especially when such errors are compared for companies in different industries.

The mean absolute percentage error (MAPE) provides the right prediction error as it considers percentage in measurement. Therefore, it does not matter whether stock prices are higher or lower for a company. The smallest mean absolute percentage error (MAPE) in ARIMA model is 0.583392, which is found from ABF.L in the manufacturing industry. It could be claimed from this result that the predictive ability of ABF.L is better than other companies in different industries. The second-lowest MAPE is 1.100702, which is achieved from AZN.L in the quaternary industry. The highest MAPE is 4.521327, which is observed from BATS.L in the manufacturing industry. This result provides evidence that the forecasting ability of BATS.L is poor. The second highest MAPE is 4.1228, which is obtained from ANTO.L in the primary industry. The third highest MAPE is 3.009562, which is shown for SVT.L in the primary industry. It could be concluded that the predictability of stock prices of primary industry is the lowest as the second highest and third highest MAPE have been obtained through the primary industry.

However, the question arises in relation to the performance of the model that details what percentage is acceptable, a model to be regarded better than a naive method. Gilliland (2010) explains in relation to MAPE that the upper limit of forecast accuracy is much more difficult to determine and it is arbitrary. Chen (2017) et al. reveal that MAPE is based on the arithmetic mean and it does not have any upper bound in case of a single error. Makridakis (1993) argue that MAPEs are not comparable directly with naïve models.

Theil inequality coefficient U_1 shows in the table below that all the values are close to zero indicating ARIMA model has provided a good fit in the future values. Moreover, the results indicate ARIMA model has predicted future values very close to the actual values. The lowest U_1 is 0.003866 found from ABF.L in the manufacturing industry. The highest U_1 is 0.024935, observed from BATS.L in the manufacturing industry. Both the highest and lowest U_1 are found in the manufacturing industry. All the values of U_1 from all series are close to zero, but not exactly zero. Therefore, it is very difficult to make decisions on the basis of U_1. Probably, for that reason, Bliemel (1973), Granger and Newbold (1973), Ahlburg (1984) and Omnia (2016) provided preference for the use of U_2 over U_1 due to limitations associated with the latter.

The Theil inequality coefficient U_2 from the FTSE-All Share Index is more than 1, indicating it is not worthy to predict future prices of this index by applying ARIMA model. Therefore, it could be claimed that naïve method would provide better forecasting than the application of ARIMA model for this series. Furthermore, the FTSE-All share Index explains that stock prices are not predictable. However, they might be predictable if all shares are categorized into different industrial sectors.

Theil inequality coefficient U_2 from the FTSE-350 General Industrial Index is 0.892477. This explains that the stock price of FTSE-350 General Industrial Index is predictable from the application of ARIMA model. Consequently, it could be claimed that naïve model does not perform better than ARIMA model in the case of this industrial index. It also indicates that the stock prices might be predictable on the basis of the industrial category.

The values of Theil inequality coefficient U_2 are more than one for ANTO.L and JMAT.L in the primary industry. Therefore, it could be claimed that naïve model is better than ARIMA model for these companies. It also indicates it is impossible to predict the stock prices of these companies on the basis of ARIMA forecasting model. The stock prices of BP.L, CNA.L and SVT.L are predictable as their U_2 are less than 1. Moreover, all the values of Theil inequality coefficient U_2 from all selected companies in the primary industry are close to 1. Consequently, it could be claimed that the stock prices of most of the companies in the primary industry are predictable on the basis of ARIMA model.

The values of Theil inequality coefficient U_2 for all companies in the manufacturing industry are less than one. The results explain that ARIMA model performs better than a naïve model for all companies in the manufacturing industry. Furthermore, it indicates the stock prices of the manufacturing industry are predictable. Moreover, it could be claimed that stock prices are predictable on the basis of the industrial category.

ARIMA model generates lower values of U_2 than one ($U_2 < 1$), for AHT.L (U_2 =0.962709) in the service industry. The result suggests that ARIMA model performs better than naïve model for this company in the service industry, although it is close to 1. However, ARIMA model generates higher values of U_2 than one for most of the companies in the service industry. The findings detail that ARIMA model fails to predict stock prices for these companies. This is because, if U_2 is more than one ($U_2 > 1$), the forecasting technique being used is worser than the naïve method (Bliemel, 1973; Granger and Newbold, 1973; Ahlburg, 1984 and Omnia, 2016). As a consequence, the stock prices of the service industry are not predictable.

AstraZeneca plc and Shire plc of the quaternary industry generate significantly higher Theil inequality coefficient U_2 than one. These results detail that the naive model performs better than ARIMA model for these companies. Therefore, it could be claimed that the application of ARIMA model is not worthy for future price prediction for these companies of the quaternary industry.

On the other hand, more than 50% of the total companies in the quaternary industry generate Theil inequality coefficient (U_2) less than one from ARIMA model. These results detail that ARIMA model performs better than the naive model for these companies. Therefore, it could be claimed that the application of ARIMA model is fruitful for future price prediction of the quaternary industry. This is because, When U_2 is less than one ($U_2<1$), it is worthy to apply the formal forecasting method and the naïve does not produce better results.

On the basis of the above discussions and arguments, it could be concluded that the weekly closing prices of a few companies in different industries provide higher forecasting errors. Therefore, it could be argued that the forecasting ability of ARIMA model for these companies is very poor. Contrary to that, it could be claimed that stock prices are predictable on the basis of the industrial category as all the companies in the manufacturing industry provide better forecasting than a naïve method.

Table 6. 12: Evaluation statistics of forecasted values from ARIMA model

Series	RMSE	MAE	MAPE	Theil U1	Theil U2
FTSE-All Share Index	60.0459	45.1256	1.1456	0.0075	1.0604
FTSE-350 General Industrial Index	111.1220	89.94700	1.562584	0.009604	0.892477
The primary industry					
ANTO.L	36.5726	34.8539	4.1228	0.0218	1.2067
BP.L	23.35308	17.46655	2.815959	0.019119	0.986113
CNA.L	7.388005	6.783906	2.118351	0.011514	0.922690
SVT.L	72.70166	71.13942	3.009562	0.015341	0.949282
JMAT.L	84.71175	53.41954	2.923678	0.023505	1.873953
The manufacturing industry					
ABF.L	6.261774	4.754611	0.583392	0.003866	0.797084
BATS.L	109.4557	97.42271	4.521327	0.024935	0.719096
BDEV.L	8.071098	7.078167	1.220913	0.007012	0.896468
BKG.L	70.87348	61.77459	1.903508	0.010949	0.901504
DGE.L	47.89654	40.04227	1.791252	0.010605	0.918546
The service industry					
ADN.L	9.995131	8.414948	2.928772	0.017792	1.124075
AHT.L	3.976416	3.051042	2.870944	0.019088	0.962709
AV.L	15.94907	12.11692	1.413938	0.009176	1.129999
BAB.L	13.63539	10.60501	1.168331	0.007604	1.119051

BARC.L	8.460138	7.314886	1.487715	0.008628	1.362048
		The quaternary industry			
AZN.L	43.97337	39.12068	1.100702	0.006214	1.064539
GSK.L	38.85497	33.56586	1.764622	0.010188	0.963569
SHP.L	38.09709	33.10405	2.246899	0.013001	1.043464
SGE.L	12.96525	7.927934	2.527741	0.022065	0.763353
SN.L	18.25925	16.69459	1.965597	0.010802	0.969098

Note: The above table analyses the weekly closing price of the following companies. ANTO.L (Antofagasta PLC), BP.L (BP PLC), CNA.L (Centrica PLC), SVT.L (Severn Trent PLC), JMAT.L (Johnson Matthey), ABF.L Associated British Foods PLC), BATS.L (British American Tobacco PLC), BDEV.L (Barratt Developments PLC), BKG.L (Berkeley Group Holdings PLC), DGE.L (Diageo PLC), ADN.L (Aberdeen Asset Management PLC), AHT.L (Ashtead Group PLC), AV.L (Aviva PLC), BAB.L (Babcock International Group PLC), BARC.L (Barclays PLC), AZN.L (Astrazeneca PLC), GSK.L (GlaxoSmithkline PLC), SHP.L (Shire PLC), SGE.L (Sage Group PLC), SN.L (Smith & Nephew PLC).

Source: Output of evaluation statistics for forecasted values from ARIMA model using Eviews, SV-11

B.6.4.2: GARCH (1, 1) model estimation

The GARCH (1, 1) model is applied for this study to detect volatilities and their impact on prediction. The following table 6.13 shows the parameters (mean and variance equations) of GARCH (1,1) model, their SIC and DW statistics from twenty-two series. The parameters of the mean equation are the same as they were found from ARIMA model. More clearly, the GARCH (1, 1) is estimated with the ARIMA (p,d,q) mean equation.

The mean equation shows coefficients of AR term, MA term and their p values. The coefficients of both AR term and MA term in the mean equation are significant as their p values are less than 5% for the FTSE-All Share Index. The FTSE-350 General Industrial Index shows that the p-value of the AR term coefficient is significant. However, its MA term is not significant. The primary industry shows that the coefficients of both AR term and MA term in the mean equation are significant as their p values are less than 5% except ANTO.L.

The manufacturing industry documents that the coefficients of the AR term are significant except BKG.L. However, the coefficients of MA term are significant except BDEV.L for the same industry. The service industry evidences that all the coefficients of AR term in the mean equation are significant except AV.L. However, all the coefficients of MA term are significant in the mean equation except ADN.L for the same industry. The quaternary industry explains that all the AR term coefficients in the mean equation are significant except GSK.L in the quaternary industry. However, the MA term shows that coefficients are significant except GSK.L and SGE.L. After estimating the mean equation, residuals are taken from it. From these residuals, a variance of that residual has been estimated.

The variance equation shows that the coefficient of ARCH is smaller than that of GARCH term, for most of the series. P-value of ARCH from the FTSE-All Share Index is not significant which explains that previous days' return information (that is ARCH) cannot influence today's return volatility. Contrary to that, p value of GARCH is significant from the same series. This indicates previous days' return volatility can influence today's return volatility.

The P value of ARCH from the FTSE-350 General Industrial Index is significant which explains that previous days' return information (that is ARCH) can influence today's return volatility. As the p-value of GARCH from the same series is significant, GARCH is also significant. This indicates previous days' return volatility can influence today's return volatility. As both ARCH and GARCH are significant, they indicate return volatility of the FTSE-350 General Industrial Index is influenced by its ARCH and GARCH factors or shocks.

The industrial category shows that ARCH term is insignificant for ANTO.L and CNA.L in the primary industry; ABF.L and BDEV.L in the manufacturing industry; ADN.L, AV.L and BAB.L in the service industry and GSK.L, SHP.L and SN.L in the quaternary industry. This insignificance of series indicates that previous days' return information cannot influence today's return volatility. The p-values for the remaining series in different industries are significant. This discloses that previous days' return information can influence today's return volatility. The coefficients of GARCH term are quite significant for all industries except DGE.L in the manufacturing industry and ADN.L in the service industry as their p values are close to zero. These results suggest that previous days' return volatility can influence today's return volatility except for ADN.L and DGE.L.

Schwarz information criterion (SIC) is selected from the model selection criterion as the sample size is large. The value of SIC is not comparable as this study only applied normal distribution. It should be the lowest possible value of SIC. However, the lowest SIC is found from AHT.L in the service industry, which is 7.57 compared to those from other series. Durbin-Watson statistic has to be close to two to be a better model. All the series evidence that they have Durbin-Watson statistic close to two except SVT.L in the primary industry.

Table 6. 13: Parameters of GARCH (1, 1) model with normal distribution on 22 series

Series	Mean equation:				Variance equation:				SIC	DW
	AR term coefficient	P value	MA term coefficient	P value	coefficient	P value	β coefficient	P value		stat

FTSE-all share	-0.18116	0.0144	-0.13698	0.0439	0.03618	0.43	0.874480	0.00	11.24	2.12
FTSE-350Gen. Industry	-0.12908	0.0352	0.103034	0.1977	-0.11159	0.002	0.872549	0.000	12.06	1.99
The Primary Industry										
ANTO.L	-0.15597	0.0626	0.135732	0.0820	0.011497	0.733	0.910910	0.02	10.05	2.16
BP.L	-0.15826	0.0313	-0.17808	0.0162	0.125813	0.049	0.773537	0.00	8.82	2.12
CNA.L	0.89526	0.0000	-0.83948	0.0000	-0.04112	0.097	0.827201	0.00	6.95	2.32
SVT.L	0.97708	0.0000	-0.28368	0.0013	0.208092	0.001	0.521092	0.00	11.45	0.87
JMAT.L	0.39630	0.0409	-0.60873	0.0004	0.091556	0.038	0.896584	0.00	11.38	2.17
The manufacturing industry										
ABF.L	-0.74512	0.0000	0.667463	0.0000	0.067567	0.226	0.880973	0.00	9.27	2.11
BATS.L	-0.32193	0.0002	-0.13906	0.0050	0.620982	0.000	0.344502	0.00	10.91	2.05
BDEV.L	0.20179	0.0084	-0.11206	0.1862	0.086018	0.189	0.846723	0.00	8.84	1.86
BKG.L	0.04992	0.5628	0.208263	0.0001	-0.04927	0.004	1.054375	0.00	12.25	1.95
DGE.L	0.62143	0.0000	-0.82704	0.0000	0.131251	0.026	0.084123	0.88	10.70	1.95
The service industry										
ADN.L	-0.15021	0.0422	-0.11989	0.0685	-0.03281	0.488	0.666302	0.40	8.69	2.07
AHT.L	0.20529	0.0001	-0.20687	0.0016	0.542314	0.000	0.352301	0.00	7.57	1.87
AV.L	-0.13915	0.1263	-0.19480	0.0112	0.058670	0.097	0.907280	0.00	10.44	2.10
BAB.L	-0.14046	0.0386	0.237734	0.0009	0.080861	0.178	0.681628	0.03	9.84	2.18
BARC.L	-0.17829	0.0133	0.233280	0.0013	0.161804	0.035	0.682077	0.00	8.81	2.08
The quaternary industry										
AZN.L	0.68305	0.0000	-0.91703	0.0000	-0.04370	0.002	0.935456	0.00	11.29	2.00
GSK.L	-0.21099	0.7437	0.120410	0.8563	-0.01779	0.261	0.948733	0.00	11.69	2.00
SHP.L	-0.14533	0.0164	0.232444	0.0062	-0.00307	0.828	0.949676	0.00	10.35	2.19
SGE.L	-0.17865	0.0211	-0.10406	0.2267	0.222174	0.000	0.840416	0.00	8.98	2.08
SN.L	-0.87556	0.0000	0.819321	0.0000	0.088410	0.610	0.862104	0.00	8.70	2.20

Source: Output from parameters of GARCH (1, 1) model using Eviews, SV-11

The evaluation of model through residual diagnostics

Three residual diagnostics tests have been selected to assess the model. The GARCH (1, 1) model is good when three conditions are met which are as follows:

1) There is no serial correlation
2) There is no ARCH effect and
3) Residuals are normally distributed.

The above three conditions are tested below in table 6.14 to evaluate the outcomes of each series from GARCH (1, 1) model through residual diagnostics.

1) **Testing serial correlation:**

Null hypothesis: There is no serial correlation
Alternative hypothesis: There is a serial correlation

Null hypothesis is rejected when p values from correlogram squared residuals are less than 5%. The table below shows that p values of Q-statistics from correlogram squared residuals are more than 5% for all 24 lags except SVT.L in the primary industry and SGE.L and GSK.L in the quaternary industry. Consequently, residuals from these series do not have any serial correlation except SVT.L, SGE.L and GSK.L. The results suggest that all the series have good models except SVT.L, SGE.L and GSK.L.

2) **Testing ARCH effect:**

Null hypothesis: There is no ARCH effect
Alternative hypothesis: There is ARCH effect

The third column shows that p values of observed R-squared found from ARCH-LM (Lagrange Multipliers) test are more than 5% for all series except SVT.L. Therefore, the null hypothesis cannot be rejected. They indicate the GARCH (1, 1) model has no ARCH effect except SVT.L. This is another requirement of a good model.

3) **Normality test**

Null hypothesis: Residuals are normally distributed
Alternative hypothesis: Residuals are not normal

Residuals are normally distributed when p value of Jarque-Bera statistics from histogram is more than 5%. The fourth column shows that p values from Jarque-Bera (JB) statistics are less than 5% except for FTSE-350 General Industrial Index; SVT.L and JMAT.L in the primary industry, BKG.L and DGE.L in the manufacturing industry and ADN.L, BAB.L and BARC.L in the service industry. Therefore, the null hypothesis is accepted for these series that their residuals are normally distributed. This indicates that residuals are not normally distributed for all remaining series, which is a bad sign. A model is considered to be good if residuals are normally distributed. However, econometricians explain that, although residuals are not normal, it could be still used the model for prediction.

Table 6. 14: Residual diagnostics test for GARCH (1,1) models

Series	P values from correlogram Q- statistic	ARCH-LM test (p values)	Normality test: p value from JB test
FTSE-All Share Index	All are more than 0.05	0.9170	0.0000
FTSE-350 General Industrial index	All are more than 0.05	0.8969	0.1895
The primary industry			
ANTO.L	All are more than 0.05	0.6350	0.0000
BP.L	All are more than 0.05	0.6325	0.0000
CNA.L	All are more than 0.05	0.7477	0.0000
SVT.L	All are LESS than 0.05	0.0324	0.4333
JMAT.L	All are more than 0.05	0.8984	0.3429
The manufacturing industry			
ABF.L	All are more than 0.05	0.8455	0.0000
BATS.L	All are more than 0.05	0.9211	0.0000
BDEV.L	All are more than 0.05	0.9439	0.0000
BKG.L	All are more than 0.05	0.8651	0.7901
DGE.L	All are more than 0.05	0.8839	0.0614
The service industry			
ADN.L	All are more than 0.05	0.6960	0.1435
AHT.L	All are more than 0.05	0.9341	0.0000
AV.L	All are more than 0.05	0.1654	0.0000
BAB.L	All are more than 0.05	0.8276	0.7714
BARC.L	All are more than 0.05	0.6626	0.8879
The quaternary industry			
AZN.L	All are more than 0.05	0.2450	0.0011
GSK.L	All are more than 0.05 except third lag	0.9186	0.0034
SHP.L	All are more than 0.05	0.7159	0.0000
SGE.L	First 8 lags are Less than 0.05	0.9589	0.0000
SN.L	All are more than 0.05	0.4487	0.0000

Note: The above table analyses the weekly closing price of the following companies. ANTO.L (Antofagasta PLC), BP.L (BP PLC), CNA.L (Centrica PLC), SVT.L (Severn Trent PLC), JMAT.L (Johnson Matthey), ABF.L Associated British Foods PLC), BATS.L (British American Tobacco PLC), BDEV.L (Barratt Developments PLC), BKG.L (Berkeley Group Holdings PLC), DGE.L (Diageo PLC), ADN.L (Aberdeen Asset Management PLC), AHT.L (Ashtead Group PLC), AV.L (Aviva PLC), BAB.L (Babcock International Group PLC), BARC.L (Barclays PLC), AZN.L (Astrazeneca PLC), GSK.L (GlaxoSmithkline PLC), SHP.L (Shire PLC), SGE.L (Sage Group PLC), SN.L (Smith & Nephew PLC).

Source: Output of residual diagnostics test for GARCH (1, 1) models using Eviews, SV-11

Comparative evaluation of forecasts from ARIMA and GARCH (1, 1) models:

Forecasts have been performed for all 22 selected series individually for 4 periods after the estimation period. Table 6.15 below shows comparative evaluation statistics for ARIMA (p,

d, q) model and ARIMA (p, d, q) GARCH (1, 1) model. Lower the error, better the model. The following table shows different errors to measure forecastability of models including MAPE, Theil inequality coefficients of U_1 and U_2. The predictability cannot be decided based on all errors. RMSE and MAE cannot measure the prediction accuracy of a series. This is because; the stock prices of some companies or series could be significantly higher than those from other companies or series in different industries. Consequently, higher RMSE and MAE will be measured for the company which has got higher stock prices and lower RMSE and MAE will be measured for the company which has got lower stock prices.

Therefore, it is not possible to measure the prediction accuracy on the basis of RMSE and MAE. RMSE and MAE do not work as benchmarks and they do not measure the forecastability of a model. Therefore, these errors could not be used to determine higher and lower predictable industries and have been omitted from the following table. However, the appendix shows their values for more details. The MAPE and Theil inequality coefficients of U_1 and U_2 work as benchmarks. Sometimes, they might contradict the outcomes for the same series. In that case, decisions would be made on the strength of the majority. This explains that if there is a contradiction between MAPE, U_1 and U_2; that model will be chosen as a better model which has got two favourable outcomes.

Both ARIMA (p, d, q) model and ARIMA (p, d, q) GARCH (1, 1) model show that stock prices of the FTSE-All Share Index are not predictable. This is because, MAPEs are significantly higher for this series. Furthermore, their Theil inequality coefficients of U_2 are more than 1, which suggest that the naïve model performs better than those models. However, ARIMA model performs better than GARCH (1, 1) model for this series; as MAPE, U_1 and U_2 are comparatively lower than those from the latter model. It could be claimed that stock prices are not predictable.

The hypothesis that was made in the first chapter that stock prices could be predictable if all the companies listed in LSE are classified into four industrial categories. Therefore, this study has taken the FTSE-350 General Industrial Index into consideration and classified all companies under four industrial sectors to test the hypothesis. The following table shows that both ARIMA (p, d, q) and ARIMA (p, d, q) GARCH (1, 1) models perform better than the naïve method for FTSE-350 General Industrial Index as their Theil inequality coefficients U_2 are less than 1. This series also documents that ARIMA performs better than the GARCH (1, 1) model.

ANTO.L in the primary industry shows that the naïve model performs better than both applied models as their Theil inequality coefficients U_2 are more than 1. Furthermore, results from this series document that ARIMA (p,d,q) model performs better than ARIMA (p,d,q) GARCH (1, 1) model. Both ARIMA (p,d,q) and ARIMA (p,d,q) GARCH (1, 1) models perform better than the naïve model for BP.L and CNA.L in the primary industry. Furthermore, GARCH (1,1) model performs better than ARIMA model for both series (BP.L and CNA.L) in relation to model's predictability. SVT.L in the primary industry explains that ARIMA model performs better than GARCH (1, 1) model. Furthermore, the naïve method performs better than GARCH model in the case of SVT.L. None of the models perform better than a naïve method for JMAT.L in the primary industry.

All the companies in the manufacturing industry evidence that both ARIMA and GARCH (1, 1) models forecast better than naïve method. This is because; the values of U_1 from all companies in the manufacturing industry are close to zero. Furthermore, the values of U_2 from all companies in the secondary industry are less than 1. Therefore, it could be claimed that the stock prices of the manufacturing industry are predictable. Furthermore, it could be stated that stock prices are predictable based on the industrial sectors. To decide on the better predictability of models, ARIMA model shows higher performance than GARCH (1, 1) model for most of the companies in the manufacturing industry.

All the companies in the service industry show that stock prices are not predictable except AHT.L and the naïve method performs better than any of the applied models (ARIMA and GARCH-1, 1) in that case. The reason is that all the values of U_2 from all companies in the service industry are more than 1 except AHT.L. Furthermore, the MAPE is significantly higher for these companies. These results suggest that the service industry is not predictable. However, GARCH (1, 1) model shows better predictability than ARIMA (p,d,q) model in the case of AHT.L.

In comparison with the results from the quaternary industry, both ARIMA and GARCH (1, 1) models confirm that the stock prices of SGE.L and SN.L are predictable as their values of Theil U_2 are less than one. On the other hand, both ARIMA and GARCH (1,1) models explain that stock prices of AZN.L and SHP.L in the same industry are not predictable as the values of U_2 are more than one. This suggests that it is not worth performing prediction using the applied forecasting models. The naïve method performs better than the applied forecasting models in that case. Furthermore, GARCH (1, 1) model demonstrates that stock prices of

GSK.L are not predictable as both MAPE and Theil U_2 are significantly higher. Contrary to that, ARIMA (p,d,q) model claims that stock prices of GSK.L are predictable as both MAPE and Theil U_2 are significantly lower. In comparison one model with another, ARIMA model claims better forecasting than GARCH (1, 1) model for most of the companies in the quaternary industry.

In comparison one industry with another, it is found from the above analysis that stock prices of the manufacturing industry are more predictable than other industries. This is because, all the companies in the manufacturing industry provide Theil U_1 close to zero and U_2 less than 1 and lower MAPE for some cases. Furthermore, the FTSE-350 General Industrial Index details that stock prices are predictable on the basis of the industrial sectors.

On the other hand, ARIMA (p,d,q) model performs better than GARCH (1, 1) model for most of the series, in terms of the predictability of models. Moreover, both models produce similar results, indicating there is no significant difference in performance for both models. GARCH (1, 1) model performs better a few series including BP.L and CNA.L in the primary industry; BDEV.L in the manufacturing industry; ADN.L, AHT.L, AV.L, and BARC.L in the service industry and SHP.L and SN.L in the quaternary industry. Thus, ARIMA (p,d,q) model is better than GARCH (1, 1) model for forecasting. Furthermore, results support that the service industry is more volatile compare to other industries as GARCH (1,1) model produces better results than ARIMA model for most of the series in that industry.

Table 6. 15: Comparative evaluations of forecasts for ARIMA (p, d, q) model and ARIMA (p, d, q) GARCH (1, 1) model

Series	model	MAPE	Theil U1	Theil U2
FTSE-all share index	ARIMA (3,1,6)	1.145679	0.007547	1.060459
	ARIMA(3,1,6) GARCH (1,1)	1.155130	0.007598	1.067716
FTSE-350 gen. ind. in	ARIMA (1,1,22)	1.562584	0.009604	0.892477
	ARIMA (1,1,22) GARCH(1,1)	1.618699	0.009764	0.903659
The primary industry				
ANTO.L	ARIMA (3,1,2)	4.122849	0.021844	1.206746
	ARIMA(3,1,2) GARCH (1,1)	4.122595	0.021872	1.204551
BP.L	ARIMA (4,1,7)	2.815959	0.019119	0.986113
	ARIMA(4,1,7) GARCH (1,1)	2.819547	0.019070	0.982496
CNA.L	ARIMA (8,1,8)	2.118351	0.011514	0.922690
	ARIMA(8,1,8) GARCH(1,1)	2.022766	0.010851	0.935223
SVT.L	ARIMA (2,0,2)	3.009562	0.015341	0.949282
	ARIMA (2,0,2) GARCH(1,1)	2.897015	0.015389	1.010646
JMAT.L	ARIMA(11,1,11)	2.923678	0.023505	1.873953

	ARIMA(11,1,11) GARCH(1,1)	2.699760	0.021583	2.086932
The manufacturing industry				
ABF.L	ARIMA(10,1,10)	0.583392	0.003866	0.797084
	ARIMA(10,1,10) GARCH(1,1)	0.667737	0.004153	0.830336
BATS.L	ARIMA(1,1,12)	4.521327	0.024935	0.719096
	ARIMA(1,1,12) GARCH(1,1)	4.538673	0.025077	0.731332
BDEV.L	ARIMA(4,1,3)	1.220913	0.007012	0.896468
	ARIMA(4,1,3) GARCH(1,1)	1.056305	0.006257	0.759193
BKG.L	ARIMA(17,1,24)	1.903508	0.010949	0.901504
	ARIMA(17,1,24) GARCH(1,1)	1.906488	0.011356	0.949258
DGE.L	ARIMA(2,1,2)	1.791252	0.010605	0.918546
	ARIMA(2,1,2) GARCH(1,1)	1.798614	0.010560	0.913910
The service industry				
ADN.L	ARIMA(3,1,18)	2.928772	0.017792	1.124075
	ARIMA(3,1,18) GARCH(1,1)	2.869895	0.017451	1.104559
AHT.L	ARIMA(13,1,16)	2.870944	0.019088	0.962709
	ARIMA(13,1,16) GARCH(1,1)	2.335542	0.015878	0.804961
AV.L	ARIMA(1,1,4)	1.413938	0.009176	1.129999
	ARIMA(1,1,4) GARCH(1,1)	1.325929	0.009044	1.121699
BAB.L	ARIMA(10,1,15)	1.168331	0.007604	1.119051
	ARIMA(10,1,15) GARCH(1,1)	1.296876	0.008070	1.187320
BARC.L	ARIMA(4,1,22)	1.487715	0.008628	1.362048
	ARIMA(4,1,22) GARCH(1,1)	1.211768	0.006894	1.149752
The quaternary industry				
AZN.L	ARIMA(12,1,12)	1.100702	0.006214	1.064539
	ARIMA(12,1,12) GARCH(1,1)	1.310470	0.006950	1.092987
GSK.L	ARIMA(1,1,1)	1.764622	0.010188	0.963569
	ARIMA(1,1,1) GARCH(1,1)	1.972891	0.011390	1.033593
SHP.L	ARIMA(8,1,14)	2.246899	0.013001	1.043464
	ARIMA(8,1,14) GARCH(1,1)	2.241766	0.012955	1.044898
SGE.L	ARIMA(1,1,15)	2.527741	0.022065	0.763353
	ARIMA(1,1,15) GARCH(1,1)	2.856003	0.025231	0.872170
SN.L	ARIMA(4,1,4)	1.965597	0.010802	0.969098
	ARIMA(4,1,4) GARCH(1,1)	1.923406	0.010788	0.942978

Note: The above table analyses the weekly closing price of the following companies. ANTO.L (Antofagasta PLC), BP.L (BP PLC), CNA.L (Centrica PLC), SVT.L (Severn Trent PLC), JMAT.L (Johnson Matthey), ABF.L Associated British Foods PLC), BATS.L (British American Tobacco PLC), BDEV.L (Barratt Developments PLC), BKG.L (Berkeley Group Holdings PLC), DGE.L (Diageo PLC), ADN.L (Aberdeen Asset Management PLC), AHT.L (Ashtead Group PLC), AV.L (Aviva PLC), BAB.L (Babcock International Group PLC), BARC.L (Barclays PLC), AZN.L (Astrazeneca PLC), GSK.L (GlaxoSmithkline PLC), SHP.L (Shire PLC), SGE.L (Sage Group PLC), SN.L (Smith & Nephew PLC).

Source: Output of comparative evaluations of forecasts for ARIMA and GARCH (1,1) models using Eviews, 11.

B.6.4.3: Double exponential smoothing technique

Holt's double exponential smoothing provides short-term forecasts. This forecasting model is used when a series exhibits trends and no seasonality. It was observed in all the line graphs and correlograms that data have trends but no seasonality. Furthermore, Friedman test documented that there is no seasonality in the selected time series data. Therefore, Holt's

double exponential smoothing is chosen for this study to examine the trends for selected time series data.

Weights ( ) for Holt's model have been selected based on fluctuation of data in the time series and they contain values from 0 to 1. The double exponential smoothing technique has produced nine results including smoothed data, level estimates, trend estimates, fits (one-period-ahead forecasts), residuals, forecasts, upper 95% prediction limits and lower 95% prediction limits. However, triple exponential smoothing produce one more result which is seasonal estimates. The following table details whether a model fits data well and the differences between the observations and the predicted values are small.

Evaluation statistics of double exponential smoothing technique:

Table 6.16 below shows forecast evaluation statistics of MAPE, Theil $\mathbf{U_1}$ and Theil $\mathbf{U_2}$ from the double exponential smoothing technique. Forecasts have been performed for all 22 series up to 4 periods as like as ARIMA and GARCH (1, 1) models after the same estimation period of 204 observations.

As the root mean squared error (RMSE) and mean absolute error (MAE) do not provide prediction accuracy of a model or company, they have been ignored from the following table. However, the appendix shows all forecast evaluation statistics including RMSE and MAE. This is because, the stock price might differ from company to company and industry to industry. Consequently, higher RMSE or MAE might be measured for the company which has got higher stock prices in value and lower RMSE or MAE also might be measured for the company which has got lower stock prices in value. Therefore, it is quite impossible to conclude the prediction accuracy on the basis of RMSE or MAE and thus, they do not work as benchmarks.

The mean absolute percentage error (MAPE) considers errors in percentage and thus, it works as a benchmark. The smallest mean absolute percentage error (MAPE) is 0.745590, which is found from BKG.L in the manufacturing industry. The second-lowest MAPE is 1.059147, achieved from AV.L in the service industry. The third lowest MAPE is obtained from BDEV.L in the manufacturing industry. These results indicate that the predictive ability of the manufacturing industry is better than any other industries. The highest and second highest MAPEs are 15.26865 and 14.71910 from SGE.L of the quaternary industry and AHT.L of the

service industry respectively. This result provides evidence that the service industry provides poor performance in prediction.

Theil inequality coefficient U_1 shows similar results as MAPE. The lowest Theil U_1 is 0.004668, generated from BKG.L in the manufacturing industry. The second-lowest U_1 is 0.005514, produced from AV plc in the service industry. The third-lowest U_1 is 0.010243, found from BDEV.L in the manufacturing industry. These results document that the BKG.L and BDEV.L in the manufacturing industry provide better prediction than any other companies from different industries. Furthermore, the second-lowest U_1 is found from AV.L of the service industry. This result indicates the service industry provides better prediction. However, the service industry does not provide a better prediction as the second-highest U_1 of 0.088603, achieved from AHT.L in the service industry. On the other hand, the highest U_1 is observed from SGE.L of the quaternary industry, which is 0.089994.

The following table explains that the values of Theil inequality coefficient of U_2 are less than one from BATS.L and BKG.L in the manufacturing industry and AV.L in the service industry. As a consequence, it could be concluded that these companies in the manufacturing industry and service industry provide better prediction than any other companies in different industries through double exponential smoothing. Thus, Holt model produces a better prediction than the naive model for these companies. Contrary to that, the values of U_2 for all remaining series or companies in different industries are significantly higher than 1. It indicates that the forecasting power is very poor and the naïve method performs better than double exponential smoothing technique for these series.

It is found from the above discussions and arguments that double exponential smoothing technique does not work better than ARIMA and GARCH (1, 1) models for most of the series. So, it is not worth using this technique. However, this technique has documented significantly better results for BATS.L and BKG.L in the manufacturing industry than those from ARIMA and GARCH (1, 1) models. This could be due to straight-line trends of these series. These series do not change values very frequently and randomly. The infrequent movements of prices have been confirmed from their line graphs in chapter four.

Table 6. 16: Forecast evaluation statistics of double exponential smoothing technique

Series	MAPE	Theil U1	Theil U2
FTSE-All Share Index	2.582081	0.014297	2.034027
FTSE-350 Gen. Indu. In.	6.050973	0.029962	2.642107
The primary industry			

ANTO.L	4.514366	0.025168	2.070696
BP.L	5.823316	0.032658	1.544930
CNA.L	5.834100	0.029684	3.929118
SVT.L	4.471125	0.024401	1.820317
JMAT.L	9.807355	0.051586	19.89782
The manufacturing industry			
ABF.L	2.728067	0.013985	2.528351
BATS.L	2.337800	0.014848	0.250096
BDEV.L	1.988697	0.010243	1.503635
BKG.L	0.745590	0.004668	0.469225
DGE.L	5.415759	0.027610	2.458514
The service industry			
ADN.L	3.352904	0.020443	1.111195
AHT.L	14.71910	0.088603	3.928435
AV.L	1.059147	0.005514	0.715380
BAB.L	2.195635	0.013136	1.907208
BARC.L	7.466937	0.038807	8.907646
The quaternary industry			
AZN.L	4.005783	0.020693	3.349079
GSK.L	5.947575	0.031527	2.933498
SHP.L	2.744445	0.015210	1.511719
SGE.L	15.26865	0.089994	2.705754
SN.L	4.240883	0.022222	2.756107

Note: The above table analyses the weekly closing price of the following companies. ANTO.L (Antofagasta PLC), BP.L (BP PLC), CNA.L (Centrica PLC), SVT.L (Severn Trent PLC), JMAT.L (Johnson Matthey), ABF.L Associated British Foods PLC), BATS.L (British American Tobacco PLC), BDEV.L (Barratt Developments PLC), BKG.L (Berkeley Group Holdings PLC), DGE.L (Diageo PLC), ADN.L (Aberdeen Asset Management PLC), AHT.L (Ashtead Group PLC), AV.L (Aviva PLC), BAB.L (Babcock International Group PLC), BARC.L (Barclays PLC), AZN.L (Astrazeneca PLC), GSK.L (GlaxoSmithkline PLC), SHP.L (Shire PLC), SGE.L (Sage Group PLC), SN.L (Smith & Nephew PLC).

Source: Output of forecast evaluation statistics from double exponential smoothing using minitab-17

B.6.4.4: Triple exponential smoothing Technique

Winters's triple exponential smoothing is applied for short-term forecasts. It is applied when observations have a seasonal pattern with or without a trend and the pattern is likely to repeat each year. Seasonality is such behaviour of time series data that repeats itself every L periods (Kalekar, 2004). Although the series do not show any strong seasonal pattern in any data set selected in this study, this method is applied simply for comparison with the other models. Furthermore, all series do not behave in the same way and thus, this technique might generate better-forecasted results for a few series.

When the time series data show steady seasonal fluctuations, that is, a fixed amount of price or sales increases or decreases in a particular month or season, the additive method is used. In the multiplicative method, the size of the seasonal fluctuations varies every year (for example 2 x 1 = 2, 2 x 2 =4, 2 x 3 = 6), meaning that the seasonal component is multiplicative in nature

depending on the overall level of the series. It increases or decreases proportionately. As the data series do not show any seasonality, it is assumed that they are additive rather than multiplicative in nature. The additive method is applied to all the selected series as there is no seasonality observed through correlogram, graphs and Friedman test.

Minitab has been used to perform forecasting through Holt-Winters' model. The seasonal length is chosen three as there are four seasons in the UK including Winter, spring, summer, autumn. The test produced nine results including smoothed data, level estimates, trend estimates, seasonality estimates, fits (one-period-ahead forecasts), residuals, forecasts, upper 95% prediction limits, lower 95% prediction limits. These results have been shown in the appendix. As the triple exponential smoothing technique takes into account seasonal component, it might produce better prediction compare to the double exponential smoothing technique.

Comparing results of evaluation statistics from double and triple exponential smoothing techniques:

Table 6.17 below shows the comparative forecast results from double and triple exponential smoothing techniques. The prediction accuracy cannot be achieved on the basis of RMSE and MAE as they do not work as benchmarks. Therefore, they have been ignored from the table below.

The mean absolute percentage error (MAPE), Theil inequality coefficients of U_1 and U_2 work as benchmarks. The results from FTSE-all share index show that triple exponential smoothing technique is better than double exponential smoothing technique. This is because, the forecast evaluation statistics are smaller from triple exponential smoothing technique. However, naïve method performs better than triple exponential smoothing technique as U_2 is significantly greater than 1. It explains that there is no point to apply this forecasting technique.

The results from FTSE-350 general industrial index document that the forecast evaluation statistics are smaller for the triple exponential smoothing technique compare to the double exponential smoothing technique. It indicates that the triple exponential smoothing technique would produce better forecasting for all industry sectors. However, the naïve method generates better forecasting power than the triple exponential smoothing technique due to having Theil inequality coefficient greater than 1. This explains that none of the industry sectors is predictable from these techniques.

The primary industry evidences that the triple exponential smoothing works better than the double exponential smoothing technique for all companies except BP.L. The results also exhibit that none of the companies in this industry is predictable. Thus, the naïve method produces better results than those forecasting techniques. It details that today's price is the best predictor for tomorrow.

On the other hand, all forecast evaluation statistics including MAPE, Theil U_1 and U_2 exhibit that a few companies in the manufacturing industry are predictable. The naïve method is not better than the applied forecasting techniques in that case. These results suggest that stock prices are predictable on the basis of the industrial category. It also indicates the stock prices of the manufacturing industry do not move instantly. It takes time to replicate the information. More specifically, BATS.L and BKG.L in the manufacturing industry confirm that stock prices are highly predictable through both the double and triple exponential smoothing techniques. The remaining companies in the same industry claim that they are not predictable through these forecasting techniques and the naïve produces better results. However, results from most of the companies explain that the triple exponential smoothing technique is better than the double exponential smoothing technique.

The outcomes from the service industry document that the stock prices of all companies are not predictable except AV.L. The AV plc claims that stock prices are predictable through the double exponential smoothing technique rather the triple exponential smoothing technique. The naïve method shows better results for those companies in this industry except AV.L. Therefore, it could be claimed that the double exponential smoothing technique works better than the triple exponential smoothing technique when stock prices are highly predictable through these techniques. However, the triple exponential smoothing shows its higher predictability compare to the double exponential smoothing technique when the naïve method beats both of the forecasting techniques.

Furthermore, similar results have been obtained from the quaternary industry. The results indicate that none of the companies is predictable and the naïve method beats both of the forecasting techniques. Moreover, the triple exponential smoothing shows better results than the double exponential smoothing.

On the basis of the above discussions and arguments, it could be claimed that stock prices are not predictable from the application of exponential smoothing techniques. ARIMA and GARCH (1, 1) models produce significantly better results than exponential smoothing

techniques for the same sub-sample periods. Additionally, the naïve method provides better forecasting than both double and triple exponential smoothing techniques. However, a few companies in the manufacturing industry are predictable through exponential smoothing techniques. It confirms the higher predictability of the manufacturing industry among all industries which draw a conclusion that stock prices are predictable on the basis of industry category.

Table 6. 17: A comparison between forecast evaluation statistics from double and triple exponential smoothing techniques

Series	Exponential smoothing	MAPE	Theil U1	Theil U2
FTSE-All S	Double exponential smoothing	2.582081	0.014297	2.034027
	Triple exponential smoothing	2.197367	0.012453	1.777845
FTSE-350 Gen Indu.	Double exponential smoothing	6.050973	0.029962	2.642107
	Triple exponential smoothing	5.138196	0.025599	2.234040
	The primary industry			
ANTO.L	Double exponential smoothing	4.514366	0.025168	2.070696
	Triple exponential smoothing	4.087236	0.022388	1.836150
BP.L	Double exponential smoothing	5.823316	0.032658	1.544930
	Triple exponential smoothing	6.028173	0.035157	1.675553
CNA.L	Double exponential smoothing	5.834100	0.029684	3.929118
	Triple exponential smoothing	5.085861	0.026222	3.483295
SVT.L	Double exponential smoothing	4.471125	0.024401	1.820317
	Triple exponential smoothing	3.961760	0.021343	1.581641
JMAT.L	Double exponential smoothing	9.807355	0.051586	19.89782
	Triple exponential smoothing	9.662958	0.050834	19.35932
	The manufacturing industry			
ABF.L	Double exponential smoothing	2.728067	0.013985	2.528351
	Triple exponential smoothing	2.624046	0.013262	2.314116
BATS.L	Double exponential smoothing	2.337800	0.014848	0.250096
	Triple exponential smoothing	2.206778	0.016285	0.128392
BDEV.L	Double exponential smoothing	1.988697	0.010243	1.503635
	Triple exponential smoothing	2.124924	0.011350	1.672187
BKG.L	Double exponential smoothing	0.745590	0.004668	0.469225
	Triple exponential smoothing	0.761496	0.004881	0.499641
DGE.L	Double exponential smoothing	5.415759	0.027610	2.458514
	Triple exponential smoothing	4.362744	0.022663	2.015039
	The service industry			
ADN.L	Double exponential smoothing	3.352904	0.020443	1.111195
	Triple exponential smoothing	3.643779	0.021992	1.255875
AHT.L	Double exponential smoothing	14.71910	0.088603	3.928435
	Triple exponential smoothing	14.66936	0.087368	3.853282
AV.L	Double exponential smoothing	1.059147	0.005514	0.715380
	Triple exponential smoothing	1.118708	00.007388	0.994948
BAB.L	Double exponential smoothing	2.195635	0.013136	1.907208
	Triple exponential smoothing	2.207764	0.012513	1.812073
BARC.L	Double exponential smoothing	7.466937	0.038807	8.907646
	Triple exponential smoothing	5.869521	0.030436	7.089522
	The quaternary industry			

AZN.L	Double exponential smoothing	4.005783	0.020693	3.349079
	Triple exponential smoothing	3.255487	0.017000	2.772819
GSK.L	Double exponential smoothing	5.947575	0.031527	2.933498
	Triple exponential smoothing	5.898024	0.031174	2.903220
SHP.L	Double exponential smoothing	2.744445	0.015210	1.511719
	Triple exponential smoothing	2.494744	0.013829	1.378084
SGE.L	Double exponential smoothing	15.26865	0.089994	2.705754
	Triple exponential smoothing	15.37389	0.093975	2.802137
SN.L	Double exponential smoothing	4.240883	0.022222	2.756107
	Triple exponential smoothing	3.902053	0.020361	2.553244

Note: The above table analyses the weekly closing price of the following companies. ANTO.L (Antofagasta PLC), BP.L (BP PLC), CNA.L (Centrica PLC), SVT.L (Severn Trent PLC), JMAT.L (Johnson Matthey), ABF.L Associated British Foods PLC), BATS.L (British American Tobacco PLC), BDEV.L (Barratt Developments PLC), BKG.L (Berkeley Group Holdings PLC), DGE.L (Diageo PLC), ADN.L (Aberdeen Asset Management PLC), AHT.L (Ashtead Group PLC), AV.L (Aviva PLC), BAB.L (Babcock International Group PLC), BARC.L (Barclays PLC), AZN.L (Astrazeneca PLC), GSK.L (GlaxoSmithkline PLC), SHP.L (Shire PLC), SGE.L (Sage Group PLC), SN.L (Smith & Nephew PLC).

Source: Output of forecast evaluation statistics from double and triple exponential smoothing using minitab-17.

B.6.5: Summary table for all applied forecasting models and techniques

The summary table shows a comparison between all models applied in this study based on forecast benchmarks including MAPE, Theil U_1 and U_2. At first, it is required to understand what upper bound value from benchmark parameters is acceptable that indicates a model to be a better model than the naive method. Gilliland (2010) explains in relation to MAPE that the upper limit of forecast accuracy is much more difficult to determine and it is arbitrary. Furthermore, Gilliland (2010) claims that there is no threshold value for MAPE. Chen (2017) et al. reveal that MAPE is based on the arithmetic mean and it does not have any upper bound in case of a single error. Makridakis (1993) argues that MAPEs are not comparable directly with naïve models (e.g. random walk).

The value of Theil coefficient U_1 lies between zero and one. If the value of U_1 is zero, it indicates a perfect fit (Omnia, 2016). Furthermore, Omnia (2016) explains that if U_2 equals one ($U_2 = 1$), the random walk or naïve method (where F_t is equal to the last observation) is as good as the forecasting technique being evaluated. If U_2 is less than one ($U_2 < 1$), the forecasting technique being used is better than the naïve method. When U_2 is greater than one ($U_2 > 1$), there is no point in using the formal forecasting method. The naïve produces better results.

Bliemel (1973) claims that U_2 provides a better interpretation of outcomes than U_1. Several papers exist that compare and contrast between Theil inequality coefficients of U_1 and U_2. Prominent studies within this literature include Granger and Newbold (1973) and Ahlburg

(1984). In these studies, all the scholars provided preference for the use of U_2 over U_1 due to limitations associated with the latter. In contrast to the criticism faced by the U_1 statistic, the U_2 statistic receives support in these studies. Therefore, the decision on predictability, mainly, will be made based on the value of Theil U_2.

However, all benchmarks parameters including MAPE, Theil U_1 and U_2 will be taken into consideration when making decisions of better predictability of the model. Furthermore, where there is a contradiction between results from MAPE, Theil U_1 and U_2, the decision has been made based on the majority to choose the best and second-best predictors in this study. The following table details the two best predictors out of 4 sequentially.

The FTSE-all share index shows that double and triple exponential smoothing techniques are significantly inferior to ARIMA and GARCH (1, 1) models based on the forecast parameters of MAPE, Theil U_1 and U_2. The results also document that the ARIMA model performs better than all other applied models for this series. Furthermore, the GARCH (1, 1) model produces the second-best results for the same series. Therefore, the forecast encompassing test will be performed between ARIMA and GARCH (1, 1) models for this series in the next section. However, the values of Theil U_2 argue that none of the models is better than the naive method.

Similar results have been documented from FTSE-350 general industrial index. This series explains that exponential smoothing techniques fail to predict the prices. This is because, their values of MAPE, Theil U_1 and U_2 are considerably higher. Moreover, their values from exponential smoothing techniques are significantly higher than those from ARIMA and GARCH (1, 1) models. On the other hand, the ARIMA model shows its better predictability than GARCH (1, 1) model. Thus, the forecast encompassing test will be conducted between ARIMA and GARCH (1, 1) models for this series. Both ARIMA and GARCH (1, 1) models perform better than the naive method. However, the naive method performs better than exponential smoothing techniques.

ANTO.L, SVT.L and JMAT.L in the primary industry argue that the ARIMA model performs better than all other models. Furthermore, ARIMA model shows better forecastability than naive method for SVT.L. However, naive method beats ARIMA model for ANTO.L and JMAT.L. Contrary to that, GARCH (1, 1) model shows that it is the second-best performer for these series. However, the naive method shows better predictability than GARCH (1, 1)

model for ANTO.L, SVT.L and JMAT.L. On the other hand, BP.L and CNA.L in the same industry show that GARCH (1, 1) model is the best predictor for those series among all applied models. Furthermore, both ARIMA and GARCH (1, 1) models beat the naive method for these series. Additionally, double and triple exponential smoothing techniques document poorer forecasting outcomes for all series in the primary industry compare to ARIMA and GARCH (1, 1) models. Moreover, the naive method shows better predictability than exponential smoothing techniques for all series in the primary industry. Therefore, the forecast encompassing test will be performed between two better predictors, are ARIMA and GARCH (1, 1) models.

ABF.L and DGE.L in the manufacturing industry evidence that ARIMA model generates significantly better prediction compare to all other applied models. Furthermore, the GARCH (1, 1) model claims that it is the second-best model for those series. Consequently, the forecast encompassing test will be done between these two models for those series in the next section. Contrary to that, GARCH (1, 1) model exhibits as the best performer for BDEV.L in the same industry. Hence, it will be examined in the next section whether ARIMA and GARCH (1, 1) models contain similar information or not. Furthermore, exponential smoothing techniques recorded as the best performers for BATS.L and BKG.L in the same industry. As a result, forecast encompassing tests will be run to examine whether double exponential smoothing technique contains additional information than triple exponential smoothing technique. ARIMA and GARCH (1, 1) models claim that all the series in the manufacturing industry are predictable as all the values of Theil U_2 are less than 1 and they both beat the naïve method, Bliemel (1973) and Omnia (2016). This result indicates that the manufacturing industry is predictable.

GARCH (1, 1) model shows better predictability than ARIMA model for ADN.L, AHT.L and BARC.L in the service industry. On the other hand, ARIMA model exhibits higher forecastability than GARCH (1, 1) model for BAB.L in the same industry Therefore, an encompassing test will be run between these two models for these series to see whether their forecast accuracy is equal or not. However, the results explain that naive model shows more precise predictability than ARIMA and GARCH (1, 1) models for ADN.L, AV.L, BAB.L and BARC.L. Contrary to that, both ARIMA and GARCH (1, 1) models beat the naive method for AHT.L. Double and triple exponential smoothing techniques confirm more precise forecasting for AV.L in the same industry than ARIMA and GARCH (1, 1) models and they beat the naive method.

ARIMA and GARCH (1, 1) models claim their more accurate forecasting power for AZN.L, GSK.L and SN.L in the quaternary industry respectively. However, GARCH (1, 1) and ARIMA models argue their better predictability than other applied forecasting techniques in this study for SHP.L and SN.L in the same industry respectively. Therefore, their encompassing tests will be conducted in the next section to see whether the two best models have similar forecast errors. However, the naive method beats GARCH (1, 1) model for AZN.L, GSK.L and SHP.L. Furthermore, the naive method evidences higher predictability than ARIMA model for AZN.L and SHP.L. Contrarily, both ARIMA and GARCH (1, 1) models beat naive method for SGE.L and SN.L in the same industry.

It is observed in the above analysis that ARIMA model performs better prediction for 11 series out of 22 series than all other applied models. In comparison with ARIMA, GARCH (1, 1) model shows better predictability for 8 series. Furthermore, double and triple exponential smoothing techniques document more forecast accuracy for the remaining 3 series than ARIMA and GARCH (1, 1) models. Additionally, it is found from Theil U_2 that all the series in the manufacturing industry are predictable. Therefore, it could be claimed that the market is predictable based on the industrial category. However, there is a contradiction regarding the forecast accuracy of Theil U_1 and U_2.

Table 6. 18: A comparison table of forecast evaluation statistics from all 4 applied models

Series	Model	MAPE	Theil U1	Theil U2	Two best predictors out of 4 models sequentially
FTSE- ALL SHARE INDEX	ARIMA	1.145679	0.007547	1.060459	ARIMA, GARCH
	GARCH	1.155130	0.007598	1.067716	
	Double	2.582081	0.014297	2.034027	
	Triple	2.197367	0.012453	1.777845	
FTSE-350 GENERAL INDUSTRIAL INDEX (GII)	ARIMA	1.562584	0.009604	0.892477	ARIMA, GARCH
	GARCH	1.618699	0.009764	0.903659	
	Double	4.514366	0.025168	2.070696	
	Triple	4.087236	0.022388	1.836150	
The primary industry					
ANTO.L	ARIMA	4.122849	0.021844	1.206746	ARIMA, GARCH
	GARCH	4.122595	0.021872	1.204551	
	Double	4.514366	0.025168	2.070696	
	Triple	4.087236	0.022388	1.836150	
BP.L	ARIMA	2.815959	0.019119	0.986113	GARCH, ARIMA
	GARCH	2.819547	0.019070	0.982496	
	Double	5.823316	0.032658	1.544930	

	Triple	6.028173	0.035157	1.675553	
CNA.L	ARIMA	2.118351	0.011514	0.922690	
	GARCH	2.022766	0.010851	0.935223	GARCH,
	Double	5.834100	0.029684	3.929118	ARIMA
	Triple	5.085861	0.026222	3.483295	
SVT.L	ARIMA	3.009562	0.015341	0.949282	
	GARCH	2.897015	0.015389	1.010646	ARIMA,
	Double	4.471125	0.024401	1.820317	GARCH
	Triple	3.961760	0.021343	1.581641	
JMAT.L	ARIMA	2.923678	0.023505	1.873953	
	GARCH	2.699760	0.021583	2.086932	ARIMA,
	Double	9.807355	0.051586	19.89782	GARCH
	Triple	9.662958	0.050834	19.35932	
The manufacturing industry					
ABF.L	ARIMA	0.583392	0.003866	0.797084	
	GARCH	0.667737	0.004153	0.830336	ARIMA,
	Double	2.728067	0.013985	2.528351	GARCH
	Triple	2.624046	0.013262	2.314116	
BATS.L	ARIMA	4.521327	0.024935	0.719096	
	GARCH	4.538673	0.025077	0.731332	Triple,
	Double	2.337800	0.014848	0.250096	Double
	Triple	2.206778	0.016285	0.128392	
BDEV.L	ARIMA	1.220913	0.007012	0.896468	
	GARCH	1.056305	0.006257	0.759193	GARCH,
	Double	1.988697	0.010243	1.503635	ARIMA
	Triple	2.124924	0.011350	1.672187	
BKG.L	ARIMA	1.903508	0.010949	0.901504	
	GARCH	1.906488	0.011356	0.949258	Double,
	Double	0.745590	0.004668	0.469225	Triple
	Triple	0.761496	0.004881	0.499641	
DGE.L	ARIMA	1.791252	0.010605	0.918546	
	GARCH	1.798614	0.010560	0.913910	ARIMA,
	Double	5.415759	0.027610	2.458514	GARCH
	Triple	4.362744	0.022663	2.015039	
The service industry					
ADN.L	ARIMA	2.928772	0.017792	1.124075	
	GARCH	2.869895	0.017451	1.104559	GARCH,
	Double	3.352904	0.020443	1.111195	ARIMA
	Triple	3.643779	0.021992	1.255875	
AHT.L	ARIMA	2.870944	0.019088	0.962709	
	GARCH	2.335542	0.015878	0.804961	GARCH,
	Double	14.71910	0.088603	3.928435	ARIMA
	Triple	14.66936	0.087368	3.853282	
AV.L	ARIMA	1.413938	0.009176	1.129999	
	GARCH	1.325929	0.009044	1.121699	Double,
	Double	1.059147	0.005514	0.715380	Triple
	Triple	1.118708	00.007388	0.994948	
BAB.L	ARIMA	1.168331	0.007604	1.119051	
	GARCH	1.296876	0.008070	1.187320	ARIMA,
	Double	2.195635	0.013136	1.907208	GARCH

	Triple	2.207764	0.012513	1.812073	
BARC.L	ARIMA	1.487715	0.008628	1.362048	
	GARCH	1.211768	0.006894	1.149752	GARCH,
	Double	7.466937	0.038807	8.907646	ARIMA
	Triple	5.869521	0.030436	7.089522	
The quaternary industry					
AZN.L	ARIMA	1.100702	0.006214	1.064539	
	GARCH	1.310470	0.006950	1.092987	ARIMA,
	Double	4.005783	0.020693	3.349079	GARCH
	Triple	3.255487	0.017000	2.772819	
GSK.L	ARIMA	1.764622	0.010188	0.963569	
	GARCH	1.972891	0.011390	1.033593	ARIMA,
	Double	5.947575	0.031527	2.933498	GARCH
	Triple	5.898024	0.031174	2.903220	
SHP.L	ARIMA	2.246899	0.013001	1.043464	
	GARCH	2.241766	0.012955	1.044898	GARCH,
	Double	2.744445	0.015210	1.511719	ARIMA
	Triple	2.494744	0.013829	1.378084	
SGE.L	ARIMA	2.527741	0.022065	0.763353	
	GARCH	2.856003	0.025231	0.872170	ARIMA,
	Double	15.26865	0.089994	2.705754	GARCH
	Triple	15.37389	0.093975	2.802137	
SN.L	ARIMA	1.965597	0.010802	0.969098	
	GARCH	1.923406	0.010788	0.942978	GARCH,
	Double	4.240883	0.022222	2.756107	ARIMA
	Triple	3.902053	0.020361	2.553244	

Note: The above table analyses the weekly closing price of the following companies. ANTO.L (Antofagasta PLC), BP.L (BP PLC), CNA.L (Centrica PLC), SVT.L (Severn Trent PLC), JMAT.L (Johnson Matthey), ABF.L Associated British Foods PLC), BATS.L (British American Tobacco PLC), BDEV.L (Barratt Developments PLC), BKG.L (Berkeley Group Holdings PLC), DGE.L (Diageo PLC), ADN.L (Aberdeen Asset Management PLC), AHT.L (Ashtead Group PLC), AV.L (Aviva PLC), BAB.L (Babcock International Group PLC), BARC.L (Barclays PLC), AZN.L (Astrazeneca PLC), GSK.L (GlaxoSmithkline PLC), SHP.L (Shire PLC), SGE.L (Sage Group PLC), SN.L (Smith & Nephew PLC).

Source: Output of forecast evaluation statistics from four applied forecasting models and techniques

B.6.4.5: Forecast encompassing tests

Two of the popular forecast encompassing tests are carried out for the purpose of determining whether one of the forecasts encompasses all the relevant information from the other. Rajbhandari (2016) explains that applied time-series researchers often want to compare the accuracy of a pair of competing forecasts. A related test is the forecast encompassing test. The resulting test statistic may lead a researcher to either combine the two forecasts or drop the forecast that contains no additional information.

This study has applied four forecasting models and techniques and selected two best models for each series based on 3 parameters of forecast evaluation statistics including MAPE, Theil $U_1$and U_2. Results from forecast encompassing tests of Fair-Shiller and Chong-Hendry are shown below:

Forecast encompassing test on the basis of Fair-Shiller (1989):

Table 6.19 below shows the forecast encompassing test of Fair and Shiller between the two best models out of 4. The table explains coefficients from encompassing test and their corresponding p values. FTSE-All Share Index exhibits that both ARIMA and GARCH (1, 1) models have similar performance. The coefficients from them are similar to each other. Furthermore, their p values are similar, but more than 10%. Therefore, it could be claimed that both models contain similar information and forecast accuracy. Furthermore, neither of the models encompass each other as p values from both models are statistically insignificant.

The FTSE-350 General Industrial Index shows that the forecasting performance of GARCH (1, 1) model is very close to that from ARIMA model. This is because, the coefficients from these models and their corresponding p values are very close to each other. However, their p values are more than 10%, which explain that neither forecast is better than the other.

All the series in the primary industry including ANTO.L, BP.L, CNA.L, SVT.L and JMAT.L show that the coefficients from ARIMA and GARCH (1, 1) models are close to each other. Furthermore, their corresponding p values are more than 10%. Consequently, the encompassing test between these models argues that one model does not dominate the other model. However, these two models might capture more information than double and triple exponential smoothing techniques.

All the series in the manufacturing industry including ABF.L, BDEV.L, and DGE.L document that both ARIMA and GARCH (1, 1) models generate similar predictability as these series have similar coefficients. Furthermore, coefficients from double and triple exponential smoothing techniques show they are similar for BATS.L and BKG.L in the same industry. As a result, the argument could be raised that all the competing models for each series have similar forecast ability. However, their p values are insignificant and bigger than 10%. Thus, it could be claimed that the applied models do not encompass.

The coefficients from ADN.L, AHT.L and BARC.L in the service industry show that they are similar to each other from ARIMA and GARCH models. However, AV.L in the same industry discloses that ARIMA and GARCH (1, 1) do not perform better than exponential smoothing techniques. Furthermore, p values from these series in the service industry claim that they are not statistically significant. Therefore, it could be argued that none of the models encompasses each other and holds similar forecast accuracy.

However, the BAB.L from the service industry exhibits that the coefficient has p value less than 5% from both ARIMA and GARCH (1, 1) models including 0.0165 and 0.0172 respectively. These results indicate that forecasts from model 1 encompass that from model 2. Thus, the null hypothesis is accepted and ARIMA model performs better than GARCH (1, 1) model for this series. Every series in this study has got individual characteristics. ARIMA model works better for a few series, however, it does not provide better results for other series. Furthermore, exponential smoothing even works better than ARIMA model for a few series. BAB.L shows ARIMA could predict better than other models and techniques. This is maybe due to the firm's microeconomic factors or series-specific characteristics.

All series in the quaternary industry including AZN.L, GSK.L, SHP.L, SGE.L and SN.L document that coefficients from GARCH (1, 1) model are similar to those from ARIMA model. Therefore, they have parallel forecast accuracy. However, p values from all series in the quaternary industry evidence that neither of the models is better than the other as they are bigger than 10%. The forecast encompassing test is not applicable for these series.

On the basis of the above discussion, it could be concluded that one model is not superior to the other. All of the applied models especially ARIMA and GARCH (1, 1) models have similar forecasting errors. They consistently contain similar information. Neither of the models is superior to the other and they do not dominate each other. Thus, forecast encompassing test is not applicable for these series except BAB.L. This could be due to insufficient forecasted periods. The stock market is always highly volatile and thus, a prediction could not be made for a long period. Forecasted values for a long period will not be reliable as stock prices change very rapidly. This is the common nature of the stock market. Thus, this study considers forecast evaluation for 4 periods. Consequently, the forecast encompassing test is not suitable for this study. Furthermore, the encompassing test of Cook (2014) might not be applicable in the stock market.

Hypothesis:
Null hypothesis: Forecasts from model 1 encompass that from model 2 or forecasts from the latter model contain no additional information
Alternative hypothesis: Forecasts from model 2 contain more information than that from model 1.

Table 6. 19: Forecast encompassing test of Fair-Shiller

Series	Models (f1 and f2)	Coefficient from f1	P value of f1	Coefficient from f2	P value of f2
FTSE-All Share Index	ARIMA-GARCH	198.1257	0.1965	-196.4468	0.1966

FTSE-350 GII	ARIMA-GARCH	37.71797	0.8797	-37.39626	0.8773
The primary industry					
ANTO.L	ARIMA-GARCH	-50.88258	0.9345	50.51296	0.9350
BP.L	ARIMA-GARCH	140.4348	0.3712	-142.0134	0.3725
CNA.L	ARIMA-GARCH	-0.562190	0.9155	1.107658	0.8464
SVT.L	ARIMA-GARCH	26.99460	0.1787	-31.65448	0.1740
JMAT.L	ARIMA-GARCH	0.496519	0.7004	-0.516960	0.7108
The manufacturing industry					
ABF.L	ARIMA-GARCH	3.039281	0.6520	-3.883761	0.6065
BATS.L	Double-Triple	3.920769	0.8531	-1.059427	0.9603
BDEV.L	ARIMA-GARCH	-23.99105	0.1508	24.24889	0.1459
BKG.L	Double-Triple	25.93383	0.2333	-24.13229	0.2433
DGE.L	ARIMA-GARCH	-149.7584	0.3961	150.3238	0.3962
The service industry					
ADN.L	ARIMA-GARCH	14.90096	0.9410	-15.55523	0.9393
AHT.L	ARIMA-GARCH	6.637091	0.6119	-5.864837	0.6509
AV.L	Double-Triple	2.771968	0.4746	0.613891	0.8299
BAB.L	ARIMA-GARCH	10.23028	0.0165	-8.847952	0.0172
BARC.L	ARIMA-GARCH	-0.955193	0.7646	1.377159	0.6864
The quaternary industry					
AZN.L	ARIMA-GARCH	3.291776	0.3849	-2.720261	0.4617
GSK.L	ARIMA-GARCH	1.316219	0.9522	-1.018634	0.9560
SHP.L	ARIMA-GARCH	40.65276	0.5113	-40.79860	0.5124
SGE.L	ARIMA-GARCH	6.103257	0.3056	-3.847003	0.5798
SN.L	ARIMA-GARCH	-9.592966	0.6611	9.092241	0.6534

Note 1: The above table analyses the weekly closing price of the following series: FTSE 350 GII (FTSE-350 General Industrial Index), ANTO.L (Antofagasta PLC), BP.L (BP PLC), CNA.L (Centrica PLC), SVT.L (Severn Trent PLC), JMAT.L (Johnson Matthey), ABF.L Associated British Foods PLC), BATS.L (British American Tobacco PLC), BDEV.L (Barratt Developments PLC), BKG.L (Berkeley Group Holdings PLC), DGE.L (Diageo PLC), ADN.L (Aberdeen Asset Management PLC), AHT.L (Ashtead Group PLC), AV.L (Aviva PLC), BAB.L (Babcock International Group PLC), BARC.L (Barclays PLC), AZN.L (Astrazeneca PLC), GSK.L (GlaxoSmithkline PLC), SHP.L (Shire PLC), SGE.L (Sage Group PLC), SN.L (Smith & Nephew PLC).

Note 2: left hand side model is F1 and right hand side model is F2 in column 2.

Source: Output of forecast encompassing test of Fair-Shiller using Eviews, version-11.

Forecast encompassing test on the basis of Chong and Hendry (1986):

All the stocks have shown specific characteristics. ARIMA model performs better for a few series. On the other hand, GARCH (1,1) model shows better predictability for some other series. Furthermore, the double exponential smoothing technique exhibits better performance for a very few series than all applied models including ARIMA, GARCH (1, 1) and Winters (triple exponential smoothing) models. Contrary, the triple exponential smoothing technique has documented better forecasting power for a very few series than all other applied models including ARIMA, GARCH (1, 1) and double exponential smoothing techniques.

The Chong-Hendry forecast encompassing test is performed to show the ability of one forecast to explain the error of another. Table 6.20 below shows coefficients from the two

best forecasting models obtained through encompassing tests of Chong and Hendry, for each of twenty-two series and their corresponding p values. In the previous sections, forecast evaluation periods of four were selected from each series using four different forecasting models. The encompassing test is performed using four actual and forecasted values generated from two best models out of four applied in this study from each series.

The FTSE-all share index documents that β_i coefficients from ARIMA and GARCH (1, 1) models are similar and their corresponding p values are not statistically significant, i.e. more than 10%. Therefore, it could be claimed that errors from both models are similar and contain similar information. They do not encompass each other for the FTSE-all share index. Similar results have been obtained in the case of the FTSE-350 general industrial index (GII). The series explains that coefficients from ARIMA and GARCH (1, 1) models are similar. Their p values are more than 10%. This result details that GARCH (1, 1) model is not inferior to ARIMA model and they do not encompass. Neither forecasts are better than the other.

Similar results have been documented from all series in the primary industry including ANTO.L, BP.L, CNA.L, SVT.L and JMAT.L through the encompassing test between GARCH (1, 1) and ARIMA models. Their coefficients and corresponding p values explain none of the models provides significant supplementary information one over the other. Therefore, it could be concluded that errors from one model mirror the other and ARIMA model does not contain significantly additional information than GARCH (1, 1) model. Thus, they do not encompass.

BATS.L and BKG.L in the manufacturing industry evidence that double and triple exponential smoothing techniques generate better forecasting power than ARIMA and GARCH (1, 1) models. Thus, the encompassing test has been conducted between these techniques. The results from ABF.L, BATS.L, BKG.L and DGE.L in the manufacturing industry suggest that competing models and techniques have similar forecast accuracy due to having similar coefficients from each competing model and techniques for those series. However, their p values are more than 10%. These results explain that neither forecasts are better than the other and they do not encompass.

However, BDEV.L in the same industry shows that the coefficients of competing models have p values less than 10%. These results indicate that the applied models encompass each other weakly. The results also explain that GARCH (1, 1) contains additional information than ARIMA model and the alternative hypothesis is true for BDEV.L. This is because, the

error (e1) = y-f1, which can be explained significantly by f2 (pval<0.05). It means the errors in y-f1 can be explained by f2. So, f2 (GARCH-1,1) is better and the null hypothesis is rejected.

The double exponential smoothing technique performs better than all other applied models for AV.L in the service industry. The triple exponential smoothing technique produces the nearest forecasting outcomes to the double exponential smoothing technique. Their encompassing test shows that coefficients are similar to each other. However, their p values are greater than 10%. As a result, it could be concluded that the models do not encompass each other.

Furthermore, ADN.L, AHT.L, BAB.L and BARC.L from the same industry confirm that GARCH (1, 1) model does not contain significantly additional information compare to ARIMA model. P values from their coefficients are bigger than 10%. Thus, the forecast encompassing test between ARIMA and GARCH (1, 1) models is not applicable for all series in the service industry. Overall, a conclusion could be made that all these models perform similarly and forecasts from one model contain insignificant information than that from another model.

Parallel results have been documented from all series including AZN.L, GSK.L, SHP.L, SGE.L and SN.L in the quaternary industry that GARCH (1, 1) model does not contain considerably higher forecast accuracy than ARIMA model. Hence, none of the forecasts is better than the other. This is because, coefficients from these two models for each series in the quaternary industry have generated p values considerably higher than 10%. Therefore, it could be concluded that these two models have parallel forecasting accuracy and they do not encompass for these all series. One forecasting model does not dominate the other model.

On the basis of the above discussion and arguments, it could be concluded that none of the applied models is better to compare to each other for all series selected in this study. Therefore, the forecast encompassing test is not applicable in this study, especially, for stock markets. This may be because of choosing a short period of forecast evaluation. The short forecasting periods have been chosen as the stock markets are highly volatile. Stock prices change rapidly. Thus, a long forecasting period could not be chosen in stock markets. A long period of forecast evaluation will be less reliable and forecast errors will be significantly higher.

In such a situation, it is required to go back to the earlier section where the forecast benchmarks have been used to identify a better prediction model. The forecasting benchmarks

are MAPE, Theil U_1 and Theil U_2. These parameters explain that ARIMA model is a better forecasting model than other applied models and techniques for most of the series. However, all the series behave distinctively. GARCH (1, 1) model documented as a second-best model among all. One model dominates the other based on the behaviour of a series. Consequently, exponential smoothing techniques have even documented better forecastability than both ARIMA and GARCH (1, 1) models for a few series.

Hypothesis:
Null hypothesis: Forecasts from model 1 encompass that from model 2 or forecasts from the latter model contain no additional information
Alternative hypothesis: Forecasts from model 2 contain more information than that from model 1.

Table 6. 20: Forecast encompassing test of Chong and Hendry

Series	Models (f1 and f2)	Coefficient from f1	P value of f1	Coefficient from f2	P value of f2
FTSE-All Share Index	ARIMA-GARCH	-0.001977	0.8347	-0.001959	0.8351
FTSE-350 GII	ARIMA-GARCH	-0.003575	0.7680	-0.002922	0.8067
The primary industry					
ANTO.L	ARIMA-GARCH	0.006915	0.8003	0.006688	0.8066
BP.L	ARIMA-GARCH	0.017014	0.4558	0.016752	0.4650
CNA.L	ARIMA-GARCH	-0.015092	0.1877	-0.014833	0.2360
SVT.L	ARIMA-GARCH	-0.009442	0.6162	-0.003336	0.8608
JMAT.L	ARIMA-GARCH	0.026086	0.2901	0.028712	0.2812
The manufacturing industry					
ABF.L	ARIMA-GARCH	0.003332	0.5037	0.002823	0.5465
BATS.L	Double-Triple	-0.013855	0.4763	-0.004813	0.7923
BDEV.L	ARIMA-GARCH	0.010672	0.0702	0.012327	0.0520
BKG.L	Double-Triple	0.004028	0.4906	0.003512	0.5336
DGE.L	ARIMA-GARCH	-0.000397	0.9761	-0.000696	0.9582
The service industry					
ADN.L	ARIMA-GARCH	0.018230	0.3725	0.019314	0.3496
AHT.L	ARIMA-GARCH	0.019214	0.2916	0.028997	0.1392
AV.L	Double-Triple	-0.009376	0.2522	-0.001542	0.8211
BAB.L	ARIMA-GARCH	0.009031	0.3297	0.009488	0.2634
BARC.L	ARIMA-GARCH	0.008265	0.2904	0.012382	0.1737
The quaternary industry					
AZN.L	ARIMA-GARCH	0.006146	0.4578	0.006810	0.3406
GSK.L	ARIMA-GARCH	0.003439	0.8089	0.003372	0.7906
SHP.L	ARIMA-GARCH	0.009945	0.5259	0.009970	0.5263
SGE.L	ARIMA-GARCH	0.020047	0.5113	0.016944	0.5288
SN.L	ARIMA-GARCH	0.011633	0.3525	0.012863	0.2926

Note 1: The above table analyses the weekly closing price of the following series: FTSE-350 GII (FTSE-350 General Industrial Index), ANTO.L (Antofagasta PLC), BP.L (BP PLC), CNA.L (Centrica PLC), SVT.L (Severn Trent PLC), JMAT.L (Johnson Matthey), ABF.L Associated British Foods PLC), BATS.L (British American Tobacco PLC), BDEV.L (Barratt Developments PLC), BKG.L (Berkeley Group Holdings PLC), DGE.L (Diageo PLC), ADN.L (Aberdeen Asset Management PLC), AHT.L (Ashtead Group PLC), AV.L (Aviva PLC),

BAB.L (Babcock International Group PLC), BARC.L (Barclays PLC), AZN.L (Astrazeneca PLC), GSK.L (GlaxoSmithkline PLC), SHP.L (Shire PLC), SGE.L (Sage Group PLC), SN.L (Smith & Nephew PLC).

Note 2: left hand side model is F1 and right hand side model is F2 in column 2.

Source: Output of forecast encompassing test of Chong and Hendry using Eviews, version-11.

B.6.6: The summary of findings

It is crucial to outline the key findings of the entire thesis. This study has reached about three major decisions based on findings. These are related to the followings

1. Weak-form efficiency
2. Forecastability of an industry
3. Better predictive model

The statistical inference was made that the London Stock Exchange (LSE) is not weak-form efficient on the basis of results found from runs test at level, ADF-unit root test at first difference, LB's serial autocorrelation at first difference and variance ratio test at level. These tests documented that stock prices of LSE have serial autocorrelation and they do not move randomly. The results support the weak-form inefficiency of the LSE over the period tested and thus, stock prices of this market should be predictable. The four statistical models and techniques have been applied to predict the prices of 22 series. The series are FTSE-All Share Index, FTSE-350 General Industrial Index and 5 companies from each of four industry sectors including the primary, secondary or manufacturing, service and quaternary industries.

The applied models and techniques are ARIMA and GARCH (1, 1) models and double and triple exponential smoothing techniques. The forecast evaluation statistics of mean absolute percentage error (MAPE), Theil inequality coefficient of U_1 and U_2 explain that a few series from different industrial sectors are predictable. However, the manufacturing industry exhibits that all the series or companies are predictable. On the other hand, most of the series in the service industry are unpredictable.

An assumption was made at beginning of thesis that stock prices could be predictable even in the developed market (the LSE), if the entire market is divided into different industry sectors based on their functions and characteristics. This is because, when new information comes into market, all the industries in that market might not be able to absorb all relevant information into stock prices instantly. All the industries might not be equally capable to update the information into prices instantly. Some industries might absorb all information into prices immediately. However, other industries might delay to embed all relevant information into prices. This advantage of delaying could be taken from these industries and stock prices

could be predicted for short period. Thus, a short period of observations (4 observations) have taken into consideration to evaluate forecasts rather than a long period of observations.

Consequently, it was found that the stock prices of the manufacturing industry are predictable. The probable reasons could be that the industry is laggard to embed all relevant information into prices. Furthermore, it could be due to industry characteristics. Moreover, it could be due to other reasons mentioned by Lo and MacKinlay (1988); Lo (2004); Rosini and Shenai (2020) who claimed that a stock market goes through different states of performance all the time, like a circle.

Therefore, documents support that the London Stock Exchange is weak-form inefficient and stock prices are predictable on the basis of industry sectors. In relation to better predictive model, this study has applied two forecast encompassing tests to decide.

The forecast encompassing tests of Fair-Shiller and Chong-Hendry have been applied to identify better predictive model among 4 models and techniques. However, the results from them show that the encompassing tests are not applicable in stock markets as the models do not encompass each other. This could be due to selecting a short forecast evalution period. However, a long period of data could not be predicted in stock market as stock prices change rapidly and randomly.

Therefore, this study has relied on forecast benchmarks including MAPE, Theil U_1 and U_2 to decide a better predictive model. These parameters (in table 6.18) show that ARIMA model performs better for 11 series out of 22 than other models and techniques. The GARCH (1, 1) model performs better for 8 series out of 22 than other models and techniques. The exponential smoothing techniques perform better for 3 series out of 22 than ARIMA and GARCH (1, 1) models. Therefore, it could be concluded that ARIMA model performs better, on average, than all other models and techniques in this study.

These are three major findings of this study. However, this study extends current literature by showing the existence of weak-form inefficiency in industry sector in the developed market, the LSE. It is found that industry sectors impact the market efficiency.

The next chapter discusses the similarities and dissimilarities between the results found from this study and those of other research papers, investigates the reasons for the similarities and differences and finally explores the originality of this study.

Overview of chapter seven

This chapter explains that this study extends the literature by considering the existence of weak-form efficiency in different industrial sectors. Furthermore, this chapter details certain econometric models are better in certain sectors that would help investors to predict and gain abnormal returns. This chapter also discusses and compares findings of all similarities and dissimilarities with the existing literature, answers all research questions and explains whether objectives have been achieved and recommends for further study.

CHAPTER SEVEN: DISCUSSION, CONCLUSION AND FURTHER RESEARCH

This chapter addresses the synthesised findings from the previous chapter (data analysis and findings), links these findings with earlier empirical findings from other research papers and finally discovers the uniqueness or originality of this study. This chapter also contains the conclusion and suggests further research, seeks to answer the research questions posed in chapter one, and evaluates whether the research's aim and objectives have been achieved. Therefore, the chapter has been divided into two parts including part a) discussion and part b) conclusion and further research.

PART- A: DISCUSSION

A.7.1 A comparison and linking of the findings of this study with the literature review

This section explains the findings from this study and compares them with findings from other studies conducted by many scholars. The findings of this study are similar to those from a few studies. However, the results from this study contradict those from some other studies as well. These are explained below:

The results found from the runs test suggesting the weekly closing prices of the FTSE-all share index, FTSE-350 general industrial index and all twenty companies selected from four different industries are not random. New information takes time to be impounded into stock prices, and the weekly closing prices do not change frequently for all 22 series in this market, causing the prices to be predictable. Therefore, documents support that the London Stock Exchange does not follow the random-walk model.

This outcome is in line with Taylor (1982), Mobarek and Keasey (2000), Chakraborty (2006), Mollah (2007), Abedini (2009), Mishra (2013), Al-Jafari (2013), Camellia (2013) and Ko and Lee (1991), who provided evidence that return series do not behave randomly in the UK, Bangladesh, Sri Lanka, Botswana, Bahrain, Kuwait and Dubai, India, Turkey, UE (Romania, Hungary, the Czech Republic, Slovakia and Estonia) and BRIC countries (Brazil, Russia, India and China) and Japan, Taiwan, Korea, Hong Kong and Singapore, respectively. This may be due to these markets sharing similar kinds of characteristics. Markets do not respond to new information instantly. They take time to incorporate new information into the stock prices. This could be because of the illiquidity of the market.

At the same time, this contradicts the findings of Hong (1977) and Hokroh (2013), who reported that stock prices change very frequently as new information enters the market continuously and causes them to change rapidly and randomly in Japan, Australia, Hong Kong and Singapore and Saudi Arabia, respectively. This may be due to the application and implementation of different market regulations or the different industrial price behaviour.

The highest and the lowest means are found in FTSE-350 general industrial index and Aberdeen Asset Management plc (ADN.L) of the service industry, respectively. There is a significant difference between the highest and the lowest mean. The highest mean from FTSE-350 general industrial index indicates that the stock price of the FTSE-350 general industrial index is higher than that of any of the other 21 series. This may be because of a higher demand for the shares of this series. The median is the highest for the same company. However, the lowest median and mode are observed in Ashtead Group plc and Babcock International Group plc respectively. There is a significant difference between the highest and the lowest mean. The median and mode are also significantly different from the mean value.

These results suggest that the stock prices of twenty-two series are not normally distributed. The data distribution of all the selected series is either platykurtic or leptokurtic. Such descriptive statistics confirm that stock prices are not normally distributed. This is maybe because, the stock market follows market regulations for which new information takes time to be incorporated into the prices. When announcements are made, the market impounds their effects quite slowly. It could be due to series or industry characteristics.

All twenty-two series are positively skewed except Centrica plc in the primary industry. The positively and negatively skewed distribution of the data also does not indicate that they are normally distributed. The highest and lowest ranges are found in Shire plc of quaternary industry and Centrica plc of the primary industry, respectively. There is a significant difference between the highest and the lowest range as well. This result suggests that the prices are not normally distributed, they are dependent and have a serial correlation. Therefore, the stock prices are predictable.

These outcomes are very similar to the findings of Chakraborty (2006), Balsara, Chen and Zheng (2007), Mobarek and Keasey (2000), Mollah (2007), Jarrett (2011), Al-Jafari (2013) and Camellia (2013), who reported through the mean, median, skewness, kurtosis and range in Sri Lanka, China, Bangladesh, Botswana, Hong Kong, Taiwan, Thailand, Malaysia and Korea, Turkey and Romania, Hungary, the Czech Republic, Slovakia, Estonia and Brazil,

Russia, India and China, respectively, that the stock prices of those stock markets do not follow a normal distribution and they are predictable. This may be due to similar stock price behaviour. Stock prices do not move abruptly. However, these results are inconsistent with the findings of Abedini (2009) in Bahrain, Kuwait and Dubai. This author documented that stock returns are normally distributed and thus future returns are not predictable on the basis of historical returns. The reasons for that could be industrial price behaviour. Furthermore, the scholar might have selected the sample from an industry in which the prices change suddenly and unexpectedly.

The Ljung-Box's serial autocorrelation test in this study at first difference argues that a few series have serial autocorrelation at different lags. This documents that they do not follow a random walk model and their future values are predictable. The results are consistent with the findings of Harvey (1994) and Claessens et al. (1995) who find significant predictability of returns in an emerging market. The first-order autocorrelations are not generally higher than 0.2 in most industrial economies. However, Claessens et al. (1995) find in eight economies in emerging market (such as Chile, Colombia, Mexico, Pakistan, Philippines, Portugal, Turkey and Venezuela) have significant first-order auto-correlation greater than 0.20 and 0.489 in Colombia. Poshokwale (1996) finds significant auto-correlation at various lags of the return series in India, Philippines, Malaysia and Thailand suggesting interdependence in returns and they are predictable based on historical information.

Single and multiple variance ratio tests evidence that weekly closing prices of all selected companies in different industries do not behave randomly. This result suggests that weekly closing prices are dependent and have serial autocorrelation. Therefore, future stock prices are predictable on the basis of historical prices. This result is consistent with the findings of Lo and MacKinlay (1988), Lai, Balachandher and Nor (2002), Balsara, Chen and Zheng (2007), Al-Jafari (2013), Camellia (2013) and Abedini (2009) who performed research in New York Stock Exchange and American Stock Exchange, Kuala Lumpur Stock Exchange Composite Index, China Stock Market, Istanbul Stock Market, the UE and BRIC emerging markets and Dubai Financial Market, Kuwait Stock Exchange and Bahrain Stock Exchange respectively.

Contradictory results could be shown against such studies from the findings of studies conducted by Li and Liu (2012), Chakraborty (2006) and Khan and Vieito (2012) in the stock markets of 34 countries, Colombo Stock Exchange, and Portuguese Stock Index (PSI-20) respectively.

The ARIMA model shows the predictability for all series in the manufacturing industry. However, the model has failed to forecast weekly stock prices of many series. The values of Theil U_1, U_2 and MAPE support in favour of prediction for all series in the manufacturing industry, which indicates stock prices are predictable on the basis of industrial category. The ARIMA model has failed to change its movements and directions in accordance with the actual price trend for many series in different industries. Therefore, the findings from the ARIMA model document that stock prices are predictable on the basis of industry sectors.

The findings of this study are consistent with those from other studies conducted by Lim et al. (2007), Bashir et al. (2011), and Narayan et al. (2015) who evidence that the returns of the banking industry are more predictable than other industries. Furthermore, Hong, Torous, and Valkanov (2007) and Tsai et al. (2018) claimed that the stock market is predictable to a short horizon under industrial categories.

This result is inconsistent with the findings of Mobarek and Keasey (2000), Mollah (2007), Balsara, Chen and Zheng (2007), Schilling and Jarrett (2008), Chakraborty (2006), Merh, Saxena and Pardasani (2011), Gaio, Alves and Junior (2009) and Mishra (2013), who documented in Bangladesh, Botswana, China, Germany, Sri Lanka, India, Brazil and India, respectively, that the ARIMA model could consistently predict stock returns and make the stock market weak-form inefficient.

GARCH (1,1) model evidences that stock prices are predictable for all companies in the manufacturing industry. Thus, one industry is stronger than another in terms of efficiency. It is not possible to predict stock prices for all companies in the market. However, stock prices are predictable for all companies or most of the companies in a particular industry. All the industries cannot perform equally. This result is consistent with the findings of Wilhelmsson (2006), Hung-Chung et al. (2009), Hansen and Lunde (2005) and Wang and Yang (2009) who evidenced the forecastability of GARCH (1,1) model. This result is not consistent with the findings of Abdmoulah (2010) who found that all 11 Arab markets are weak-form efficient using GARCH (1, 1).

Double and triple exponential smoothing techniques document that stock prices are predictable for a few companies in the manufacturing industry. However, there is a significant difference between the actual price and the forecasted price for all other remaining series. The forecast benchmarks, Theil U_1, U_2 and MAPE from exponential smoothing techniques are significantly higher for most of the series which indicate that naïve forecasting is better than

those applied techniques. The results from the application of exponential smoothing techniques in this study are not consistent with the findings of Makridakis et al. (1982) and Makridakis and Hibon (2000) who found that exponential smoothing methods have performed surprisingly well in forecasting competitions against more sophisticated approaches.

This study is closely related to the findings of Lo and MacKinlay (1988); Lo (2004); Rosini and Shenai (2020) who claimed that a stock market goes through different states of performance. This study found that the LSE is weak-form inefficient for the sub-periods it studied. However, it could be weak-form efficient for other periods.

The next section analyses the findings from this research in terms of better predictability of model and highly predictable industry. The next section also explains the contributions that this study made and similar studies with this study.

A.7.2 Empirical findings of this research

Figure 7.1 below shows results that are found from the applied models and a linkage between findings from this research and relevant theory. The statistical inference of weak-form inefficiency in the London Stock Exchange was made on the basis of results found from runs test, unit root test, variance ratio test and serial autocorrelation test. Furthermore, the results from all applied models are consistent. It is found from both ARIMA and GARCH (1, 1) models that stock prices are predictable for the manufacturing industry. The Theil inequality coefficients of U_1 and U_2 and MAPE support in favour of all companies in the manufacturing industry.

Therefore, it could be claimed that stock prices are predictable based on the industrial category. Furthermore, the exponential smoothing techniques show better predictability for a few series in the manufacturing industry. The forecast evaluation statistics of benchmarks document that most of the series in the other three industries are not predictable as they generate higher Theil inequality coefficients of U_1 and U_2 and MAPE, indicating the naive model is better than the applied models.

Therefore, there is support for the idea that stock prices of LSC are unpredictable for primary, service and quaternary industries. The reason has been found from the line graph that when companies make announcements and disclosures due to market regulation, prices move sharply upwards or downwards based on the nature of disclosures. Stock prices change every

moment because new information in the form of disclosures and announcements arrive in the market all the time, and new prices are set by relevant new information that is either good or bad for investors. All applied models document that the naive model performs significantly better than forecasting models in the case of the primary, service and quaternary industries. The best predictor for tomorrow is today's price for these three industries. Thus, industrial classification helps to make investment decisions.

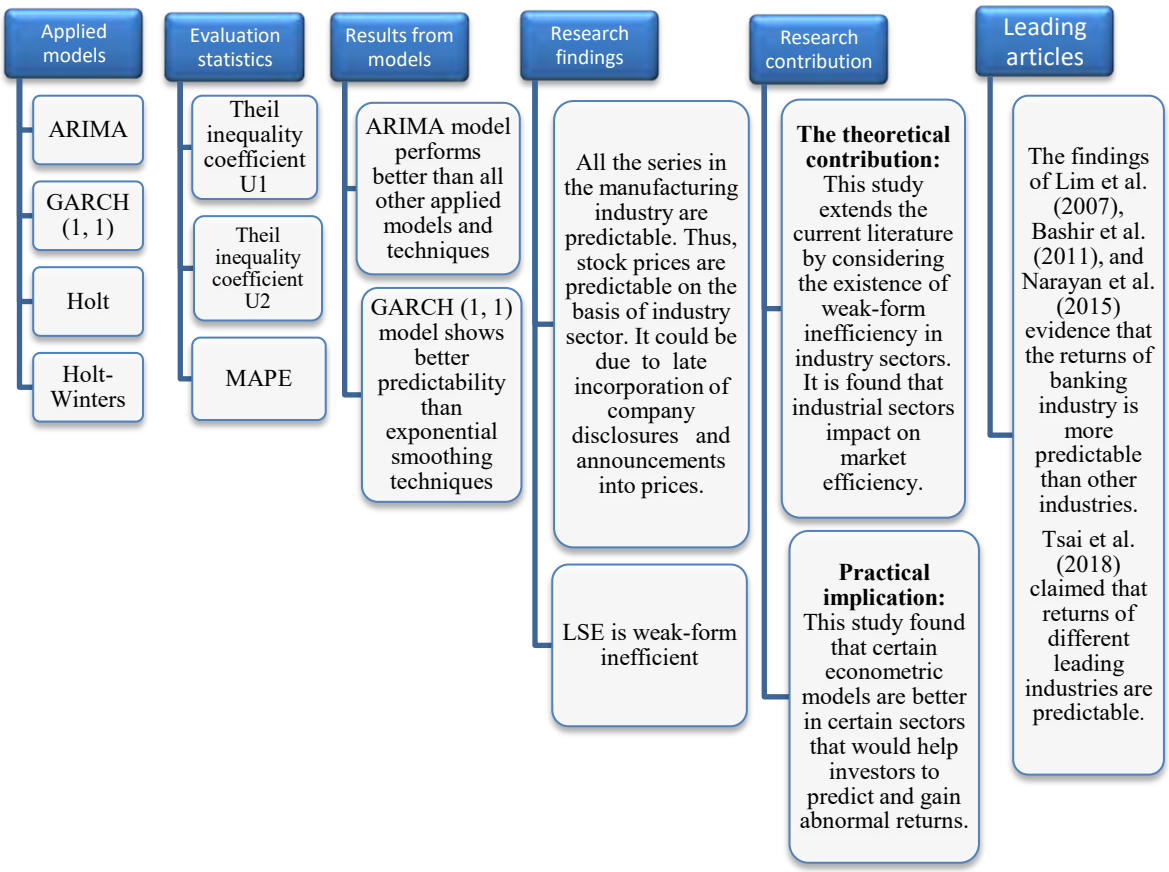
As a consequence of these empirical findings, the weak-form market hypothesis (EMH) within the context of the London Stock Exchange is not accepted. It implies that stock prices are predictable if the market is divided into different industry sectors based on their nature and functions. The hypothesis was made in the beginning that all the industries of LSE cannot perform equally. The performance could differ from industry to industry. Documents support the hypothesis that stock prices of the manufacturing industry are predictable.

The findings of related studies conducted by Kirkwood and Nahm (2005), Lim et al. (2007), Bashir et al. (2011), and Narayan et al. (2015) evidence that the returns of the banking industry are more predictable than other industries. Furthermore, Tsai et al. (2018) claimed that returns of different leading industries are predictable. Additionally, Chen and Lai (2013) found that the biotechnology and medical care industry has significant positive stock returns and they are predictable. They found that the electronic industry provides the complete opposite picture.

Similarly, Sofat (2016) analysed the stock price behaviour of eight companies from the IT industry in the National Stock Exchange (NSE), India, and claimed that they are not weak-form efficient. Moreover, Gaganis et. al. (2013) and Onwukwe and Ali (2018) claimed that the returns of the insurance industry are predictable. Furthermore, Parwada (2012) showed in the Australian securities exchange that a wide range of industry sectors successfully predict the direction of stock price movements due to their nature. Therefore, it could be claimed that the findings of this study are consistent with the findings of the above scholars.

To conclude, the aim of the research project, which was to evaluate, critically and rigorously, the weak-form market efficiency and the forecasting power of technical analysis in different industrial sectors in the UK, is fulfilled. Particularly, the empirical evidence demonstrates the applicability of existing theoretical frameworks and the reliability of the conceptual framework applied to the current research. The empirical findings, research contribution of the thesis and relevant articles are shown below in figure 7.1.

Figure 7. 1: Research contribution and the link between research findings and relevant theory



Source: Figure created by author with research contributions and link of research findings and relevant theories.

A.7.3 The contributions of this study

After a critical, fastidious and detailed examination of the data and findings, this research found its original contribution or uniqueness. This study has made two unique contributions in the literature which are discussed below:

1. **Contribution made due to revealing weak-form inefficiency of LSE on the basis of industry sectors:**

This study extends the current literature by examining the existence of weak-form inefficiency in industrial sectors in the developed market, the LSE. Millions of studies have been conducted on the predictability of technical analysis. Most of them which are conducted on developed markets have documented that developed markets are weak-form efficient. This

study believed that a developed market could be weak-form efficient. However, all the industries in a developed market could not be sufficiently efficient in incorporating all relevant new information into stock prices at the same time. This research assumed at the beginning of chapter one that some industries might hold weak-form efficiency and some do not. Some industries might be laggard to embed all relevant information into stock prices. Consequently, their stock prices are predictable. However, the existing literature has largely neglected this assumption.

All the scholars including Kirkwood and Nahm (2005), Lim et al. (2007), Bashir et al. (2011), Parwada (2012), Narayan et al. (2015), Gaganis et. al. (2013), Sofat (2016), Tsai et al. (2018) and Onwukwe and Ali (2018) performed their studies on a specific category of industry, for example, the banking industry, IT industry, insurance industry and so on. However, this study has divided the London Stock Exchange into four industrial categories based on their origin, functions and nature to investigate the predictability of each sector. For example, this study has kept all service related companies under one category and all production and manufacturing related companies under another category.

On the other hand, a significant number of research has been conducted on technical analysis and its predictability. In these papers, researchers have shown that most of the stock markets which have been researched in developed markets are weak-form efficient. This study also assumed that developed markets could be weak-form efficient. However, when disclosure in terms of new information enters a market, even in a developed market, all industries in that market cannot embed them into stock prices at the same time.

On the basis of the above assumption, this paper investigated all industrial sectors to see the predictability of those sectors in a developed market, the London Stock Exchange. This paper has evidenced that the developed market, the London Stock Exchange is not weak-form efficient when the market is divided into different industrial sectors. This paper has divided the London Stock Exchange into 4 industrial categories, including the primary industry, which involves extracting and collecting natural resources from the land, including oil, gas, gold and platinum. The primary industry also involves fishing and farming. The manufacturing industry, which involves manufacturing and selling different products based on the customers' needs, wants and demands. The service industry deals with providing services. The final one is the quaternary industry, which is engaged in the research and development of new products and services.

This study has evidenced that all industries do not perform equally in adjusting the effects of all relevant new information into prices. No researchers have considered in their analysis whether industry-based analysis of historical prices might not lead to weak-form efficiency in a developed market. The empirical evidence support this study that a developed stock market is not always weak-form efficient when the whole market is divided into different industry sectors.

For investigating purpose, data were collected from 20 companies in four different industries listed on FTSE 100. Furthermore, this study collected data from the FTSE-all share index and FTSE-350 general industrial index as a proxy to compare results. The application of different models in the FTSE-all share index shows that stock prices are not predictable. However, forecasting benchmark parameters of MAPE, Theil U_1 and U_2 from both ARIMA and GARCH (1, 1) models evidence that stock prices of FTSE-350 general industrial index are predictable. This result indicates that stock prices are predictable based on industrial sectors. Consequently, all 20 series from different industrial sectors were examined.

Stock prices on the industry sectors of the LSE do not rigorously pass weak-form market efficiency issuing a range of econometric tests. The results reveal that the well-known models, ARIMA and GARCH (1, 1) generate consistent results in predicting stock prices for all series in the manufacturing industry in the London Stock Exchange. These models document that the stock prices of the manufacturing industry are predictable. Furthermore, exponential smoothing techniques predicted stock prices for a few series in the manufacturing industry. Thus, all the companies in the manufacturing industry do not reflect all relevant information into stock prices. This industry is laggard and takes time to embed all relevant information into prices or this could be the characteristics of this industry.

On the other hand, it is found from all applied models that the stock prices of most of the companies in all other different industries are not predictable. The best model, ARIMA in this study, also fail to forecast stock prices for these series. Therefore, it could be claimed that information is incorporated instantly for these companies in all other industries. All other industries, especially the service industry can embed all relevant information into stock prices without delay.

The results suggest that stock prices are predictable based on the industry sector. Therefore, this study strongly suggests that institutional investors and retail individual investors should

keep in mind the industrial price behaviour factors play a significant role in the analysis of stock prices in a developed stock market.

When new information enters the market continuously and randomly, prices do not change all over the industries. Some industries take time to incorporate the impact of information into prices. Consequently, prices are predictable. All the industries have no the same performance level in incorporating all the relevant information into stock prices instantly. Therefore, their prices are predictable due to industry characteristics and investors even in the developed market would be benefitted. This is because, all industrial sectors do not reflect all relevant information into stock prices equally at the same time. They could generate revenues by investing in different industries, especially in the manufacturing industry. This information would help all types of investors to make their investment decisions in the real life.

The findings of this study do not support the theory of weak-form market efficiency in the developed stock market (the London Stock Exchange) after prediction is made by dividing the whole market into different industrial sectors. This research found that all industries do not adjust all relevant information into stock prices at the same time in the LSE.

2. **Contribution made due to identifying models' performance based on series and/or industry characteristics:**

Certain econometric models are better in certain sectors. The results show that both ARIMA and GARCH (1, 1) models could predict stock prices for the FTSE-350 general industrial index. The forecasting benchmark parameters of MAPE, Theil U_1 and U_2 suggest that stock prices of the FTSE-350 general industrial index are predictable. However, the forecasting benchmarks from double and triple exponential smoothing techniques argue that these techniques fail to predict stock prices of the FTSE-350 general industrial index. This could be due to some common characteristics that exist with both models and series. Consequently, ARIMA and GARCH (1, 1) models could predict better for this series. Furthermore, the same models fail to predict stock prices for different series or industry. This is because, the criteria or characteristics that exist with the models do not match with series or industry. Therefore, it is required to identify this industry or series related characteristics or issues that help the models to perform better.

The ARIMA and GARCH (1, 1) models performed better for FTSE-350 general industrial index. This indicates certain industries could be predictable using these models. As a

consequence, this study found that all the series in the manufacturing industry are predictable. Relevant information for all the series or companies in this industry is reflected slowly. This industry takes time to absorb all available information. This could be the nature of the manufacturing industry. Furthermore, it could due to industry-specific characteristics. Moreover, the demand and supply for all stocks in this industry could be in an equilibrium point that causes stock prices not to move.

An efficient market incorporates all relevant and new information instantaneously. However, the manufacturing industry is not competent to reflect all relevant information including company announcements and disclosures into stock prices instantly. This industry takes time to incorporate all relevant information into prices. This could be due to be less demanded and less frequently traded stocks of this industry. Furthermore, the stock in this industry might involve high transaction costs. Consequently, the stocks in this industry are less liquidate.

Exponential smoothing of double and triple techniques have shown that a few series including BATS.L and BKG.L are highly predictable in the manufacturing industry. Their MAPE, Theil U_1 and U_2 suggest that exponential smoothing techniques perform statistically and significantly better than both ARIMA and GARCH (1, 1) models. The reasons could be due to the trend and level of exponential smoothing techniques. These series might not fluctuate over time and they exhibit trends in the data. The line graphs, Histogram and Kernel Density graphs from BATS.L and BKG.L document that these series have sluggish upward trends. When a series exhibits trends and trends are sluggish, exponential smoothing techniques are very effective for this series. Consequently, exponential smoothing techniques have generated significantly better forecasting power than ARIMA and GARCH (1, 1) models. The reasons for sluggish upward trends could be stable macro-economic factors.

Furthermore, ARIMA model performs better for most of the series in this study. The reasons could be due to a stable economic environment. The economic environmental factors including employment, income, inflation, interest rates, tax rates, economic growth, law and regulations and market regulations based announcements and disclosures policies might change over time. However, the changes might not take significantly. The line graphs, histogram and kernel density graphs show that these series fluctuated slowly over the period. Thus, ARIMA model produced better results for these series.

On the contrary to ARIMA model, GARCH (1, 1) model performs better for a few series in this study. This could be due to cognitive biases to select particular stocks, over-optimism,

irrationality and herding behaviour of investors for specific stocks that caused these series to fluctuate very frequently and randomly over time. Therefore, GARCH (1, 1) model captured the fluctuations very well, where ARIMA model did not. Furthermore, it was out of question for exponential smoothing techniques as they only consider trend and seasonality in data.

On the basis of the above discussions, it could be argued that when stock prices move slowly and show either an upward or downward trend, exponential smoothing techniques work effectively for this series. However, when the stock prices of a series fluctuate slowly and volatility is low, ARIMA model works very effectively for this series. Furthermore, when stock prices move randomly with higher volatility, GARCH model works very well.

The following part of chapter seven draws a conclusion by answering the research questions and achieving the research objectives from the research findings after statistical analysis of the weekly closing price data of FTSE-all share index, FTSE-350 general industrial index and twenty companies from 4 different industries listed on the FTSE 100, finds the limitations of this study and recommends for further research from the limitations.

PART- B: CONCLUSION AND FURTHER RESEARCH

This part of chapter seven provides answers to the research questions made in chapter one, and will analyse whether research objectives have been achieved and how they have attained from research findings after statistical analysis of weekly closing price data of FTSE-all share index, FTSE-350 general industrial index and 20 companies from four different industries listed on FTSE 100. It will also discuss the limitations of this research and recommends for further research.

B.7.1 Answers to the research questions

The research questions have been answered after analysing all the sampled and sub-sample data through statistical techniques and models.

7.1.1 Research Question 1

In relation to the research question regarding stock prices in the industrial sectors of the UK stock market are weak-form efficient or not, this research applied different statistical techniques to answer this question. The descriptive statistics table (especially kurtosis) evidenced that the weekly closing prices of all series are not normally distributed. The histograms and kernel density graphs also documented that all the selected series in this study

are not normally distributed. Therefore, their weekly closing prices do not change randomly, abruptly, and unpredictably and they do not follow the random-walk model.

Furthermore, results of runs test on 22 series for the selected sub-sample period documented that the weekly closing prices do not follow the random walk model. This is because, the runs test at level shows that all the p-values (level of significance) from all series are less than 5% (0.000<0.05) which indicate the weekly closing prices of FTSE-all share index, FTSE-350 general industrial index and all 20 selected companies from four different industries are not random. Thus, the London Stock Exchange does not follow a random-walk model. Moreover, ADF-unit root test for all series at first difference shows that prices do not have unit root for the selected sub-sample period except SVT.L in the primary industry.

Overwhelmingly, multiple variance ratio tests exhibit that all the series except AV.L in the service industry follow a martingale model. However, the single variance ratio test documents that all the series except SVT.L in the primary industry and AZN.L in the quaternary industry do not follow a random walk model. Both SVT.L and AZN.L show that they follow a random walk model in period 2. Therefore, it could be claimed that weekly closing prices for most of the series do not move randomly. Furthermore, serial autocorrelation test at first difference shows that some series have do not have serial autocorrelation and some series have.

On the basis of the above findings, the statistical inference was made that the London Stock Exchange is weak-form inefficient and future prices from this market are predictable. Thus, this study applied several forecasting models and techniques to predict stock prices of the London Stock Exchange.

The double exponential smoothing technique (Holt model) shows through the forecast evaluation statistics (MAPE, Theil U_1 and U_2) that stock prices for a few companies in the manufacturing industry are predictable. The forecast error, MAPE details that Holt model fails to forecast stock prices for all series except BATS.L and BKG.L in the manufacturing industry and AV.L in the service industry. Theil U_1 from the same technique indicates that stock prices for all series are not predictable except BATS.L and BKG.L in the manufacturing industry and AV.L in the service industry. The values of U_1 from BATS.L, BKG.L and AV.L are close to zero. Furthermore, Theil U_2 from Holt model explains that stock prices of BATS.L and BKG.L in the manufacturing industry and AV.L in the service industry are predictable as their Theil U_2 are less than one.

Triple exponential smoothing technique also documents that stock prices for a few series in the manufacturing industry are predictable. This technique documents through MAPEs that BATS.L and BKG.L in the manufacturing industry and AV.L in the service industry are predictable even better than ARIMA and GARCH (1, 1) models. This is because, MAPEs from this technique are significantly lower than those from ARIMA and GARCH (1, 1) models. Furthermore, the values of Theil $U_1$are close to zero from these three series in Winters' model. In addition to that, the values of U_2 from triple exponential smoothing technique are less than 1 for these three series. However, MAPE, Theil U_1 and U_2 evidence that triple exponential smoothing technique is not capable to predict for all remaining series in this study.

GARCH (1,1) model shows better results for a significant number of series especially for all series in the manufacturing industry. The forecast errors, RMSE and MAE are smaller in GARCH model for all series in the manufacturing industry. However, these errors do not provide accuracy of measurements as the size of stock price is different for each series. Consequently, the price which is large size, may provide a larger error. However, it does not happen in case of MAPE. MAPEs are smaller for all series in the manufacturing industry in the case of GARCH (1, 1) model than that from other series in different industries, FTSE-all industrial index and FTSE-350 general industrial index. The values of Theil U_1 are comparatively smaller (close to zero) for all series in the manufacturing industry compare to other series in this study. Theil U_2 from GARCH (1, 1) model discloses that all the series in the manufacturing industry provide significantly better prediction than that from other series in this research as their values of Theil U_2 are lower than 1.

ARIMA model documents that 11 series out of 22 series are predictable and it includes all five series of the manufacturing industry. The forecast errors, RMSE and MAE (are shown in the appendix), are significantly smaller for all series in that industry than those from FTSE-all share index, FTSE-350 general industrial index and 15 series in different industry sectors. The MAPEs are also smaller for these 11 series out of 22 series. However, they are significantly smaller for all series in the manufacturing industry. Furthermore, Theil U_1 is very close to zero for these series in the manufacturing industry. Additionally, Theil U_2 from ARIMA model is less than one for all series in the manufacturing industry. All the evaluation statistics including MAPE, Theil U_1 and Theil U_2 from ARIMA model suggest that all the series from the manufacturing industry are highly predictable.

On the basis of the above discussion, it could be argued that the inference of weak-form inefficiency in the LSE over the period tested found from a range of tests including runs test, ADF-unit root test, variance ratio test and autocorrelation test are supported by several forecasting models and techniques. Therefore, it could be concluded based on the supports from different non-forecasting and forecasting related statistical tests and models that LSE is weak-form inefficient over the period tested. However, the LSE might be weak-form efficient for other sub-sample periods. Therefore, it could be argued that a market goes through periods of efficiency and inefficiency depending on the macroeconomic variables. A few scholars found the new theory of adaptive market hypothesis that explains that markets go through periods of efficiency and inefficiency depending upon external environmental conditions. Consequently, the application of forecasting models to predict stock prices is not ruled out.

7.1.2 Research Question 2

Referring to the research question regarding the forecasting power of different econometric models estimated using the principles of technical analysis (ARIMA, GARCH, exponential smoothing techniques), this study investigates the forecasting power of different econometric models following the principles. The forecasting principles detail that the number of observations for estimating should not be larger. They should be around 200 as most time series do not work for very long time series (Hyndman and Athanasopoulos, 2018). Therefore, the estimation period for this study includes 204 observations. The validation period has been selected 4 more observations after that period for out-of-sample forecasts.

This research chose the validation period for comparing predictive prices and trends with actual prices and trends from four applied models and techniques. The results evidence that no model can predict stock prices that are same as the actual prices. However, the prediction power varies from applied model to model. The forecast encompassing tests were applied to answer this question to derive a better forecasting model. However, the results from these tests reveal that none of the models and techniques encompasses each other. None of the applied models is better to compare to each other for all series selected in this study.

Consequently, the forecast encompassing test is not applicable in this study, especially for stock markets. This may be because of choosing the short prediction or evaluation period. The short forecasting period has been chosen as the stock markets are highly volatile. The stock prices change rapidly. A long evaluation period for stock prices would provide greater

forecast error. Thus, a long forecasting period could not be chosen in stock markets and it was concluded that forecast encompassing tests are not applicable for stock prices.

Therefore, this study answers this question on the basis of 3 forecast evaluation of benchmark parameters including MAPE, Theil U_1 and U_2 from 4 applied forecasting models and techniques. These parameters explain that ARIMA model is a better forecasting model than other applied models and techniques for most of the series in this study. Furthermore, it could be observed through the analysis of graphs and figures that the predicted price trend from the ARIMA model is close to that of the actual price trend compared to those from other models for most of the series. The gap between the actual price and the predicted price found from the application of the ARIMA model is smaller compare to those from other applied models.

The mean absolute percentage errors (MAPEs) are smaller for most of the series in ARIMA model than those from GARCH (1, 1), Holt and Winters' models. Furthermore, the values of Theil $U_1$and U_2 from ARIMA model are smaller for most of the selected series than those from GARCH (1, 1), Holt and Winters' models. The results from these benchmark parameters explain that ARIMA model is the best model among all applied models in this study. This is because, ARIMA model performs better for 11 (including all five series from the manufacturing industry) out of 22 series than all other model and techniques. ARIMA model shows more accuracy in prediction than all other models for these series. This is because, the ARIMA model produces forecasts based on the weight of previously observed values in the time series (AR terms), stationary of time series data by differencing between successive observations (d) and the errors made by previous predictions (MA terms). This typically allows the model to rapidly adjust for sudden changes in the trend, resulting in more accurate forecasts.

GARCH (1, 1) model exhibits better forecasting power than exponential smoothing techniques. The results from GARCH (1, 1) model indicate that it is the best performer for 8 out of 22 series. Thus, it performs even better than ARIMA model for several series. All the series behave distinctively. Therefore, one model dominates the other based on the behaviour of a series or industry characteristics. The values of MAPE, Theil U_1 and U_2 from GARCH (1, 1) model confirm that all the series in the manufacturing industry are predictable. This result details that the manufacturing industry is more predictable than other industries. This also explains that GARCH (1,1) model has better prediction accuracy. This could be due to considering the volatility in the measurements.

The traditional forecasting techniques including double and triple exponential smoothing techniques provide forecasting errors significantly large for most of the series in this study. Their values of MAPE, Theil U_1 and U_2 are significantly higher compare to those from ARIMA and GARCH (1, 1) models. However, these three parameters explain that exponential smoothing techniques perform significantly better for BATS.L and BKG.L in the manufacturing industry and AV.L in the service industry even than GARCH (1, 1) and ARIMA models. In this case, double exponential smoothing technique exhibits better forecasting power than triple exponential smoothing technique for 2 series out of 3. This is because, triple exponential smoothing technique considers seasonality in data and data series in this study do not exhibit any seasonality evidenced through correlogram, line graphs and Friedman test.

However, these smoothing techniques do not perform better than GARCH (1, 1) and ARIMA models for the remaining 19 series. This may be because, the trend lines from Holt's model flow in a straight line rather than changing its movements and directions like the actual price trends. Furthermore, triple exponential smoothing technique considers seasonality in data. However, data do not show seasonality. As a consequence, there is a significant gap between the actual price and the predicted price or higher prediction errors for the remaining 19 series from exponential smoothing techniques. Furthermore, the predicted price trends from Holt's model and Winters' model are significantly far away from the actual price trends for most of the series in this study. This could be due to considering the only trend and/or seasonality in the data. It is also documented that GARCH (1, 1) model provides better predictability than these exponential smoothing techniques.

On the basis of the above findings and arguments from different models and forecasting techniques, it could be claimed that ARIMA model is the best performer among all applied models and techniques for most of the series. However, it is also found that ARIMA model is the least performer for a few series. Therefore, it could be argued that all the series in this study behave distinctively. The predictability of stock price depends on both choices of series or industry and model. When the characteristics of a model match with those from a series or industry, this model provides better forecasting for that series or industry. When they do not match, a significant gap occurs between actual and predicted prices.

A particular industry is more predictable than others applying the same models and its price difference is lower compare to that from others. It could be due to series or industry

characteristics in the form of illiquidity, infrequent trading and reporting delays of the stocks in that industry that cause stock prices to move slowly and thus, stock prices from these series or industries are more predictable. Furthermore, every model has its characteristics, for example, GARCH model performs better when a series show higher volatility. Therefore, it could be argued that a model has better forecasting power when its characteristics match with those from a series or industry.

7.1.3 Research question 3

In relation to the research question 'What is the conclusion on the use of technical analysis for estimating econometric models and forecasting stock prices?', this study synthesizes the findings and draws a conclusion.

Many scholars argue that a developed market is usually weak-form efficient. This study believes that a developed market could be weak-form efficient. However, all industries in the developed market could not be efficient equally to embed all relevant and new information into stock prices at the same time. The speed in the incorporation of stock price might differ from industry to industry in the same market.

The stock prices might fluctuate randomly in a particular industry or for a few industries. The same level of fluctuations might not happen in all industries. The stock prices of a particular industry may be more predictable than others because of the industrial nature of non-randomness in price movements or slow incorporation of news in that industry. Therefore, this study is conducted using a developed stock market, the London Stock Exchange to test this hypothesis.

For the purpose of testing this hypothesis, this study collected data from the FTSE-all share index, the FTSE-350 general industrial index and five different companies from each of four industrial sectors: the primary industry, manufacturing industry, service industry and quaternary industry for the periods between 3 March 1997 and 16 July 2017 and hypothesis was tested for different sub-sample periods.

The FTSE- all share index shows that none of the models could predict the prices. However, the FTSE-350 general industrial index explains that stock prices are predictable for the period tested. This indicates that stock prices are predictable on the strength of industrial sectors. Consequently, all the companies in the manufacturing industry have shown that they are predictable for the selected sub-sample periods. This is because, their values of Theil U_1 are

very close to zero, Theil U_2 less than one and MAPEs are significantly low from both ARIMA and GARCH (1, 1) models.

The results indicate that future values of all series in the manufacturing industry are predictable using ARIMA and GARCH (1, 1) models. A conclusion could be made that the naïve model does not forecast better than ARIMA and GARCH (1, 1) models for all series in the manufacturing industry as the benchmark parameters of forecasting errors are significantly lower for all series in this industry.

Furthermore, the exponential smoothing techniques document that the forecasting errors of benchmarks are significantly lower for a few series in the manufacturing industry. Moreover, both ARIMA and GARCH (1, 1) models show that a few series in different industries are predictable. Therefore, it could be claimed that the stock prices are predictable using technical analysis on the industrial sector even in the developed market, the LSE. This could work better in an underdeveloped or developing country.

In terms of the use of technical analysis for estimating econometric models, it is found that all the prediction models do not perform equally. Success in predicting stock prices may depend on the choice of a prediction model. The empirical examination of the performance of the models in this study disclosed that the ARIMA model has an extensively better prediction power than any other applied models and techniques including the GARCH (1, 1) model, double and triple exponential smoothing techniques. However, it is also found that exponential smoothing techniques performed better for a few series even than ARIMA and GARCH (1, 1) models. Furthermore, GARCH (1, 1) model performed better for several series than all other models and techniques.

Therefore, it could be argued that the performance of the model depends on both model's characteristics and series or industry characteristics. When they match each other, the model performs well for that series or industry. There are some other technical analyses such as ANN (artificial neural network), other family member of GARCH, MACD (moving average convergence divergence), RSI (the relative strength index) and so on. These methods of technical analysis could perform better than ARIMA, GARCH (1, 1) models and exponential smoothing techniques.

However, it could be claimed from the applied technical analysis that stock prices are predictable if the market is weak-form inefficient. The stock market is not always efficient.

When a market is not efficient, stock prices are predictable using technical analysis. The statistical inference was made that the LSE is weak-form inefficient on the basis of several statistical tests including run test, variance ratio test, unit root test and serial correlation test. Furthermore, econometric models of technical analysis have documented stock prices of the LSE are predictable. Therefore, the LSE is weak-form inefficient.

The market is dynamic and it goes through different states of efficiency at different point in time. The LSE might pass from efficieny to inefficiency. Furthermore, the LSE could be weak-form efficient for different sub-sample periods. Lo and MacKinlay (1988); Lo (2004); Rosini and Shenai (2020) claimed that market efficiency is dynamic and can go through different states of efficiency, reverting from efficiency to inefficiency and vice versa depending on environmental factors and market participants' actions. Consequently, it could be claimed that the London Stock Exchange is weak-form inefficient for the studied period.

The research questions have been answered based on findings from this research. The next section explains whether the objectives of this study have been achieved or not.

B.7.2 Objectives of the research

The objectives of this research that were drawn in chapter one, have been achieved by analysing the data and findings. This part of thesis explains how each of all objectives have been achieved.

7.2.1 Objective 1

The first objective of this study was to make a critical review of existing literature on weak-form market efficiency and forecasting models using technical analysis.

This objective is achieved in chapter two. In relation to this objective, the key scholars written books and journal articles in the area of technical analysis were examined. The scholars are Civelek (1991), Harvey (1994), Butler and Malaikah (1992), Gilmore and McManus (2003), Smith and Ryoo (2003), Appiah-Kusi and Menyah (2003), Urrutia (1995), Hassan, Haque, and Lawrence (2006), McGowan (2011), Chen and Metghalchi (2012), Liu (2011), Abdmoulah (2010), Mishra and Smyth (2017) from developing markets. Some of the scholars have shown that technical analysis could predict stock prices and some of the them found contradictory results. Furthermore, some of the scholars have found weak-form efficiency for a few sub-sample periods and weak-form inefficiency for the remaining sub-sample periods.

The prominent scholars from the developed markets are Fama (1970, 1965), Kendall (1953), Cootner (1962), Osborne (1962), Fama and French (1988), Poterba and Summers (1988), Hudson, Dempsey, and Keasey (1996), Lee et. al (1999), Summers, Griffiths, and Hudson (2004), Narayan (2005), Otilia (2011), Shynkevich (2012), Arevalo et. al. (2017), Adebayo (2013), Konak and Seker (2014), Chittedi (2014), Lin (2018) and so on. The most of the scholars documented that stock prices are not predictable through technical analysis and markets are weak-form efficient.

The collection of the leading articles for the concepts of weak-form efficiency and technical analysis were made possible by the use of keywords put into search engines of peer-reviewed databases. Notable amongst them were Emerald, Ebscohost, Science Direct, JSTOR, Ethos, Osiris, Oxford and Cambridge journals, Social Science Research Network (SSRN). Google and Google scholar were also instrumental in the retrieval of relevant journals for the review of literature. This review shaped the finalization of the research questions, and set up the theoretical foundation of the thesis.

7.2.2 Objective 2

The second objective was to develop a conceptual framework for simultaneously testing market efficiency and the forecasting power of technical analysis in the industry sectors of the UK stock market.

In relation to this objective, a comprehensive conceptual framework is designed within the context of weak-form efficiency and technical analysis in the industrial sectors of the UK stock market in chapter 3 (Figure 3.1). To achieve this objective, data were collected from different industrial sectors including the primary, secondary or manufacturing, service and quaternary industries. Furthermore, data were collected from FTSE-all share index and FTSE-350 general industrial index to proxy and compare results. To test the data, the most common and easy to understand methods of non-forecasting and forecasting related statistical tools, models and techniques including ARIMA, GARCH (1, 1) and exponential smoothing, were designed to apply for a sub-period from each of 22 series where there is no structural breaks.

The non-forecasting related statistical tools including runs test, variance ratio test, ADF-unit root test and Ljung-Box's serial correlation test were designed to draw statistical inference on weak-form efficiency of LSE. The forecasting related models and techniques were designed to test simultaneously the forecastability of models and industry sectors. The benchmarks

evaluation statistics of MAPE, Theil U_1 and U_2 were planned to evaluate the performance. It was plotted to synthesize and articulate the findings and draw a conclusion on forecastability of industrial sectors and performance of models. Furthermore, forecast encompassing tests were planned to decide on better predictive model. However, they did not work eventually. Consequently, forecast benchmarks were used to measure that.

7.2.3 Objective 3

The third objective was to examine whether stocks in the industrial sectors in the London Stock Exchange are weak-form efficient using a range of econometric tests. This objective was achieved by applying different statistical tools and techniques and analysing graphs and figures of selected series. At first, the descriptive statistics of data and line graphs, histogram and kernel density graphs were examined. Secondly, runs test, ADF-unit root test, variance ratio test and autocorrelation test were performed to draw statistical inference regarding weak-form efficiency. Thirdly, different models and techniques were applied to test weak-form efficiency for different industry sectors, the FTSE-all share index and FTSE-350 general industrial index. Finally, evaluation statistics of benchmarks were compared with those from the forecasted results to draw conclusion regarding weak-form efficiency and forecastability of models.

The descriptive statistics table evidenced that the weekly closing price of FTSE-all share index, FTSE-350 general industrial index, 20 companies from four different industries are not normally distributed. The histograms and kernel density graphs showed that all the stock prices are either leptokurtic or platykurtic in distribution. Therefore, they are not normally distributed. Non-normal distribution of stock prices suggests that future stock prices are foreseeable from the analysis of historical prices.

The runs test at level shows that all the series including FTSE-all share index, FTSE-350 general industrial index and 20 companies from four different industries do not follow a random walk model for the selected sub-sample period as their p values are less than 5%. The ADF unit root tests at first difference show that all the series do not have unit root at first difference. The results of the Ljung-Box's autocorrelation test at first difference are mixed. It is found that some of the series have autocorrelations up to 24 lags and others do not.

Overwhelmingly, single and multiple variance ratio tests on selected sub-sample period showed that series do not behave randomly. The joint test of Chow-Denning statistic at level

shows that the variance is constant at different lags. Furthermore, the multiple variance ratio test of Chow-Denning maximum |z| statistic explain that all the series except AV.L in the service industry accept the null hypothesis that they follow a martingale model.

However, the single variance ratio test of Lo and MacKinlay documents that all the series except SVT.L in the primary industry and AZN.L in the quaternary industry do not follow a random walk model. Both SVT.L and AZN.L show that they follow a random walk model in period 2. Therefore, it could be claimed that weekly closing prices of all series do not move randomly, however, some of them follow a martingale.

In summary, none of the series, in a period without a structural break robustly passes the criteria required for weak-form market efficiency. Therefore, statistical inference was made that the LSE is not weak-form efficient.

However, forecast evaluation statistics from all prediction models and techniques documented that half of the selected series have significantly larger errors. Their MAPEs, Theil U_1 and U_2 evidence that half of the selected series are not predictable. Therefore, naïve model performs better than applied forecasting models and techniques for those series in this developed stock market, the London Stock Exchange..

It is found that the ARIMA model has significantly stronger prediction power than the GARCH (1, 1) model and exponential smoothing techniques. The prices forecasted by the ARIMA model are closer to the actual prices than those from GARCH (1, 1), Holt and Winters' models for 11 out of 22 series. Moreover, the gap is significantly large and ARIMA model fails to predict stock prices precisely for all remaining series. However, ARIMA model consistently documented that stock prices of all companies in the manufacturing industry are predictable as their MAPEs, Theil U_1 and U_2 are significantly lower.

Furthermore, GARCH (1, 1) model evidenced that the stock prices of all companies in the manufacturing industry are predictable. Additionally, all applied models especially ARIMA and GARCH (1, 1) models have shown that a number of series including FTSE-350 general industrial index, BP.L and CNA.L in the primary industry, AHT.L in the service industry, SGE.L and SN.L in the quaternary industry are predictable. Their values of U_1 are close to zero and U_2 are less than 1 for these series. Moreover, MAPEs are significantly low for these series.

Nevertheless, exponential smoothing techniques evidence that most of the series are not predictable except three series including BATS.L and BKG.L in the manufacturing industry and AV.L in the service industry. As a result, exponential smoothing techniques reveal through MAPE, Theil U_1 and U_2 that stock prices of all 19 series are not predictable.

Therefore, it may be claimed that the developed stock market, the London Stock Exchange is not weak-form efficient for the period tested when prediction is made on the basis of industrial categories.

7.2.4 Objective 4

The fourth objective was to estimate different econometric models using technical analysis (ARIMA, GARCH, exponential smoothing techniques) and test their forecasting power. To achieve this objective, this study have chosen most commonly used and easy to understand econometric models of technical analysis. They are ARIMA and GARCH (1, 1) models and exponential smoothing techniques. This objective was achieved by analysing the forecast errors from these models and techniques that were applied to all 20 series in four different industries, the FTSE-all share index and FTSE-350 general industrial index.

The application of ARIMA model reveals that 11 out of 22 series are predictable. This model also documents that stock prices of all 5 series from the manufacturing industry and 5 more series from all other industries and FTSE-350 general industrial index are predictable. Their MAPEs are significantly lower compare to those from other models and techniques. Theil U_1 are close zero and U_2 are less than 1. However, the forecast benchmarks of evaluation statistics are significantly higher for all remaining 11 series including FTSE-all share index, ANTO.L, SVT.L and JMAT.L in the primary industry, all 5 series in the service industry and AZN.L and SHP.L in the quaternary industry and thus, they are not predictable.

GARCH (1, 1) model shows through MAPE, Theil U_1 and U_2 that 14 series are unpredictable as their values are considerably higher and naive model performs better for those series. Thus, these series are not predictable. The remaining 8 series including FTSE-350 general industrial index, all five series in the manufacturing industry and SGE.L and SN.L in the quaternary industry are predictable as errors from their benchmarks are quite low. Their MAPEs are comparatively lower, Theil U_1 are close to zero and U_2 are less than 1. Both ARIMA and GARCH (1, 1) models explain that all the series in the manufacturing industry are predictable and thus, the manufacturing industry incorporates information slowly.

Both double and triple exponential smoothing techniques evidence that most of the series are not predictable except 3 series including BATS.L and BKG.L in the manufacturing industry and AV.L in the service industry. Furthermore, both exponential smoothing techniques show better predictability even than ARIMA and GARCH (1, 1) models for these series. Thus, exponential smoothing techniques reveal through MAPE, Theil U_1 and U_2 that stock prices of all 19 series are not predictable. However, double exponential smoothing technique performs better than triple exponential smoothing technique in this study.

On the basis of above findings and arguements, it could be concluded that ARIMA model is the best predictor among all applied models. GARCH (1, 1) model is better in prediction than exponential smoothing techniques. Furthermore, double exponential smoothing technique documents higher performance than triple exponential smoothing technique in this study.

7.2.5 Objective 5

In relation to the fifth objective, to compare the results from this study with findings from previous research and synthesize the entire research towards assessing market efficiency and the ability of forecasting models using technical analysis.

This study found that stock prices of the London Stock Exchange do not move randomly over the period tested. Furthermore, this study evidenced that both ARIMA and GARCH (1, 1) models could predict stock prices for all series in the manufacturing industry. Contrary to that, the same models claim that most of the series of the service industry are unpredictable. Moreover, exponential smoothing techniques revealed that a few series in the manufacturing industry are highly predictable.

Therefore, this study supports that stock prices of the LSE are predictable on industrial sectors. The findings of this study are similar with the results from studies conducted by Summers, Griffiths, and Hudson (2004), Al-Loughani and Chappel (1997), McMillan, Speight, and Apgwilym (2000), Maris et al. (2004) and Otilia (2011). They claimed that stock prices of the London Stock Exchange do not behave randomly and returns are predictable from the application of technical analysis.

However, contradictory results found from the studies conducted by Hudson, Dempsey, and Keasey (1996), Lee (1992), Lee (1992), Choudhry (1994), Chan et al. (1997), Worthington and Higgs (2006), Andrews and Hellen (2010), Adebayo (2013), Smith (2012) and Ahmad et al. (2017) who claimed that the London Stock Exchange is strongly weak-form efficient.

On the basis of above analysis of results and arguments, it could be concluded that results from the technical analysis in the same stock market (the London Stock Exchange) are contradictory. All the results have come through econometric models of technical analysis. No economic model can be a perfect description of reality. The same models applied for the same market, however, the results are contradictory and polemic. Only one difference is found which is time period of study. All the studies have been performed for the different sample periods. Therefore, it could be argued that the UK stock market is weak-form efficient for a few time periods and weak-form inefficient for other time periods. History repeats itself.

Therefore, it could be argued that a developed stock market goes through different states of efficiency, which is relevant with adaptive market hypothesis. Ito and Sugiyama (2009) and Lim et al. (2013) argue that markets must go through periods of efficiency and inefficiency. This could be due to macroeconomical and industry specific factors and investors' actions.

There are some restrictions that have impeded the research from attaining the research aim entirely. The identified limitations of this research are discussed in the next section.

B.7.3 Limitations of this research

The acknowledgement of limitations in research benefits and makes suggestions for further research. Limitations exert a significant impact on the results of research and its conclusion. Therefore, this section explains and critically appraises the impact of the limitations of this research, which include the following:

i. The results of the research are limited to the industrial sectors of the LSE.

ii. This study did not consider transaction costs. Therefore, the estimation of the actual returns from prediction was ignored. It was only investigated the prediction power of technical analysis and forecastability of different industries.

After synthesising the whole study and acknowledging its limitations, the next section provides recommendations for further research.

B.7.4 Recommendations for further research

This research does not stop here. This research is a new and ongoing research. It opens a new avenue for further research that more research will be undertaken in the future by considering other secors of the LSE and other stock markets in different periods.

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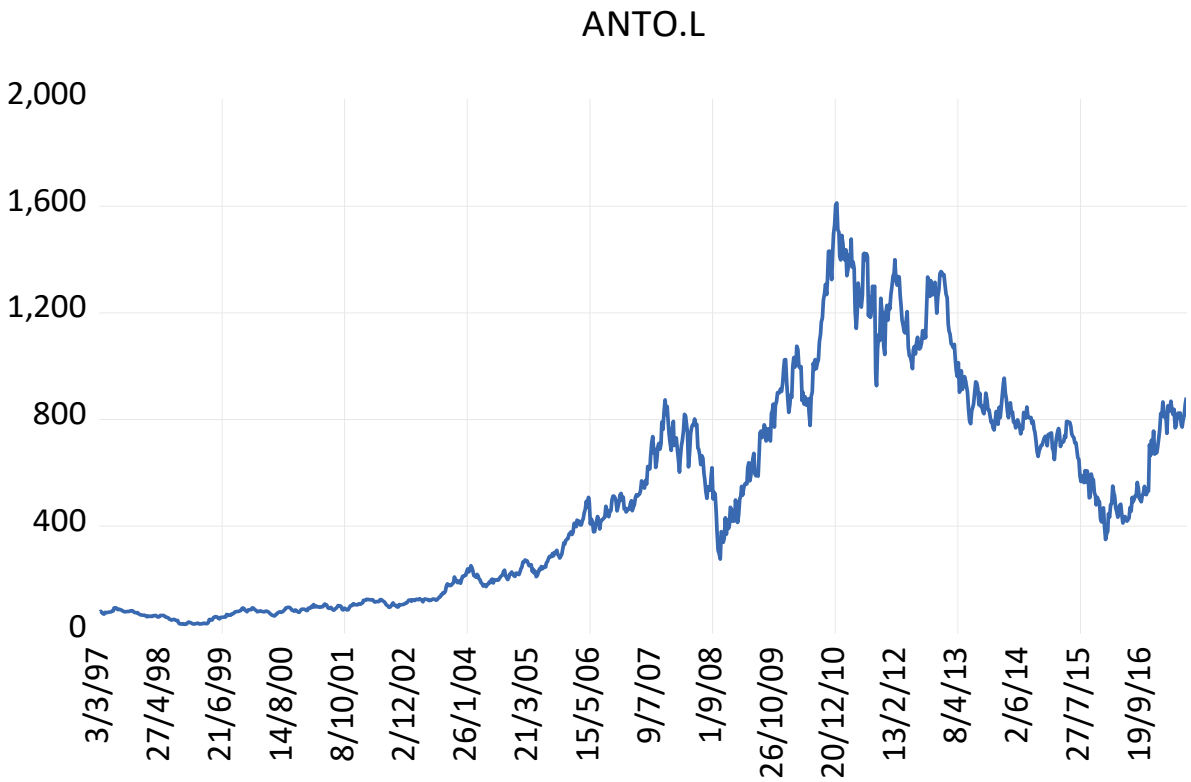
Appendices:

(i) Visual inspection of series:

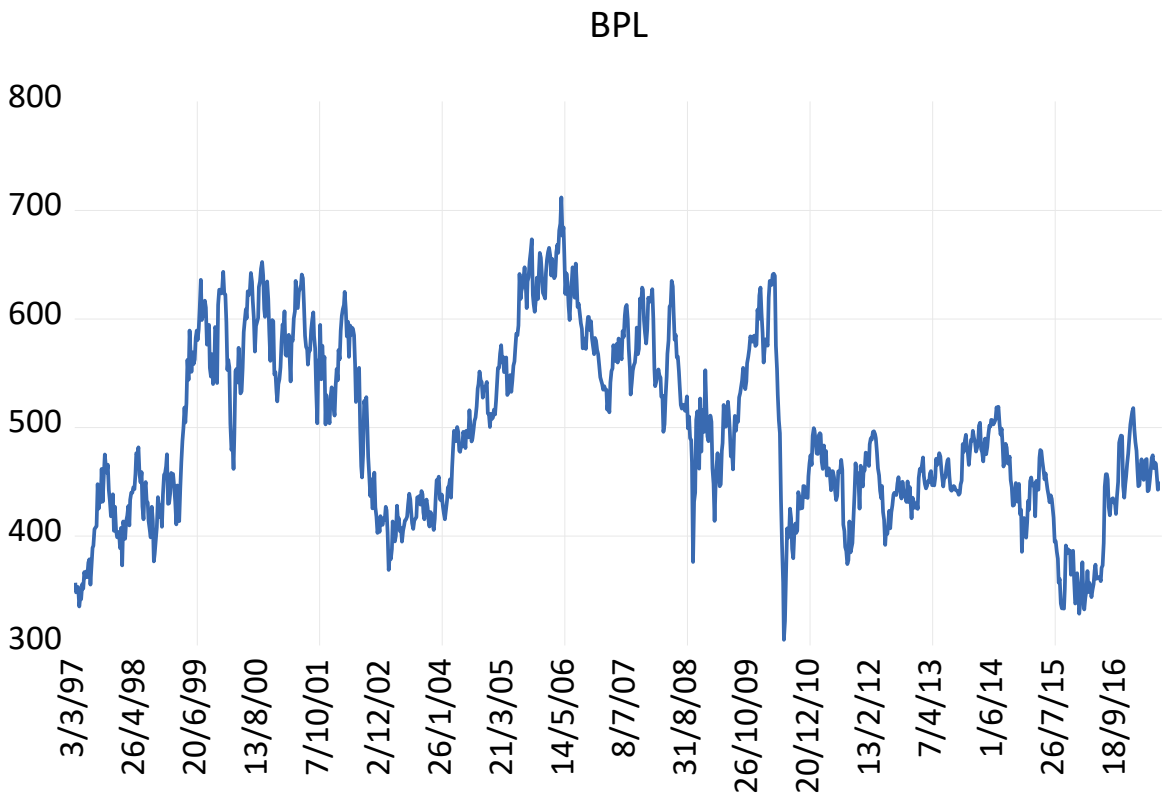
1. FTSE-350 General Industrial Index

The primary industry

2. ANTO.L



3. BP.L


BPL
800
700
600
500
400
300
3/3/97
26/4/98
20/6/99
13/8/00
7/10/01
2/12/02
26/1/04
21/3/05
14/5/06
8/7/07
31/8/08
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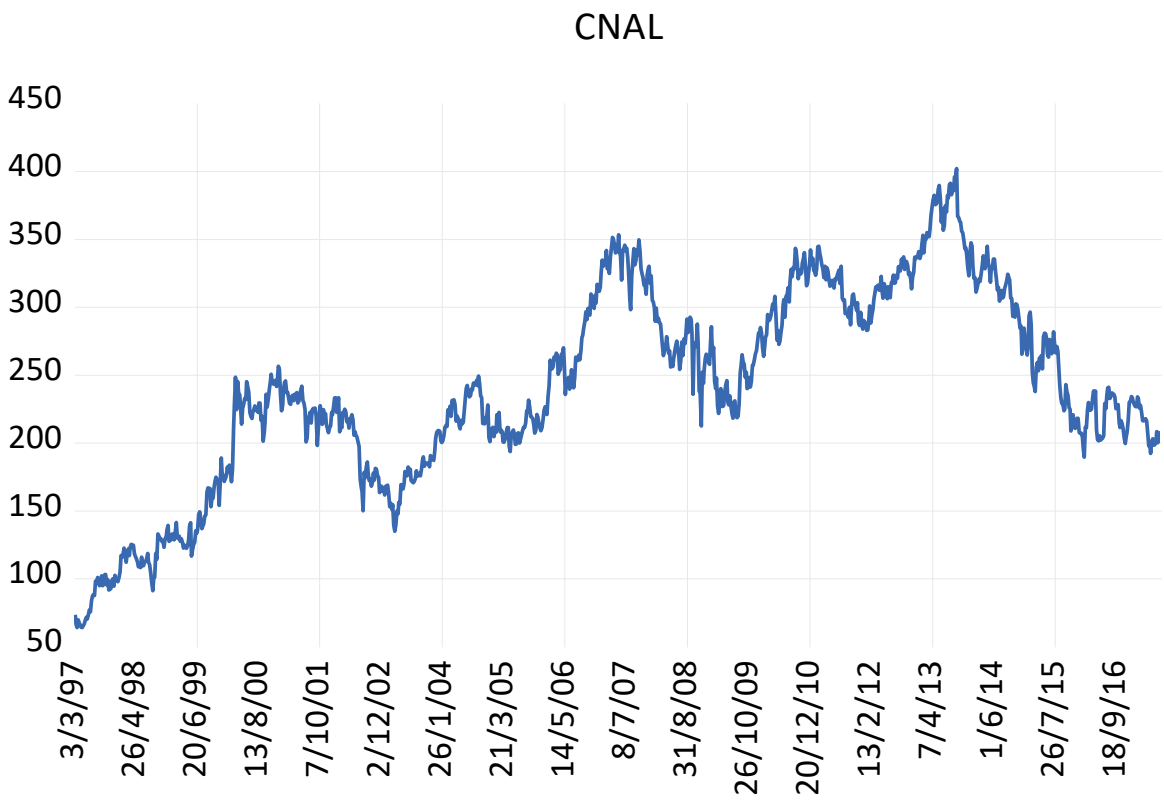
13/2/12
7/4/13
1/6/14
26/7/15
18/9/16

4. CNA.L


CNAL
450
400
350
300
250
200
150
100
50
3/3/97
26/4/98
20/6/99
13/8/00
7/10/01
2/12/02
26/1/04
21/3/05
14/5/06
8/7/07
31/8/08
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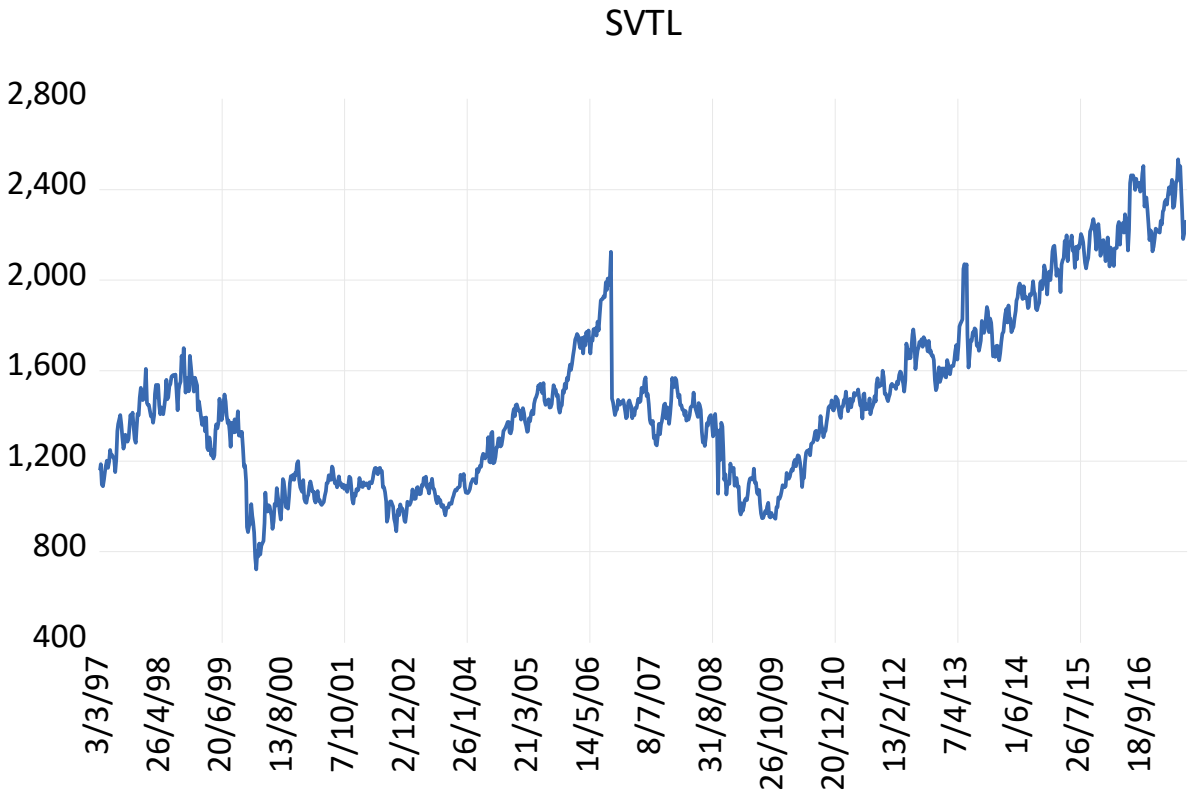
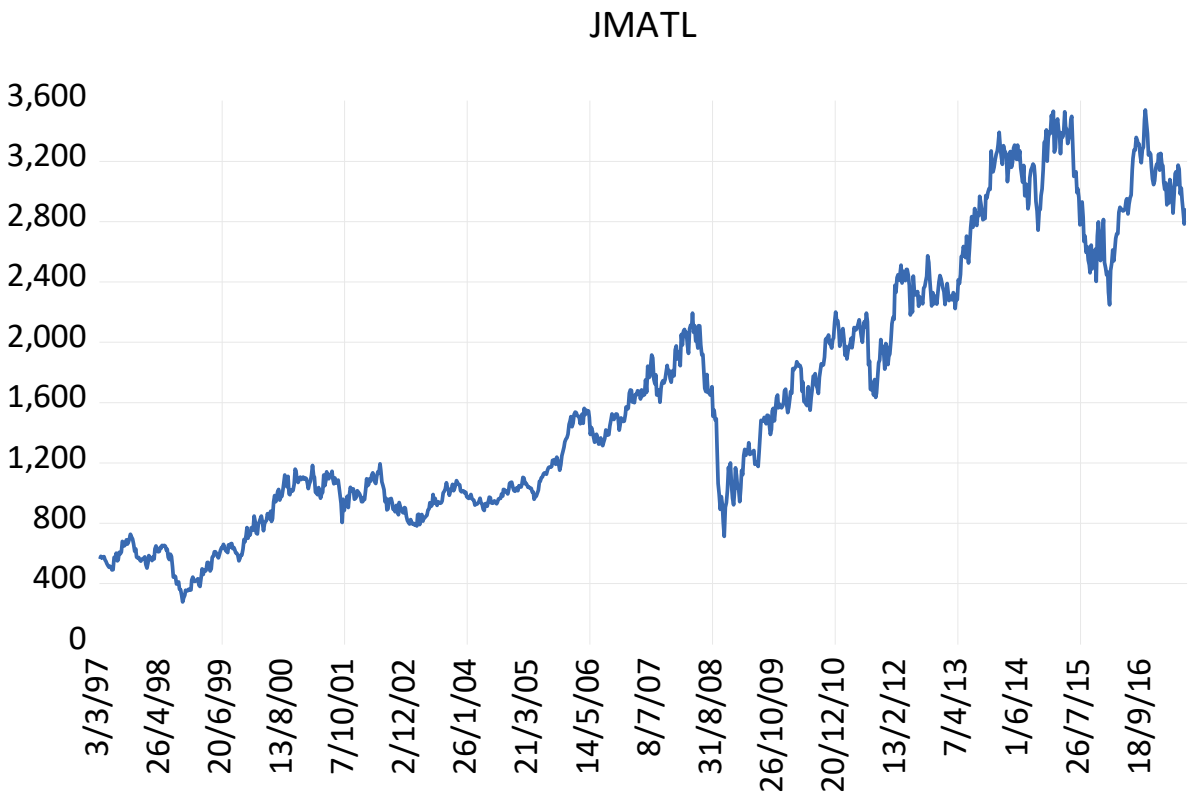
1/6/14
26/7/15
18/9/16

5. SVT.L



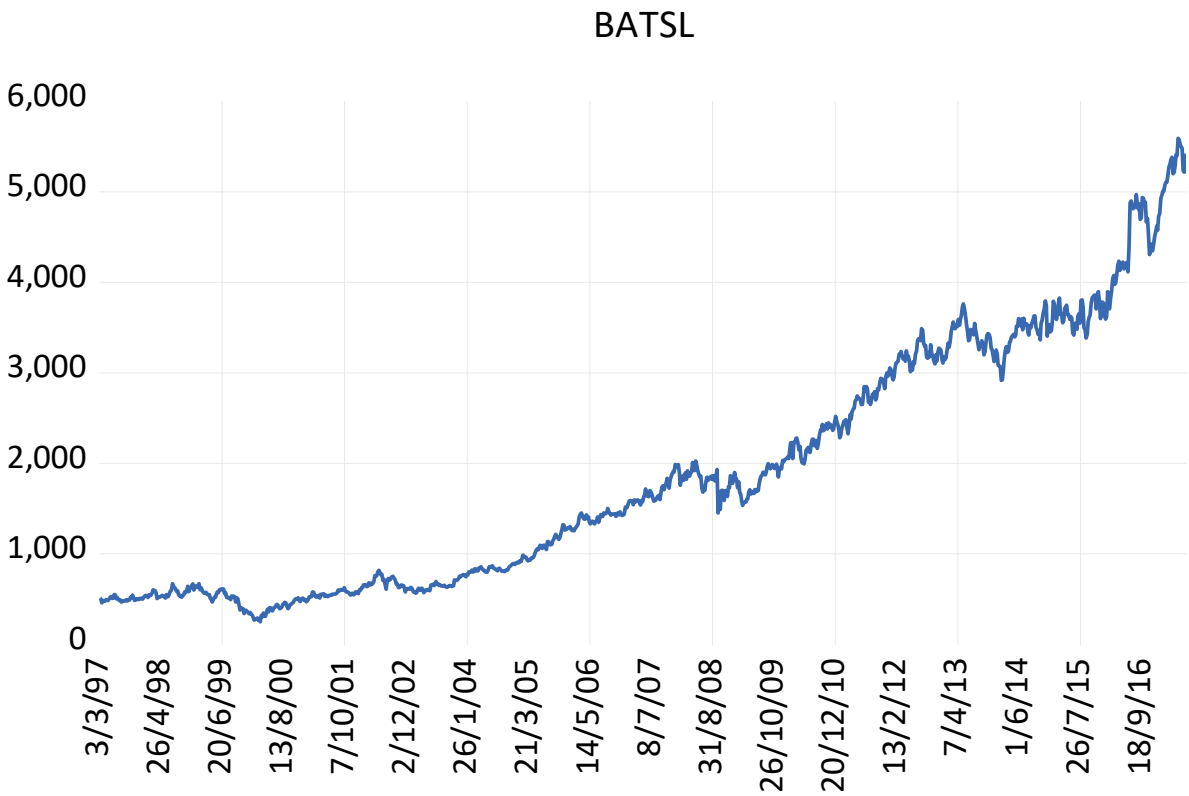
6. JMAT.L



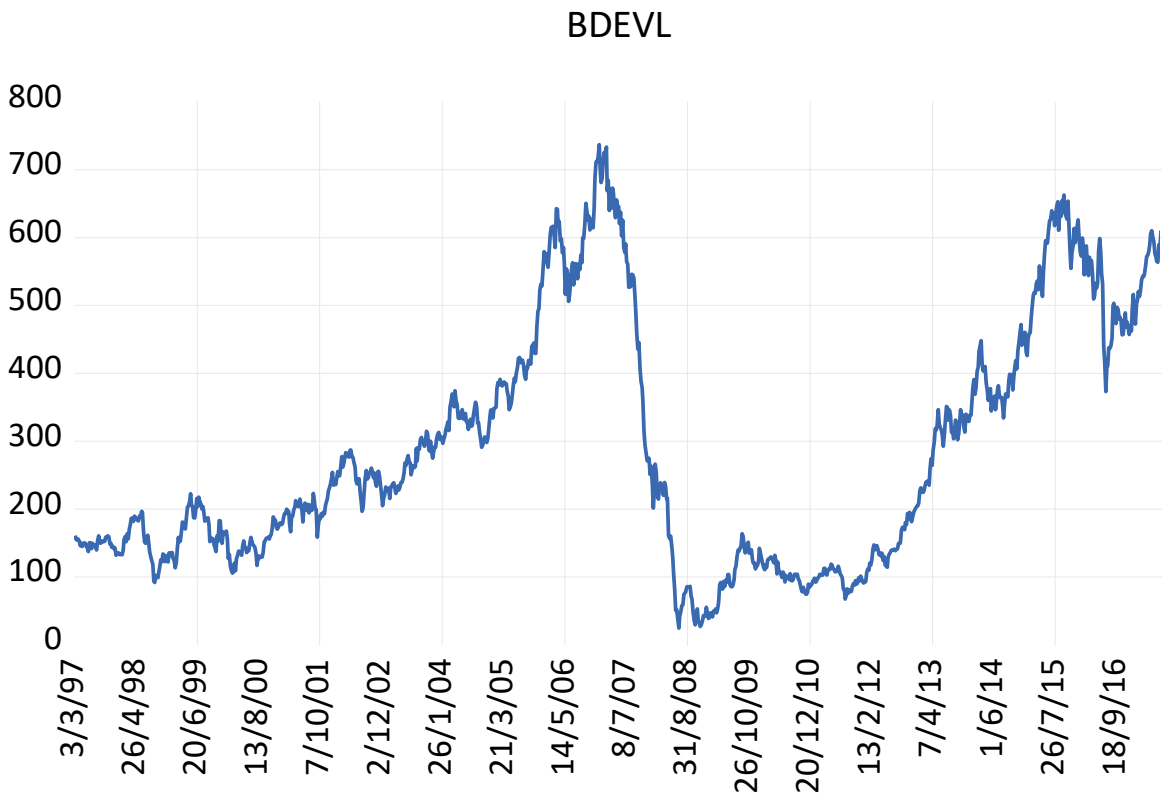
The manufacturing industry:

7. **ABF.L**

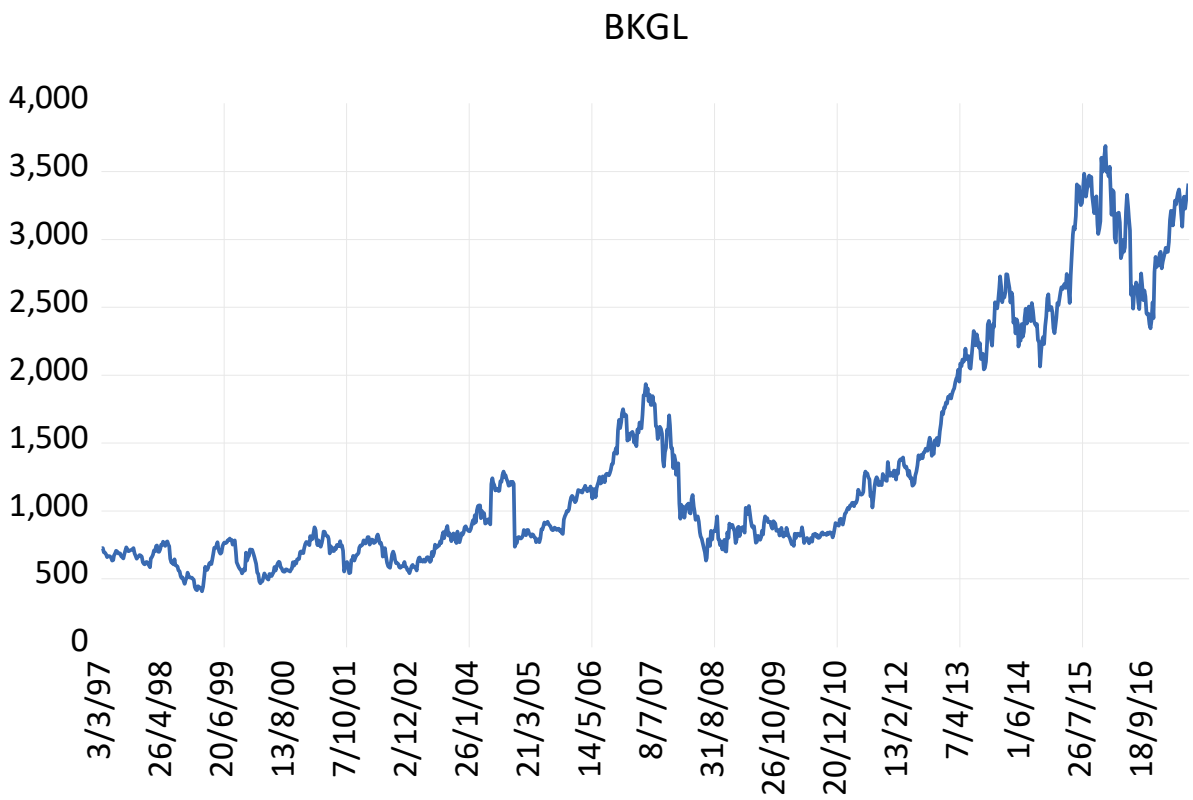
8. **BATS.L**



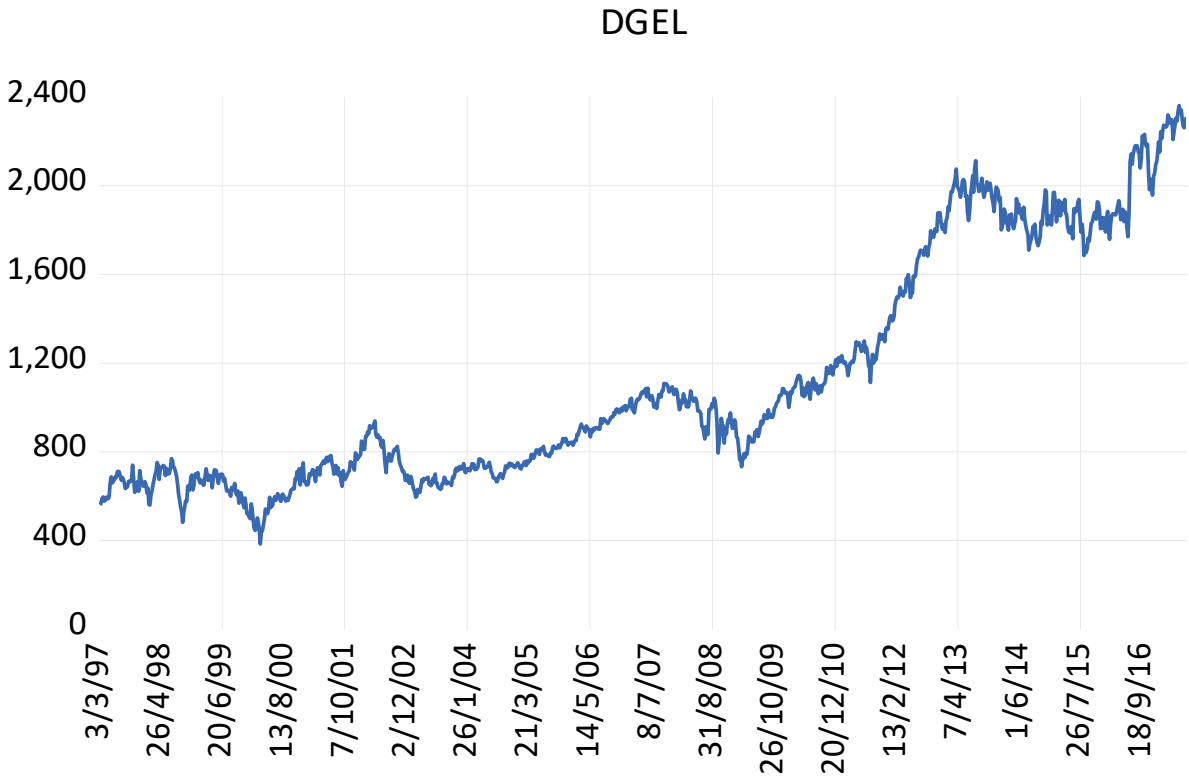
9. BDEV.L



10. BKG.L

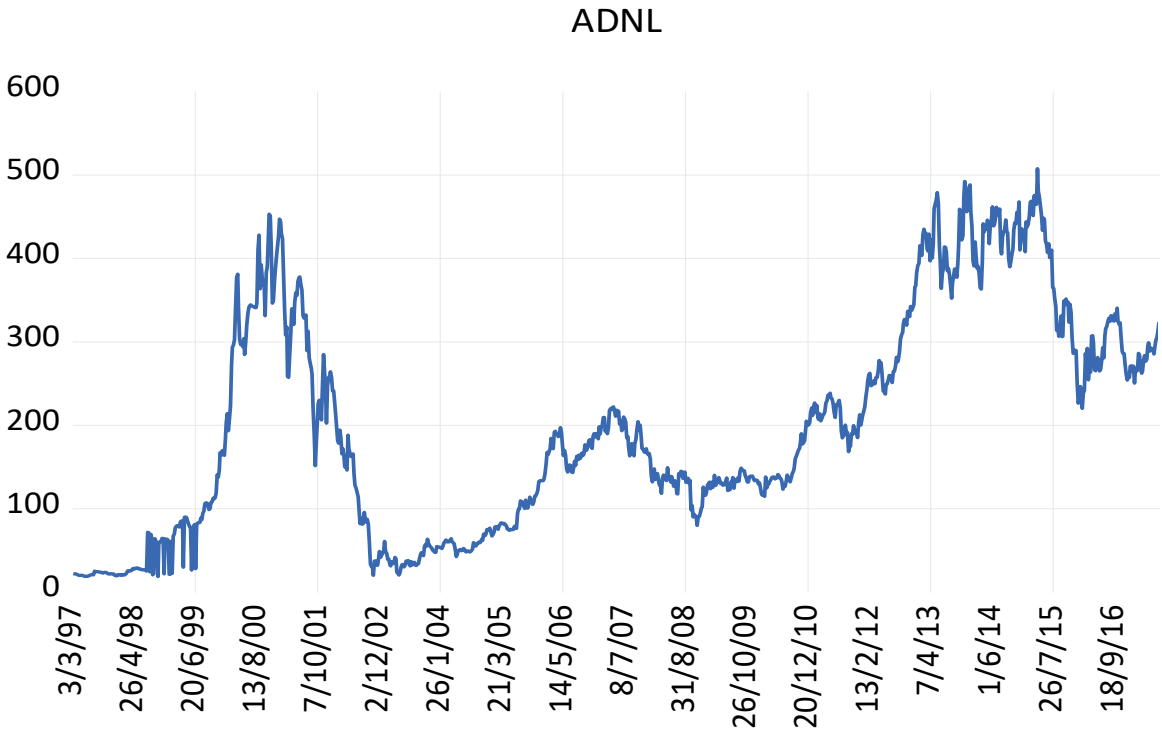


11. DGE.L

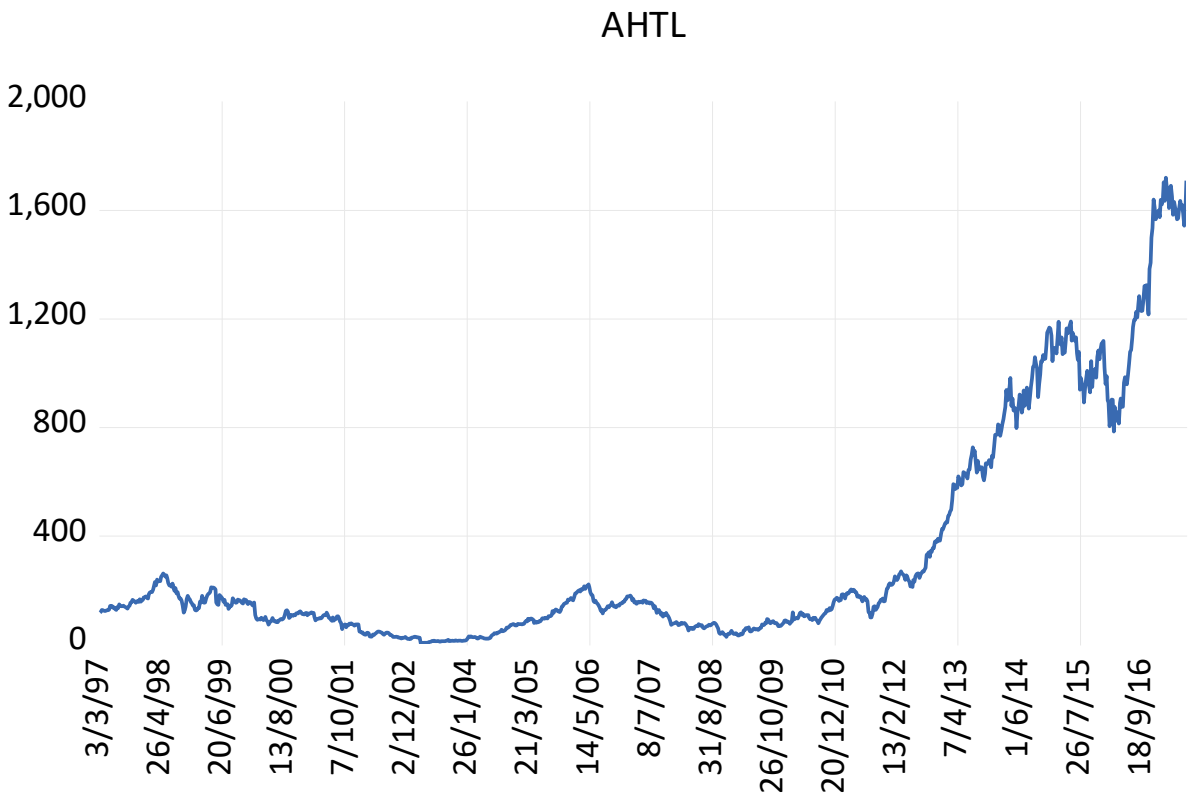


The service industry

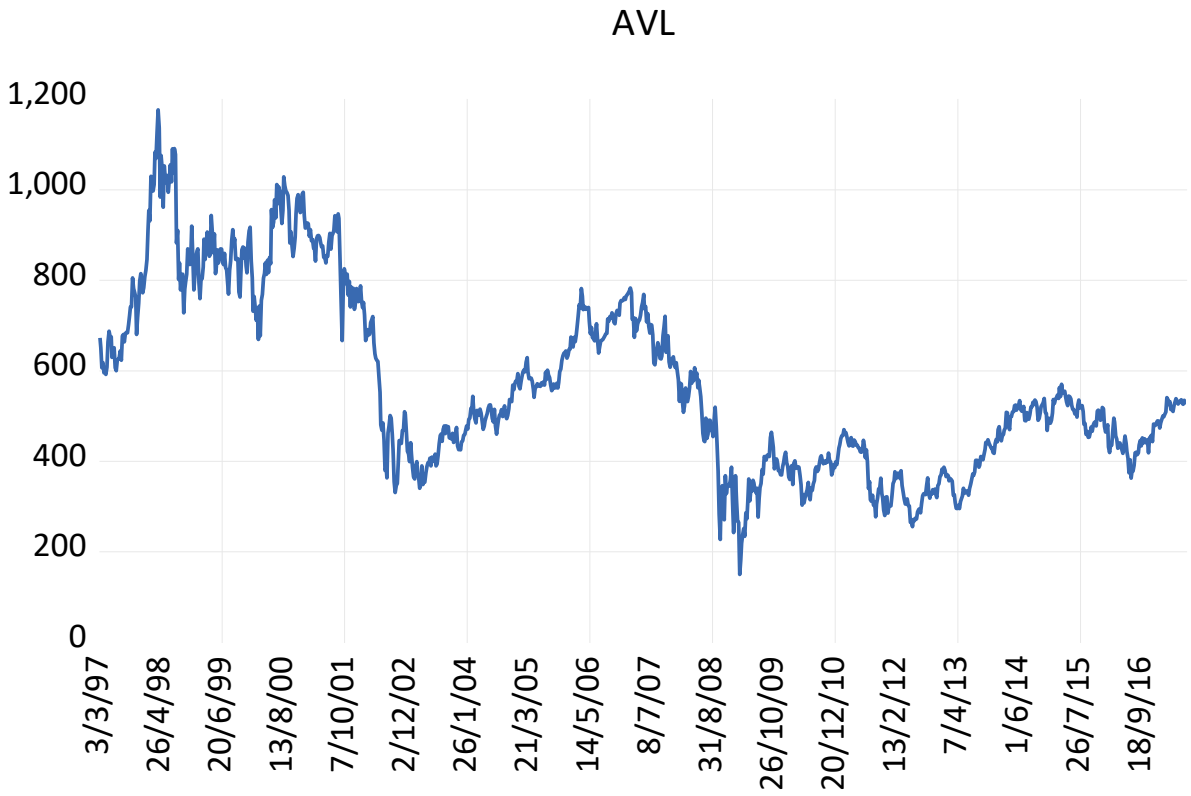
12. ADN.L



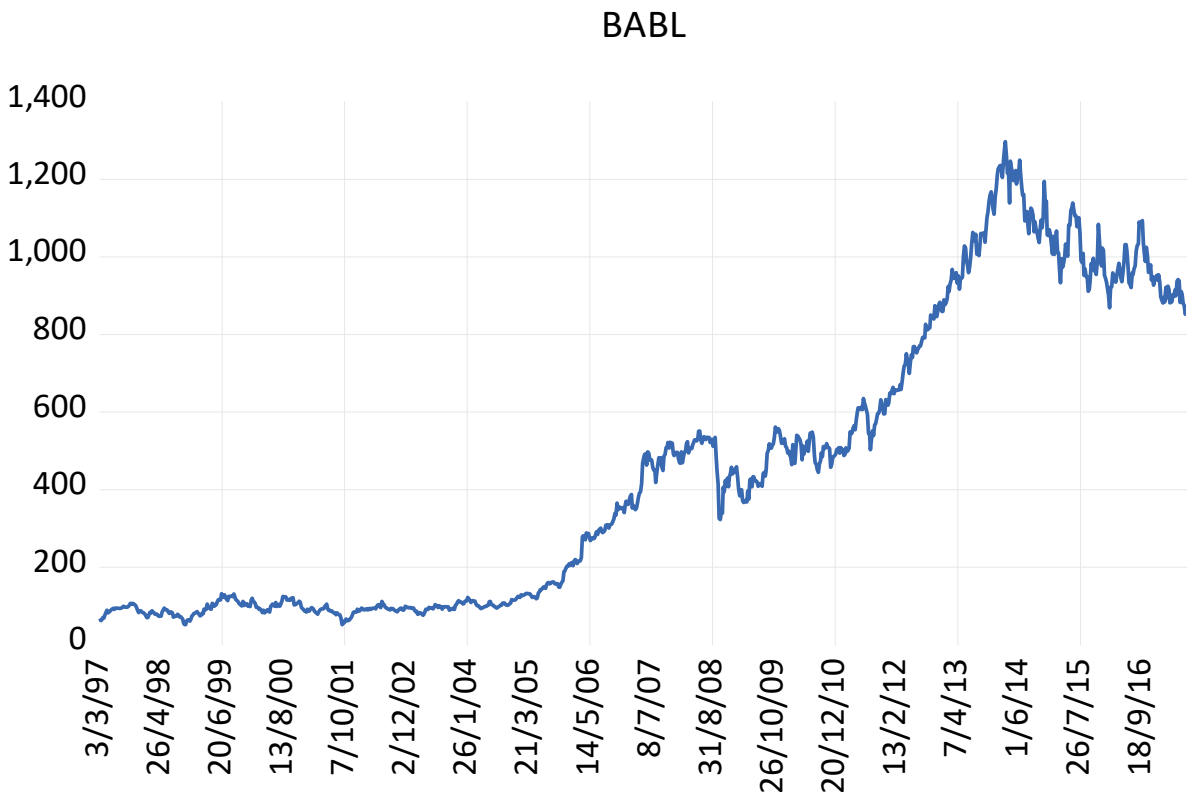
13. AHT.L



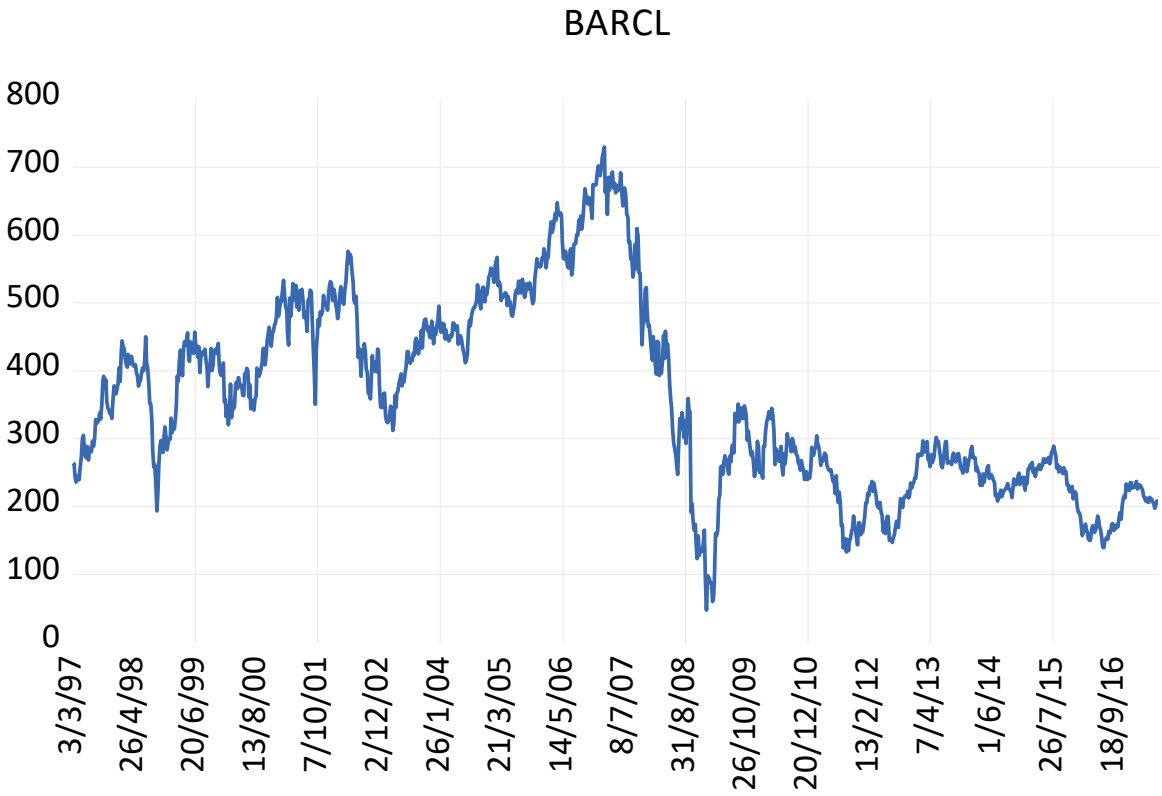
14. AV.L



15. BAB.L

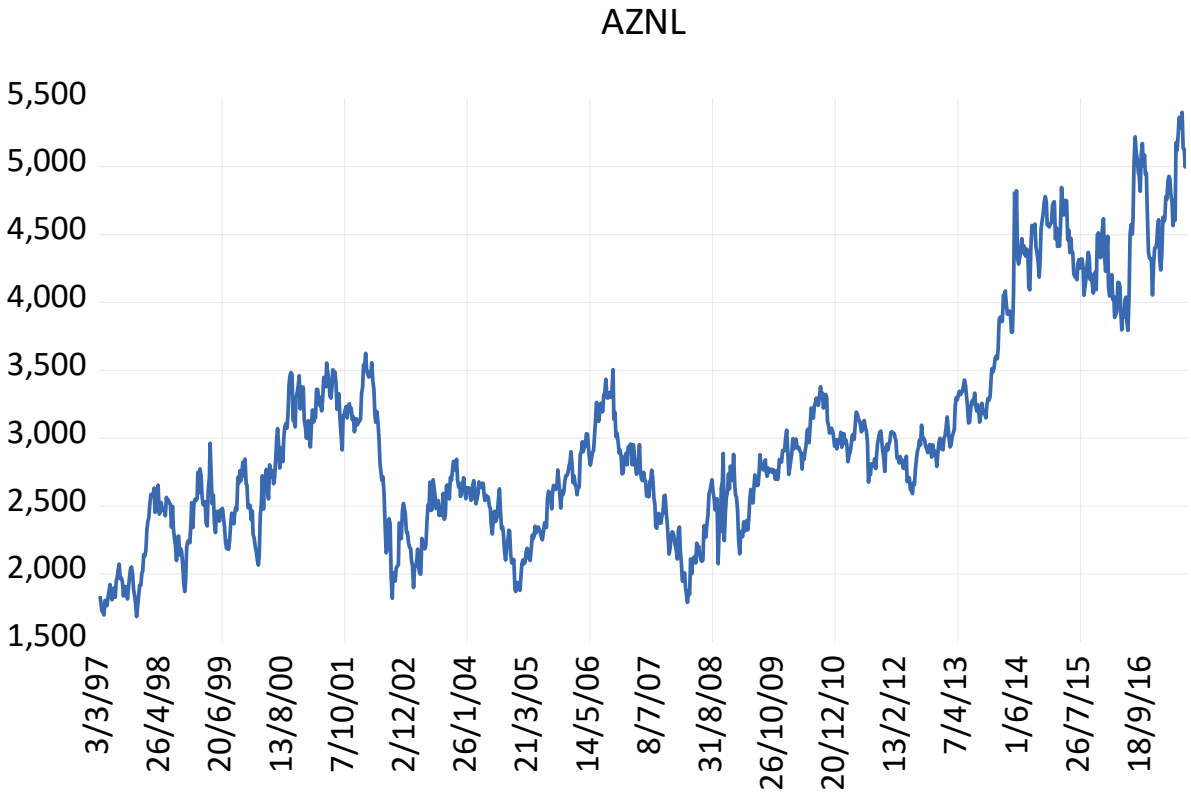


16. BARC.L

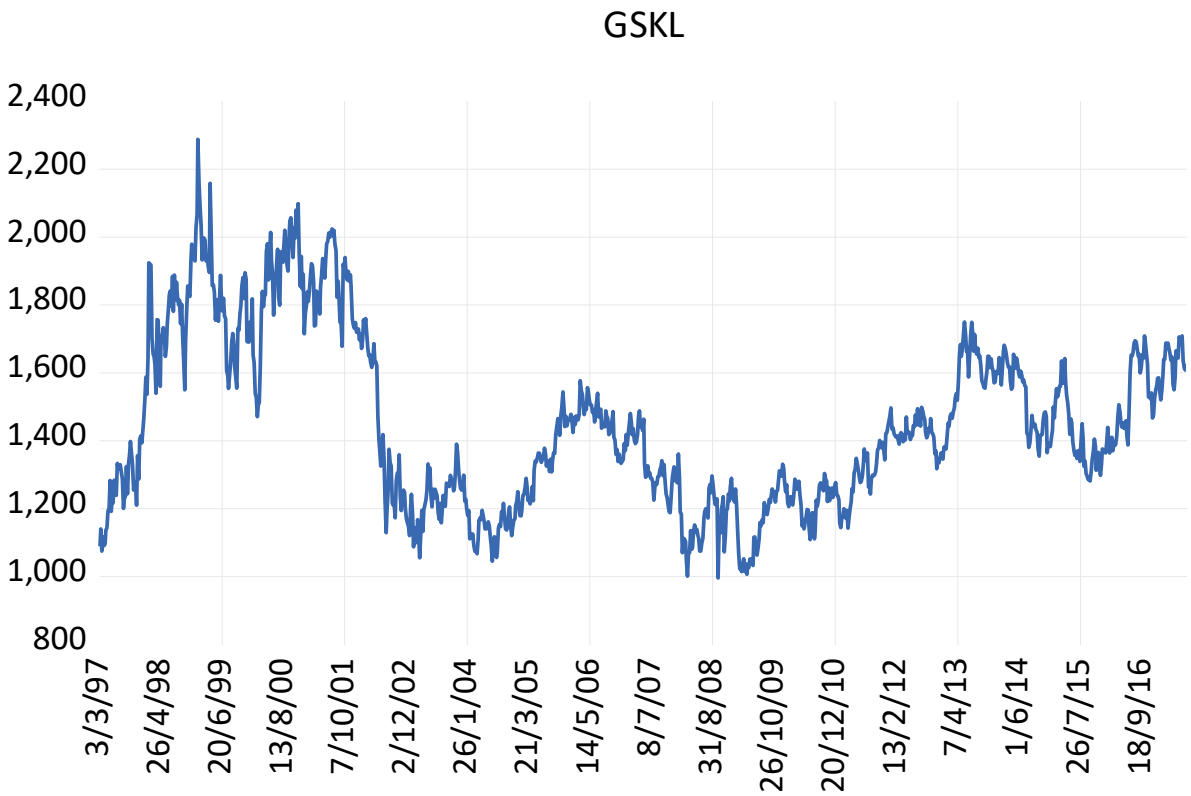


The quaternary industry

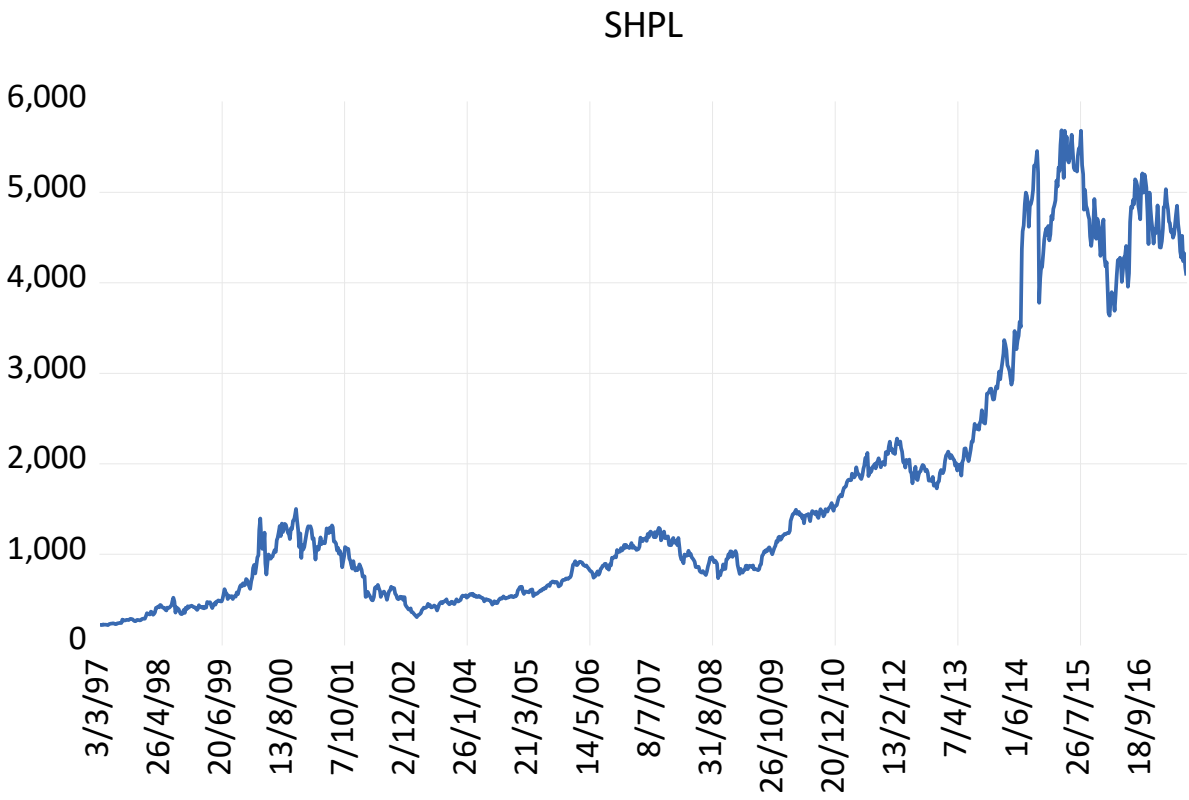
17. AZN.L



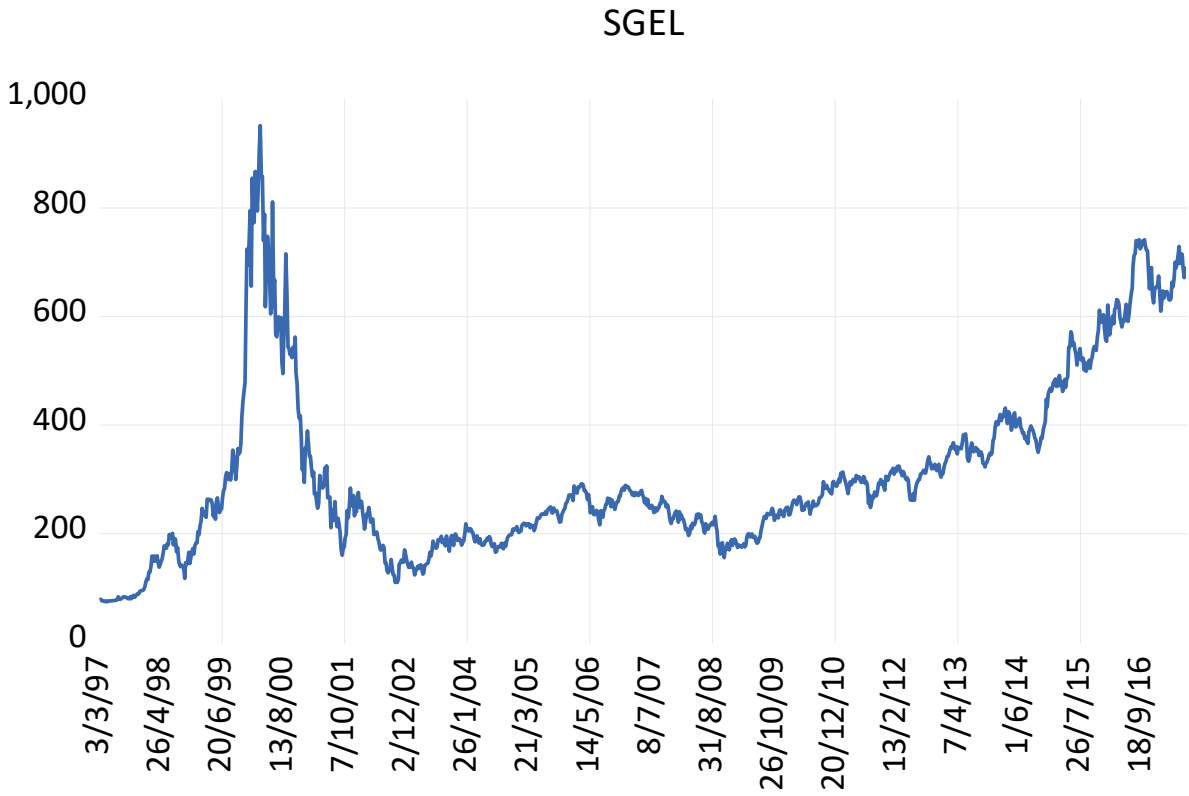
18. GSK.L



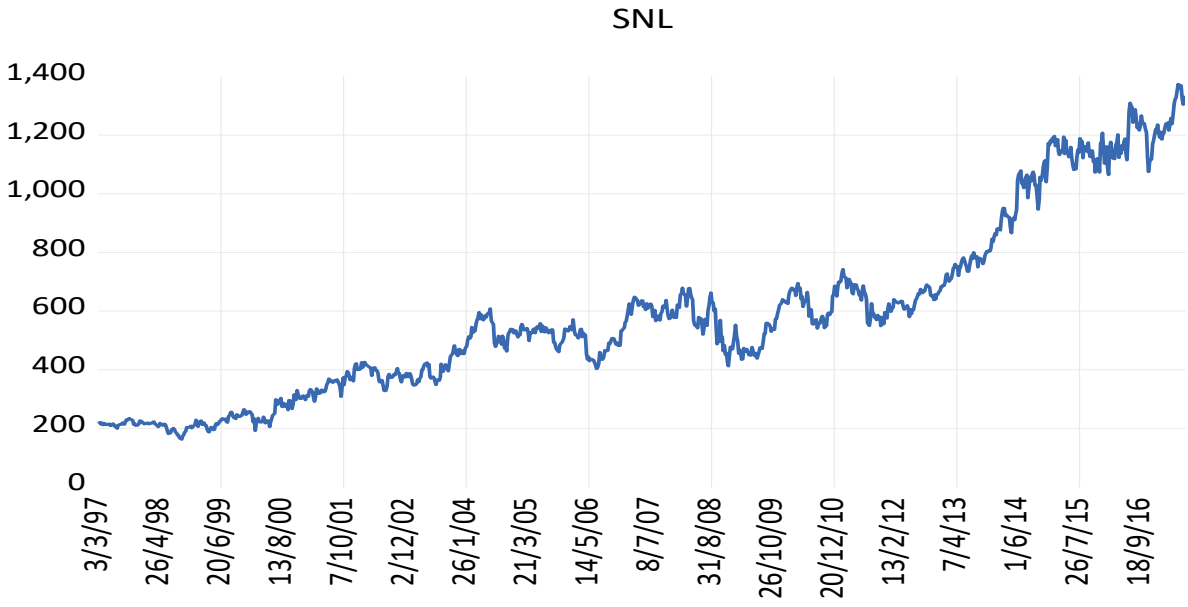
19. SHP.L



20. SGE.L



21. SN.L



(ii) Seasonality detection through Friedman test

1. FTSE-ALL SHARE INDEX

Descriptive Statistics

	N	Mean	Std. Deviation	Minimum	Maximum
Subsample1	266	2713.538939	296.7839811	2065.0200	3261.5701
Subsample2	266	2472.671283	453.5620288	1685.0000	3433.8601
Subsample3	266	2802.279512	375.8511083	1789.1300	3478.9900
Subsample4	266	3531.005151	270.1107143	2861.5200	4130.1499

Ranks

	Mean Rank
Subsample1	2.22
Subsample2	1.59
Subsample3	2.31
Subsample4	3.88

Test Statistics[a]

N	266
Chi-Square	456.122
df	3
Asymp. Sig.	.000

a. Friedman Test

2. FTSE-350 General Industrial Index:

Descriptive Statistics

	N	Mean	Std. Deviation	Minimum	Maximum
Industrialindex1	106	2550.781887	510.7953445	1548.7600	3402.0800
Industrialindex2	106	3210.208019	414.1186793	2428.5200	4019.7000
Industrialindex3	106	4208.101132	224.8681758	3725.1800	4618.8000
Industrialindex4	106	5037.858208	682.3413686	4098.8500	6212.6900

Ranks

	Mean Rank
Industrialindex1	1.00
Industrialindex2	2.00
Industrialindex3	3.14
Industrialindex4	3.86

Test Statistics[a]

N	106
Chi-Square	302.547
df	3
Asymp. Sig.	.000

a. Friedman Test

The primary industry

3. ANTO.L

Descriptive Statistics

	N	Mean	Std. Deviation	Minimum	Maximum
ANTO.L1	266	76.0327	21.80252	32.00	126.20
ANTO.L2	266	262.0765	133.27736	96.00	570.00
ANTO.L3	266	905.2613	322.37683	276.50	1612.00
ANTO.L4	266	781.0203	231.32875	350.60	1355.00

Ranks

	Mean Rank
ANTO.L1	1.00
ANTO.L2	2.03
ANTO.L3	3.56
ANTO.L4	3.42

Test Statistics[a]

N	266
Chi-Square	707.310
df	3
Asymp. Sig.	.000

a. Friedman Test

4. BP.L

Descriptive Statistics

	N	Mean	Std. Deviation	Minimum	Maximum
BP.L1	266	514.3899	86.60525	335.25	652.50
BP.L2	266	525.9765	85.25301	369.00	712.00
BP.L3	266	503.5066	70.98460	304.60	641.80
BP.L4	266	440.0437	44.65011	328.70	519.20

Ranks

	Mean Rank
BP.L1	2.69
BP.L2	2.63
BP.L3	2.77
BP.L4	1.91

Test Statistics[a]

N	266
Chi-Square	76.862
df	3
Asymp. Sig.	.000

a. Friedman Test

5. CNA.L

Descriptive Statistics

	N	Mean	Std. Deviation	Minimum	Maximum
CNA.L1	266	165.5661	57.89209	64.08	256.49
CNA.L2	266	222.4416	47.77904	135.02	351.43
CNA.L3	266	291.9190	33.86027	212.50	353.43
CNA.L4	266	283.4405	59.29125	189.60	402.20

Ranks

	Mean Rank
CNA.L1	1.39
CNA.L2	2.30
CNA.L3	3.40
CNA.L4	2.91

Test Statistics[a]

N	266
Chi-Square	356.459
df	3
Asymp. Sig.	.000

a. Friedman Test

6. SVT.L

Descriptive Statistics

	N	Mean	Std. Deviation	Minimum	Maximum
SVT.L1	266	1229.2549	210.32564	721.50	1699.50
SVT.L2	266	1326.6615	272.55803	890.25	2125.50
SVT.L3	266	1330.1974	194.65750	945.50	1782.00
SVT.L4	266	2006.7594	259.95395	1513.00	2534.00

Ranks

	Mean Rank
SVT.L1	1.85
SVT.L2	2.06
SVT.L3	2.09
SVT.L4	4.00

Test Statistics[a]

N	266
Chi-Square	482.072
df	3
Asymp. Sig.	.000

a. Friedman Test

7. JMAT.L

Descriptive Statistics

	N	Mean	Std. Deviation	Minimum	Maximum
JMAT.L1	266	750.7354	240.39129	277.62	1183.81
JMAT.L2	266	1138.2797	249.26480	783.09	1683.52
JMAT.L3	266	1756.0751	368.73111	713.95	2511.14
JMAT.L4	266	2904.9942	366.11776	2223.00	3540.00

Ranks

	Mean Rank
JMAT.L1	1.00
JMAT.L2	2.05
JMAT.L3	2.95
JMAT.L4	4.00

Test Statistics[a]

N	266
Chi-Square	783.162
df	3
Asymp. Sig.	.000

a. Friedman Test

The manufacturing industry

8. ABF.L

Descriptive Statistics

	N	Mean	Std. Deviation	Minimum	Maximum
ABF.L1	266	512.0078	108.03783	294.50	732.96
ABF.L2	266	696.3383	125.79306	474.00	945.50
ABF.L3	266	925.0733	161.68491	611.50	1231.00
ABF.L4	266	2573.6752	622.26510	1234.00	3516.00

Ranks

	Mean Rank
ABF.L1	1.36
ABF.L2	1.67
ABF.L3	2.97
ABF.L4	4.00

Test Statistics[a]

N	266
Chi-Square	709.674
df	3
Asymp. Sig.	.000

a. Friedman Test

9. BATS.L

Descriptive Statistics

	N	Mean	Std. Deviation	Minimum	Maximum
BATS.L1	266	513.1525	87.96396	249.25	680.00
BATS.L2	266	986.2162	322.25384	565.00	1596.00
BATS.L3	266	2172.3346	479.03872	1450.00	3244.00
BATS.L4	266	3828.6266	657.35336	2916.00	5591.00

Ranks

	Mean Rank
BATS.L1	1.02
BATS.L2	1.98
BATS.L3	3.00
BATS.L4	4.00

Test Statistics[a]

N	266
Chi-Square	793.272
df	3
Asymp. Sig.	.000

a. Friedman Test

10. BDEV.L

Descriptive Statistics

	N	Mean	Std. Deviation	Minimum	Maximum
BDEV.L1	266	167.8797	36.57672	91.70	282.96
BDEV.L2	266	398.8602	150.37782	196.50	737.08
BDEV.L3	266	151.5297	133.16207	24.60	645.68
BDEV.L4	266	427.5665	141.80370	135.70	662.50

Ranks

	Mean Rank
BDEV.L1	1.82
BDEV.L2	3.26
BDEV.L3	1.50
BDEV.L4	3.42

Test Statistics[a]

N	266
Chi-Square	461.129
df	3
Asymp. Sig.	.000

a. Friedman Test

11. BKG.L

Descriptive Statistics

	N	Mean	Std. Deviation	Minimum	Maximum
BKG.L1	266	655.7304	100.77246	408.00	880.00
BKG.L2	266	979.2105	305.47989	541.50	1855.00
BKG.L3	266	1042.1692	278.30312	634.50	1935.00
BKG.L4	266	2562.3910	573.65952	1335.00	3688.00

Ranks

	Mean Rank
BKG.L1	1.19
BKG.L2	2.44
BKG.L3	2.44
BKG.L4	3.93

Test Statistics[a]

N	266
Chi-Square	603.329
df	3
Asymp. Sig.	.000

a. Friedman Test

12. DGE.L

Descriptive Statistics

	N	Mean	Std. Deviation	Minimum	Maximum
DGE.L1	266	658.8302	86.20112	384.00	918.00
DGE.L2	266	795.5132	113.07465	595.00	1068.50
DGE.L3	266	1100.5094	184.59799	733.00	1599.00
DGE.L4	266	1935.0695	166.26788	1594.00	2361.50

Ranks

	Mean Rank
DGE.L1	1.14
DGE.L2	1.86
DGE.L3	3.00
DGE.L4	4.00

Test Statistics[a]

N	266
Chi-Square	760.647
df	3
Asymp. Sig.	.000

a. Friedman Test

The service industry

13. ADN.L

Descriptive Statistics

	N	Mean	Std. Deviation	Minimum	Maximum
ADN.L1	266	164.0728	138.54716	18.82	453.01
ADN.L2	266	98.6412	57.60858	20.27	222.00
ADN.L3	266	166.5117	44.57206	80.00	277.80
ADN.L4	266	361.5629	73.11928	220.40	507.50

Ranks

	Mean Rank
ADN.L1	2.27
ADN.L2	1.34
ADN.L3	2.60
ADN.L4	3.79

Test Statistics[a]

N	266
Chi-Square	492.212
df	3
Asymp. Sig.	.000

a. Friedman Test

14. AHT.L

Descriptive Statistics

	N	Mean	Std. Deviation	Minimum	Maximum
AHT.L1	266	134.9100	48.29966	29.52	262.43
AHT.L2	266	80.8627	62.72370	4.15	222.07
AHT.L3	266	116.0205	59.97049	29.25	270.80
AHT.L4	266	947.2136	369.51924	246.00	1721.00

Ranks

	Mean Rank
AHT.L1	2.18
AHT.L2	1.51
AHT.L3	2.32
AHT.L4	4.00

Test Statistics[a]

N	266
Chi-Square	538.408
df	3
Asymp. Sig.	.000

a. Friedman Test

15. AV.L

Descriptive Statistics

	N	Mean	Std. Deviation	Minimum	Maximum
AV.L1	266	842.4072	116.97803	592.14	1176.93
AV.L2	266	557.2975	119.81466	331.01	782.93
AV.L3	266	422.6105	122.17427	150.15	769.14
AV.L4	266	449.8500	74.55847	272.60	570.00

Ranks

	Mean Rank
AV.L1	3.85
AV.L2	2.63
AV.L3	1.68
AV.L4	1.83

Test Statistics[a]

N	266
Chi-Square	471.821
df	3
Asymp. Sig.	.000

a. Friedman Test

16. BAB.L

Descriptive Statistics

	N	Mean	Std. Deviation	Minimum	Maximum
BAB.L1	266	91.7063	16.57418	51.69	131.91
BAB.L2	266	164.8012	94.98036	75.83	467.74
BAB.L3	266	516.2573	82.95152	322.70	768.84
BAB.L4	266	1002.0247	114.82049	752.53	1296.98

Ranks

	Mean Rank
BAB.L1	1.20
BAB.L2	1.80
BAB.L3	3.00
BAB.L4	4.00

Test Statistics[a]

N	266
Chi-Square	747.798
df	3
Asymp. Sig.	.000

a. Friedman Test

17. BARC.L

Descriptive Statistics

	N	Mean	Std. Deviation	Minimum	Maximum
BARC.L1	266	400.6123	76.43413	193.52	533.46
BARC.L2	266	508.3896	94.51875	312.23	729.76
BARC.L3	266	296.8898	134.53196	47.30	691.89
BARC.L4	266	229.3230	39.69618	139.25	301.88

Ranks

	Mean Rank
BARC.L1	2.89
BARC.L2	3.69
BARC.L3	2.09
BARC.L4	1.33

Test Statistics[a]

N	266
Chi-Square	496.480
df	3
Asymp. Sig.	.000

a. Friedman Test

The quaternary industry

18. AZN.L

Descriptive Statistics

	N	Mean	Std. Deviation	Minimum	Maximum
AZN.L1	266	2636.7981	519.53192	1686.12	3625.00
AZN.L2	266	2580.7068	364.52174	1822.00	3556.00
AZN.L3	266	2709.3346	341.62448	1790.00	3379.50
AZN.L4	266	4044.6222	686.81163	2771.50	5401.00

Ranks

	Mean Rank
AZN.L1	2.06
AZN.L2	1.86
AZN.L3	2.11
AZN.L4	3.97

Test Statistics[a]

N	266
Chi-Square	465.609
df	3
Asymp. Sig.	.000

a. Friedman Test

19. GSK.L

Descriptive Statistics

	N	Mean	Std. Deviation	Minimum	Maximum
GSK.L1	266	1729.80639	248.469411	1075.000	2288.000
GSK.L2	266	1308.07143	140.218316	1045.000	1686.000
GSK.L3	266	1240.03571	108.994442	995.000	1497.000
GSK.L4	266	1516.44737	119.381666	1281.500	1749.500

Ranks

	Mean Rank
GSK.L1	3.64
GSK.L2	1.92
GSK.L3	1.40
GSK.L4	3.04

Test Statistics[a]

N	266
Chi-Square	498.191
df	3
Asymp. Sig.	.000

a. Friedman Test

20. SHP.L

Descriptive Statistics

	N	Mean	Std. Deviation	Minimum	Maximum
SHP.L1	266	692.2237	371.78957	217.00	1501.00
SHP.L2	266	640.7068	208.04549	306.30	1182.00
SHP.L3	266	1358.9117	438.73923	734.50	2278.00
SHP.L4	266	3803.8747	1240.92139	1729.00	5685.00

Ranks

	Mean Rank
SHP.L1	1.50
SHP.L2	1.50
SHP.L3	3.00
SHP.L4	4.00

Test Statistics[a]

N	266
Chi-Square	716.405
df	3
Asymp. Sig.	.000

a. Friedman Test

21. SGE.L

Descriptive Statistics

	N	Mean	Std. Deviation	Minimum	Maximum
SGE.L1	266	297.1889	208.38170	74.22	951.49
SGE.L2	266	209.0954	46.57789	110.46	292.18
SGE.L3	266	248.0037	41.08851	156.11	324.53
SGE.L4	266	483.2799	135.11954	281.82	741.50

Ranks

	Mean Rank
SGE.L1	2.15
SGE.L2	1.58
SGE.L3	2.41
SGE.L4	3.85

Test Statistics[a]

N	266
Chi-Square	447.325
df	3
Asymp. Sig.	.000

a. Friedman Test

22. SN.L

Descriptive Statistics

	N	Mean	Std. Deviation	Minimum	Maximum	Percentiles		
						25th	50th (Median)	75th
SN.L1	266	259.7610	66.04152	161.94	426.00	212.6670	229.3500	307.1250
SN.L2	266	477.8628	77.77626	327.50	648.00	405.8750	488.3750	536.1250
SN.L3	266	589.5882	70.00234	412.50	742.00	553.7500	597.2500	637.5000
SN.L4	266	1011.8859	211.28668	620.00	1374.00	786.0000	1086.5000	1176.2500

Ranks

	Mean Rank
SN.L1	1.00
SN.L2	2.17
SN.L3	2.84
SN.L4	4.00

Test Statistics[a]

N	266
Chi-Square	752.540
df	3
Asymp. Sig.	.000

a. Friedman Test

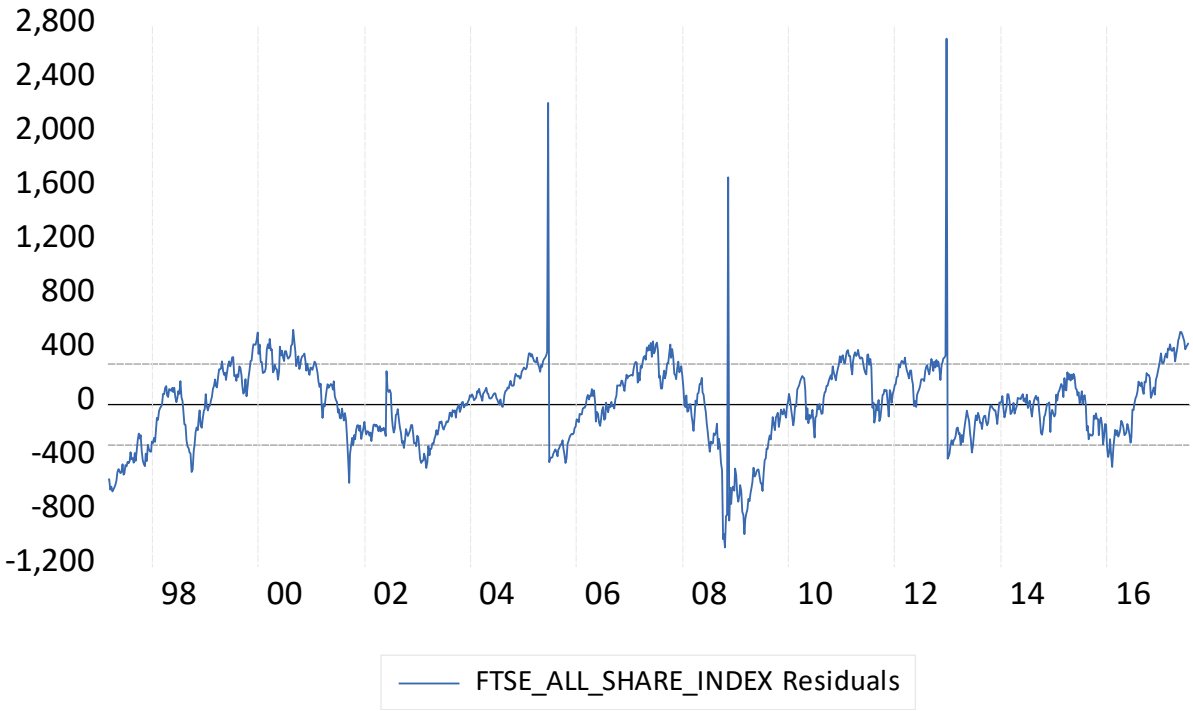
(iii)Bai-Perron multiple breakpoints test

1. FTSE ALL SHARE INDEX

Dependent Variable: FTSE ALL SHARE INDEX
Method: Least Squares with Breaks
Date: 17/11/20 Time: 21:59
Sample: 3/03/1997 17/07/2017
Included observations: 1064
Break type: Bai-Perron tests of L+1 vs. L sequentially determined breaks
Breaks: 3/06/2002, 27/06/2005, 17/11/2008, 31/12/2012
Selection: Trimming 0.15, Max. breaks 5, Sig. level 0.05

Variable	Coefficient	Std. Error	t-Statistic	Prob.
3/03/1997 - 27/05/2002 -- 274 obs				
C	2707.823	18.13106	149.3472	0.0000
3/06/2002 - 20/06/2005 -- 160 obs				
C	2154.072	23.72677	90.78658	0.0000
27/06/2005 - 10/11/2008 -- 177 obs				
C	3009.600	22.55859	133.4126	0.0000
17/11/2008 - 24/12/2012 -- 215 obs				
C	2749.679	20.46819	134.3392	0.0000
31/12/2012 - 17/07/2017 -- 238 obs				
C	3591.628	19.45405	184.6210	0.0000

R-squared	0.682538	Mean dependent var	2879.874
Adjusted R-squared	0.681339	S.D. dependent var	531.6601
S.E. of regression	300.1225	Akaike info criterion	14.25095
Sum squared resid	95387858	Schwarz criterion	14.27430
Log likelihood	-7576.504	Hannan-Quinn criter.	14.25980
F-statistic	569.2083	Durbin-Watson stat	0.448751
Prob(F-statistic)	0.000000		

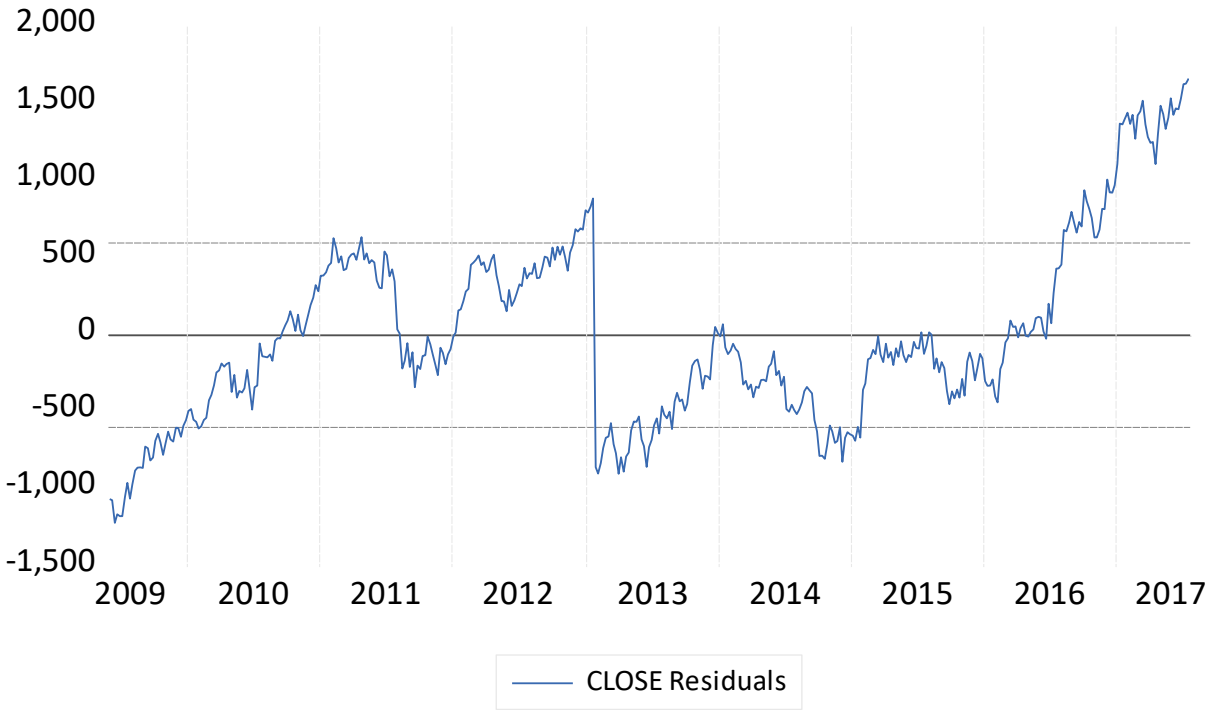


2. FTSE 350 General Industrial Index

Dependent Variable: CLOSE
Method: Least Squares with Breaks
Date: 17/11/20 Time: 20:26
Sample: 31/05/2009 16/07/2017
Included observations: 425
Break type: Fixed number of sequentially determined breaks
Break: 27/01/2013

Variable	Coefficient	Std. Error	t-Statistic	Prob.
31/05/2009 - 20/01/2013 -- 191 obs				
C	2766.341	43.31939	63.85918	0.0000
27/01/2013 - 16/07/2017 -- 234 obs				
C	4547.299	39.13732	116.1883	0.0000

R-squared	0.687503	Mean dependent var	3746.915
Adjusted R-squared	0.686764	S.D. dependent var	1069.704
S.E. of regression	598.6859	Akaike info criterion	15.63205
Sum squared resid	1.52E+08	Schwarz criterion	15.65111
Log likelihood	-3319.810	Hannan-Quinn criter.	15.63958
F-statistic	930.6133	Durbin-Watson stat	0.043119
Prob(F-statistic)	0.000000		



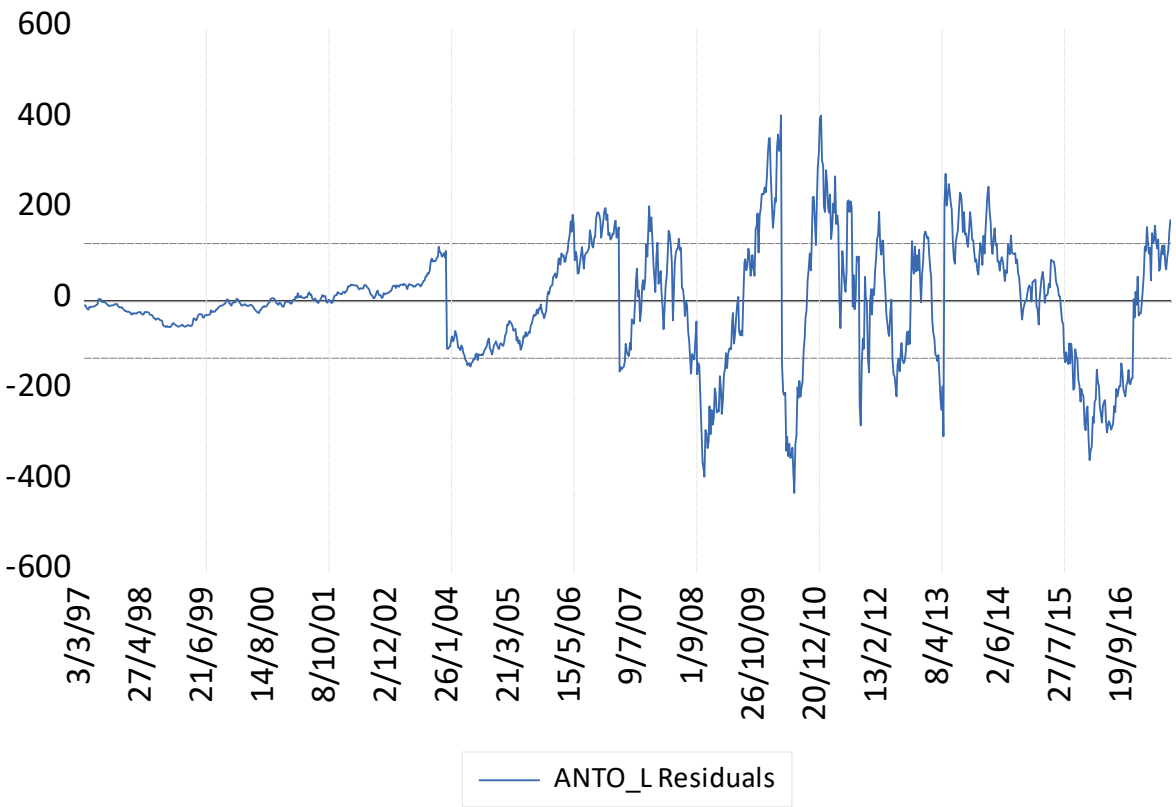
3. ANTO.L

Dependent Variable: ANTO_L
Method: Least Squares with Breaks
Date: 23/11/20 Time: 22:44
Sample: 3/03/1997 17/07/2017
Included observations: 1064
Break type: Bai-Perron tests of L+1 vs. L sequentially determined breaks
Breaks: 22/12/2003, 19/03/2007, 4/04/2010, 22/04/2013
Selection: Trimming 0.15, Max. breaks 5, Sig. level 0.05

Variable	Coefficient	Std. Error	t-Statistic	Prob.
3/03/1997 - 15/12/2003 -- 355 obs				
C	90.01090	6.741834	13.35110	0.0000
22/12/2003 - 12/03/2007 -- 169 obs				
C	318.0589	9.771222	32.55057	0.0000
19/03/2007 - 28/03/2010 -- 159 obs				
C	664.8192	10.07381	65.99483	0.0000
4/04/2010 - 15/04/2013 -- 159 obs				
C	1201.906	10.07381	119.3100	0.0000
22/04/2013 - 17/07/2017 -- 222 obs				
C	702.5806	8.525419	82.41010	0.0000

R-squared	0.901840	Mean dependent var	506.0977
Adjusted R-squared	0.901470	S.D. dependent var	404.6756

S.E. of regression	127.0259	Akaike info criterion	12.53135
Sum squared resid	17087573	Schwarz criterion	12.55470
Log likelihood	-6661.677	Hannan-Quinn criter.	12.54020
F-statistic	2432.386	Durbin-Watson stat	0.119325
Prob(F-statistic)	0.000000		



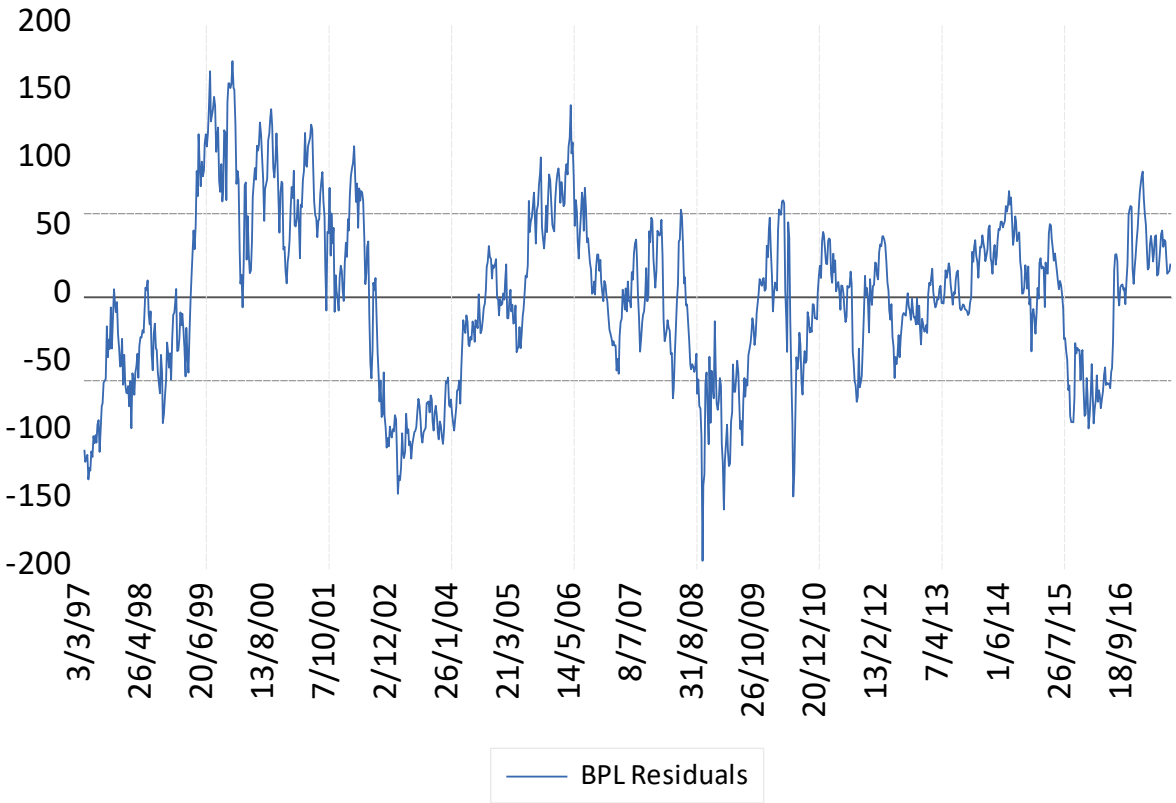
4. BP.L

Dependent Variable: BPL
Method: Least Squares with Breaks
Date: 24/11/20 Time: 10:04
Sample: 3/03/1997 16/07/2017
Included observations: 1064
Break type: Bai-Perron tests of L+1 vs. L sequentially determined breaks
Breaks: 20/03/2000, 7/02/2005, 16/05/2010, 6/07/2014
Selection: Trimming 0.15, Max. breaks 5, Sig. level 0.05

Variable	Coefficient	Std. Error	t-Statistic	Prob.
3/03/1997 - 13/03/2000 -- 159 obs				
C	469.4511	4.883307	96.13386	0.0000
20/03/2000 - 31/01/2005 -- 255 obs				
C	513.8343	3.856048	133.2541	0.0000
7/02/2005 - 9/05/2010 -- 275 obs				
C	570.5004	3.713182	153.6419	0.0000

16/05/2010 - 29/06/2014 -- 216 obs				
C	451.4279	4.189727	107.7464	0.0000
6/07/2014 - 16/07/2017 -- 159 obs				
C	425.5053	4.883307	87.13468	0.0000

R-squared	0.422596	Mean dependent var	495.9792
Adjusted R-squared	0.420415	S.D. dependent var	80.88242
S.E. of regression	61.57615	Akaike info criterion	11.08311
Sum squared resid	4015328.	Schwarz criterion	11.10647
Log likelihood	-5891.217	Hannan-Quinn criter.	11.09196
F-statistic	193.7680	Durbin-Watson stat	0.086716
Prob(F-statistic)	0.000000		



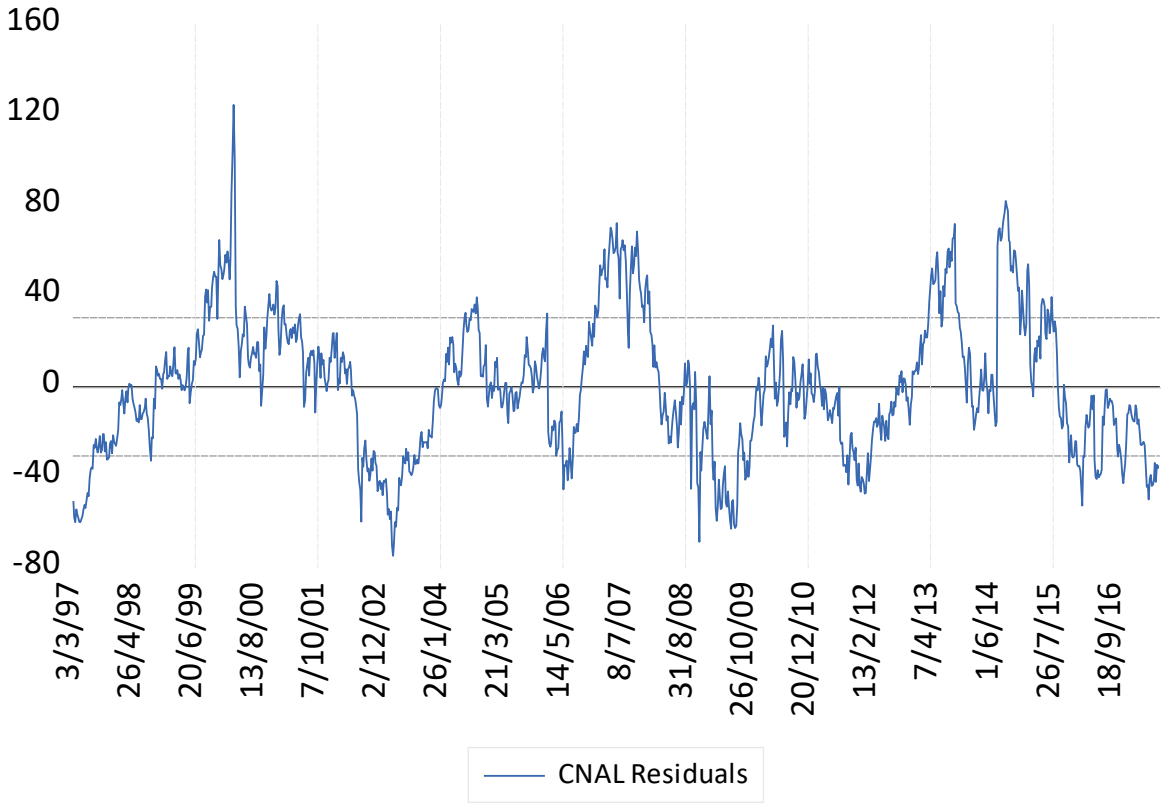
5. CNA.L

Dependent Variable: CNAL
Method: Least Squares with Breaks
Date: 24/11/20 Time: 11:38
Sample: 3/03/1997 16/07/2017
Included observations: 1064
Break type: Bai-Perron tests of L+1 vs. L sequentially determined breaks
Breaks: 20/03/2000, 30/01/2006, 4/07/2010, 6/07/2014
Selection: Trimming 0.15, Max. breaks 5, Sig. level 0.05

Variable	Coefficient	Std. Error	t-Statistic	Prob.
3/03/1997 - 13/03/2000 -- 159 obs				

C	123.8954	2.425080	51.08921	0.0000
20/03/2000 - 23/01/2006 -- 306 obs				
C	209.6426	1.748090	119.9266	0.0000
30/01/2006 - 27/06/2010 -- 231 obs				
C	280.9675	2.011956	139.6489	0.0000
4/07/2010 - 29/06/2014 -- 209 obs				
C	330.1683	2.115200	156.0932	0.0000
6/07/2014 - 16/07/2017 -- 159 obs				
C	242.1195	2.425080	99.83981	0.0000

R-squared	0.820037	Mean dependent var	240.8418
Adjusted R-squared	0.819357	S.D. dependent var	71.94718
S.E. of regression	30.57909	Akaike info criterion	9.683198
Sum squared resid	990250.6	Schwarz criterion	9.706552
Log likelihood	-5146.461	Hannan-Quinn criter.	9.692048
F-statistic	1206.382	Durbin-Watson stat	0.084955
Prob(F-statistic)	0.000000		



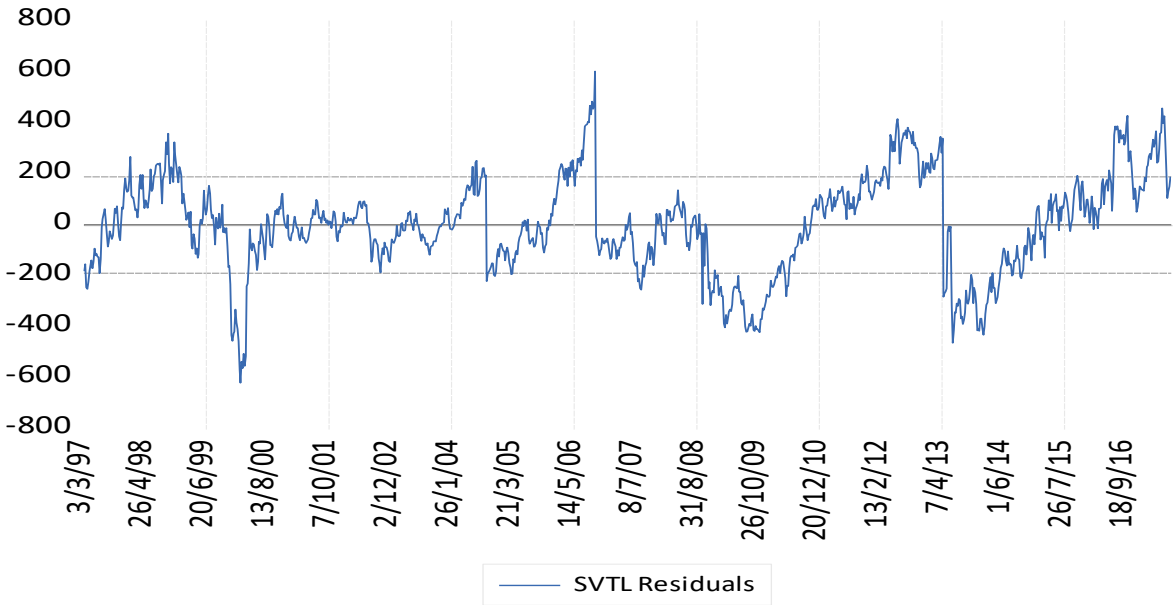
6. SVT.L

Dependent Variable: SVTL
Method: Least Squares with Breaks
Date: 24/11/20 Time: 12:00
Sample: 3/03/1997 16/07/2017

Included observations: 1064
Break type: Bai-Perron tests of L+1 vs. L sequentially determined breaks
Breaks: 20/03/2000, 19/09/2004, 4/02/2008, 14/04/2013
Selection: Trimming 0.15, Max. breaks 5, Sig. level 0.05

Variable	Coefficient	Std. Error	t-Statistic	Prob.
3/03/1997 - 13/03/2000 -- 159 obs				
C	1340.603	14.96827	89.56296	0.0000
20/03/2000 - 12/09/2004 -- 235 obs				
C	1076.927	12.31222	87.46821	0.0000
19/09/2004 - 28/01/2008 -- 176 obs				
C	1522.989	14.22702	107.0491	0.0000
4/02/2008 - 7/04/2013 -- 271 obs				
C	1366.127	11.46530	119.1532	0.0000
14/04/2013 - 16/07/2017 -- 223 obs				
C	2076.251	12.63915	164.2715	0.0000

R-squared	0.767220	Mean dependent var	1473.218
Adjusted R-squared	0.766341	S.D. dependent var	390.4618
S.E. of regression	188.7427	Akaike info criterion	13.32333
Sum squared resid	37725606	Schwarz criterion	13.34669
Log likelihood	-7083.014	Hannan-Quinn criter.	13.33218
F-statistic	872.5893	Durbin-Watson stat	0.091413
Prob(F-statistic)	0.000000		

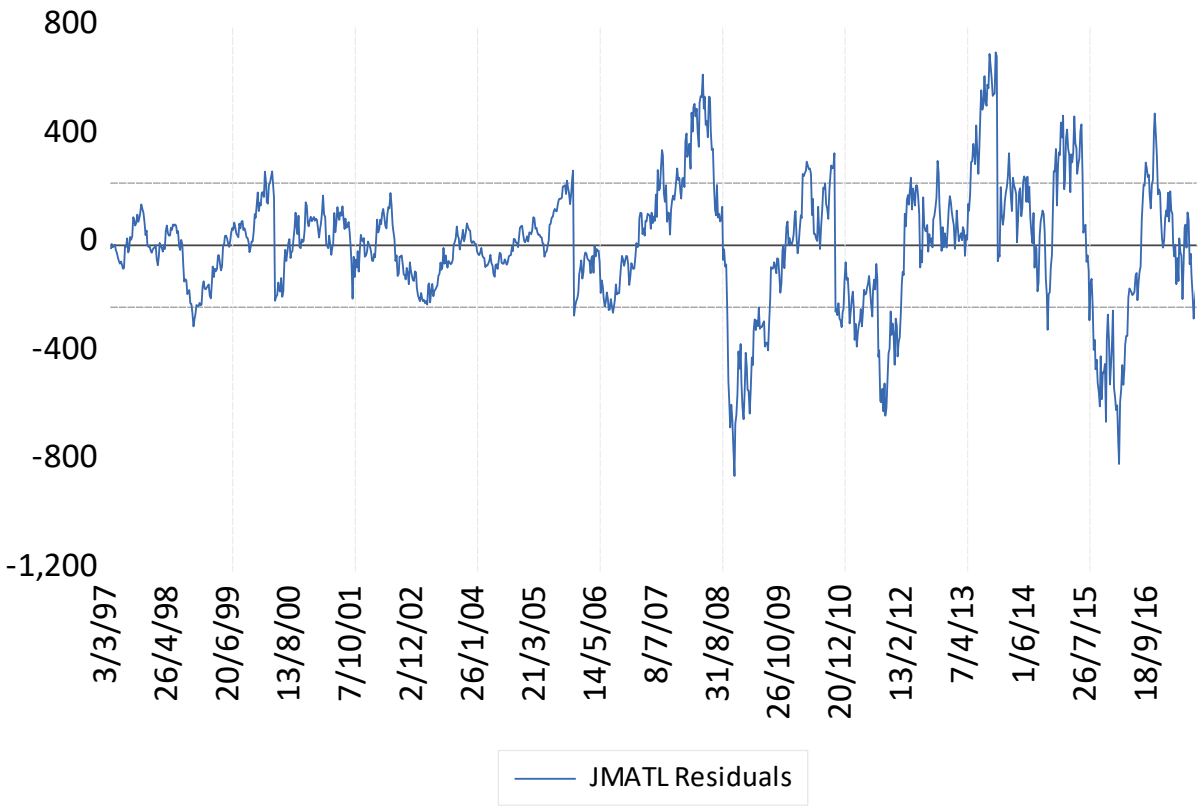


7. JMAT.L

Dependent Variable: JMATL
Method: Least Squares with Breaks
Date: 24/11/20 Time: 13:15
Sample: 3/03/1997 16/07/2017
Included observations: 1064
Break type: Bai-Perron tests of L+1 vs. L sequentially determined breaks
Breaks: 2/04/2000, 14/11/2005, 10/10/2010, 28/10/2013
Selection: Trimming 0.15, Max. breaks 5, Sig. level 0.05

Variable	Coefficient	Std. Error	t-Statistic	Prob.
3/03/1997 - 26/03/2000 -- 161 obs				
C	576.8835	17.98081	32.08328	0.0000
2/04/2000 - 7/11/2005 -- 293 obs				
C	1001.783	13.32872	75.15974	0.0000
14/11/2005 - 3/10/2010 -- 256 obs				
C	1564.249	14.25944	109.6992	0.0000
10/10/2010 - 20/10/2013 -- 159 obs				
C	2262.911	18.09355	125.0673	0.0000
28/10/2013 - 16/07/2017 -- 195 obs				
C	3054.724	16.33823	186.9679	0.0000

R-squared	0.931935	Mean dependent var	1637.521
Adjusted R-squared	0.931678	S.D. dependent var	872.8542
S.E. of regression	228.1510	Akaike info criterion	13.70258
Sum squared resid	55123980	Schwarz criterion	13.72593
Log likelihood	-7284.773	Hannan-Quinn criter.	13.71143
F-statistic	3624.914	Durbin-Watson stat	0.108745
Prob(F-statistic)	0.000000		



The manufacturing industry

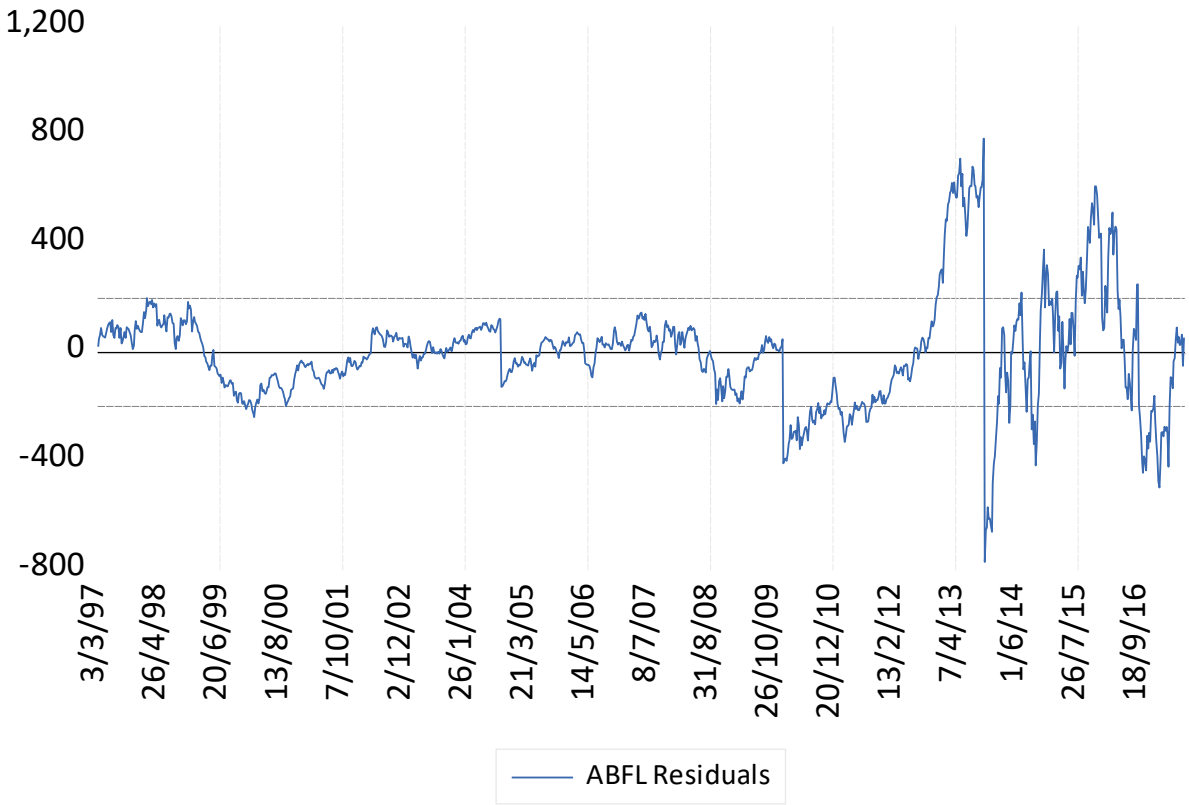
8. ABF.L

Dependent Variable: ABFL
Method: Least Squares with Breaks
Date: 24/11/20 Time: 13:50
Sample: 3/03/1997 16/07/2017
Included observations: 1064
Break type: Bai-Perron tests of L+1 vs. L sequentially determined breaks
Breaks: 26/09/2004, 11/01/2010, 20/10/2013
Selection: Trimming 0.15, Max. breaks 5, Sig. level 0.05

Variable	Coefficient	Std. Error	t-Statistic	Prob.
3/03/1997 - 19/09/2004 -- 395 obs				
C	533.0660	10.02907	53.15209	0.0000
26/09/2004 - 4/01/2010 -- 276 obs				
C	801.5344	11.99788	66.80632	0.0000
11/01/2010 - 13/10/2013 -- 197 obs				
C	1274.071	14.20123	89.71552	0.0000
20/10/2013 - 16/07/2017 -- 196 obs				

C	2904.646	14.23742	204.0150	0.0000

R-squared	0.949363	Mean dependent var	1176.774
Adjusted R-squared	0.949220	S.D. dependent var	884.5274
S.E. of regression	199.3238	Akaike info criterion	13.43149
Sum squared resid	42113781	Schwarz criterion	13.45017
Log likelihood	-7141.553	Hannan-Quinn criter.	13.43857
F-statistic	6624.429	Durbin-Watson stat	0.121134
Prob(F-statistic)	0.000000		



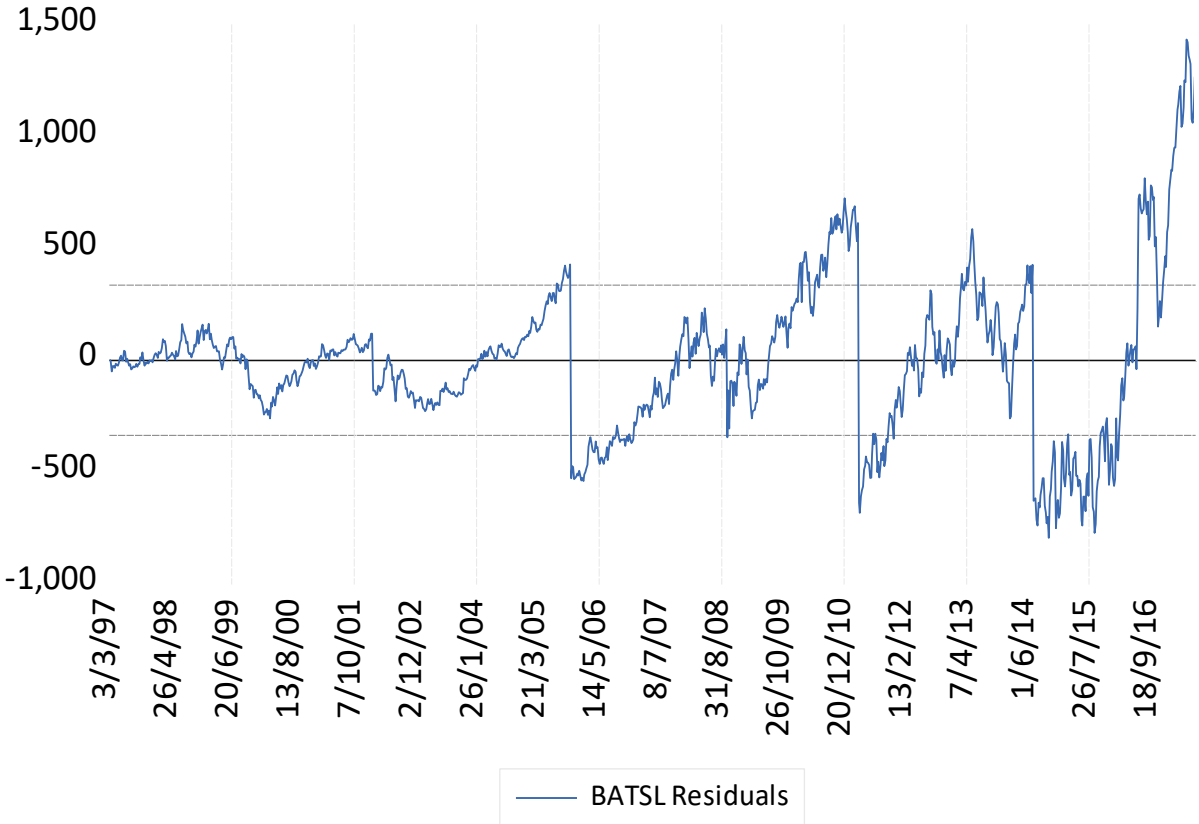
9. BATS.L

Dependent Variable: BATSL
Method: Least Squares with Breaks
Date: 24/11/20 Time: 14:03
Sample: 3/03/1997 16/07/2017
Included observations: 1064
Break type: Bai-Perron tests of L+1 vs. L sequentially determined breaks
Breaks: 11/02/2002, 31/10/2005, 27/03/2011, 6/07/2014
Selection: Trimming 0.15, Max. breaks 5, Sig. level 0.05

Variable	Coefficient	Std. Error	t-Statistic	Prob.
3/03/1997 - 4/02/2002 -- 258 obs				
C	508.6767	20.92538	24.30907	0.0000
11/02/2002 - 23/10/2005 -- 194 obs				
C	793.3015	24.13139	32.87426	0.0000

31/10/2005 - 21/03/2011 -- 282 obs				
C	1794.351	20.01514	89.64968	0.0000
27/03/2011 - 29/06/2014 -- 171 obs				
C	3175.735	25.70308	123.5546	0.0000
6/07/2014 - 16/07/2017 -- 159 obs				
C	4156.547	26.65537	155.9366	0.0000

R-squared	0.938557	Mean dependent var	1875.082
Adjusted R-squared	0.938324	S.D. dependent var	1353.402
S.E. of regression	336.1114	Akaike info criterion	14.47745
Sum squared resid	1.20E+08	Schwarz criterion	14.50080
Log likelihood	-7697.004	Hannan-Quinn criter.	14.48630
F-statistic	4044.090	Durbin-Watson stat	0.063463
Prob(F-statistic)	0.000000		

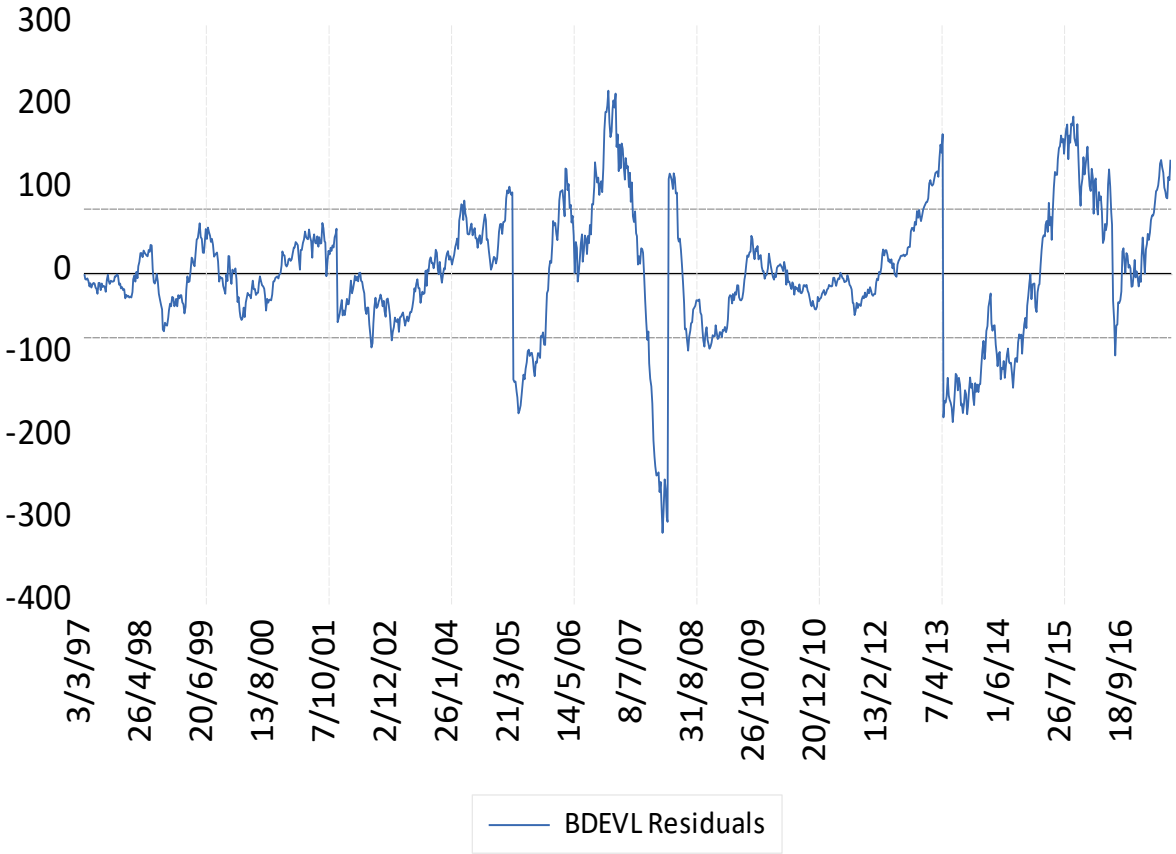


10. BDEV.L

Dependent Variable: BDEVL
Method: Least Squares with Breaks
Date: 24/11/20 Time: 15:05
Sample: 3/03/1997 16/07/2017
Included observations: 1064
Break type: Bai-Perron tests of L+1 vs. L sequentially determined breaks
Breaks: 3/12/2001, 21/03/2005, 18/02/2008, 14/04/2013
Selection: Trimming 0.15, Max. breaks 5, Sig. level 0.05

Variable	Coefficient	Std. Error	t-Statistic	Prob.
3/03/1997 - 26/11/2001 -- 248 obs				
C	161.7811	4.939656	32.75149	0.0000
3/12/2001 - 14/03/2005 -- 172 obs				
C	285.9968	5.931415	48.21730	0.0000
21/03/2005 - 11/02/2008 -- 152 obs				
C	515.7032	6.309585	81.73331	0.0000
18/02/2008 - 7/04/2013 -- 269 obs				
C	117.9069	4.742927	24.85951	0.0000
14/04/2013 - 16/07/2017 -- 223 obs				
C	472.5354	5.209189	90.71190	0.0000

R-squared	0.809362	Mean dependent var	286.4590
Adjusted R-squared	0.808642	S.D. dependent var	177.8277
S.E. of regression	77.78978	Akaike info criterion	11.55059
Sum squared resid	6408274.	Schwarz criterion	11.57394
Log likelihood	-6139.911	Hannan-Quinn criter.	11.55943
F-statistic	1124.009	Durbin-Watson stat	0.088380
Prob(F-statistic)	0.000000		

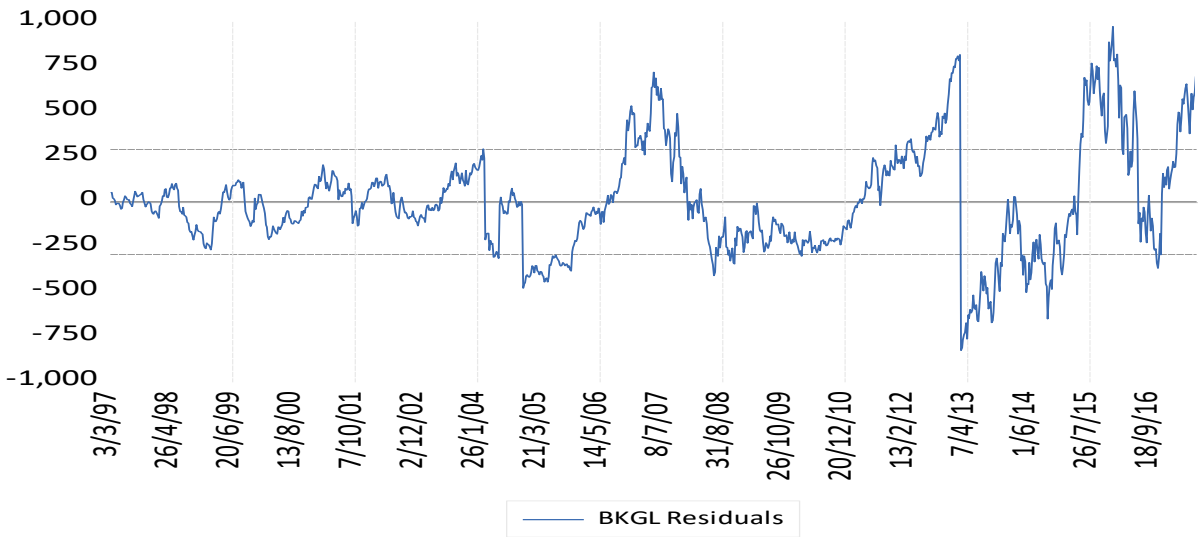


11. BKG.L

Dependent Variable: BKGL
Method: Least Squares with Breaks
Date: 04/04/21 Time: 12:01
Sample: 3/03/1997 16/07/2017
Included observations: 1064
Break type: Bai-Perron tests of L+1 vs. L sequentially determined breaks
Breaks: 15/03/2004, 31/12/2007, 18/02/2013
Selection: Trimming 0.15, Max. breaks 5, Sig. level 0.05

Variable	Coefficient	Std. Error	t-Statistic	Prob.
3/03/1997 - 8/03/2004 -- 367 obs				
C	673.2500	15.21294	44.25509	0.0000
15/03/2004 - 24/12/2007 -- 198 obs				
C	1213.871	20.71160	58.60829	0.0000
31/12/2007 - 11/02/2013 -- 268 obs				
C	1043.213	17.80241	58.59952	0.0000
18/02/2013 - 16/07/2017 -- 231 obs				
C	2712.974	19.17521	141.4834	0.0000

R-squared	0.873979	Mean dependent var	1309.875
Adjusted R-squared	0.873622	S.D. dependent var	819.8059
S.E. of regression	291.4380	Akaike info criterion	14.19128
Sum squared resid	90032271	Schwarz criterion	14.20997
Log likelihood	-7545.763	Hannan-Quinn criter.	14.19836
F-statistic	2450.433	Durbin-Watson stat	0.079636
Prob(F-statistic)	0.000000		

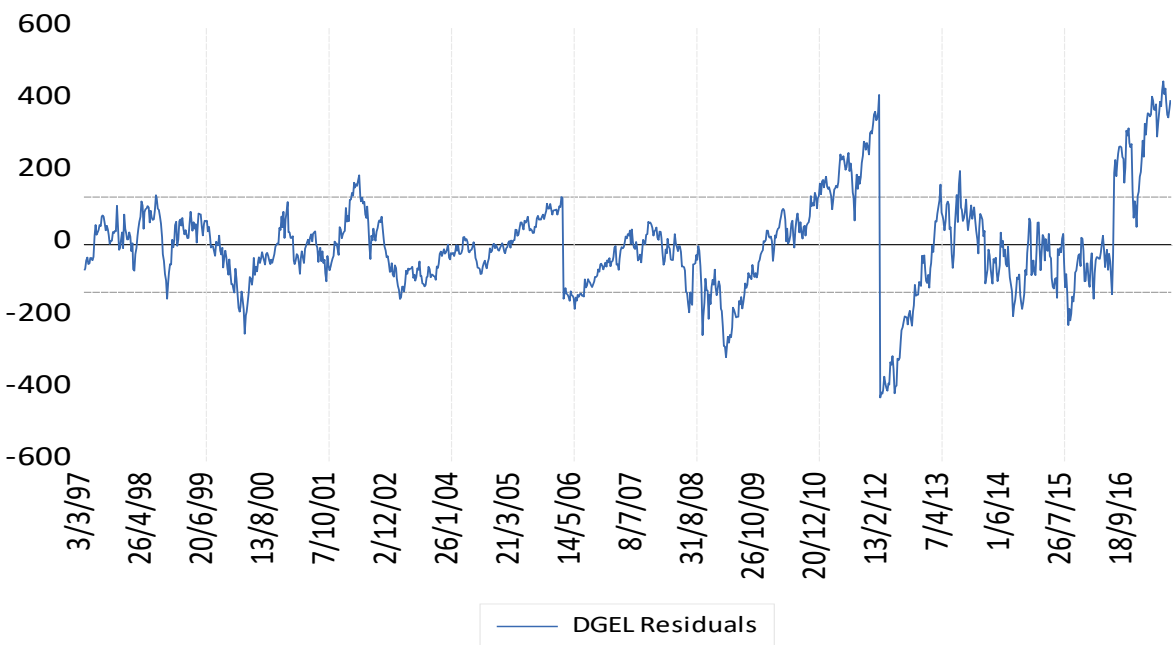


12. DGE.L

Dependent Variable: DGEL
Method: Least Squares with Breaks
Date: 24/11/20 Time: 15:49
Sample: 3/03/1997 16/07/2017
Included observations: 1064
Break type: Bai-Perron tests of L+1 vs. L sequentially determined breaks
Breaks: 5/02/2001, 27/02/2006, 6/02/2012
Selection: Trimming 0.15, Max. breaks 5, Sig. level 0.05

Variable	Coefficient	Std. Error	t-Statistic	Prob.
3/03/1997 - 29/01/2001 -- 205 obs				
C	631.5406	9.218665	68.50674	0.0000
5/02/2001 - 20/02/2006 -- 264 obs				
C	746.0909	8.123496	91.84357	0.0000
27/02/2006 - 30/01/2012 -- 310 obs				
C	1045.256	7.496596	139.4308	0.0000
6/02/2012 - 16/07/2017 -- 285 obs				
C	1908.267	7.818483	244.0712	0.0000

R-squared	0.934769	Mean dependent var	1122.481
Adjusted R-squared	0.934585	S.D. dependent var	516.0654
S.E. of regression	131.9912	Akaike info criterion	12.60710
Sum squared resid	18466975	Schwarz criterion	12.62578
Log likelihood	-6702.977	Hannan-Quinn criter.	12.61418
F-statistic	5063.327	Durbin-Watson stat	0.102657
Prob(F-statistic)	0.000000		



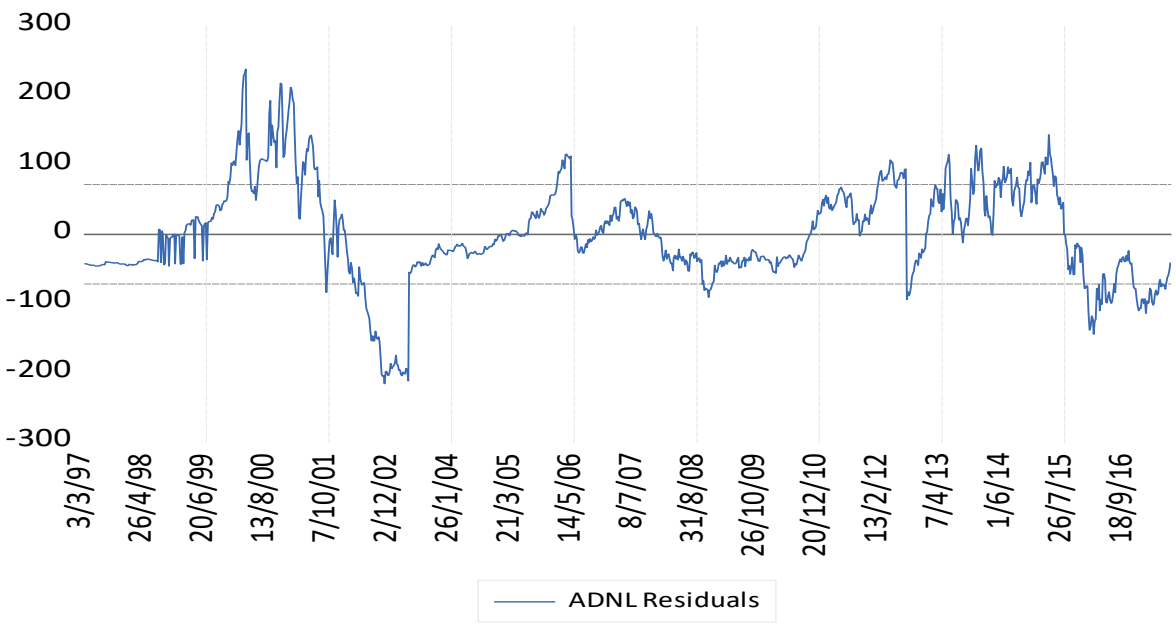
The service industry

13. ADN.L

Dependent Variable: ADNL
Method: Least Squares with Breaks
Date: 24/11/20 Time: 20:07
Sample: 3/03/1997 16/07/2017
Included observations: 1064
Break type: Bai-Perron tests of L+1 vs. L sequentially determined breaks
Breaks: 20/03/2000, 6/04/2003, 23/04/2006, 5/08/2012
Selection: Trimming 0.15, Max. breaks 5, Sig. level 0.05

Variable	Coefficient	Std. Error	t-Statistic	Prob.
3/03/1997 - 13/03/2000 -- 159 obs				
C	64.64126	5.686024	11.36845	0.0000
20/03/2000 - 30/03/2003 -- 159 obs				
C	235.3798	5.686024	41.39621	0.0000
6/04/2003 - 16/04/2006 -- 159 obs				
C	77.26295	5.686024	13.58822	0.0000
23/04/2006 - 29/07/2012 -- 328 obs				
C	170.7261	3.958861	43.12504	0.0000
5/08/2012 - 16/07/2017 -- 259 obs				
C	364.3375	4.455099	81.77990	0.0000

R-squared	0.701239	Mean dependent var	197.6971
Adjusted R-squared	0.700110	S.D. dependent var	130.9261
S.E. of regression	71.69803	Akaike info criterion	11.38749
Sum squared resid	5443903.	Schwarz criterion	11.41085
Log likelihood	-6053.146	Hannan-Quinn criter.	11.39634
F-statistic	621.4084	Durbin-Watson stat	0.055013
Prob(F-statistic)	0.000000		



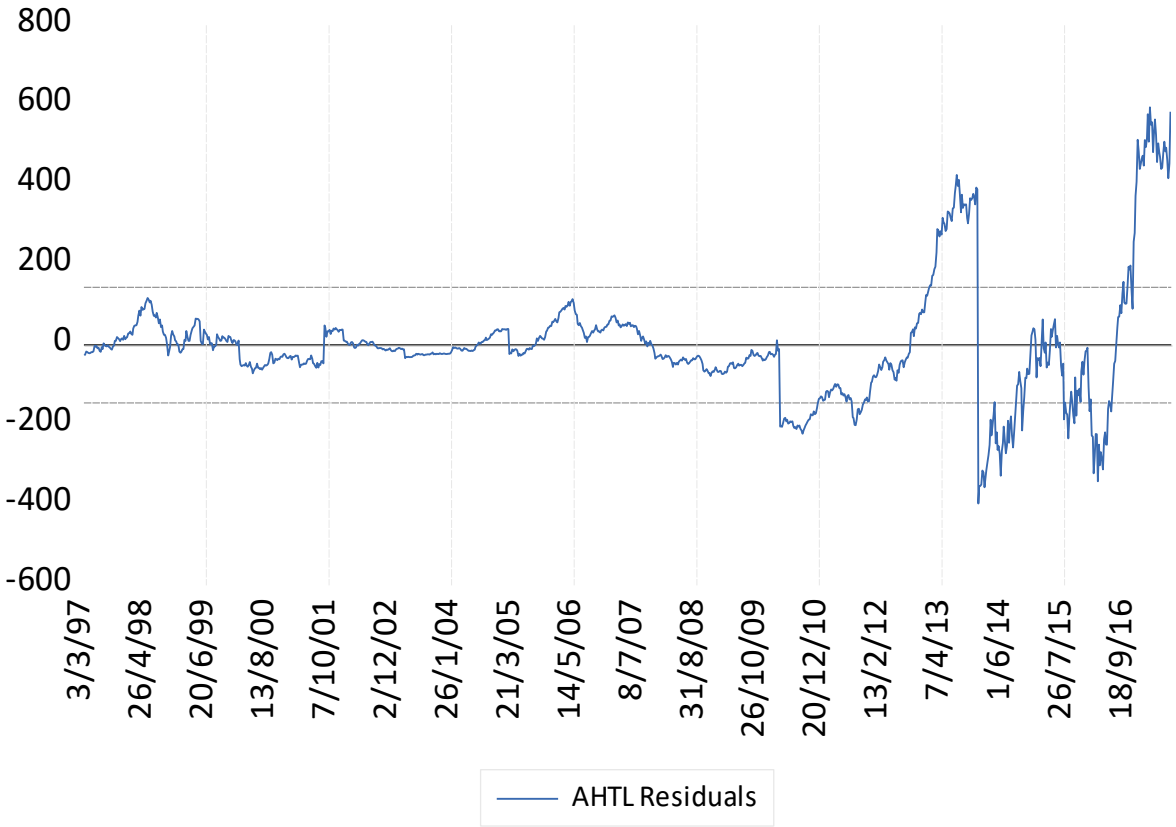
14. AHT.L

Dependent Variable: AHTL
Method: Least Squares with Breaks
Date: 24/11/20 Time: 20:09
Sample: 3/03/1997 16/07/2017
Included observations: 1064
Break type: Bai-Perron tests of L+1 vs. L sequentially determined breaks
Breaks: 2/09/2001, 21/02/2005, 22/03/2010, 9/12/2013
Selection: Trimming 0.15, Max. breaks 5, Sig. level 0.05

Variable	Coefficient	Std. Error	t-Statistic	Prob.
3/03/1997 - 26/08/2001 -- 235 obs				
C	144.6520	9.457034	15.29570	0.0000
2/09/2001 - 14/02/2005 -- 181 obs				
C	36.71143	10.77580	3.406840	0.0007
21/02/2005 - 15/03/2010 -- 265 obs				
C	107.0100	8.905656	12.01595	0.0000
22/03/2010 - 2/12/2013 -- 194 obs				
C	301.2106	10.40850	28.93891	0.0000
9/12/2013 - 16/07/2017 -- 189 obs				
C	1125.848	10.54528	106.7633	0.0000

R-squared	0.875542	Mean dependent var	319.7517
Adjusted R-squared	0.875071	S.D. dependent var	410.1644
S.E. of regression	144.9736	Akaike info criterion	12.79567

Sum squared resid	22257362	Schwarz criterion	12.81902
Log likelihood	-6802.296	Hannan-Quinn criter.	12.80452
F-statistic	1862.466	Durbin-Watson stat	0.052720
Prob(F-statistic)	0.000000		



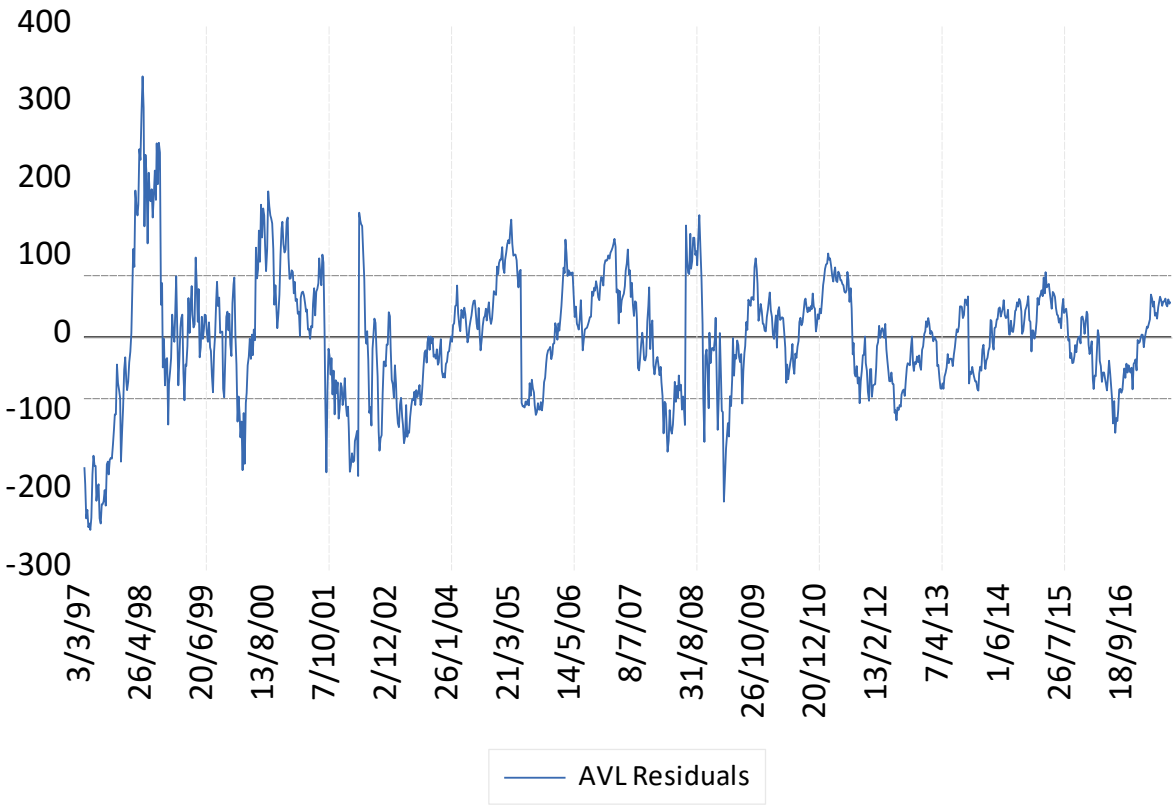
15. AV.L

Dependent Variable: AVL
Method: Least Squares with Breaks
Date: 24/11/20 Time: 20:23
Sample: 3/03/1997 16/07/2017
Included observations: 1064
Break type: Bai-Perron tests of L+1 vs. L sequentially determined breaks
Breaks: 28/04/2002, 15/05/2005, 15/06/2008, 6/10/2013
Selection: Trimming 0.15, Max. breaks 5, Sig. level 0.05

Variable	Coefficient	Std. Error	t-Statistic	Prob.
3/03/1997 - 21/04/2002 -- 269 obs				
C	840.7971	4.827527	174.1673	0.0000
28/04/2002 - 8/05/2005 -- 159 obs				
C	477.3895	6.279171	76.02747	0.0000
15/05/2005 - 8/06/2008 -- 161 obs				
C	656.2813	6.240048	105.1725	0.0000

15/06/2008 - 29/09/2013 -- 277 obs				
C	362.3426	4.757305	76.16552	0.0000
6/10/2013 - 16/07/2017 -- 198 obs				
C	486.2949	5.626888	86.42342	0.0000

R-squared	0.842885	Mean dependent var	568.0413
Adjusted R-squared	0.842291	S.D. dependent var	199.3761
S.E. of regression	79.17733	Akaike info criterion	11.58595
Sum squared resid	6638923.	Schwarz criterion	11.60930
Log likelihood	-6158.723	Hannan-Quinn criter.	11.59479
F-statistic	1420.320	Durbin-Watson stat	0.160073
Prob(F-statistic)	0.000000		



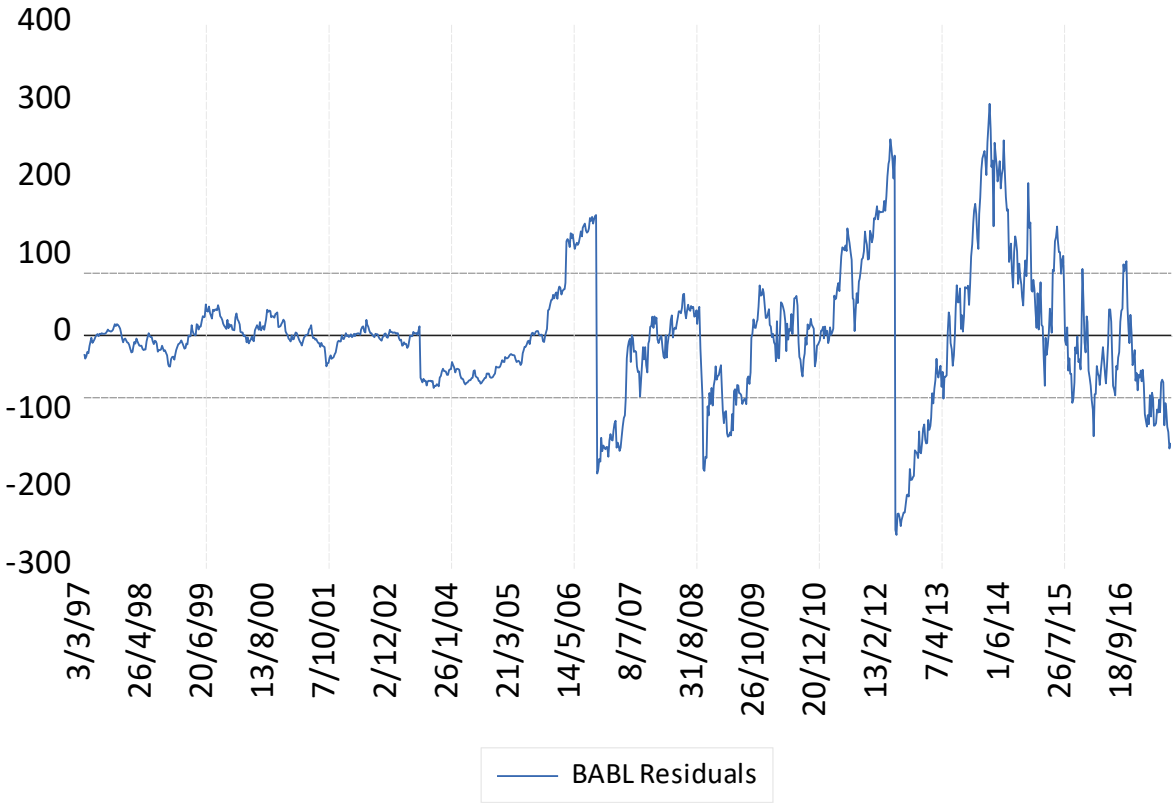
16. BAB.L

Dependent Variable: BABL
Method: Least Squares with Breaks
Date: 24/11/20 Time: 20:36
Sample: 3/03/1997 16/07/2017
Included observations: 1064
Break type: Bai-Perron tests of L+1 vs. L sequentially determined breaks
Breaks: 22/06/2003, 15/10/2006, 20/05/2012
Selection: Trimming 0.15, Max. breaks 5, Sig. level 0.05

Variable	Coefficient	Std. Error	t-Statistic	Prob.
3/03/1997 - 15/06/2003 -- 329 obs				

C	91.86930	4.430662	20.73490	0.0000
22/06/2003 - 8/10/2006 -- 173 obs				
C	156.5569	6.110032	25.62293	0.0000
15/10/2006 - 13/05/2012 -- 292 obs				
C	497.3290	4.703001	105.7472	0.0000
20/05/2012 - 16/07/2017 -- 270 obs				
C	998.3873	4.890853	204.1336	0.0000

R-squared	0.953028	Mean dependent var	443.6974
Adjusted R-squared	0.952895	S.D. dependent var	370.2840
S.E. of regression	80.36492	Akaike info criterion	11.61478
Sum squared resid	6846032.	Schwarz criterion	11.63347
Log likelihood	-6175.066	Hannan-Quinn criter.	11.62186
F-statistic	7168.934	Durbin-Watson stat	0.100165
Prob(F-statistic)	0.000000		



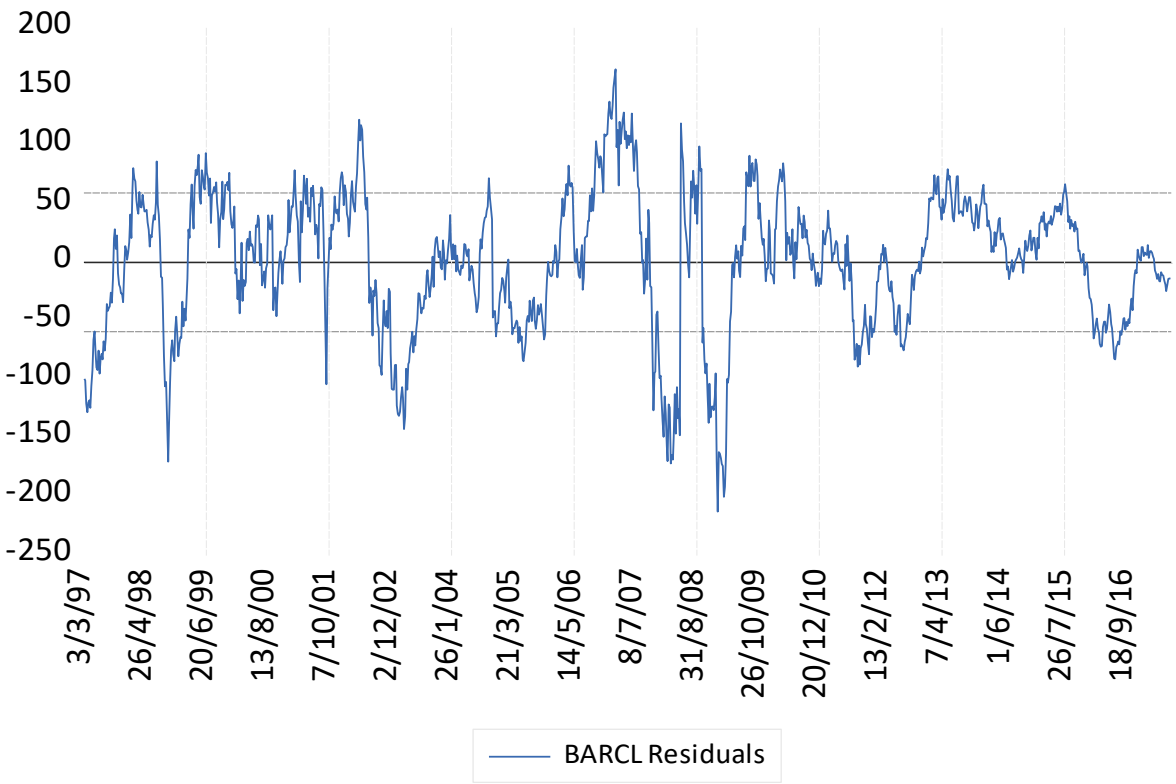
17. BARC.L

Dependent Variable: BARCL
Method: Least Squares with Breaks
Date: 24/11/20 Time: 20:47
Sample: 3/03/1997 16/07/2017
Included observations: 1064
Break type: Bai-Perron tests of L+1 vs. L sequentially determined breaks

Breaks: 17/09/2000, 1/11/2004, 11/05/2008, 12/06/2011
Selection: Trimming 0.15, Max. breaks 5, Sig. level 0.05

Variable	Coefficient	Std. Error	t-Statistic	Prob.
3/03/1997 - 10/09/2000 -- 185 obs				
C	363.8077	4.355903	83.52060	0.0000
17/09/2000 - 24/10/2004 -- 215 obs				
C	454.6747	4.040591	112.5268	0.0000
1/11/2004 - 4/05/2008 -- 184 obs				
C	564.8336	4.367724	129.3199	0.0000
11/05/2008 - 5/06/2011 -- 161 obs				
C	260.2135	4.669293	55.72866	0.0000
12/06/2011 - 16/07/2017 -- 319 obs				
C	222.2066	3.317178	66.98663	0.0000

R-squared	0.823203	Mean dependent var	358.8037
Adjusted R-squared	0.822535	S.D. dependent var	140.6395
S.E. of regression	59.24669	Akaike info criterion	11.00599
Sum squared resid	3717270.	Schwarz criterion	11.02934
Log likelihood	-5850.184	Hannan-Quinn criter.	11.01483
F-statistic	1232.726	Durbin-Watson stat	0.116514
Prob(F-statistic)	0.000000		



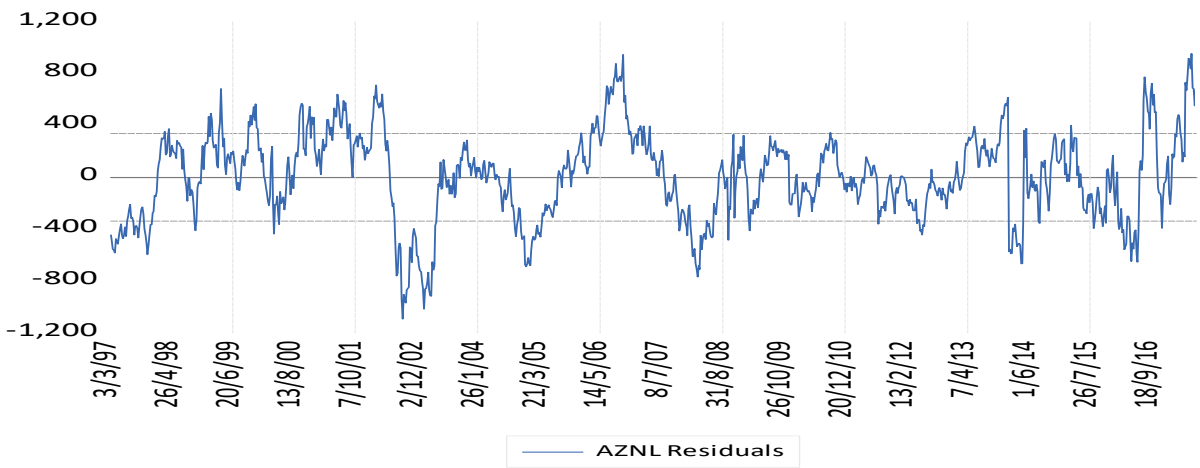
The quaternary industry

18. AZN.L

Dependent Variable: AZNL
Method: Least Squares with Breaks
Date: 24/11/20 Time: 21:38
Sample: 3/03/1997 16/07/2017
Included observations: 1064
Break type: Bai-Perron tests of L+1 vs. L sequentially determined breaks
Breaks: 20/03/2000, 6/04/2003, 30/11/2009, 13/01/2014
Selection: Trimming 0.15, Max. breaks 5, Sig. level 0.05

Variable	Coefficient	Std. Error	t-Statistic	Prob.
3/03/1997 - 13/03/2000 -- 159 obs				
C	2280.698	26.79514	85.11611	0.0000
20/03/2000 - 30/03/2003 -- 159 obs				
C	2914.240	26.79514	108.7600	0.0000
6/04/2003 - 23/11/2009 -- 347 obs				
C	2558.226	18.13802	141.0422	0.0000
30/11/2009 - 6/01/2014 -- 215 obs				
C	3035.205	23.04281	131.7203	0.0000
13/01/2014 - 16/07/2017 -- 184 obs				
C	4446.413	24.90839	178.5106	0.0000

R-squared	0.816050	Mean dependent var	2992.865
Adjusted R-squared	0.815355	S.D. dependent var	786.2960
S.E. of regression	337.8739	Akaike info criterion	14.48791
Sum squared resid	1.21E+08	Schwarz criterion	14.51127
Log likelihood	-7702.569	Hannan-Quinn criter.	14.49676
F-statistic	1174.500	Durbin-Watson stat	0.121294
Prob(F-statistic)	0.000000		

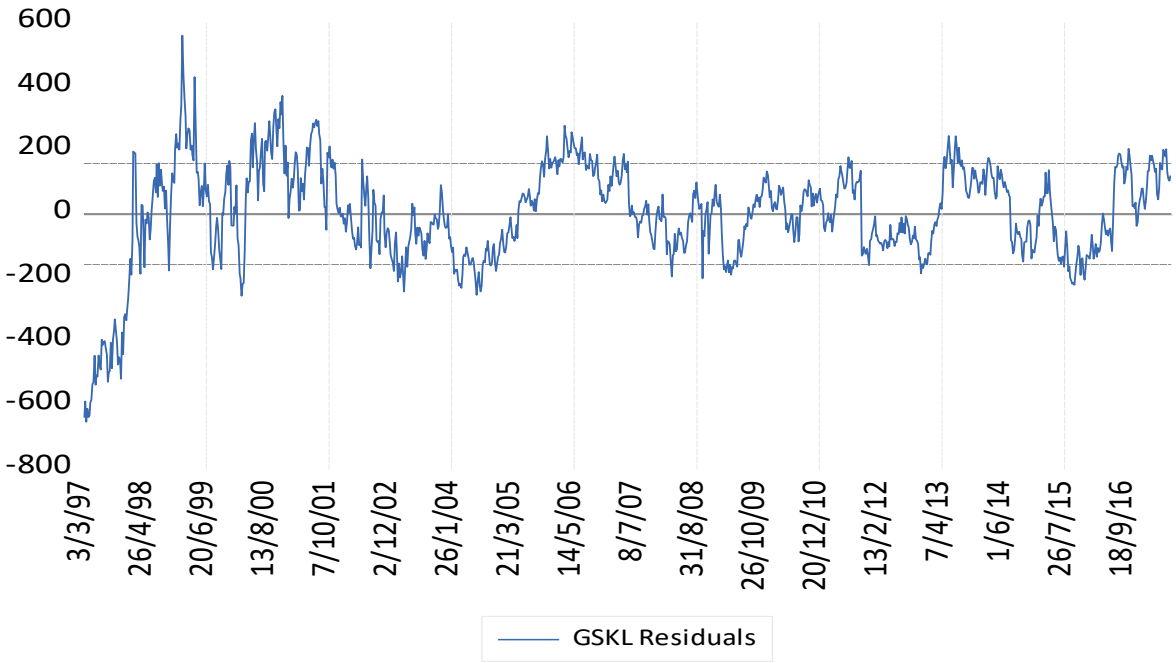


19. GSK.L

Dependent Variable: GSKL
Method: Least Squares with Breaks
Date: 24/11/20 Time: 22:09
Sample: 3/03/1997 16/07/2017
Included observations: 1064
Break type: Bai-Perron tests of L+1 vs. L sequentially determined breaks
Breaks: 19/05/2002, 21/01/2008, 2/10/2011
Selection: Trimming 0.15, Max. breaks 5, Sig. level 0.05

Variable	Coefficient	Std. Error	t-Statistic	Prob.
3/03/1997 - 12/05/2002 -- 272 obs				
C	1727.756	9.608227	179.8204	0.0000
19/05/2002 - 14/01/2008 -- 296 obs				
C	1299.084	9.210471	141.0443	0.0000
21/01/2008 - 25/09/2011 -- 193 obs				
C	1197.080	11.40641	104.9480	0.0000
2/10/2011 - 16/07/2017 -- 303 obs				
C	1504.241	9.103458	165.2384	0.0000

R-squared	0.606128	Mean dependent var	1448.590
Adjusted R-squared	0.605014	S.D. dependent var	252.1371
S.E. of regression	158.4629	Akaike info criterion	12.97267
Sum squared resid	26617132	Schwarz criterion	12.99135
Log likelihood	-6897.461	Hannan-Quinn criter.	12.97975
F-statistic	543.7442	Durbin-Watson stat	0.103090
Prob(F-statistic)	0.000000		

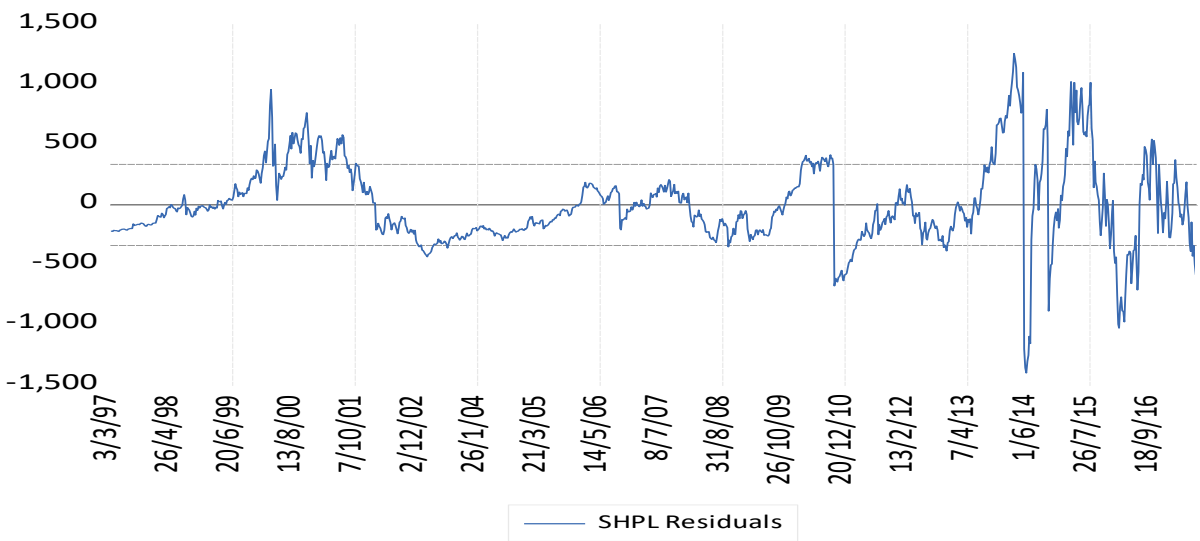


20. SHP.L

Dependent Variable: SHPL
Method: Least Squares with Breaks
Date: 24/11/20 Time: 22:20
Sample: 3/03/1997 16/07/2017
Included observations: 1064
Break type: Bai-Perron tests of L+1 vs. L sequentially determined breaks
Breaks: 20/03/2000, 24/09/2006, 3/10/2010, 27/04/2014
Selection: Trimming 0.15, Max. breaks 5, Sig. level 0.05

Variable	Coefficient	Std. Error	t-Statistic	Prob.
3/03/1997 - 13/03/2000 -- 159 obs				
C	437.1792	26.79110	16.31808	0.0000
20/03/2000 - 17/09/2006 -- 340 obs				
C	736.5000	18.32102	40.19973	0.0000
24/09/2006 - 26/09/2010 -- 210 obs				
C	1083.050	23.31199	46.45892	0.0000
3/10/2010 - 20/04/2014 -- 186 obs				
C	2110.801	24.77037	85.21474	0.0000
27/04/2014 - 16/07/2017 -- 169 obs				
C	4662.069	25.98637	179.4044	0.0000

R-squared	0.946946	Mean dependent var	1623.929
Adjusted R-squared	0.946745	S.D. dependent var	1463.894
S.E. of regression	337.8229	Akaike info criterion	14.48761
Sum squared resid	1.21E+08	Schwarz criterion	14.51096
Log likelihood	-7702.408	Hannan-Quinn criter.	14.49646
F-statistic	4725.413	Durbin-Watson stat	0.140509
Prob(F-statistic)	0.000000		

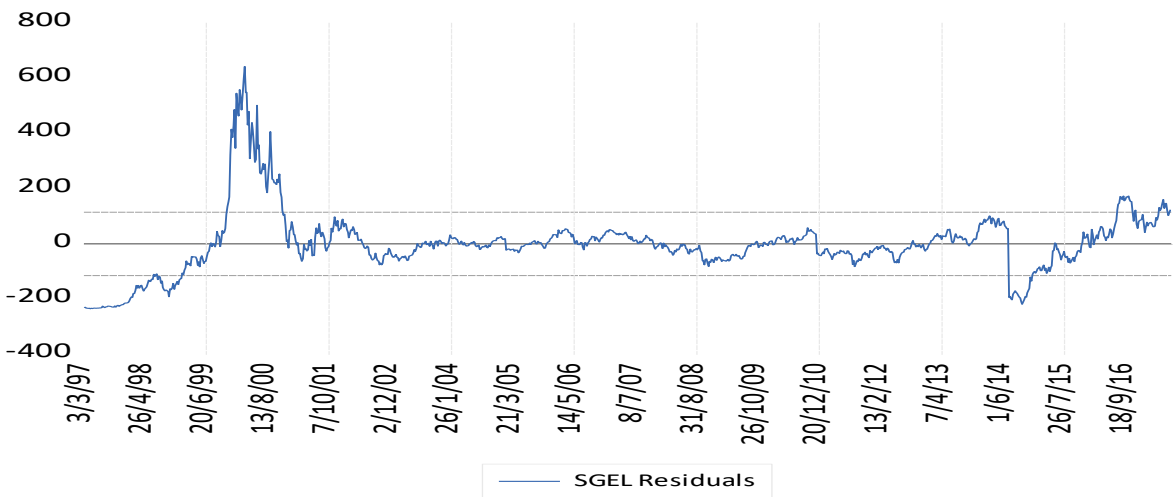


21. SGE.L

Dependent Variable: SGEL
Method: Least Squares with Breaks
Date: 24/11/20 Time: 22:34
Sample: 3/03/1997 16/07/2017
Included observations: 1064
Break type: Bai-Perron tests of L+1 vs. L sequentially determined breaks
Breaks: 1/07/2001, 31/01/2005, 29/11/2010, 6/07/2014
Selection: Trimming 0.15, Max. breaks 5, Sig. level 0.05

Variable	Coefficient	Std. Error	t-Statistic	Prob.
3/03/1997 - 24/06/2001 -- 226 obs				
C	308.9978	7.641660	40.43595	0.0000
1/07/2001 - 24/01/2005 -- 187 obs				
C	186.0359	8.400809	22.14500	0.0000
31/01/2005 - 22/11/2010 -- 304 obs				
C	237.4321	6.588782	36.03581	0.0000
29/11/2010 - 29/06/2014 -- 188 obs				
C	330.0121	8.378436	39.38827	0.0000
6/07/2014 - 16/07/2017 -- 159 obs				
C	568.2340	9.110524	62.37116	0.0000

R-squared	0.520198	Mean dependent var	309.3920
Adjusted R-squared	0.518385	S.D. dependent var	165.5358
S.E. of regression	114.8793	Akaike info criterion	12.33033
Sum squared resid	13975899	Schwarz criterion	12.35368
Log likelihood	-6554.735	Hannan-Quinn criter.	12.33918
F-statistic	287.0396	Durbin-Watson stat	0.039041
Prob(F-statistic)	0.000000		

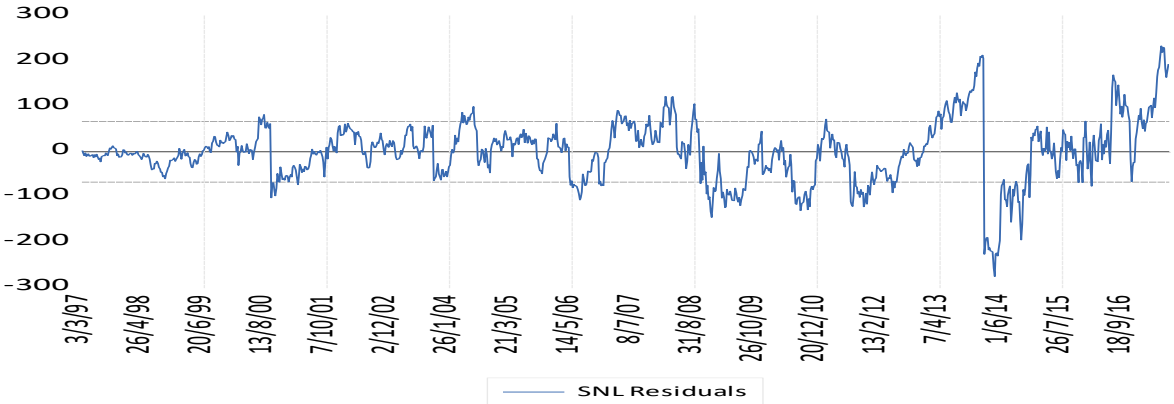


22. SN.L

Dependent Variable: SNL
Method: Least Squares with Breaks
Date: 24/11/20 Time: 22:45
Sample: 3/03/1997 16/07/2017
Included observations: 1064
Break type: Bai-Perron tests of L+1 vs. L sequentially determined breaks
Breaks: 17/09/2000, 5/10/2003, 13/11/2006, 7/12/2009, 3/02/2014
Selection: Trimming 0.15, Max. breaks 5, Sig. level 0.05

Variable	Coefficient	Std. Error	t-Statistic	Prob.
3/03/1997 - 10/09/2000 -- 185 obs				
C	221.4225	4.927352	44.93743	0.0000
17/09/2000 - 28/09/2003 -- 159 obs				
C	363.3994	5.314971	68.37278	0.0000
5/10/2003 - 6/11/2006 -- 162 obs				
C	508.7824	5.265529	96.62513	0.0000
13/11/2006 - 30/11/2009 -- 160 obs				
C	556.9809	5.298336	105.1237	0.0000
7/12/2009 - 27/01/2014 -- 217 obs				
C	670.2535	4.549562	147.3226	0.0000
3/02/2014 - 16/07/2017 -- 181 obs				
C	1140.727	4.981501	228.9927	0.0000

R-squared	0.950270	Mean dependent var	584.7744
Adjusted R-squared	0.950035	S.D. dependent var	299.8236
S.E. of regression	67.01924	Akaike info criterion	11.25346
Sum squared resid	4752090.	Schwarz criterion	11.28148
Log likelihood	-5980.841	Hannan-Quinn criter.	11.26408
F-statistic	4043.365	Durbin-Watson stat	0.144089
Prob(F-statistic)	0.000000		



(iv) Runs test

FTSE-ALL SHARE INDEX

Descriptive Statistics

	N	Mean	Std. Deviation	Minimum	Maximum
FTSEAllShare	204	3579.215588	175.4101190	3129.6299	4038.3799

Runs Test

	FTSEAllShare
Test Value[a]	3568.5601
Cases < Test Value	102
Cases >= Test Value	102
Total Cases	204
Number of Runs	20
Z	-11.651
Asymp. Sig. (2-tailed)	.000

a. Median

FTSE-350 GENERAL INDUSTRIAL INDEX

Descriptive Statistics

	N	Mean	Std. Deviation	Minimum	Maximum
FTSE350IndustrialIndex	204	4487.698873	549.9404847	3693.9500	6069.8700

Runs Test

	FTSE350IndustrialIndex
Test Value[a]	4372.4150
Cases < Test Value	102
Cases >= Test Value	102
Total Cases	204
Number of Runs	22
Z	-11.370
Asymp. Sig. (2-tailed)	.000

a. Median

The primary industry

Descriptive Statistics

	N	Mean	Std. Deviation	Minimum	Maximum
ANTO.L	204	691.168627	155.1728533	350.6000	961.0000
BP.L	204	556.409314	55.4325907	376.2500	712.0000
CNA.L	204	330.507255	25.6123390	283.0000	402.2000
SVT.L	204	2057.617647	213.8246390	1614.0000	2505.0000
JMAT.L	204	1545.287024	298.9634695	713.9520	2192.6699

Runs Test

	ANTO.L	BP.L	CNA.L	SVT.L	JMAT.L
Test Value[a]	732.0000	560.0000	327.5500	2086.0000	1554.1400
Cases < Test Value	101	100	102	102	102
Cases >= Test Value	103	104	102	102	102
Total Cases	204	204	204	204	204
Number of Runs	13	9	30	16	9
Z	-12.634	-13.195	-10.247	-12.213	-13.195
Asymp. Sig. (2-tailed)	.000	.000	.000	.000	.000

a. Median

The manufacturing industry

Descriptive Statistics

	N	Mean	Std. Deviation	Minimum	Maximum
ABF.L	204	806.850490	77.6299226	611.5000	948.5000
BATS.L	204	1709.443627	205.9253667	1331.0000	2229.5000
BDEV.L	204	467.305882	103.2407822	292.6000	662.5000
BKG.L	204	2712.656863	418.8382595	2043.0000	3688.0000
DGE.L	204	1933.210784	142.6588724	1684.5000	2319.0000

Runs Test

	ABF.L	BATS.L	BDEV.L	BKG.L	DGE.L
Test Value[a]	829.0000	1703.0000	461.4500	2615.5000	1891.2500
Cases < Test Value	102	101	102	102	102
Cases >= Test Value	102	103	102	102	102
Total Cases	204	204	204	204	204
Number of Runs	28	18	10	20	37
Z	-10.528	-11.932	-13.055	-11.651	-9.265
Asymp. Sig. (2-tailed)	.000	.000	.000	.000	.000

a. Median

The service industry

Descriptive Statistics

	N	Mean	Std. Deviation	Minimum	Maximum
ADN.L	204	369.141763	74.9788909	220.4000	507.5000
AHT.L	204	149.456008	42.9458913	74.2550	262.4300
AV.L	204	864.840571	112.7672170	600.4190	1176.9301
BAB.L	204	1041.233765	97.5710789	868.5000	1296.9800
BARC.L	204	452.964411	54.7304886	312.2260	576.4170

Runs Test

	ADN.L	AHT.L	AV.L	BAB.L	BARC.L
Test Value[a]	386.1500	149.0865	862.9295	1029.0300	457.6005
Cases < Test Value	102	102	102	102	102
Cases >= Test Value	102	102	102	102	102
Total Cases	204	204	204	204	204
Number of Runs	12	17	34	19	26
Z	-12.774	-12.072	-9.686	-11.791	-10.809
Asymp. Sig. (2-tailed)	.000	.000	.000	.000	.000

a. Median

The quaternary industry

Descriptive Statistics

	N	Mean	Std. Deviation	Minimum	Maximum
AZN.L	204	3023.634804	184.0987640	2592.0000	3513.5000
GSK.L	204	1741.904412	229.7816257	1200.5000	2288.0000
SHP.L	204	1074.718137	195.2967181	734.5000	1494.0000
SGE.L	204	324.643754	227.4681683	77.0290	951.4870
SN.L	204	662.522059	68.7350754	540.5000	815.5000

Runs Test

	AZN.L	GSK.L	SHP.L	SGE.L	SN.L
Test Value[a]	2998.5000	1797.5000	1051.5000	256.8360	657.5000
Cases < Test Value	102	102	102	102	101
Cases >= Test Value	102	102	102	102	103
Total Cases	204	204	204	204	204
Number of Runs	28	34	10	8	18
Z	-10.528	-9.686	-13.055	-13.336	-11.932
Asymp. Sig. (2-tailed)	.000	.000	.000	.000	.000

a. Median

(v) Autocorrelation : Ljung-Box test

1. FTSE-ALL SHARE INDEX

Date: 18/11/20 Time: 13:11
Sample (adjusted): 13/05/2013 27/03/2017
Included observations: 203 after adjustments

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
.|. |	.|. |	1	-0.044	-0.044	0.4054	0.524
*|. |	*|. |	2	-0.092	-0.094	2.1687	0.338
*|. |	*|. |	3	-0.155	-0.166	7.1841	0.066
.|* |	.|. |	4	0.079	0.054	8.4921	0.075
.|. |	.|. |	5	-0.012	-0.036	8.5199	0.130
*|. |	*|. |	6	-0.117	-0.138	11.436	0.076
*|. |	*|. |	7	-0.074	-0.076	12.603	0.082
.|. |	.|. |	8	-0.012	-0.062	12.635	0.125
.|* |	.|. |	9	0.123	0.069	15.903	0.069
.|. |	.|. |	10	-0.005	-0.012	15.908	0.102
.|. |	.|. |	11	0.041	0.051	16.273	0.131
.|. |	.|. |	12	0.035	0.061	16.548	0.167
.|. |	.|. |	13	0.037	0.023	16.853	0.206
.|. |	.|. |	14	-0.064	-0.043	17.751	0.218
.|. |	.|. |	15	-0.038	-0.009	18.064	0.259
.|. |	.|. |	16	0.053	0.065	18.684	0.285
.|. |	.|. |	17	-0.009	-0.006	18.702	0.346
.|. |	.|. |	18	-0.060	-0.047	19.511	0.361
.|. |	.|. |	19	-0.046	-0.023	19.996	0.395
.|. |	.|. |	20	0.042	0.001	20.394	0.434
.|. |	.|. |	21	0.003	-0.039	20.396	0.496
.|* |	.|* |	22	0.076	0.075	21.728	0.476
.|. |	.|. |	23	0.027	0.056	21.891	0.527
.|. |	.|. |	24	0.002	0.002	21.892	0.586

2. FTSE-350 General Industrial Index

Date: 19/12/20 Time: 09:58
Sample (adjusted): 12/05/2013 26/03/2017
Included observations: 203 after adjustments

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
*|. |	*|. |	1	-0.139	-0.139	3.9746	0.046
.|* |	.|* |	2	0.113	0.095	6.5988	0.037
*|. |	.|. |	3	-0.066	-0.040	7.5057	0.057
.|. |	.|. |	4	-0.005	-0.029	7.5101	0.111
.|. |	.|. |	5	-0.062	-0.057	8.3109	0.140
.|. |	.|. |	6	-0.004	-0.019	8.3148	0.216
.|. |	.|. |	7	0.044	0.053	8.7293	0.273
.|. |	.|. |	8	-0.060	-0.054	9.4856	0.303
.|* |	.|* |	9	0.107	0.084	11.959	0.216
*|. |	*|. |	10	-0.106	-0.075	14.387	0.156
.|. |	*|. |	11	-0.057	-0.106	15.081	0.179
.|. |	.|. |	12	-0.041	-0.031	15.442	0.218
.|. |	.|. |	13	-0.010	-0.015	15.465	0.279
.|. |	.|. |	14	0.063	0.069	16.329	0.294
.|. |	.|* |	15	0.066	0.077	17.303	0.301
.|. |	.|. |	16	0.040	0.022	17.651	0.345

.|. |	.|. |	17	0.001	0.012	17.652	0.411
*|. |	*|. |	18	-0.072	-0.090	18.829	0.402
.|. |	.|. |	19	0.011	0.015	18.855	0.466
.|. |	.|. |	20	0.001	0.039	18.856	0.531
.|. |	.|. |	21	0.019	0.006	18.935	0.589
.|* |	.|* |	22	0.096	0.097	21.034	0.519
.|. |	.|. |	23	0.026	0.023	21.185	0.570
.|. |	.|. |	24	0.038	0.028	21.527	0.607

3. ANTO.L

Date: 27/11/20 Time: 13:22
Sample (adjusted): 13/05/2013 27/03/2017
Included observations: 203 after adjustments

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
*|. |	*|. |	1	-0.102	-0.102	2.1251	0.145
.|* |	.|* |	2	0.134	0.125	5.8551	0.054
*|. |	*|. |	3	-0.164	-0.143	11.458	0.009
.|. |	*|. |	4	-0.058	-0.104	12.165	0.016
.|. |	.|. |	5	-0.058	-0.035	12.878	0.025
.|. |	.|. |	6	-0.012	-0.025	12.910	0.044
.|. |	.|. |	7	0.022	0.005	13.012	0.072
.|. |	*|. |	8	-0.049	-0.067	13.528	0.095
.|* |	.|. |	9	0.086	0.062	15.110	0.088
.|. |	.|. |	10	-0.007	0.020	15.119	0.128
.|. |	.|. |	11	0.069	0.038	16.164	0.135
.|. |	.|. |	12	0.001	0.025	16.165	0.184
*|. |	*|. |	13	-0.085	-0.092	17.738	0.168
.|. |	.|. |	14	-0.036	-0.033	18.022	0.206
.|. |	.|. |	15	-0.017	0.015	18.089	0.258
.|. |	.|. |	16	0.050	0.036	18.645	0.287
.|. |	.|. |	17	0.046	0.042	19.120	0.322
.|. |	.|. |	18	0.040	0.018	19.475	0.363
.|. |	.|. |	19	0.009	0.017	19.491	0.426
.|. |	.|. |	20	-0.009	0.001	19.511	0.489
.|* |	.|* |	21	0.102	0.117	21.905	0.405
.|. |	.|. |	22	-0.052	-0.014	22.524	0.429
.|* |	.|. |	23	0.076	0.056	23.864	0.411
.|. |	.|* |	24	0.043	0.121	24.291	0.445

4. BP.L

Date: 27/11/20 Time: 13:36
Sample (adjusted): 9/04/2006 22/02/2010
Included observations: 203 after adjustments

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
*|. |	*|. |	1	-0.083	-0.083	1.4266	0.232
.|. |	.|. |	2	0.045	0.039	1.8492	0.397
*|. |	*|. |	3	-0.089	-0.083	3.5135	0.319
*|. |	*|. |	4	-0.160	-0.177	8.8362	0.065
.|. |	.|. |	5	0.070	0.051	9.8751	0.079
.|. |	.|. |	6	0.050	0.069	10.395	0.109
*|. |	**|. |	7	-0.175	-0.214	16.927	0.018
.|. |	.|. |	8	0.071	0.021	18.002	0.021

.|.	|	.|.	|	9	-0.060	0.003	18.783	0.027
.|.	|	.|.	|	10	-0.017	-0.062	18.843	0.042
.|.	|	.|.	|	11	0.066	0.002	19.801	0.048
*|.	|	*|.	|	12	-0.148	-0.115	24.550	0.017
.|.	|	.|.	|	13	0.045	0.017	25.000	0.023
.|.	|	*|.	|	14	-0.040	-0.068	25.351	0.031
.|.	|	.|.	|	15	0.030	0.027	25.555	0.043
.|.	|	.|.	|	16	0.011	-0.036	25.583	0.060
.|.	|	.|.	|	17	-0.040	-0.052	25.933	0.076
.|.	|	.|.	|	18	0.030	0.047	26.139	0.097
.|.	|	.|.	|	19	0.033	-0.004	26.385	0.120
.|.	|	.|.	|	20	-0.035	-0.035	26.665	0.145
.|.	|	.|.	|	21	0.020	-0.021	26.753	0.179
*|.	|	.|.	|	22	-0.089	-0.064	28.586	0.157
.|.	|	.|.	|	23	0.027	0.015	28.759	0.188
.|.	|	.|.	|	24	0.010	-0.034	28.781	0.228

5. CNA.L

Date: 27/11/20 Time: 13:43
Sample (adjusted): 18/07/2010 1/06/2014
Included observations: 203 after adjustments

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
*|. |	*|. |	1	-0.149	-0.149	4.5884	0.032
.|. |	.|. |	2	-0.006	-0.028	4.5947	0.101
*|. |	*|. |	3	-0.086	-0.093	6.1186	0.106
.|. |	.|. |	4	-0.000	-0.028	6.1186	0.190
.|. |	.|. |	5	0.016	0.007	6.1707	0.290
.|. |	.|. |	6	-0.038	-0.045	6.4826	0.371
.|. |	.|. |	7	0.005	-0.010	6.4879	0.484
.|* |	.|* |	8	0.120	0.123	9.5582	0.297
.|. |	.|. |	9	-0.019	0.012	9.6350	0.381
*|. |	*|. |	10	-0.095	-0.096	11.590	0.313
.|. |	.|. |	11	0.011	0.005	11.615	0.393
.|. |	.|. |	12	-0.057	-0.062	12.330	0.420
*|. |	*|. |	13	-0.109	-0.158	14.922	0.312
.|* |	.|. |	14	0.098	0.069	17.044	0.254
.|. |	.|. |	15	-0.016	-0.005	17.101	0.313
.|** |	.|* |	16	0.223	0.189	28.123	0.031
.|* |	.|* |	17	0.095	0.203	30.126	0.025
*|. |	.|. |	18	-0.122	-0.047	33.469	0.015
.|. |	*|. |	19	-0.061	-0.076	34.317	0.017
.|. |	.|. |	20	-0.014	-0.005	34.360	0.024
.|. |	.|. |	21	-0.018	-0.041	34.435	0.033
.|* |	.|* |	22	0.116	0.079	37.551	0.021
.|. |	.|. |	23	0.000	0.039	37.551	0.028
.|. |	.|. |	24	0.043	0.012	37.980	0.035

6. SVT.L

Date: 27/11/20 Time: 13:51
Sample (adjusted): 19/05/2013 2/04/2017
Included observations: 203 after adjustments

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
.|. |	.|. |	1	-0.004	-0.004	0.0040	0.949

*|.	|	*|.	|	2	-0.143	-0.143	4.2184	0.121
*|.	|	*|.	|	3	-0.114	-0.117	6.9058	0.075
.|*	|	.|*	|	4	0.103	0.083	9.1307	0.058
.|.	|	.|.	|	5	-0.022	-0.054	9.2307	0.100
*|.	|	*|.	|	6	-0.150	-0.144	13.957	0.030
.|.	|	.|.	|	7	-0.038	-0.032	14.268	0.047
.|.	|	*|.	|	8	-0.021	-0.082	14.359	0.073
.|*	|	.|*	|	9	0.124	0.088	17.636	0.040
.|.	|	.|.	|	10	-0.031	-0.030	17.847	0.058
.|.	|	.|.	|	11	0.023	0.033	17.960	0.083
.|.	|	.|.	|	12	0.015	0.020	18.006	0.116
.|.	|	.|.	|	13	-0.022	-0.056	18.112	0.153
.|.	|	.|.	|	14	0.025	0.039	18.250	0.196
.|.	|	.|.	|	15	-0.038	-0.026	18.567	0.234
.|.	|	.|.	|	16	-0.034	-0.043	18.830	0.278
.|.	|	.|.	|	17	-0.033	-0.009	19.069	0.325
.|.	|	.|.	|	18	-0.018	-0.059	19.142	0.383
*|.	|	*|.	|	19	-0.105	-0.124	21.632	0.303
.|.	|	.|.	|	20	0.027	0.013	21.802	0.351
.|.	|	.|.	|	21	0.038	-0.017	22.139	0.392
*|.	|	*|.	|	22	-0.081	-0.113	23.654	0.366
.|.	|	.|.	|	23	-0.020	-0.025	23.748	0.418
.|*	|	.|.	|	24	0.095	0.057	25.860	0.360

7. JMAT.L

Date: 27/11/20 Time: 13:57
Sample (adjusted): 9/04/2006 22/02/2010
Included observations: 203 after adjustments

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
.|. |	.|. |	1	-0.060	-0.060	0.7483	0.387
.|. |	.|. |	2	0.012	0.008	0.7771	0.678
.|. |	.|. |	3	-0.016	-0.015	0.8305	0.842
.|. |	.|. |	4	-0.020	-0.022	0.9107	0.923
.|* |	.|* |	5	0.090	0.089	2.6307	0.757
.|. |	.|. |	6	-0.021	-0.010	2.7239	0.843
.|. |	.|. |	7	-0.027	-0.031	2.8767	0.896
.|* |	.|* |	8	0.088	0.089	4.5472	0.805
.|. |	.|. |	9	0.014	0.027	4.5866	0.869
.|. |	.|. |	10	-0.023	-0.033	4.7003	0.910
*|. |	*|. |	11	-0.108	-0.109	7.2333	0.780
.|. |	*|. |	12	-0.063	-0.068	8.1057	0.777
.|* |	.|* |	13	0.107	0.088	10.602	0.644
.|* |	.|* |	14	0.127	0.141	14.156	0.438
.|. |	.|. |	15	0.032	0.054	14.388	0.496
.|* |	.|* |	16	0.134	0.155	18.360	0.303
.|. |	.|* |	17	0.050	0.087	18.915	0.333
.|. |	.|. |	18	-0.007	-0.018	18.925	0.396
.|. |	.|. |	19	0.045	0.043	19.382	0.433
.|. |	.|. |	20	-0.020	0.007	19.474	0.491
*|. |	*|. |	21	-0.073	-0.126	20.678	0.479
.|. |	*|. |	22	-0.058	-0.140	21.464	0.492
.|. |	.|. |	23	0.065	0.042	22.452	0.493
*|. |	*|. |	24	-0.075	-0.080	23.763	0.475

The manufacturing industry

8. ABF.L

Date: 28/11/20 Time: 10:09
Sample (adjusted): 9/01/2006 23/11/2009
Included observations: 203 after adjustments

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
.|. |	.|. |	1	-0.011	-0.011	0.0231	0.879
.|. |	.|. |	2	-0.003	-0.003	0.0245	0.988
.|. |	.|. |	3	-0.048	-0.048	0.5116	0.916
.|. |	.|. |	4	0.064	0.063	1.3608	0.851
.|. |	.|. |	5	-0.056	-0.055	2.0099	0.848
.|. |	.|. |	6	0.010	0.007	2.0312	0.917
*|. |	*|. |	7	-0.109	-0.104	4.5435	0.715
.|* |	.|* |	8	0.115	0.108	7.3806	0.496
.|. |	.|. |	9	-0.063	-0.060	8.2345	0.511
*|. |	*|. |	10	-0.139	-0.154	12.389	0.260
*|. |	*|. |	11	-0.139	-0.122	16.566	0.121
.|. |	.|. |	12	-0.014	-0.049	16.606	0.165
.|. |	.|. |	13	-0.011	-0.008	16.633	0.217
*|. |	*|. |	14	-0.088	-0.114	18.344	0.192
.|. |	.|. |	15	0.037	0.055	18.640	0.231
.|* |	.|. |	16	0.084	0.052	20.221	0.210
.|. |	.|. |	17	0.035	0.013	20.502	0.249
.|. |	.|* |	18	0.057	0.077	21.220	0.268
.|. |	.|. |	19	-0.002	-0.004	21.221	0.325
.|* |	.|. |	20	0.087	0.070	22.952	0.291
.|* |	.|. |	21	0.078	0.032	24.356	0.276
.|. |	.|. |	22	-0.044	-0.044	24.804	0.307
*|. |	*|. |	23	-0.090	-0.105	26.680	0.270
.|* |	.|* |	24	0.118	0.082	29.905	0.188

9. BATS.L

Date: 28/11/20 Time: 10:14
Sample (adjusted): 9/04/2006 22/02/2010
Included observations: 203 after adjustments

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
**|. |	**|. |	1	-0.337	-0.337	23.346	0.000
.|* |	.|. |	2	0.106	-0.008	25.670	0.000
.|. |	.|. |	3	-0.041	-0.008	26.013	0.000
.|. |	.|. |	4	-0.018	-0.038	26.080	0.000
.|* |	.|. |	5	0.076	0.067	27.299	0.000
.|. |	.|. |	6	-0.035	0.015	27.562	0.000
*|. |	*|. |	7	-0.080	-0.108	28.932	0.000
.|. |	.|. |	8	0.000	-0.065	28.932	0.000
.|. |	.|. |	9	0.029	0.025	29.114	0.001
*|. |	*|. |	10	-0.094	-0.096	31.031	0.001
.|. |	.|. |	11	0.022	-0.051	31.133	0.001
*|. |	*|. |	12	-0.156	-0.162	36.426	0.000
.|. |	.|. |	13	0.062	-0.052	37.275	0.000
.|. |	.|. |	14	-0.018	-0.024	37.348	0.001

.|.	|	.|.	|	15	0.025	0.016	37.484	0.001
.|.	|	.|.	|	16	0.005	0.017	37.490	0.002
.|.	|	.|.	|	17	0.045	0.061	37.952	0.002
.|.	|	.|.	|	18	-0.028	-0.018	38.131	0.004
.|.	|	.|.	|	19	0.042	-0.003	38.538	0.005
.|.	|	.|.	|	20	-0.026	-0.029	38.696	0.007
.|*	|	.|*	|	21	0.133	0.136	42.757	0.003
.|.	|	.|.	|	22	-0.040	0.022	43.127	0.005
.|.	|	.|.	|	23	0.019	0.005	43.214	0.007
.|*	|	.|*	|	24	0.080	0.095	44.705	0.006

10. BDEV.L

Date: 28/11/20 Time: 10:20
Sample (adjusted): 19/05/2013 2/04/2017
Included observations: 203 after adjustments

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
.|.	|	.|.	|	1	0.023	0.023	0.1062	0.745
.|.	|	.|.	|	2	-0.034	-0.035	0.3524	0.838
*|.	|	*|.	|	3	-0.134	-0.133	4.1032	0.251
.|*	|	.|*	|	4	0.180	0.188	10.892	0.028
*|.	|	*|.	|	5	-0.120	-0.149	13.933	0.016
.|.	|	.|.	|	6	-0.054	-0.049	14.544	0.024
*|.	|	*|.	|	7	-0.158	-0.120	19.846	0.006
.|.	|	.|.	|	8	0.013	-0.050	19.885	0.011
.|.	|	.|.	|	9	-0.027	-0.002	20.040	0.018
.|.	|	.|.	|	10	0.041	0.005	20.405	0.026
.|.	|	.|.	|	11	0.002	0.033	20.406	0.040
.|*	|	.|*	|	12	0.108	0.078	22.937	0.028
.|*	|	.|*	|	13	0.092	0.087	24.772	0.025
.|.	|	.|.	|	14	-0.000	-0.030	24.772	0.037
*|.	|	.|.	|	15	-0.069	-0.046	25.813	0.040
.|*	|	.|*	|	16	0.083	0.089	27.343	0.038
.|.	|	.|.	|	17	0.050	0.036	27.902	0.046
.|.	|	.|*	|	18	0.057	0.101	28.639	0.053
*|.	|	*|.	|	19	-0.129	-0.070	32.400	0.028
.|.	|	.|.	|	20	0.002	0.014	32.401	0.039
.|.	|	.|.	|	21	-0.002	0.010	32.402	0.053
.|.	|	.|.	|	22	-0.008	-0.065	32.416	0.071
.|.	|	.|*	|	23	0.024	0.110	32.553	0.089
.|*	|	.|*	|	24	0.102	0.084	34.960	0.069

11. BKG.L

Date: 28/11/20 Time: 10:26
Sample (adjusted): 19/05/2013 2/04/2017
Included observations: 203 after adjustments

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
.|.	|	.|.	|	1	0.010	0.010	0.0218	0.883
*|.	|	*|.	|	2	-0.094	-0.094	1.8441	0.398
.|.	|	.|.	|	3	-0.042	-0.040	2.2080	0.530
.|.	|	.|.	|	4	0.012	0.004	2.2361	0.692
.|.	|	.|.	|	5	-0.032	-0.040	2.4472	0.784

.|.	|	.|.	|	6	-0.006	-0.006	2.4560	0.873
*|.	|	*|.	|	7	-0.075	-0.082	3.6400	0.820
.|.	|	.|.	|	8	-0.019	-0.022	3.7155	0.882
*|.	|	*|.	|	9	-0.068	-0.084	4.6942	0.860
.|.	|	.|.	|	10	0.038	0.027	5.0028	0.891
.|.	|	.|.	|	11	-0.001	-0.018	5.0029	0.931
.|.	|	.|.	|	12	0.035	0.030	5.2699	0.948
.|.	|	.|.	|	13	-0.000	-0.002	5.2700	0.969
.|.	|	.|.	|	14	0.026	0.020	5.4236	0.979
.|.	|	.|.	|	15	-0.000	0.000	5.4237	0.988
.|*	|	.|.	|	16	0.077	0.071	6.7482	0.978
.|*	|	.|*	|	17	0.084	0.093	8.3252	0.959
.|.	|	.|.	|	18	0.046	0.058	8.7934	0.964
*|.	|	.|.	|	19	-0.095	-0.060	10.817	0.930
*|.	|	.|.	|	20	-0.070	-0.055	11.927	0.919
.|.	|	.|.	|	21	-0.015	-0.013	11.980	0.940
.|.	|	.|.	|	22	0.025	0.014	12.129	0.955
*|.	|	*|.	|	23	-0.090	-0.080	13.987	0.927
.|*	|	.|*	|	24	0.107	0.125	16.660	0.863

12. DGE.L

Date: 28/11/20 Time: 10:30
Sample (adjusted): 19/05/2013 2/04/2017
Included observations: 203 after adjustments

Autocorrelation		Partial Correlation			AC	PAC	Q-Stat	Prob
.|.	|	.|.	|	1	0.019	0.019	0.0708	0.790
*|.	|	*|.	|	2	-0.159	-0.159	5.2889	0.071
.|.	|	.|.	|	3	-0.049	-0.044	5.7841	0.123
.|.	|	.|.	|	4	0.023	-0.001	5.8907	0.207
.|.	|	.|.	|	5	0.021	0.007	5.9863	0.308
*|.	|	*|.	|	6	-0.169	-0.173	12.043	0.061
.|.	|	.|.	|	7	-0.039	-0.030	12.366	0.089
.|.	|	*|.	|	8	-0.031	-0.087	12.568	0.128
.|.	|	.|.	|	9	0.059	0.034	13.304	0.149
*|.	|	*|.	|	10	-0.165	-0.203	19.193	0.038
.|*	|	.|*	|	11	0.074	0.103	20.382	0.040
.|.	|	.|.	|	12	0.070	-0.028	21.443	0.044
.|.	|	.|.	|	13	0.008	0.017	21.458	0.064
.|.	|	.|.	|	14	0.007	-0.015	21.469	0.090
*|.	|	*|.	|	15	-0.098	-0.075	23.609	0.072
.|.	|	.|.	|	16	0.031	-0.032	23.828	0.093
.|.	|	*|.	|	17	-0.062	-0.075	24.680	0.102
.|.	|	.|.	|	18	-0.001	-0.020	24.680	0.134
.|.	|	.|.	|	19	-0.028	-0.027	24.855	0.165
.|*	|	.|*	|	20	0.119	0.091	28.095	0.107
.|.	|	*|.	|	21	-0.056	-0.093	28.822	0.118
.|.	|	.|.	|	22	-0.055	-0.014	29.508	0.131
.|*	|	.|.	|	23	0.077	0.018	30.870	0.126
.|.	|	.|.	|	24	0.068	0.068	31.932	0.129

The service industry

13. ADN.L

Date: 28/11/20 Time: 12:28
Sample (adjusted): 19/05/2013 2/04/2017
Included observations: 203 after adjustments

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
.|. |	.|. |	1	-0.021	-0.021	0.0945	0.758
.|. |	.|. |	2	-0.050	-0.050	0.6117	0.736
*|. |	*|. |	3	-0.166	-0.168	6.3255	0.097
.|* |	.|* |	4	0.108	0.100	8.7676	0.067
.|. |	.|. |	5	0.056	0.045	9.4233	0.093
.|. |	.|. |	6	0.032	0.017	9.6402	0.141
.|. |	.|. |	7	-0.026	0.014	9.7877	0.201
.|. |	.|. |	8	-0.065	-0.061	10.702	0.219
.|. |	.|. |	9	-0.014	-0.020	10.743	0.294
.|. |	.|. |	10	-0.017	-0.034	10.802	0.373
.|. |	.|. |	11	0.046	0.024	11.260	0.422
*|. |	*|. |	12	-0.089	-0.086	12.997	0.369
*|. |	*|. |	13	-0.103	-0.107	15.322	0.288
*|. |	*|. |	14	-0.089	-0.086	17.055	0.253
.|* |	.|. |	15	0.110	0.068	19.729	0.183
.|. |	.|. |	16	-0.014	-0.039	19.772	0.231
*|. |	*|. |	17	-0.084	-0.086	21.356	0.211
*|. |	*|. |	18	-0.123	-0.082	24.742	0.132
.|. |	.|. |	19	0.057	0.033	25.481	0.145
.|. |	.|. |	20	0.003	-0.042	25.484	0.184
.|. |	.|. |	21	0.058	0.032	26.253	0.197
.|. |	.|* |	22	0.053	0.083	26.890	0.215
.|. |	.|. |	23	0.047	0.060	27.402	0.239
*|. |	*|. |	24	-0.079	-0.069	28.867	0.225

14. AHT.L

Date: 28/11/20 Time: 12:33
Sample (adjusted): 8/06/1997 22/04/2001
Included observations: 203 after adjustments

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
.|. |	.|. |	1	0.058	0.058	0.6976	0.404
.|. |	.|. |	2	0.053	0.050	1.2798	0.527
*|. |	*|. |	3	-0.163	-0.170	6.7882	0.079
*|. |	.|. |	4	-0.074	-0.059	7.9424	0.094
.|* |	.|* |	5	0.075	0.105	9.1092	0.105
.|. |	.|. |	6	-0.022	-0.054	9.2105	0.162
.|. |	.|. |	7	0.000	-0.032	9.2105	0.238
.|. |	.|. |	8	0.013	0.048	9.2448	0.322
.|. |	.|. |	9	0.030	0.031	9.4412	0.398
.|. |	*|. |	10	-0.058	-0.090	10.167	0.426
.|* |	.|* |	11	0.097	0.124	12.215	0.348
.|* |	.|* |	12	0.106	0.129	14.647	0.261
.|* |	.|* |	13	0.189	0.139	22.442	0.049
.|. |	*|. |	14	-0.059	-0.082	23.212	0.057
.|. |	.|. |	15	-0.025	0.036	23.348	0.077

**|. |	**|. |	16	-0.252	-0.217	37.522	0.002
*|. |	*|. |	17	-0.097	-0.108	39.635	0.001
.|. |	.|. |	18	-0.054	-0.048	40.300	0.002
.|. |	*|. |	19	-0.036	-0.070	40.598	0.003
.|* |	.|. |	20	0.078	0.006	41.984	0.003
.|. |	.|* |	21	0.055	0.089	42.670	0.003
*|. |	*|. |	22	-0.072	-0.122	43.865	0.004
*|. |	*|. |	23	-0.099	-0.111	46.139	0.003
.|. |	.|* |	24	0.068	0.108	47.211	0.003

15. AV.L

Date: 28/11/20 Time: 12:38
Sample (adjusted): 8/06/1997 22/04/2001
Included observations: 203 after adjustments

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
**|. |	**|. |	1	-0.207	-0.207	8.8351	0.003
.|. |	.|. |	2	0.018	-0.026	8.9002	0.012
.|. |	.|. |	3	0.064	0.065	9.7483	0.021
*|. |	*|. |	4	-0.151	-0.130	14.529	0.006
.|. |	.|. |	5	0.072	0.016	15.616	0.008
.|. |	.|. |	6	-0.052	-0.040	16.194	0.013
.|* |	.|* |	7	0.100	0.104	18.320	0.011
.|. |	.|. |	8	-0.058	-0.045	19.030	0.015
*|. |	*|. |	9	-0.094	-0.107	20.937	0.013
.|* |	.|* |	10	0.131	0.077	24.617	0.006
*|. |	*|. |	11	-0.138	-0.069	28.758	0.002
.|. |	*|. |	12	-0.044	-0.106	29.179	0.004
.|* |	.|. |	13	0.109	0.063	31.803	0.003
*|. |	*|. |	14	-0.125	-0.069	35.265	0.001
.|. |	.|. |	15	0.065	0.008	36.195	0.002
.|* |	.|* |	16	0.082	0.105	37.676	0.002
.|. |	.|* |	17	0.060	0.106	38.492	0.002
.|. |	.|. |	18	-0.048	-0.039	39.009	0.003
.|. |	.|. |	19	-0.015	-0.005	39.060	0.004
.|. |	*|. |	20	-0.020	-0.067	39.146	0.006
.|. |	.|. |	21	-0.035	0.001	39.425	0.009
.|. |	.|. |	22	-0.004	-0.028	39.429	0.013
.|* |	.|. |	23	0.090	0.042	41.320	0.011
.|. |	.|. |	24	-0.022	0.029	41.430	0.015

16. BAB.L

Date: 28/11/20 Time: 12:43
Sample (adjusted): 19/05/2013 2/04/2017
Included observations: 203 after adjustments

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
*|. |	*|. |	1	-0.082	-0.082	1.3786	0.240
.|. |	.|. |	2	-0.021	-0.027	1.4657	0.481
*|. |	*|. |	3	-0.074	-0.079	2.6142	0.455
.|. |	.|. |	4	-0.040	-0.054	2.9427	0.567
.|. |	.|. |	5	0.038	0.026	3.2448	0.662
*|. |	*|. |	6	-0.114	-0.119	5.9897	0.424

.|*	|	.|.	|	7	0.096	0.073	7.9459	0.337
.|.	|	.|.	|	8	0.013	0.023	7.9836	0.435
.|.	|	.|.	|	9	0.027	0.020	8.1376	0.520
*|.	|	*|.	|	10	-0.129	-0.125	11.710	0.305
*|.	|	*|.	|	11	-0.104	-0.111	14.067	0.229
.|.	|	.|.	|	12	0.016	-0.024	14.120	0.293
.|.	|	.|.	|	13	0.057	0.052	14.819	0.319
.|.	|	.|.	|	14	-0.014	-0.039	14.863	0.388
.|*	|	.|*	|	15	0.104	0.108	17.278	0.303
.|.	|	.|.	|	16	-0.056	-0.064	17.983	0.325
.|.	|	.|.	|	17	-0.052	-0.062	18.584	0.353
*|.	|	*|.	|	18	-0.122	-0.117	21.955	0.234
.|.	|	.|.	|	19	0.021	0.023	22.053	0.282
.|.	|	.|.	|	20	0.041	-0.009	22.438	0.317
.|.	|	.|.	|	21	0.001	-0.010	22.439	0.375
.|.	|	.|.	|	22	0.011	-0.042	22.467	0.432
.|.	|	.|.	|	23	-0.036	-0.021	22.767	0.474
.|*	|	.|*	|	24	0.116	0.099	25.899	0.358

17. BARC.L

Date: 28/11/20 Time: 12:47
Sample (adjusted): 8/10/2000 22/08/2004
Included observations: 203 after adjustments

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
.|. |	.|. |	1	-0.039	-0.039	0.3065	0.580
.|. |	.|. |	2	-0.045	-0.047	0.7288	0.695
.|. |	.|. |	3	-0.006	-0.009	0.7355	0.865
*|. |	*|. |	4	-0.180	-0.183	7.4869	0.112
*|. |	*|. |	5	-0.109	-0.129	9.9669	0.076
.|* |	.|* |	6	0.128	0.103	13.443	0.037
.|. |	.|. |	7	-0.028	-0.034	13.614	0.058
.|. |	.|. |	8	0.047	0.019	14.092	0.079
.|. |	*|. |	9	-0.035	-0.078	14.362	0.110
.|. |	.|* |	10	0.052	0.083	14.951	0.134
*|. |	.|. |	11	-0.068	-0.055	15.967	0.142
.|* |	.|* |	12	0.093	0.092	17.868	0.120
.|. |	*|. |	13	-0.065	-0.074	18.788	0.130
*|. |	*|. |	14	-0.152	-0.158	23.888	0.047
.|. |	.|. |	15	0.035	0.031	24.160	0.062
.|* |	.|* |	16	0.097	0.094	26.264	0.050
.|. |	.|. |	17	-0.033	-0.009	26.505	0.066
.|* |	.|. |	18	0.108	0.008	29.105	0.047
*|. |	*|. |	19	-0.113	-0.113	32.006	0.031
.|. |	.|. |	20	-0.046	0.007	32.487	0.038
.|. |	.|. |	21	-0.030	-0.017	32.691	0.050
.|* |	.|* |	22	0.107	0.108	35.311	0.036
.|. |	.|. |	23	-0.030	-0.061	35.522	0.046
.|. |	.|. |	24	0.058	0.013	36.299	0.051

The quaternary industry:

18. AZN.L

Date: 28/11/20 Time: 14:07
Sample (adjusted): 11/01/2010 25/11/2013
Included observations: 203 after adjustments

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
.|. |	.|. |	1	-0.002	-0.002	0.0010	0.975
.|. |	.|. |	2	-0.031	-0.031	0.2045	0.903
.|. |	.|. |	3	-0.023	-0.023	0.3106	0.958
.|. |	.|. |	4	-0.060	-0.061	1.0655	0.900
.|. |	.|. |	5	-0.006	-0.008	1.0737	0.956
.|. |	.|. |	6	-0.021	-0.026	1.1664	0.979
.|. |	.|. |	7	0.004	0.001	1.1698	0.992
.|. |	.|. |	8	-0.027	-0.033	1.3291	0.995
.|. |	.|. |	9	-0.012	-0.014	1.3608	0.998
.|. |	*|. |	10	-0.065	-0.070	2.2691	0.994
.|. |	.|. |	11	-0.016	-0.019	2.3219	0.997
*|. |	*|. |	12	-0.096	-0.108	4.3401	0.976
.|. |	.|. |	13	0.020	0.012	4.4308	0.986
.|. |	.|. |	14	0.050	0.031	4.9832	0.986
.|. |	.|. |	15	0.017	0.010	5.0470	0.992
.|. |	.|. |	16	-0.017	-0.032	5.1111	0.995
.|. |	.|. |	17	-0.027	-0.027	5.2766	0.997
*|. |	*|. |	18	-0.071	-0.080	6.4058	0.994
.|. |	.|. |	19	0.011	0.007	6.4327	0.997
.|. |	.|. |	20	0.013	-0.007	6.4738	0.998
*|. |	*|. |	21	-0.090	-0.103	8.3242	0.994
*|. |	*|. |	22	-0.110	-0.141	11.109	0.973
.|. |	.|. |	23	-0.012	-0.028	11.142	0.982
.|. |	.|. |	24	-0.028	-0.059	11.327	0.986

19. GSK.L

Date: 28/11/20 Time: 14:49
Sample (adjusted): 8/06/1997 22/04/2001
Included observations: 203 after adjustments

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
*|. |	*|. |	1	-0.094	-0.094	1.8326	0.176
.|. |	.|. |	2	-0.037	-0.047	2.1216	0.346
*|. |	*|. |	3	-0.133	-0.143	5.7971	0.122
.|. |	.|. |	4	-0.000	-0.031	5.7971	0.215
.|. |	.|. |	5	-0.016	-0.033	5.8479	0.321
.|. |	.|. |	6	0.002	-0.025	5.8489	0.440
.|. |	.|. |	7	-0.012	-0.022	5.8810	0.554
*|. |	*|. |	8	-0.070	-0.085	6.9377	0.543
.|. |	.|. |	9	0.049	0.027	7.4484	0.591
.|. |	.|. |	10	-0.009	-0.016	7.4653	0.681
.|. |	.|. |	11	-0.026	-0.049	7.6132	0.747
.|. |	.|. |	12	0.025	0.023	7.7467	0.805
.|. |	.|. |	13	0.021	0.015	7.8394	0.854
*|. |	*|. |	14	-0.083	-0.090	9.3380	0.809
.|. |	*|. |	15	-0.059	-0.076	10.097	0.814

*|. |	*|. |	16	-0.122	-0.156	13.384	0.645
.|. |	*|. |	17	-0.023	-0.090	13.507	0.702
.|. |	.|. |	18	0.041	-0.022	13.882	0.737
.|* |	.|. |	19	0.106	0.051	16.425	0.629
.|. |	.|. |	20	0.030	0.033	16.631	0.677
.|. |	.|. |	21	0.025	0.034	16.774	0.725
.|. |	.|. |	22	0.029	0.044	16.967	0.765
.|. |	.|. |	23	0.029	0.051	17.163	0.801
.|. |	.|. |	24	0.019	0.033	17.249	0.838

20. SHP.L

Date: 28/11/20 Time: 14:54
Sample (adjusted): 8/10/2006 22/08/2010
Included observations: 203 after adjustments

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
*|. |	*|. |	1	-0.104	-0.104	2.2487	0.134
.|* |	.|* |	2	0.099	0.089	4.2822	0.118
*|. |	.|. |	3	-0.082	-0.064	5.6811	0.128
.|. |	.|. |	4	0.068	0.046	6.6371	0.156
.|. |	.|. |	5	0.027	0.051	6.7875	0.237
.|. |	.|. |	6	-0.052	-0.062	7.3592	0.289
.|. |	.|. |	7	0.025	0.017	7.4909	0.380
*|. |	*|. |	8	-0.144	-0.132	11.927	0.155
.|. |	.|. |	9	0.035	-0.005	12.187	0.203
.|. |	.|. |	10	-0.044	-0.010	12.608	0.246
*|. |	*|. |	11	-0.138	-0.172	16.724	0.116
.|. |	.|. |	12	0.055	0.054	17.378	0.136
.|. |	.|. |	13	-0.022	0.016	17.487	0.178
.|* |	.|* |	14	0.202	0.170	26.506	0.022
*|. |	.|. |	15	-0.077	-0.009	27.815	0.023
.|* |	.|* |	16	0.131	0.081	31.650	0.011
*|. |	.|. |	17	-0.070	-0.032	32.750	0.012
.|* |	.|* |	18	0.139	0.093	37.111	0.005
.|. |	.|. |	19	0.062	0.060	37.969	0.006
.|. |	.|. |	20	0.050	0.064	38.545	0.008
.|. |	.|. |	21	0.028	0.028	38.724	0.011
.|. |	.|. |	22	-0.037	-0.007	39.047	0.014
.|. |	.|. |	23	0.044	0.026	39.503	0.017
.|. |	.|. |	24	-0.022	0.031	39.618	0.023

21. SGE.L

Date: 28/11/20 Time: 14:58
Sample (adjusted): 8/06/1997 22/04/2001
Included observations: 203 after adjustments

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
**|. |	**|. |	1	-0.224	-0.224	10.324	0.001
.|. |	.|. |	2	0.042	-0.008	10.692	0.005
.|. |	.|. |	3	-0.021	-0.014	10.781	0.013
.|. |	.|. |	4	-0.052	-0.062	11.337	0.023
.|* |	.|* |	5	0.097	0.077	13.321	0.021
.|* |	.|** |	6	0.181	0.235	20.280	0.002

*|. |	.|. |	7	-0.139	-0.057	24.406	0.001
.|* |	.|* |	8	0.201	0.168	33.055	0.000
*|. |	.|. |	9	-0.120	-0.023	36.162	0.000
.|. |	.|. |	10	0.008	-0.029	36.177	0.000
*|. |	*|. |	11	-0.113	-0.184	38.940	0.000
.|** |	.|** |	12	0.260	0.232	53.683	0.000
.|. |	.|* |	13	-0.013	0.081	53.718	0.000
.|* |	.|* |	14	0.172	0.153	60.247	0.000
**|. |	*|. |	15	-0.219	-0.138	70.898	0.000
.|. |	*|. |	16	-0.027	-0.081	71.058	0.000
.|. |	.|. |	17	0.046	0.024	71.522	0.000
.|. |	*|. |	18	-0.062	-0.189	72.377	0.000
*|. |	*|. |	19	-0.071	-0.139	73.507	0.000
.|* |	.|. |	20	0.123	-0.009	76.921	0.000
*|. |	.|. |	21	-0.135	0.025	81.096	0.000
.|* |	.|. |	22	0.144	0.070	85.880	0.000
*|. |	.|. |	23	-0.162	0.014	91.951	0.000
.|. |	.|. |	24	-0.005	-0.012	91.956	0.000

22. SN.L

Date: 28/11/20 Time: 15:02
Sample (adjusted): 11/01/2010 25/11/2013
Included observations: 203 after adjustments

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
*|. |	*|. |	1	-0.101	-0.101	2.0880	0.148
.|. |	.|. |	2	-0.023	-0.033	2.1931	0.334
.|. |	.|. |	3	0.008	0.002	2.2059	0.531
*|. |	**|. |	4	-0.205	-0.207	10.985	0.027
.|. |	.|. |	5	0.035	-0.007	11.249	0.047
.|. |	.|. |	6	0.039	0.031	11.566	0.072
.|* |	.|* |	7	0.074	0.085	12.728	0.079
.|* |	.|* |	8	0.111	0.094	15.380	0.052
.|. |	.|* |	9	0.060	0.100	16.148	0.064
.|. |	.|. |	10	-0.051	-0.012	16.706	0.081
.|. |	.|. |	11	0.006	0.038	16.714	0.117
*|. |	.|. |	12	-0.098	-0.065	18.787	0.094
.|. |	.|. |	13	0.018	0.021	18.858	0.128
.|. |	.|. |	14	0.013	-0.024	18.894	0.169
*|. |	*|. |	15	-0.067	-0.090	19.881	0.177
.|* |	.|. |	16	0.119	0.052	23.023	0.113
.|. |	.|. |	17	-0.002	0.012	23.023	0.148
*|. |	*|. |	18	-0.128	-0.131	26.697	0.085
*|. |	*|. |	19	-0.082	-0.135	28.208	0.080
.|. |	.|. |	20	-0.019	-0.007	28.290	0.103
.|. |	.|. |	21	-0.023	-0.021	28.410	0.129
.|* |	.|. |	22	0.097	0.051	30.580	0.105
.|. |	.|. |	23	-0.015	-0.028	30.632	0.132
*|. |	*|. |	24	-0.078	-0.085	32.051	0.126

vi) Variance ratio tests

1. FTSE-ALL SHARE INDEX

Null Hypothesis: FTSE_ALL_SHARE_INDEX is a martingale
Date: 29/11/20 Time: 19:48
Sample: 6/05/2013 27/03/2017
Included observations: 203 (after adjustments)
Heteroskedasticity robust standard error estimates
User-specified lags: 2 4 8 16

Joint Tests	Value	df	Probability
Max |z| (at period 8)*	1.913084	203	0.2050

Individual Tests

Period	Var. Ratio	Std. Error	z-Statistic	Probability
2	0.963225	0.072407	-0.507890	0.6115
4	0.784510	0.133109	-1.618899	0.1055
8	0.597077	0.210614	-1.913084	0.0557
16	0.564584	0.314602	-1.384019	0.1664

*Probability approximation using studentized maximum modulus with parameter value 4 and infinite degrees of freedom

Test Details (Mean = 2.46300487685)

Period	Variance	Var. Ratio	Obs.
1	3994.84	--	203
2	3847.93	0.96323	202
4	3133.99	0.78451	200
8	2385.23	0.59708	196
16	2255.42	0.56458	188

2. FTSE-350 General Industrial Index

Null Hypothesis: FTSE_350_INDUS__INDEX is a martingale
Date: 19/12/20 Time: 10:15
Sample: 5/05/2013 26/03/2017
Included observations: 203 (after adjustments)
Heteroskedasticity robust standard error estimates
User-specified lags: 2 4 8 16

Joint Tests	Value	df	Probability
Max |z| (at period 2)*	2.043209	203	0.1543

Individual Tests

Period	Var. Ratio	Std. Error	z-Statistic	Probability
2	0.866883	0.065151	-2.043209	0.0410
4	0.881349	0.122038	-0.972251	0.3309
8	0.833632	0.193392	-0.860263	0.3896
16	0.790008	0.292437	-0.718075	0.4727

*Probability approximation using studentized maximum modulus

with parameter value 4 and infinite degrees of freedom

Test Details (Mean = 9.3781773399)

Period	Variance	Var. Ratio	Obs.
1	9203.62	--	203
2	7978.46	0.86688	202
4	8111.59	0.88135	200
8	7672.43	0.83363	196
16	7270.93	0.79001	188

The primary industry

3. ANTO.L

Null Hypothesis: ANTO_L is a martingale
Date: 29/11/20 Time: 19:51
Sample: 6/05/2013 27/03/2017
Included observations: 203 (after adjustments)
Heteroskedasticity robust standard error estimates
User-specified lags: 2 4 8 16

Joint Tests	Value	df	Probability
Max |z| (at period 2)*	1.351129	203	0.5405

Individual Tests

Period	Var. Ratio	Std. Error	z-Statistic	Probability
2	0.906304	0.069346	-1.351129	0.1767
4	0.914488	0.133418	-0.640939	0.5216
8	0.750404	0.216731	-1.151640	0.2495
16	0.693235	0.318087	-0.964404	0.3348

*Probability approximation using studentized maximum modulus with parameter value 4 and infinite degrees of freedom

Test Details (Mean = -0.386699507389)

Period	Variance	Var. Ratio	Obs.
1	1215.34	--	203
2	1101.47	0.90630	202
4	1111.41	0.91449	200
8	911.997	0.75040	196
16	842.518	0.69324	188

4. BP.L

Null Hypothesis: BP_L is a martingale
Date: 29/11/20 Time: 20:02
Sample: 2/04/2006 22/02/2010
Included observations: 203 (after adjustments)
Heteroskedasticity robust standard error estimates
User-specified lags: 2 4 8 16

Joint Tests	Value	df	Probability
Max |z| (at period 16)*	1.154561	203	0.6807

Individual Tests

Period	Var. Ratio	Std. Error	z-Statistic	Probability
2	0.925580	0.098211	-0.757752	0.4486
4	0.897481	0.178131	-0.575527	0.5649
8	0.717025	0.277533	-1.019610	0.3079
16	0.534327	0.403334	-1.154561	0.2483

*Probability approximation using studentized maximum modulus with parameter value 4 and infinite degrees of freedom

Test Details (Mean = -0.506403881773)

Period	Variance	Var. Ratio	Obs.
1	408.645	--	203
2	378.233	0.92558	202
4	366.751	0.89748	200
8	293.008	0.71702	196
16	218.350	0.53433	188

5. CNA.L

Null Hypothesis: CNA_L is a martingale
Date: 29/11/20 Time: 20:11
Sample: 11/07/2010 1/06/2014
Included observations: 203 (after adjustments)
Heteroskedasticity robust standard error estimates
User-specified lags: 2 4 8 16

Joint Tests	Value	df	Probability
Max |z| (at period 2)*	2.074847	203	0.1436

Individual Tests

Period	Var. Ratio	Std. Error	z-Statistic	Probability
2	0.858088	0.068396	-2.074847	0.0380
4	0.744885	0.127981	-1.993390	0.0462
8	0.641590	0.199158	-1.799631	0.0719
16	0.594580	0.293518	-1.381246	0.1672

*Probability approximation using studentized maximum modulus with parameter value 4 and infinite degrees of freedom

Test Details (Mean = 0.129556591133)

Period	Variance	Var. Ratio	Obs.
1	58.8352	--	203
2	50.4858	0.85809	202
4	43.8255	0.74488	200
8	37.7481	0.64159	196
16	34.9822	0.59458	188

6. SVT.L

Null Hypothesis: SVT_L is a martingale
Date: 29/11/20 Time: 20:19
Sample: 12/05/2013 2/04/2017
Included observations: 203 (after adjustments)
Heteroskedasticity robust standard error estimates
User-specified lags: 2 4 8 16

Joint Tests	Value	df	Probability
Max |z| (at period 8)*	1.907670	203	0.2073

Individual Tests

Period	Var. Ratio	Std. Error	z-Statistic	Probability
2	1.004890	0.096686	0.050581	0.9597
4	0.817306	0.163559	-1.116992	0.2640
8	0.563819	0.228646	-1.907670	0.0564
16	0.432137	0.308518	-1.840612	0.0657

*Probability approximation using studentized maximum modulus with parameter value 4 and infinite degrees of freedom

Test Details (Mean = 1.73891625616)

Period	Variance	Var. Ratio	Obs.
1	3095.66	--	203
2	3110.80	1.00489	202
4	2530.10	0.81731	200
8	1745.39	0.56382	196
16	1337.75	0.43214	188

7. JMAT.L

Null Hypothesis: JMAT_L is a martingale
Date: 29/11/20 Time: 20:31
Sample: 2/04/2006 22/02/2010
Included observations: 203 (after adjustments)
Heteroskedasticity robust standard error estimates
User-specified lags: 2 4 8 16

Joint Tests	Value	df	Probability
Max |z| (at period 2)*	0.639336	203	0.9481

Individual Tests

Period	Var. Ratio	Std. Error	z-Statistic	Probability
2	0.948230	0.080975	-0.639336	0.5226
4	0.937994	0.148448	-0.417697	0.6762
8	0.979155	0.236704	-0.088064	0.9298
16	1.109165	0.358330	0.304649	0.7606

*Probability approximation using studentized maximum modulus with parameter value 4 and infinite degrees of freedom

Test Details (Mean = 0.500591108374)

Period	Variance	Var. Ratio	Obs.
1	5111.02	--	203
2	4846.42	0.94823	202
4	4794.11	0.93799	200
8	5004.48	0.97915	196
16	5668.97	1.10916	188

The manufacturing industry

7. ABF.L

Null Hypothesis: ABF_L is a martingale
Date: 29/11/20 Time: 22:06
Sample: 2/01/2006 23/11/2009
Included observations: 203 (after adjustments)
Heteroskedasticity robust standard error estimates
User-specified lags: 2 4 8 16

Joint Tests	Value	df	Probability
Max |z| (at period 16)*	0.685922	203	0.9338

Individual Tests

Period	Var. Ratio	Std. Error	z-Statistic	Probability
2	0.993352	0.087261	-0.076190	0.9393
4	0.978726	0.167605	-0.126930	0.8990
8	0.973126	0.261292	-0.102852	0.9181
16	0.743272	0.374281	-0.685922	0.4928

*Probability approximation using studentized maximum modulus with parameter value 4 and infinite degrees of freedom

Test Details (Mean = -0.233990147783)

Period	Variance	Var. Ratio	Obs.
1	591.553	--	203
2	587.620	0.99335	202
4	578.968	0.97873	200
8	575.655	0.97313	196
16	439.685	0.74327	188

8. BATS.L

Null Hypothesis: BATS_L is a martingale
Date: 29/11/20 Time: 22:15
Sample: 2/04/2006 22/02/2010
Included observations: 203 (after adjustments)
Heteroskedasticity robust standard error estimates
User-specified lags: 2 4 8 16

Joint Tests	Value	df	Probability
Max |z| (at period 2)*	2.159905	203	0.1176

Individual Tests

Period	Var. Ratio	Std. Error	z-Statistic	Probability
2	0.669947	0.152809	-2.159905	0.0308
4	0.587832	0.274698	-1.500437	0.1335
8	0.534676	0.390854	-1.190533	0.2338
16	0.345249	0.496541	-1.318625	0.1873

*Probability approximation using studentized maximum modulus with parameter value 4 and infinite degrees of freedom

Test Details (Mean = 4.16502463054)

Period	Variance	Var. Ratio	Obs.
1	3934.03	--	203
2	2635.59	0.66995	202
4	2312.55	0.58783	200
8	2103.43	0.53468	196
16	1358.22	0.34525	188

9. BDEV.L

Null Hypothesis: BDEV_L is a martingale
Date: 29/11/20 Time: 22:23
Sample: 12/05/2013 2/04/2017
Included observations: 203 (after adjustments)
Heteroskedasticity robust standard error estimates
User-specified lags: 2 4 8 16

Joint Tests	Value	df	Probability
Max |z| (at period 16)*	0.587464	203	0.9614

Individual Tests

Period	Var. Ratio	Std. Error	z-Statistic	Probability
2	1.028786	0.076012	0.378707	0.7049
4	0.950936	0.150124	-0.326824	0.7438
8	0.880500	0.238198	-0.501685	0.6159
16	0.797610	0.344515	-0.587464	0.5569

*Probability approximation using studentized maximum modulus with parameter value 4 and infinite degrees of freedom

Test Details (Mean = 1.04532025616)

Period	Variance	Var. Ratio	Obs.
1	378.516	--	203
2	389.412	1.02879	202
4	359.944	0.95094	200
8	333.283	0.88050	196
16	301.908	0.79761	188

10. BKG.L

Null Hypothesis: BKG_L is a martingale
Date: 29/11/20 Time: 22:32
Sample: 12/05/2013 2/04/2017
Included observations: 203 (after adjustments)
Heteroskedasticity robust standard error estimates
User-specified lags: 2 4 8 16

Joint Tests	Value	df	Probability
Max |z| (at period 16)*	0.827549	203	0.8771

Individual Tests

Period	Var. Ratio	Std. Error	z-Statistic	Probability
2	1.016611	0.062841	0.264330	0.7915
4	0.922964	0.125880	-0.611983	0.5405
8	0.837447	0.210876	-0.770845	0.4408
16	0.732744	0.322949	-0.827549	0.4079

*Probability approximation using studentized maximum modulus
with parameter value 4 and infinite degrees of freedom

Test Details (Mean = 4.47783251232)

Period	Variance	Var. Ratio	Obs.
1	11664.4	--	203
2	11858.2	1.01661	202
4	10765.9	0.92296	200
8	9768.35	0.83745	196
16	8547.04	0.73274	188

11. DGE.L

Null Hypothesis: DGE_L is a martingale
Date: 29/11/20 Time: 22:42
Sample: 12/05/2013 2/04/2017
Included observations: 203 (after adjustments)
Heteroskedasticity robust standard error estimates
User-specified lags: 2 4 8 16

Joint Tests	Value	df	Probability
Max |z| (at period 16)*	1.655575	203	0.3375

Individual Tests

Period	Var. Ratio	Std. Error	z-Statistic	Probability
2	1.028569	0.077723	0.367581	0.7132
4	0.862598	0.139723	-0.983387	0.3254
8	0.698675	0.209714	-1.436838	0.1508
16	0.500027	0.301994	-1.655575	0.0978

*Probability approximation using studentized maximum modulus
with parameter value 4 and infinite degrees of freedom

Test Details (Mean = 1.24876847291)

Period	Variance	Var. Ratio	Obs.
1	2434.12	--	203
2	2503.67	1.02857	202
4	2099.67	0.86260	200
8	1700.66	0.69867	196
16	1217.13	0.50003	188

The service industry

12. ADN.L

Null Hypothesis: ADN_L is a martingale
Date: 30/11/20 Time: 20:48
Sample: 12/05/2013 2/04/2017
Included observations: 203 (after adjustments)
Heteroskedasticity robust standard error estimates
User-specified lags: 2 4 8 16

Joint Tests	Value	df	Probability
Max |z| (at period 4)*	1.219777	203	0.6347

Individual Tests

Period	Var. Ratio	Std. Error	z-Statistic	Probability
2	0.985880	0.066028	-0.213842	0.8307
4	0.846526	0.125821	-1.219777	0.2225
8	0.835804	0.201446	-0.815084	0.4150
16	0.726280	0.304200	-0.899802	0.3682

*Probability approximation using studentized maximum modulus with parameter value 4 and infinite degrees of freedom

Test Details (Mean = -0.943842394089)

Period	Variance	Var. Ratio	Obs.
1	323.797	--	203
2	319.225	0.98588	202
4	274.102	0.84653	200
8	270.631	0.83580	196
16	235.167	0.72628	188

13. AHT.L

Null Hypothesis: AHT_L is a martingale
Date: 30/11/20 Time: 20:57
Sample: 1/06/1997 22/04/2001
Included observations: 203 (after adjustments)
Heteroskedasticity robust standard error estimates
User-specified lags: 2 4 8 16

Joint Tests	Value	df	Probability

Max |z| (at period 2)*	0.970797	203	0.8005

Individual Tests

Period	Var. Ratio	Std. Error	z-Statistic	Probability
2	1.068591	0.070654	0.970797	0.3316
4	1.089791	0.133228	0.673964	0.5003
8	1.012303	0.222384	0.055324	0.9559
16	1.228876	0.325734	0.702648	0.4823

*Probability approximation using studentized maximum modulus with parameter value 4 and infinite degrees of freedom

Test Details (Mean = -0.194256147783)

Period	Variance	Var. Ratio	Obs.
1	104.669	--	203
2	111.848	1.06859	202
4	114.067	1.08979	200
8	105.957	1.01230	196
16	128.625	1.22888	188

14. AV.L

Null Hypothesis: AV_L is a martingale
Date: 30/11/20 Time: 21:05
Sample: 1/06/1997 22/04/2001
Included observations: 203 (after adjustments)
Heteroskedasticity robust standard error estimates
User-specified lags: 2 4 8 16

Joint Tests	Value	df	Probability
Max |z| (at period 2)*	2.727086	203	0.0253

Individual Tests

Period	Var. Ratio	Std. Error	z-Statistic	Probability
2	0.800610	0.073115	-2.727086	0.0064
4	0.758239	0.147256	-1.641777	0.1006
8	0.689784	0.236726	-1.310444	0.1900
16	0.616564	0.342888	-1.118255	0.2635

*Probability approximation using studentized maximum modulus with parameter value 4 and infinite degrees of freedom

Test Details (Mean = 1.177655)

Period	Variance	Var. Ratio	Obs.
1	1921.07	--	203
2	1538.03	0.80061	202
4	1456.63	0.75824	200
8	1325.12	0.68978	196
16	1184.46	0.61656	188

15.BAB.L

Null Hypothesis: BAB_L is a martingale
Date: 30/11/20 Time: 21:11
Sample: 12/05/2013 2/04/2017
Included observations: 203 (after adjustments)
Heteroskedasticity robust standard error estimates
User-specified lags: 2 4 8 16

Joint Tests	Value	df	Probability
Max |z| (at period 8)*	1.218662	203	0.6355

Individual Tests

Period	Var. Ratio	Std. Error	z-Statistic	Probability
2	0.925447	0.078245	-0.952813	0.3407
4	0.839145	0.141787	-1.134488	0.2566
8	0.733709	0.218511	-1.218662	0.2230
16	0.640621	0.315042	-1.140733	0.2540

*Probability approximation using studentized maximum modulus
with parameter value 4 and infinite degrees of freedom

Test Details (Mean = -0.586748694581)

Period	Variance	Var. Ratio	Obs.
1	971.235	--	203
2	898.827	0.92545	202
4	815.007	0.83914	200
8	712.604	0.73371	196
16	622.193	0.64062	188

16. BARC.L

Null Hypothesis: BARC_L is a
martingale
Date: 30/11/20 Time: 21:17
Sample: 1/10/2000 22/08/2004
Included observations: 203 (after adjustments)
Heteroskedasticity robust standard error estimates
User-specified lags: 2 4 8 16

Joint Tests	Value	df	Probability
Max |z| (at period 8)*	1.299479	203	0.5775

Individual Tests

Period	Var. Ratio	Std. Error	z-Statistic	Probability
2	0.965955	0.093737	-0.363197	0.7165
4	0.916881	0.168717	-0.492654	0.6223
8	0.671853	0.252522	-1.299479	0.1938
16	0.604375	0.352791	-1.121416	0.2621

*Probability approximation using studentized maximum modulus

with parameter value 4 and infinite degrees of freedom

Test Details (Mean = 0.230935985222)

Period	Variance	Var. Ratio	Obs.
1	392.044	--	203
2	378.696	0.96595	202
4	359.457	0.91688	200
8	263.396	0.67185	196
16	236.941	0.60437	188

The quaternary industry

17. AZN.L

Null Hypothesis: AZN_L is a martingale
Date: 30/11/20 Time: 21:33
Sample: 4/01/2010 25/11/2013
Included observations: 203 (after adjustments)
Heteroskedasticity robust standard error estimates
User-specified lags: 2 4 8 16

Joint Tests	Value	df	Probability
Max |z| (at period 16)*	1.100206	203	0.7179

Individual Tests

Period	Var. Ratio	Std. Error	z-Statistic	Probability
2	1.001560	0.078813	0.019799	0.9842
4	0.950084	0.135756	-0.367694	0.7131
8	0.837240	0.200453	-0.811960	0.4168
16	0.682980	0.288146	-1.100206	0.2712

*Probability approximation using studentized maximum modulus
with parameter value 4 and infinite degrees of freedom

Test Details (Mean = 2.9802955665)

Period	Variance	Var. Ratio	Obs.
1	4831.71	--	203
2	4839.25	1.00156	202
4	4590.53	0.95008	200
8	4045.30	0.83724	196
16	3299.96	0.68298	188

18. GSK.L

Null Hypothesis: GSK_L is a martingale
Date: 30/11/20 Time: 21:51
Sample: 1/06/1997 22/04/2001
Included observations: 203 (after adjustments)
Heteroskedasticity robust standard error estimates
User-specified lags: 2 4 8 16

Joint Tests	Value	df	Probability
Max |z| (at period 8)*	1.756048	203	0.2807

Individual Tests

Period	Var. Ratio	Std. Error	z-Statistic	Probability
2	0.910741	0.071741	-1.244181	0.2134
4	0.774836	0.133208	-1.690325	0.0910
8	0.635108	0.207791	-1.756048	0.0791
16	0.518642	0.306531	-1.570340	0.1163

*Probability approximation using studentized maximum modulus with parameter value 4 and infinite degrees of freedom

Test Details (Mean = 3.12807881773)

Period	Variance	Var. Ratio	Obs.
1	6217.63	--	203
2	5662.65	0.91074	202
4	4817.64	0.77484	200
8	3948.87	0.63511	196
16	3224.72	0.51864	188

19. SHP.L

Null Hypothesis: SHP_L is a martingale
Date: 30/11/20 Time: 21:59
Sample: 1/10/2006 22/08/2010
Included observations: 203 (after adjustments)
Heteroskedasticity robust standard error estimates
User-specified lags: 2 4 8 16

Joint Tests	Value	df	Probability
Max |z| (at period 2)*	1.465738	203	0.4599

Individual Tests

Period	Var. Ratio	Std. Error	z-Statistic	Probability
2	0.893883	0.072398	-1.465738	0.1427
4	0.907882	0.130047	-0.708348	0.4787
8	0.958477	0.202220	-0.205336	0.8373
16	0.832196	0.306902	-0.546767	0.5845

*Probability approximation using studentized maximum modulus with parameter value 4 and infinite degrees of freedom

Test Details (Mean = 2.58620689655)

Period	Variance	Var. Ratio	Obs.
1	1710.68	--	203
2	1529.15	0.89388	202
4	1553.09	0.90788	200
8	1639.64	0.95848	196
16	1423.62	0.83220	188

20. SGE.L

Null Hypothesis: SGE_L is a martingale
Date: 30/11/20 Time: 22:08
Sample: 1/06/1997 22/04/2001
Included observations: 203 (after adjustments)
Heteroskedasticity robust standard error estimates
User-specified lags: 2 4 8 16

Joint Tests	Value	df	Probability
Max |z| (at period 2)*	1.499518	203	0.4369

Individual Tests

Period	Var. Ratio	Std. Error	z-Statistic	Probability
2	0.783355	0.144477	-1.499518	0.1337
4	0.714968	0.252479	-1.128930	0.2589
8	0.773724	0.368649	-0.613798	0.5393
16	1.061861	0.530465	0.116616	0.9072

*Probability approximation using studentized maximum modulus
with parameter value 4 and infinite degrees of freedom

Test Details (Mean = 1.04689661084)

Period	Variance	Var. Ratio	Obs.
1	1761.68	--	203
2	1380.02	0.78335	202
4	1259.55	0.71497	200
8	1363.06	0.77372	196
16	1870.66	1.06186	188

21.SN.L

Null Hypothesis: SN_L is a martingale
Date: 30/11/20 Time: 22:14
Sample: 4/01/2010 25/11/2013
Included observations: 203 (after adjustments)
Heteroskedasticity robust standard error estimates
User-specified lags: 2 4 8 16

Joint Tests	Value	df	Probability
Max |z| (at period 8)*	1.357909	203	0.5356

Individual Tests

Period	Var. Ratio	Std. Error	z-Statistic	Probability
2	0.907586	0.069450	-1.330658	0.1833
4	0.854376	0.131108	-1.110717	0.2667
8	0.698200	0.222253	-1.357909	0.1745
16	0.838090	0.334402	-0.484178	0.6283

*Probability approximation using studentized maximum modulus
with parameter value 4 and infinite degrees of freedom

Test Details (Mean = 0.899014778325)

Period	Variance	Var. Ratio	Obs.
1	338.766	--	203
2	307.459	0.90759	202
4	289.433	0.85438	200
8	236.526	0.69820	196
16	283.916	0.83809	188

(vii) ARIMA MODEL

1. FTSE-350 General Industrial Index

Dependent Variable: D(FTSE_350_INDUS__INDEX)
Method: ARMA Maximum Likelihood (OPG - BHHH)
Date: 19/12/20 Time: 13:46
Sample: 12/05/2013 26/03/2017
Included observations: 203
Convergence achieved after 11 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	9.540233	6.432523	1.483125	0.1396
AR(1)	-0.146730	0.074552	-1.968145	0.0504
MA(22)	0.110744	0.080410	1.377243	0.1700
SIGMASQ	8863.912	875.3489	10.12615	0.0000

R-squared	0.032142	Mean dependent var	9.378177
Adjusted R-squared	0.017551	S.D. dependent var	95.93548
S.E. of regression	95.08986	Akaike info criterion	11.96847
Sum squared resid	1799374.	Schwarz criterion	12.03376
Log likelihood	-1210.800	Hannan-Quinn criter.	11.99489
F-statistic	2.202903	Durbin-Watson stat	1.966914
Prob(F-statistic)	0.088971		

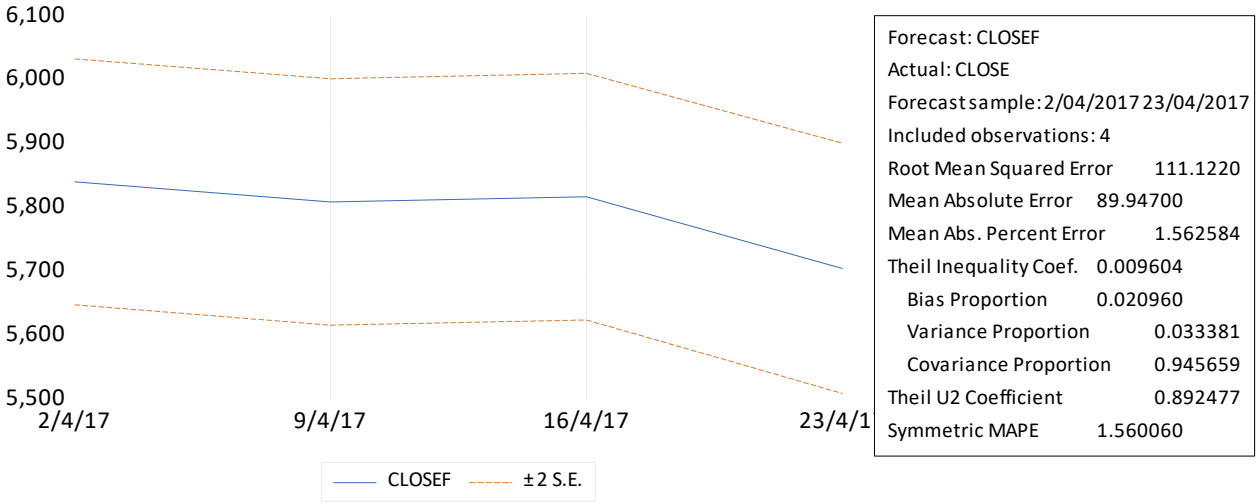
Inverted AR Roots	-.15			
Inverted MA Roots	.90-.13i	.90+.13i	.82-.38i	.82+.38i
	.68-.59i	.68+.59i	.49+.76i	.49-.76i
	.25+.87i	.25-.87i	.00+.90i	-.00-.90i
	-.25+.87i	-.25-.87i	-.49+.76i	-.49-.76i
	-.68-.59i	-.68+.59i	-.82+.38i	-.82-.38i
	-.90+.13i	-.90-.13i		

Correlogram Squared Residuals:

Date: 19/12/20 Time: 13:44
Sample (adjusted): 12/05/2013 26/03/2017
Included observations: 203 after adjustments

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
.|. |	.|. |	1	-0.058	-0.058	0.6912	0.406
.|. |	.|. |	2	-0.026	-0.029	0.8280	0.661
*|. |	*|. |	3	-0.155	-0.159	5.8534	0.119
.|. |	.|. |	4	0.010	-0.011	5.8737	0.209

.|.	|	.|.	|	5	0.006	-0.005	5.8802	0.318
.|.	|	.|.	|	6	-0.003	-0.029	5.8827	0.436
.|.	|	.|.	|	7	-0.016	-0.018	5.9347	0.547
.|.	|	.|.	|	8	0.025	0.022	6.0648	0.640
*|.	|	*|.	|	9	-0.073	-0.079	7.2211	0.614
.|.	|	.|.	|	10	-0.041	-0.056	7.5760	0.670
.|.	|	.|.	|	11	0.052	0.049	8.1587	0.699
.|.	|	.|.	|	12	-0.009	-0.032	8.1758	0.771
.|.	|	.|.	|	13	0.043	0.029	8.5797	0.804
.|.	|	.|.	|	14	-0.020	0.000	8.6699	0.852
.|.	|	.|.	|	15	0.001	-0.007	8.6700	0.894
.|.	|	.|.	|	16	-0.048	-0.046	9.1933	0.905
.|*	|	.|*	|	17	0.094	0.094	11.175	0.847
.|.	|	.|.	|	18	-0.065	-0.064	12.129	0.840
.|.	|	.|.	|	19	-0.032	-0.059	12.355	0.870
.|.	|	.|*	|	20	0.042	0.075	12.750	0.888
.|.	|	.|.	|	21	0.045	0.029	13.216	0.901
.|.	|	.|.	|	22	-0.041	-0.055	13.601	0.915
.|.	|	.|.	|	23	-0.062	-0.040	14.489	0.912
.|.	|	.|.	|	24	0.006	0.010	14.498	0.935



Date	close	forecast
2/04/2017	5795.67	5840.512
9/04/2017	5801.53	5809.057
16/04/2017	5657.35	5817.050
23/04/2017	5852.57	5704.851

The primary industry

2. ANTO.L

Dependent Variable: D(ANTO_L)
Method: ARMA Maximum Likelihood (OPG - BHHH)
Date: 01/12/20 Time: 19:12
Sample: 13/05/2013 27/03/2017
Included observations: 203
Convergence achieved after 13 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.456378	2.514464	-0.181501	0.8562
AR(3)	-0.155627	0.080217	-1.940076	0.0538
MA(2)	0.136707	0.065233	2.095683	0.0374
SIGMASQ	1156.312	80.92620	14.28847	0.0000

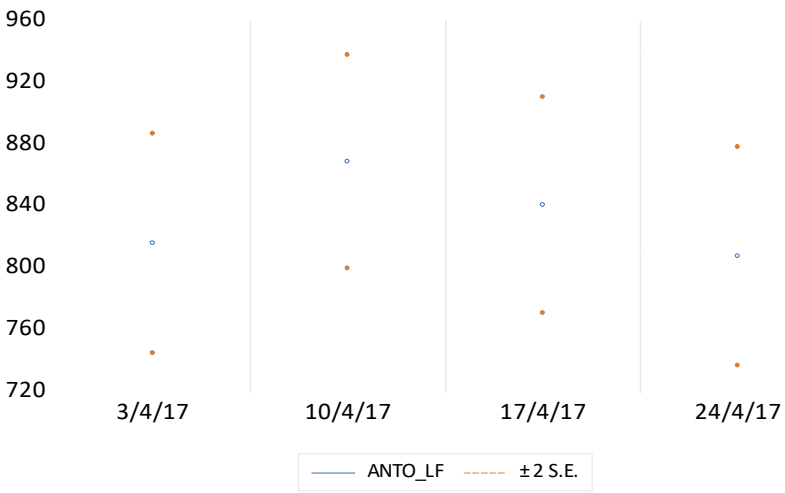
R-squared	0.043861	Mean dependent var	-0.386700
Adjusted R-squared	0.029447	S.D. dependent var	34.86175
S.E. of regression	34.34464	Akaike info criterion	9.930825
Sum squared resid	234731.3	Schwarz criterion	9.996110
Log likelihood	-1003.979	Hannan-Quinn criter.	9.957237
F-statistic	3.042889	Durbin-Watson stat	2.160802
Prob(F-statistic)	0.029993		

Inverted AR Roots	.27+.47i	.27-.47i	-.54
Inverted MA Roots	-.00+.37i	-.00-.37i	

Correlogram Squared residuals

Date: 01/12/20 Time: 19:13
Sample (adjusted): 13/05/2013 27/03/2017
Included observations: 203 after adjustments

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
.|. |	.|. |	1	-0.020	-0.020	0.0807	0.776
.|. |	.|. |	2	0.026	0.026	0.2204	0.896
.|. |	.|. |	3	-0.048	-0.047	0.6960	0.874
.|. |	.|. |	4	0.064	0.062	1.5467	0.818
.|* |	.|* |	5	0.105	0.110	3.8637	0.569
.|. |	.|. |	6	-0.010	-0.012	3.8851	0.692
.|. |	.|. |	7	-0.036	-0.037	4.1662	0.760
.|. |	.|. |	8	-0.040	-0.036	4.5117	0.808
.|. |	.|. |	9	-0.022	-0.037	4.6119	0.867
.|. |	.|. |	10	0.004	-0.009	4.6149	0.915
.|. |	.|* |	11	0.070	0.077	5.6760	0.894
.|. |	.|. |	12	-0.003	0.012	5.6775	0.931
.|* |	.|* |	13	0.082	0.091	7.1447	0.895
.|. |	.|. |	14	-0.035	-0.022	7.4212	0.917
.|. |	.|. |	15	-0.014	-0.035	7.4640	0.943
.|. |	*|. |	16	-0.051	-0.066	8.0379	0.948
.|* |	.|* |	17	0.126	0.113	11.575	0.825
.|* |	.|* |	18	0.151	0.157	16.727	0.542
.|. |	.|. |	19	0.005	0.023	16.733	0.608
*|. |	.|. |	20	-0.070	-0.052	17.845	0.598
.|. |	.|. |	21	-0.011	-0.009	17.873	0.657
.|. |	*|. |	22	-0.028	-0.086	18.058	0.703
.|. |	*|. |	23	-0.019	-0.071	18.137	0.750
.|. |	.|. |	24	0.020	0.030	18.232	0.792



Forecast: ANTO_LF
Actual: ANTO_L
Forecast sample: 3/04/2017 24/04/2017
Included observations: 4

Root Mean Squared Error	36.57267
Mean Absolute Error	34.85392
Mean Abs. Percent Error	4.122849
Theil Inequality Coef.	0.021844
Bias Proportion	0.031563
Variance Proportion	0.023495
Covariance Proportion	0.944942
Theil U2 Coefficient	1.206746
Symmetric MAPE	4.156662

Date	close	forecast
3/04/2017	869.0000	816.3645
10/04/2017	835.0000	869.1670
17/04/2017	818.5000	841.0457
24/04/2017	838.0000	807.9326

3. BP.L

Dependent Variable: D(BP_L)
Method: ARMA Maximum Likelihood (OPG - BHHH)
Date: 01/12/20 Time: 21:59
Sample: 9/04/2006 22/02/2010
Included observations: 203
Convergence achieved after 25 iterations
Coefficient covariance computed using outer product of gradients

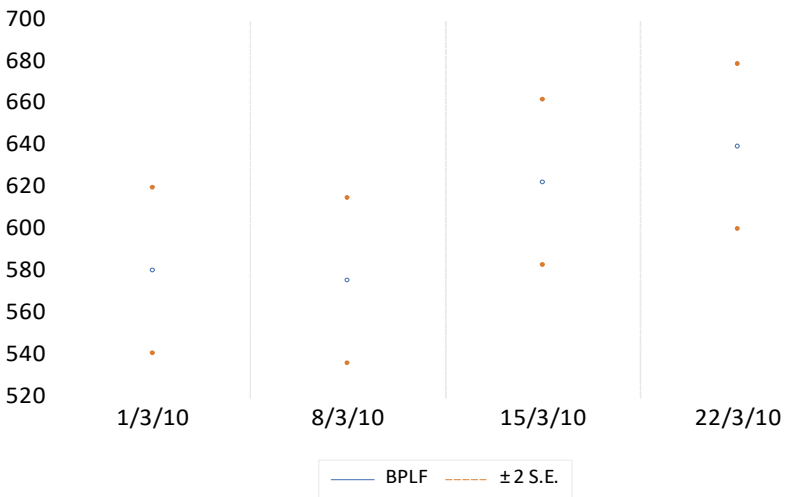
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.436369	0.912389	-0.478271	0.6330
AR(4)	-0.182926	0.065478	-2.793728	0.0057
MA(7)	-0.226023	0.059377	-3.806554	0.0002
SIGMASQ	378.2420	26.69438	14.16935	0.0000

R-squared	0.069817	Mean dependent var	-0.506404
Adjusted R-squared	0.055794	S.D. dependent var	20.21496
S.E. of regression	19.64293	Akaike info criterion	8.815299
Sum squared resid	76783.12	Schwarz criterion	8.880584
Log likelihood	-890.7528	Hannan-Quinn criter.	8.841711
F-statistic	4.978766	Durbin-Watson stat	2.153409
Prob(F-statistic)	0.002365		

Inverted AR Roots	.46-.46i	.46+.46i	-.46+.46i	-.46+.46i
Inverted MA Roots	.81	.50-.63i	.50+.63i	-.18-.79i
	-.18+.79i	-.73-.35i	-.73+.35i	

Date: 01/12/20 Time: 22:35
Sample (adjusted): 9/04/2006 22/02/2010
Included observations: 203 after adjustments

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
.|* |	.|* |	1	0.202	0.202	8.4333	0.004
.|* |	.|. |	2	0.077	0.038	9.6750	0.008
.|** |	.|** |	3	0.254	0.241	23.088	0.000
.|* |	.|. |	4	0.082	-0.015	24.484	0.000
.|* |	.|* |	5	0.103	0.082	26.718	0.000
.|* |	.|* |	6	0.175	0.091	33.193	0.000
.|* |	.|* |	7	0.183	0.134	40.271	0.000
.|* |	.|. |	8	0.085	-0.009	41.817	0.000
.|* |	.|. |	9	0.107	0.038	44.252	0.000
.|. |	*|. |	10	-0.042	-0.162	44.637	0.000
.|. |	.|. |	11	-0.023	-0.027	44.749	0.000
.|* |	.|* |	12	0.152	0.109	49.810	0.000
.|. |	.|. |	13	0.062	0.030	50.648	0.000
.|. |	.|. |	14	-0.013	-0.057	50.684	0.000
.|. |	*|. |	15	-0.002	-0.067	50.685	0.000
.|. |	.|. |	16	0.001	-0.000	50.685	0.000
.|. |	.|. |	17	-0.029	0.011	50.872	0.000
.|. |	.|. |	18	0.044	0.062	51.305	0.000
.|. |	.|. |	19	0.030	-0.014	51.505	0.000
.|. |	*|. |	20	-0.054	-0.081	52.177	0.000
.|* |	.|* |	21	0.106	0.117	54.760	0.000
.|. |	.|. |	22	0.015	0.020	54.812	0.000
.|. |	.|* |	23	0.043	0.117	55.247	0.000
.|. |	*|. |	24	0.006	-0.110	55.256	0.000



Forecast: BPLF
Actual: BPL
Forecast sample: 1/03/2010 22/03/2010
Included observations: 4
Root Mean Squared Error 23.35308
Mean Absolute Error 17.46655
Mean Abs. Percent Error 2.815959
Theil Inequality Coef. 0.019119
Bias Proportion 0.207928
Variance Proportion 0.022177
Covariance Proportion 0.769895
Theil U2 Coefficient 0.986113
Symmetric MAPE 2.882644

Date	PB.L	ARIMA
01/03/2010	575.5	580.7712
08/03/2010	619.9	575.9295
15/03/2010	635.1	622.8398
22/03/2010	631.6	639.9643

4. CNA.L

Dependent Variable: D(CNA_L)
Method: ARMA Maximum Likelihood (OPG - BHHH)
Date: 02/12/20 Time: 10:38
Sample: 18/07/2010 1/06/2014
Included observations: 203

Convergence achieved after 16 iterations
Coefficient covariance computed using outer product of gradients

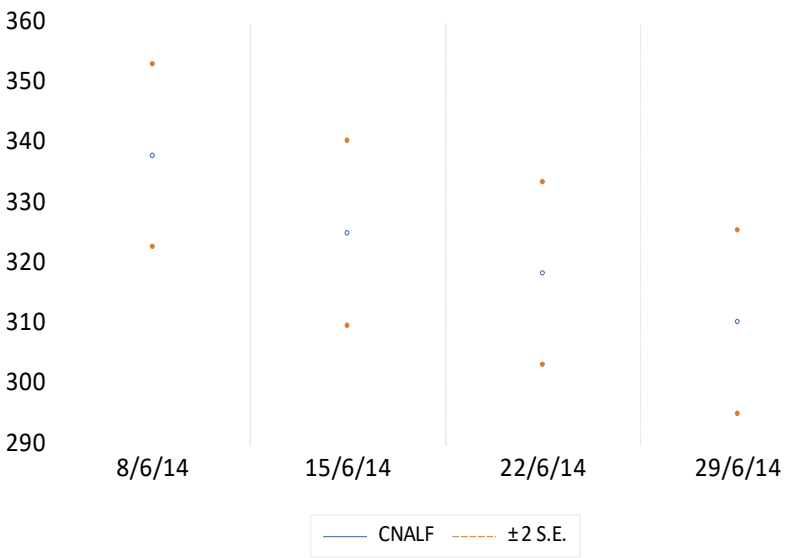
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.152134	0.932094	0.163217	0.8705
AR(8)	0.870110	0.141156	6.164186	0.0000
MA(8)	-0.754188	0.179447	-4.202851	0.0000
SIGMASQ	55.53298	4.182388	13.27782	0.0000

R-squared	0.051454	Mean dependent var	0.129557
Adjusted R-squared	0.037155	S.D. dependent var	7.670412
S.E. of regression	7.526567	Akaike info criterion	6.899020
Sum squared resid	11273.19	Schwarz criterion	6.964305
Log likelihood	-696.2505	Hannan-Quinn criter.	6.925432
F-statistic	3.598296	Durbin-Watson stat	2.322139
Prob(F-statistic)	0.014502		

Inverted AR Roots	.98	.69+.69i	.69-.69i	-.00+.98i
	-.00-.98i	-.69+.69i	-.69+.69i	-.98
Inverted MA Roots	.97	.68-.68i	.68+.68i	-.00-.97i
	-.00+.97i	-.68+.68i	-.68+.68i	-.97

Date: 02/12/20 Time: 10:36
Sample (adjusted): 18/07/2010 1/06/2014
Included observations: 203 after adjustments

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
.|. |	.|. |	1	0.000	0.000	5.E-05	0.995
.|. |	.|. |	2	-0.027	-0.027	0.1506	0.927
.|. |	.|. |	3	-0.008	-0.008	0.1630	0.983
.|. |	.|. |	4	-0.026	-0.027	0.3084	0.989
.|. |	.|. |	5	-0.059	-0.059	1.0393	0.959
.|. |	.|. |	6	-0.028	-0.029	1.1991	0.977
.|. |	.|. |	7	-0.049	-0.053	1.6998	0.975
.|. |	.|. |	8	0.029	0.026	1.8850	0.984
.|. |	.|. |	9	-0.026	-0.033	2.0279	0.991
.|. |	.|. |	10	0.005	0.000	2.0330	0.996
.|. |	.|. |	11	-0.004	-0.011	2.0360	0.998
.|* |	.|* |	12	0.156	0.152	7.3339	0.835
.|. |	.|. |	13	-0.043	-0.046	7.7382	0.860
.|. |	.|. |	14	0.029	0.036	7.9178	0.894
.|. |	.|. |	15	0.058	0.060	8.6627	0.894
.|* |	.|* |	16	0.198	0.212	17.356	0.363
.|. |	.|. |	17	-0.017	0.005	17.419	0.426
.|. |	.|. |	18	-0.009	0.013	17.439	0.493
.|. |	.|. |	19	-0.008	0.017	17.455	0.559
.|. |	.|. |	20	-0.044	-0.032	17.895	0.594
.|. |	.|. |	21	-0.064	-0.029	18.838	0.596
.|. |	.|. |	22	-0.034	-0.031	19.100	0.639
.|. |	.|. |	23	-0.028	-0.017	19.283	0.685
.|. |	.|. |	24	-0.005	-0.053	19.290	0.736



Forecast: CNALF	
Actual: CNAL	
Forecast sample: 8/06/2014 29/06/2014	
Included observations: 4	
Root Mean Squared Error	7.388005
Mean Absolute Error	6.783906
Mean Abs. Percent Error	2.118351
Theil Inequality Coef.	0.011514
Bias Proportion	0.394669
Variance Proportion	0.440181
Covariance Proportion	0.165149
Theil U2 Coefficient	0.922690
Symmetric MAPE	2.097088

Date	close	forecast
8/06/2014	326.3000	338.0701
15/06/2014	319.8000	325.1899
22/06/2014	312.8000	318.4904
29/06/2014	314.7000	310.4149

5. SVT.L

Dependent Variable: SVT_L
Method: ARMA Maximum Likelihood (OPG - BHHH)
Date: 03/12/20 Time: 11:26
Sample: 12/05/2013 2/04/2017
Included observations: 204
Convergence achieved after 28 iterations
Coefficient covariance computed using outer product of gradients

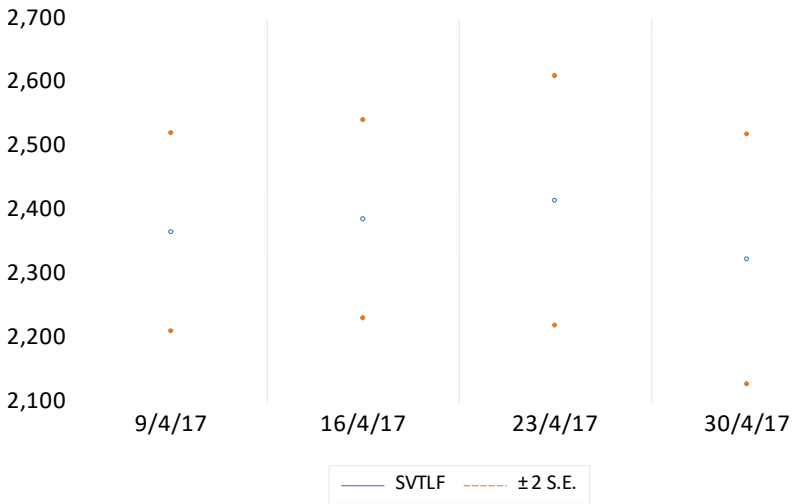
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	2108.789	108.3510	19.46257	0.0000
AR(2)	0.957506	0.025702	37.25473	0.0000
MA(2)	-0.186027	0.077945	-2.386636	0.0179
SIGMASQ	5790.537	300.7804	19.25171	0.0000

R-squared	0.873605	Mean dependent var	2060.441
Adjusted R-squared	0.871709	S.D. dependent var	214.5661
S.E. of regression	76.85277	Akaike info criterion	11.56195
Sum squared resid	1181270.	Schwarz criterion	11.62701
Log likelihood	-1175.319	Hannan-Quinn criter.	11.58827
F-statistic	460.7792	Durbin-Watson stat	0.942395
Prob(F-statistic)	0.000000		

Inverted AR Roots	.98	-.98
Inverted MA Roots	.43	-.43

Date: 03/12/20 Time: 11:28
Sample: 12/05/2013 2/04/2017
Included observations: 204

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
.|*** |	.|*** |	1	0.413	0.413	35.288	0.000
.|. |	**|. |	2	-0.002	-0.208	35.289	0.000
.|. |	.|. |	3	-0.053	0.044	35.866	0.000
.|. |	.|. |	4	-0.050	-0.053	36.398	0.000
.|. |	.|. |	5	-0.047	-0.015	36.864	0.000
.|. |	.|. |	6	-0.038	-0.020	37.164	0.000
.|. |	.|. |	7	-0.036	-0.024	37.437	0.000
.|. |	.|. |	8	-0.006	0.016	37.446	0.000
.|. |	.|. |	9	-0.001	-0.018	37.446	0.000
.|. |	.|. |	10	-0.017	-0.016	37.506	0.000
.|. |	.|. |	11	-0.003	0.012	37.508	0.000
.|. |	.|. |	12	0.018	0.010	37.575	0.000
.|. |	.|. |	13	0.020	0.007	37.665	0.000
.|. |	.|. |	14	-0.003	-0.017	37.666	0.001
.|. |	.|. |	15	-0.011	0.001	37.694	0.001
.|. |	.|. |	16	-0.027	-0.028	37.853	0.002
.|. |	.|. |	17	-0.016	0.009	37.908	0.003
.|. |	.|. |	18	0.012	0.015	37.942	0.004
.|. |	.|. |	19	-0.004	-0.025	37.946	0.006
.|. |	.|. |	20	0.011	0.032	37.975	0.009
.|. |	.|. |	21	-0.007	-0.037	37.987	0.013
.|. |	.|. |	22	-0.019	0.003	38.067	0.018
.|. |	.|. |	23	0.003	0.012	38.069	0.025
.|* |	.|* |	24	0.077	0.084	39.465	0.024



Forecast: SVTLF
Actual: SVTL
Forecast sample: 9/04/2017 30/04/2017
Included observations: 4
Root Mean Squared Error 72.70166
Mean Absolute Error 71.13942
Mean Abs. Percent Error 3.009562
Theil Inequality Coef. 0.015341
Bias Proportion 0.009891
Variance Proportion 0.050700
Covariance Proportion 0.939409
Theil U2 Coefficient 0.949282
Symmetric MAPE 2.999499

Date	close	forecast
9/04/2017	2444.000	2365.780
16/04/2017	2320.000	2386.535
23/04/2017	2325.000	2415.205
30/04/2017	2373.000	2323.402

6. JMAT.L

Dependent Variable: D(JMAT_L)
Method: ARMA Maximum Likelihood (OPG - BHHH)
Date: 03/12/20 Time: 13:25
Sample: 9/04/2006 22/02/2010

Included observations: 203
Convergence achieved after 14 iterations
Coefficient covariance computed using outer product of gradients

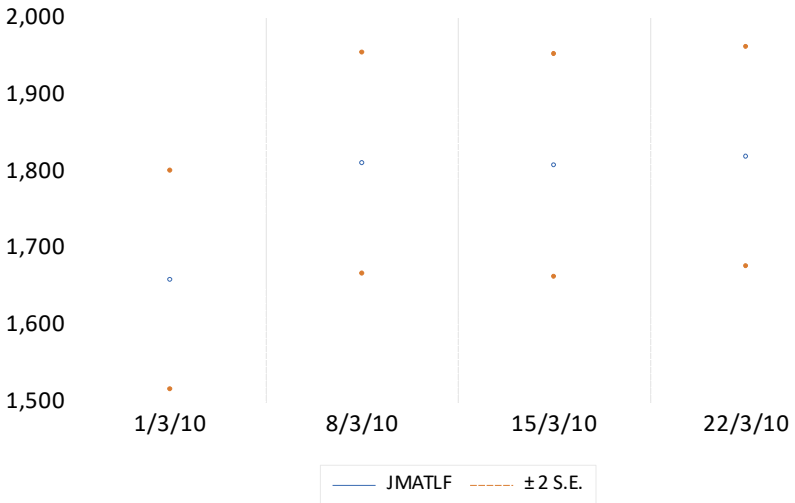
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.095157	3.292994	0.028897	0.9770
AR(11)	0.749223	0.211339	3.545129	0.0005
MA(11)	-0.853746	0.183186	-4.660536	0.0000
SIGMASQ	4949.904	427.5434	11.57755	0.0000

R-squared	0.026729	Mean dependent var	0.500591
Adjusted R-squared	0.012057	S.D. dependent var	71.49142
S.E. of regression	71.05913	Akaike info criterion	11.38916
Sum squared resid	1004831.	Schwarz criterion	11.45444
Log likelihood	-1152.000	Hannan-Quinn criter.	11.41557
F-statistic	1.821736	Durbin-Watson stat	2.170685
Prob(F-statistic)	0.144433		

Inverted AR Roots	.97	.82-.53i	.82+.53i	.40-.89i
	.40+.89i	-.14-.96i	-.14+.96i	-.64-.74i
	-.64+.74i	-.93-.27i	-.93+.27i	
Inverted MA Roots	.99	.83-.53i	.83+.53i	.41-.90i
	.41+.90i	-.14-.98i	-.14+.98i	-.65-.74i
	-.65+.74i	-.95-.28i	-.95+.28i	

Date: 03/12/20 Time: 13:24
Sample (adjusted): 9/04/2006 22/02/2010
Included observations: 203 after adjustments

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
.|* |	.|* |	1	0.136	0.136	3.8145	0.051
.|. |	.|. |	2	0.031	0.013	4.0187	0.134
.|* |	.|* |	3	0.093	0.088	5.8081	0.121
.|* |	.|. |	4	0.088	0.066	7.4453	0.114
.|* |	.|* |	5	0.200	0.183	15.891	0.007
.|** |	.|** |	6	0.323	0.285	37.899	0.000
.|* |	.|. |	7	0.106	0.044	40.298	0.000
.|* |	.|* |	8	0.151	0.131	45.182	0.000
.|. |	.|. |	9	0.059	-0.021	45.917	0.000
.|* |	.|. |	10	0.100	0.036	48.070	0.000
.|* |	.|. |	11	0.132	0.000	51.852	0.000
.|* |	.|. |	12	0.189	0.069	59.663	0.000
.|. |	.|. |	13	0.072	-0.032	60.797	0.000
.|* |	.|. |	14	0.145	0.067	65.449	0.000
.|. |	.|. |	15	0.043	-0.033	65.856	0.000
.|. |	*|. |	16	-0.040	-0.136	66.210	0.000
.|* |	.|. |	17	0.128	0.053	69.868	0.000
.|* |	.|. |	18	0.144	0.023	74.557	0.000
.|. |	.|. |	19	0.058	-0.001	75.318	0.000
.|. |	*|. |	20	0.007	-0.096	75.330	0.000
.|. |	.|. |	21	-0.002	-0.003	75.330	0.000
.|. |	*|. |	22	-0.061	-0.112	76.180	0.000
.|* |	.|* |	23	0.185	0.155	84.135	0.000
.|* |	.|. |	24	0.126	0.052	87.843	0.000



Forecast: JMATLF
Actual: JMATL
Forecast sample: 1/03/2010 22/03/2010
Included observations: 4

Root Mean Squared Error	84.71175
Mean Absolute Error	53.41954
Mean Abs. Percent Error	2.923678
Theil Inequality Coef.	0.023505
Bias Proportion	0.397661
Variance Proportion	0.502292
Covariance Proportion	0.100047
Theil U2 Coefficient	1.873953
Symmetric MAPE	3.036287

Date	close	forecast
1/03/2010	1826.000	1659.086
8/03/2010	1818.670	1811.521
15/03/2010	1830.190	1808.368
22/03/2010	1837.520	1819.727

The manufacturing industry

4. ABF.L

Dependent Variable: D(ABF_L)
Method: ARMA Maximum Likelihood (OPG - BHHH)
Date: 03/12/20 Time: 16:29
Sample: 9/01/2006 23/11/2009
Included observations: 203
Convergence achieved after 17 iterations
Coefficient covariance computed using outer product of gradients

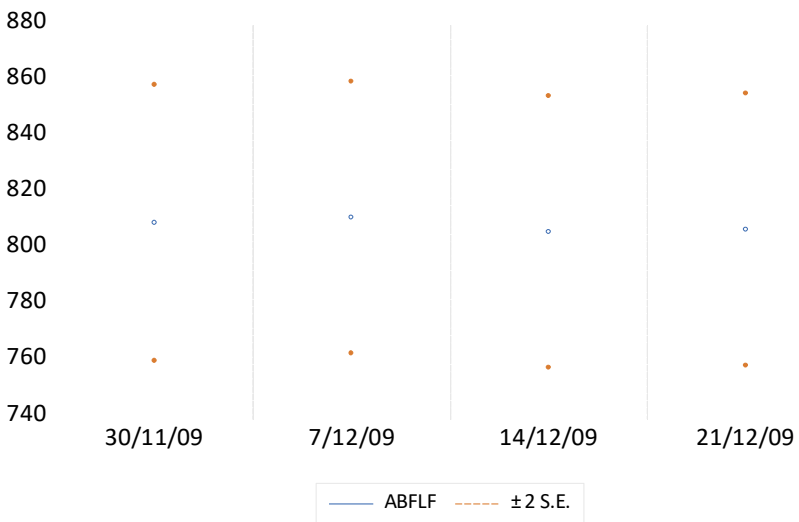
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.242091	1.587558	-0.152492	0.8790
AR(10)	-0.675649	0.230632	-2.929549	0.0038
MA(10)	0.547890	0.266126	2.058763	0.0408
SIGMASQ	570.0740	48.57439	11.73610	0.0000

R-squared	0.031538	Mean dependent var	-0.233990
Adjusted R-squared	0.016938	S.D. dependent var	24.32186
S.E. of regression	24.11499	Akaike info criterion	9.225122
Sum squared resid	115725.0	Schwarz criterion	9.290407
Log likelihood	-932.3499	Hannan-Quinn criter.	9.251534
F-statistic	2.160161	Durbin-Watson stat	2.079900
Prob(F-statistic)	0.093973		

Inverted AR Roots	.91+.30i	.91-.30i	.57+.78i	.57-.78i
	.00+.96i	-.00-.96i	-.57-.78i	-.57+.78i
	-.91-.30i	-.91+.30i		
Inverted MA Roots	.90+.29i	.90-.29i	.55-.76i	.55+.76i
	.00-.94i	-.00+.94i	-.55-.76i	-.55+.76i
	-.90-.29i	-.90+.29i		

Date: 03/12/20 Time: 16:31
Sample (adjusted): 9/01/2006 23/11/2009
Included observations: 203 after adjustments

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
.|* |	.|* |	1	0.185	0.185	7.0878	0.008
.|* |	.|* |	2	0.204	0.176	15.739	0.000
.|* |	.|* |	3	0.206	0.152	24.575	0.000
.|. |	.|. |	4	0.040	-0.050	24.909	0.000
.|* |	.|. |	5	0.104	0.047	27.191	0.000
.|* |	.|. |	6	0.093	0.049	29.028	0.000
.|* |	.|* |	7	0.164	0.138	34.750	0.000
.|. |	.|. |	8	0.032	-0.058	34.965	0.000
.|* |	.|. |	9	0.076	0.015	36.188	0.000
.|. |	.|. |	10	0.020	-0.041	36.274	0.000
.|. |	.|. |	11	-0.045	-0.054	36.715	0.000
.|. |	.|. |	12	-0.014	-0.034	36.755	0.000
.|. |	.|. |	13	-0.024	-0.008	36.877	0.000
.|. |	.|* |	14	0.070	0.086	37.943	0.001
.|. |	.|. |	15	-0.034	-0.047	38.194	0.001
.|. |	.|. |	16	0.038	0.028	38.521	0.001
.|. |	.|. |	17	0.014	0.005	38.567	0.002
.|. |	.|. |	18	-0.008	0.021	38.581	0.003
.|. |	.|. |	19	0.045	0.032	39.044	0.004
.|. |	.|. |	20	0.033	0.032	39.289	0.006
.|. |	.|. |	21	0.066	0.030	40.273	0.007
.|. |	.|. |	22	-0.015	-0.049	40.325	0.010
.|. |	.|. |	23	0.053	0.020	40.983	0.012
.|. |	.|. |	24	-0.021	-0.045	41.086	0.016



Forecast: ABFLF
Actual: ABFL
Forecast sample: 30/11/2009 21/12/...
Included observations: 4
Root Mean Squared Error 6.261774
Mean Absolute Error 4.754611
Mean Abs. Percent Error 0.583392
Theil Inequality Coef. 0.003866
Bias Proportion 0.133712
Variance Proportion 0.276309
Covariance Proportion 0.589979
Theil U2 Coefficient 0.797084
Symmetric MAPE 0.585851

Date	close	forecast
30/11/2009	812.0000	809.6874
7/12/2009	808.5000	811.5414
14/12/2009	804.5000	806.3884
21/12/2009	819.0000	807.2240

5. BATS.L

Dependent Variable: D(BATS_L)
Method: ARMA Maximum Likelihood (OPG - BHHH)
Date: 03/12/20 Time: 17:19
Sample: 9/04/2006 22/02/2010
Included observations: 203
Convergence achieved after 16 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	4.024147	3.245974	1.239735	0.2165
AR(1)	-0.338322	0.058746	-5.759087	0.0000
MA(12)	-0.146584	0.072770	-2.014354	0.0453
SIGMASQ	3383.784	170.8493	19.80567	0.0000

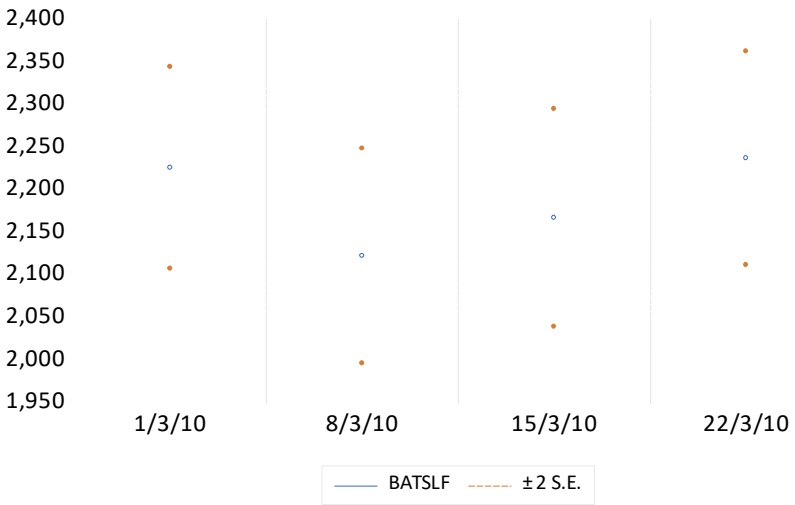
R-squared	0.135610	Mean dependent var	4.165025
Adjusted R-squared	0.122579	S.D. dependent var	62.72183
S.E. of regression	58.75202	Akaike info criterion	11.00592
Sum squared resid	686908.1	Schwarz criterion	11.07120
Log likelihood	-1113.101	Hannan-Quinn criter.	11.03233
F-statistic	10.40670	Durbin-Watson stat	2.019789
Prob(F-statistic)	0.000002		

Inverted AR Roots	-.34			
Inverted MA Roots	.85	.74+.43i	.74-.43i	.43-.74i
	.43+.74i	.00-.85i	-.00+.85i	-.43+.74i
	-.43-.74i	-.74+.43i	-.74-.43i	-.85

Date: 03/12/20 Time: 17:17
Sample (adjusted): 9/04/2006 22/02/2010
Included observations: 203 after adjustments

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
.|. |	.|. |	1	0.029	0.029	0.1704	0.680
.|. |	.|. |	2	0.037	0.037	0.4613	0.794
.|* |	.|* |	3	0.101	0.099	2.5944	0.458
.|. |	.|. |	4	0.006	-0.001	2.6020	0.626
.|. |	.|. |	5	-0.011	-0.019	2.6291	0.757
.|. |	.|. |	6	0.029	0.019	2.8011	0.833
.|. |	.|. |	7	0.005	0.004	2.8064	0.902
.|. |	.|. |	8	-0.024	-0.023	2.9315	0.939
.|. |	.|. |	9	0.001	-0.003	2.9316	0.967
.|. |	.|. |	10	0.010	0.011	2.9542	0.982
.|. |	.|. |	11	0.005	0.011	2.9606	0.991
.|. |	.|. |	12	0.020	0.019	3.0465	0.995
.|. |	.|. |	13	-0.019	-0.024	3.1237	0.997
.|. |	.|. |	14	0.023	0.023	3.2412	0.999
.|. |	.|. |	15	0.037	0.034	3.5378	0.999
.|* |	.|* |	16	0.101	0.103	5.8251	0.990
.|. |	.|. |	17	-0.007	-0.019	5.8359	0.994
.|. |	.|. |	18	0.012	-0.003	5.8692	0.997
.|. |	.|. |	19	0.047	0.030	6.3593	0.997
.|. |	.|. |	20	0.009	0.011	6.3788	0.998
.|. |	.|. |	21	0.048	0.045	6.9051	0.998
.|. |	.|. |	22	0.026	0.011	7.0643	0.999

.|.	|	.|.	|	23	0.014	0.010	7.1088	0.999
.|.	|	.|.	|	24	-0.009	-0.014	7.1284	1.000



Forecast: BATSLF
Actual: BATSL
Forecast sample: 1/03/2010 22/03/2010
Included observations: 4

Root Mean Squared Error	109.4557
Mean Absolute Error	97.42271
Mean Abs. Percent Error	4.521327
Theil Inequality Coef.	0.024935
Bias Proportion	0.011120
Variance Proportion	0.130384
Covariance Proportion	0.858496
Theil U2 Coefficient	0.719096
Symmetric MAPE	4.484425

Date	close	forecast
1/03/2010	2054.000	2225.761
8/03/2010	2233.500	2122.228
15/03/2010	2233.500	2166.925
22/03/2010	2277.000	2236.917

9. BDEV.L

Dependent Variable: D(BDEV_L)
Method: ARMA Maximum Likelihood (OPG - BHHH)
Date: 03/12/20 Time: 18:11
Sample: 19/05/2013 2/04/2017
Included observations: 203
Convergence achieved after 11 iterations
Coefficient covariance computed using outer product of gradients

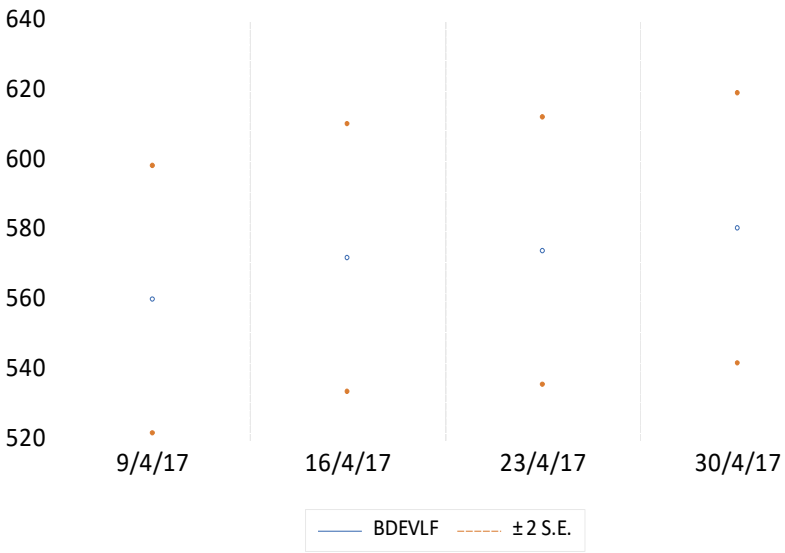
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1.041873	1.480097	0.703922	0.4823
AR(4)	0.166290	0.074207	2.240884	0.0261
MA(3)	-0.136737	0.071575	-1.910402	0.0575
SIGMASQ	358.3731	27.38215	13.08784	0.0000

R-squared	0.048527	Mean dependent var	1.045320
Adjusted R-squared	0.034183	S.D. dependent var	19.45548
S.E. of regression	19.12006	Akaike info criterion	8.759692
Sum squared resid	72749.74	Schwarz criterion	8.824977
Log likelihood	-885.1087	Hannan-Quinn criter.	8.786104
F-statistic	3.383146	Durbin-Watson stat	1.862838
Prob(F-statistic)	0.019225		

Inverted AR Roots	.64	.00+.64i	-.00-.64i	-.64
Inverted MA Roots	.52	-.26+.45i	-.26-.45i	

Date: 03/12/20 Time: 18:22
Sample (adjusted): 19/05/2013 2/04/2017
Included observations: 203 after adjustments

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
.|. |	.|. |	1	0.060	0.060	0.7370	0.391
.|* |	.|* |	2	0.121	0.118	3.7899	0.150
.|. |	.|. |	3	0.027	0.014	3.9426	0.268
.|. |	.|. |	4	-0.019	-0.036	4.0199	0.403
.|* |	.|* |	5	0.203	0.205	12.666	0.027
.|. |	.|. |	6	-0.028	-0.047	12.829	0.046
.|. |	*|. |	7	-0.047	-0.096	13.289	0.065
.|. |	.|. |	8	-0.011	0.002	13.316	0.101
.|* |	.|* |	9	0.128	0.172	16.810	0.052
.|* |	.|. |	10	0.106	0.049	19.236	0.037
.|. |	.|. |	11	-0.005	-0.052	19.242	0.057
.|. |	.|. |	12	-0.052	-0.049	19.834	0.070
.|. |	.|. |	13	0.015	0.046	19.880	0.098
.|. |	.|. |	14	0.042	-0.003	20.275	0.122
.|. |	*|. |	15	-0.024	-0.072	20.404	0.157
.|* |	.|* |	16	0.077	0.121	21.736	0.152
.|. |	.|. |	17	-0.044	0.002	22.174	0.178
.|* |	.|* |	18	0.138	0.088	26.477	0.089
.|* |	.|* |	19	0.132	0.087	30.440	0.046
.|. |	.|. |	20	-0.024	-0.042	30.574	0.061
.|. |	.|. |	21	-0.003	-0.059	30.575	0.081
.|. |	.|. |	22	-0.042	-0.008	30.983	0.096
.|. |	.|. |	23	-0.014	-0.042	31.027	0.122
.|. |	.|. |	24	0.002	-0.025	31.028	0.153



Forecast: BDEVLF
Actual: BDEVL
Forecast sample: 9/04/2017 30/04/2017
Included observations: 4

Root Mean Squared Error	8.071098
Mean Absolute Error	7.078167
Mean Abs. Percent Error	1.220913
Theil Inequality Coef.	0.007012
Bias Proportion	0.769089
Variance Proportion	0.000607
Covariance Proportion	0.230304
Theil U2 Coefficient	0.896468
Symmetric MAPE	1.230704

Date	close	forecast
9/04/2017	572.0000	560.3445
16/04/2017	574.0000	572.2768
23/04/2017	579.5000	574.2957
30/04/2017	590.5000	580.7704

10. BKG.L

Dependent Variable: D(BKG_L)
Method: ARMA Maximum Likelihood (OPG - BHHH)
Date: 03/12/20 Time: 22:37
Sample: 19/05/2013 2/04/2017
Included observations: 203
Convergence achieved after 15 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	4.881773	9.256543	0.527386	0.5985
AR(17)	0.090334	0.079734	1.132944	0.2586
MA(24)	0.126826	0.062137	2.041058	0.0426
SIGMASQ	11333.48	872.7869	12.98539	0.0000

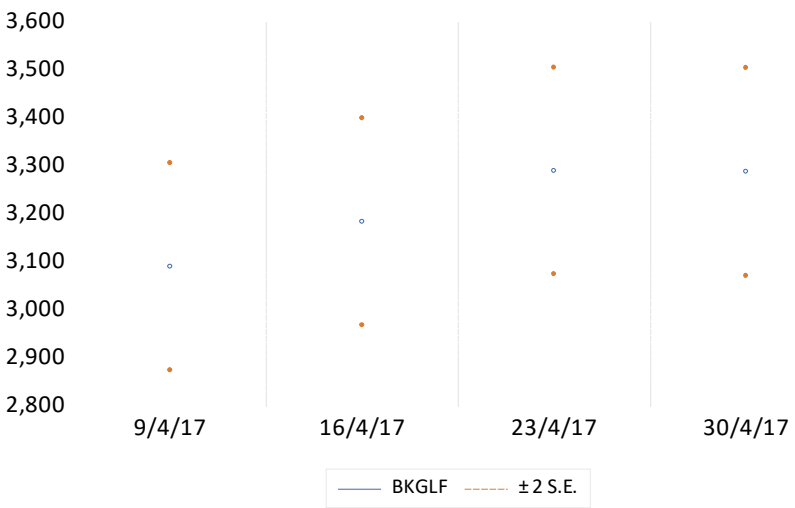
R-squared	0.023563	Mean dependent var	4.477833
Adjusted R-squared	0.008843	S.D. dependent var	108.0020
S.E. of regression	107.5234	Akaike info criterion	12.21541
Sum squared resid	2300697.	Schwarz criterion	12.28069
Log likelihood	-1235.864	Hannan-Quinn criter.	12.24182
F-statistic	1.600744	Durbin-Watson stat	1.973657
Prob(F-statistic)	0.190474		

Inverted AR Roots	.87	.81+.31i	.81-.31i	.64-.58i
	.64+.58i	.39-.78i	.39+.78i	.08-.86i
	.08+.86i	-.24+.83i	-.24-.83i	-.52+.69i
	-.52-.69i	-.74+.46i	-.74-.46i	-.85+.16i
	-.85-.16i			
Inverted MA Roots	.91-.12i	.91+.12i	.85+.35i	.85-.35i
	.73+.56i	.73-.56i	.56+.73i	.56-.73i
	.35+.85i	.35-.85i	.12-.91i	.12+.91i
	-.12-.91i	-.12+.91i	-.35-.85i	-.35+.85i
	-.56+.73i	-.56-.73i	-.73-.56i	-.73+.56i
	-.85-.35i	-.85+.35i	-.91-.12i	-.91+.12i

Date: 03/12/20 Time: 22:38
Sample (adjusted): 19/05/2013 2/04/2017
Included observations: 203 after adjustments

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
.|. |	.|. |	1	-0.013	-0.013	0.0342	0.853
.|. |	.|. |	2	0.033	0.033	0.2575	0.879
.|. |	.|. |	3	-0.018	-0.017	0.3261	0.955
.|. |	.|. |	4	0.052	0.051	0.9020	0.924
.|* |	.|* |	5	0.108	0.110	3.3338	0.649
.|. |	.|. |	6	0.000	-0.000	3.3339	0.766
.|. |	.|. |	7	-0.049	-0.055	3.8482	0.797
.|. |	.|. |	8	-0.015	-0.015	3.8941	0.867
.|. |	.|. |	9	0.052	0.045	4.4810	0.877
.|* |	.|* |	10	0.107	0.098	6.9615	0.729
.|. |	.|. |	11	0.012	0.017	6.9922	0.800
.|. |	.|. |	12	-0.052	-0.047	7.5855	0.817
.|* |	.|* |	13	0.075	0.076	8.8251	0.786
.|. |	.|. |	14	0.057	0.043	9.5308	0.796

.|.	|	.|.	|	15	0.067	0.039	10.527	0.785
.|*	|	.|*	|	16	0.078	0.089	11.886	0.752
.|.	|	.|.	|	17	-0.043	-0.029	12.305	0.781
.|.	|	.|.	|	18	0.012	-0.013	12.336	0.829
.|*	|	.|*	|	19	0.147	0.131	17.202	0.576
.|.	|	.|.	|	20	-0.038	-0.060	17.529	0.618
.|.	|	.|.	|	21	0.026	0.012	17.689	0.669
.|.	|	.|.	|	22	-0.037	-0.008	18.000	0.706
.|*	|	.|*	|	23	0.177	0.161	25.235	0.338
.|*	|	.|*	|	24	0.165	0.149	31.558	0.138



Forecast: BKGLF
Actual: BKGL
Forecast sample: 9/04/2017 30/04/2017
Included observations: 4

Root Mean Squared Error	70.87348
Mean Absolute Error	61.77459
Mean Abs. Percent Error	1.903508
Theil Inequality Coef.	0.010949
Bias Proportion	0.419074
Variance Proportion	0.226362
Covariance Proportion	0.354564
Theil U2 Coefficient	0.901504
Symmetric MAPE	1.925377

Date	close	forecast
9/04/2017	3180.000	3090.002
16/04/2017	3286.000	3183.781
23/04/2017	3258.000	3289.788
30/04/2017	3311.000	3287.907

11. DGE.L

Dependent Variable: D(DGE_L)
Method: ARMA Maximum Likelihood (OPG - BHHH)
Date: 04/12/20 Time: 00:12
Sample: 19/05/2013 2/04/2017
Included observations: 203
Convergence achieved after 17 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1.327753	1.668832	0.795618	0.4272
AR(2)	0.610638	0.152232	4.011242	0.0001
MA(2)	-0.814035	0.125501	-6.486261	0.0000
SIGMASQ	2272.318	183.0108	12.41631	0.0000

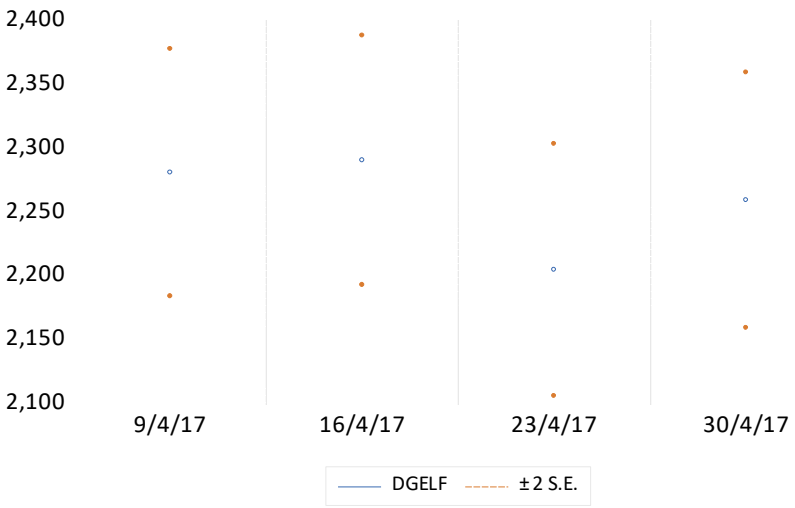
R-squared	0.061853	Mean dependent var	1.248768
Adjusted R-squared	0.047710	S.D. dependent var	49.33685
S.E. of regression	48.14554	Akaike info criterion	10.60760

Sum squared resid	461280.6	Schwarz criterion	10.67289
Log likelihood	-1072.672	Hannan-Quinn criter.	10.63401
F-statistic	4.373402	Durbin-Watson stat	1.972075
Prob(F-statistic)	0.005240		

Inverted AR Roots	.78	-.78
Inverted MA Roots	.90	-.90

Date: 04/12/20 Time: 00:12
Sample (adjusted): 19/05/2013 2/04/2017
Included observations: 203 after adjustments

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
.|* |	.|* |	1	0.077	0.077	1.2061	0.272
.|. |	.|. |	2	0.003	-0.003	1.2074	0.547
.|. |	.|. |	3	-0.012	-0.012	1.2379	0.744
.|. |	.|. |	4	-0.019	-0.017	1.3128	0.859
.|. |	.|. |	5	-0.049	-0.046	1.8076	0.875
.|. |	.|. |	6	0.010	0.017	1.8283	0.935
.|. |	.|. |	7	-0.022	-0.025	1.9324	0.963
.|. |	.|. |	8	-0.052	-0.051	2.5193	0.961
.|. |	.|. |	9	-0.028	-0.022	2.6929	0.975
.|. |	.|. |	10	-0.047	-0.046	3.1659	0.977
.|. |	.|. |	11	-0.011	-0.005	3.1917	0.988
.|. |	.|. |	12	0.054	0.051	3.8357	0.986
.|. |	*|. |	13	-0.065	-0.080	4.7537	0.980
*|. |	*|. |	14	-0.088	-0.082	6.4591	0.954
.|. |	.|. |	15	-0.053	-0.047	7.0815	0.955
*|. |	*|. |	16	-0.081	-0.080	8.5250	0.932
*|. |	*|. |	17	-0.078	-0.074	9.8962	0.908
.|* |	.|* |	18	0.140	0.136	14.322	0.708
.|. |	.|. |	19	0.052	0.022	14.942	0.726
.|. |	.|. |	20	0.025	0.013	15.089	0.771
.|. |	.|. |	21	-0.007	-0.024	15.099	0.818
.|. |	.|. |	22	-0.031	-0.044	15.323	0.848
.|. |	.|. |	23	0.028	0.032	15.507	0.876
.|. |	.|. |	24	-0.008	-0.038	15.522	0.905



Forecast: DGELF	
Actual: DGEL	
Forecast sample: 9/04/2017 30/04/2017	
Included observations: 4	
Root Mean Squared Error	47.89654
Mean Absolute Error	40.04227
Mean Abs. Percent Error	1.791252
Theil Inequality Coef.	0.010605
Bias Proportion	0.000507
Variance Proportion	0.000224
Covariance Proportion	0.999269
Theil U2 Coefficient	0.918546
Symmetric MAPE	1.780194

Date	close	forecast
9/04/2017	2298.000	2280.620
16/04/2017	2208.000	2290.241
23/04/2017	2246.500	2204.445
30/04/2017	2277.500	2259.007

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12. ADN.L

Dependent Variable: D(ADN_L)
Method: ARMA Maximum Likelihood (OPG - BHHH)
Date: 04/12/20 Time: 12:31
Sample: 19/05/2013 2/04/2017
Included observations: 203
Convergence achieved after 16 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.895182	0.948279	-0.944007	0.3463
AR(3)	-0.153445	0.073801	-2.079175	0.0389
MA(18)	-0.131089	0.062633	-2.092989	0.0376
SIGMASQ	308.4526	26.33344	11.71334	0.0000

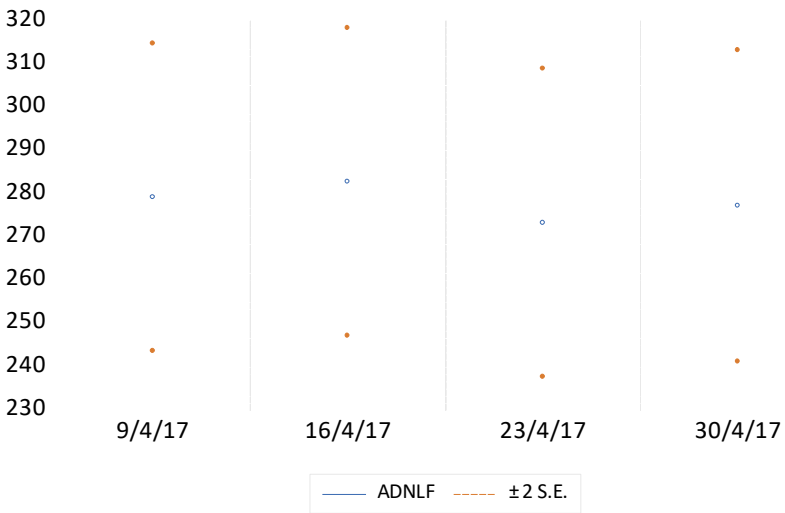
R-squared	0.042672	Mean dependent var	-0.943842
Adjusted R-squared	0.028240	S.D. dependent var	17.99435
S.E. of regression	17.73845	Akaike info criterion	8.610743
Sum squared resid	62615.87	Schwarz criterion	8.676028
Log likelihood	-869.9904	Hannan-Quinn criter.	8.637155
F-statistic	2.956755	Durbin-Watson stat	2.033629
Prob(F-statistic)	0.033558		

Inverted AR Roots	.27+.46i	.27-.46i	-.54	
Inverted MA Roots	.89	.84-.31i	.84+.31i	.68-.57i
	.68+.57i	.45+.77i	.45-.77i	.16+.88i
	.16-.88i	-.16+.88i	-.16-.88i	-.45+.77i
	-.45-.77i	-.68-.57i	-.68+.57i	-.84+.31i
	-.84-.31i	-.89		

Date: 04/12/20 Time: 12:30
Sample (adjusted): 19/05/2013 2/04/2017
Included observations: 203 after adjustments

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
.|. |	.|. |	1	-0.010	-0.010	0.0189	0.891
.|. |	.|. |	2	-0.042	-0.042	0.3820	0.826
.|. |	.|. |	3	-0.029	-0.030	0.5543	0.907
.|. |	.|. |	4	-0.038	-0.040	0.8491	0.932
.|. |	.|. |	5	-0.028	-0.032	1.0188	0.961
.|. |	.|. |	6	0.044	0.040	1.4357	0.964
.|. |	.|. |	7	0.054	0.050	2.0543	0.957
.|. |	.|. |	8	0.047	0.050	2.5347	0.960
.|. |	.|. |	9	-0.015	-0.009	2.5848	0.979
.|. |	.|. |	10	-0.058	-0.049	3.3017	0.973
.|* |	.|* |	11	0.127	0.135	6.7900	0.816

*|. |	*|. |	12	-0.074	-0.074	7.9947	0.786
.|. |	.|. |	13	0.028	0.034	8.1695	0.832
.|. |	.|. |	14	-0.011	-0.022	8.1947	0.879
.|. |	.|. |	15	-0.023	-0.023	8.3123	0.911
.|. |	.|. |	16	-0.025	-0.020	8.4553	0.934
.|* |	.|* |	17	0.126	0.120	11.992	0.801
.|* |	.|* |	18	0.092	0.091	13.886	0.736
.|* |	.|* |	19	0.187	0.199	21.836	0.292
.|. |	.|. |	20	-0.017	0.006	21.904	0.346
*|. |	.|. |	21	-0.083	-0.041	23.497	0.318
.|. |	.|. |	22	-0.036	-0.041	23.802	0.358
.|. |	.|. |	23	0.011	0.040	23.831	0.413
.|. |	.|. |	24	0.063	0.036	24.751	0.419



Forecast: ADNLF
Actual: ADNL
Forecast sample: 9/04/2017 30/04/2017
Included observations: 4
Root Mean Squared Error 9.995131
Mean Absolute Error 8.414948
Mean Abs. Percent Error 2.928772
Theil Inequality Coef. 0.017792
Bias Proportion 0.295907
Variance Proportion 0.126779
Covariance Proportion 0.577314
Theil U2 Coefficient 1.124075
Symmetric MAPE 2.977622

Date	close	forecast
9/04/2017	283.5000	279.2068
16/04/2017	276.8000	282.7557
23/04/2017	279.0000	273.2810
30/04/2017	294.9000	277.2082

13. AHT.L

Dependent Variable: D(AHT_L)
Method: ARMA Maximum Likelihood (OPG - BHHH)
Date: 05/12/20 Time: 11:09
Sample: 8/06/1997 22/04/2001
Included observations: 203
Convergence achieved after 24 iterations
Coefficient covariance computed using outer product of gradients

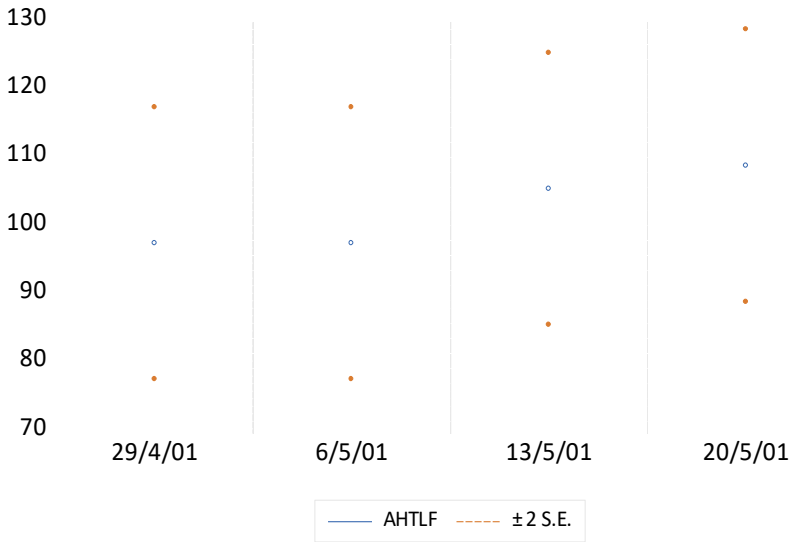
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.200664	0.694435	-0.288960	0.7729
AR(13)	0.150194	0.071165	2.110514	0.0361
MA(16)	-0.174854	0.082314	-2.124219	0.0349
SIGMASQ	96.32052	5.782604	16.65695	0.0000

R-squared	0.075206	Mean dependent var	-0.194256
Adjusted R-squared	0.061264	S.D. dependent var	10.23079
S.E. of regression	9.912447	Akaike info criterion	7.448876
Sum squared resid	19553.07	Schwarz criterion	7.514161
Log likelihood	-752.0609	Hannan-Quinn criter.	7.475287
F-statistic	5.394352	Durbin-Watson stat	1.908784
Prob(F-statistic)	0.001371		

Inverted AR Roots	.86	.77-.40i	.77+.40i	.49+.71i
	.49-.71i	.10-.86i	.10+.86i	-.31-.81i
	-.31+.81i	-.65+.57i	-.65-.57i	-.84-.21i
	-.84+.21i			
Inverted MA Roots	.90	.83-.34i	.83+.34i	.63-.63i
	.63+.63i	.34+.83i	.34-.83i	.00-.90i
	.00+.90i	-.34-.83i	-.34+.83i	-.63+.63i
	-.63-.63i	-.83-.34i	-.83+.34i	-.90

Date: 05/12/20 Time: 11:10
Sample (adjusted): 8/06/1997 22/04/2001
Included observations: 203 after adjustments

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
.|. |	.|. |	1	0.031	0.031	0.2031	0.652
.|. |	.|. |	2	-0.041	-0.042	0.5581	0.756
.|* |	.|* |	3	0.157	0.160	5.6663	0.129
.|. |	.|. |	4	0.007	-0.007	5.6755	0.225
.|. |	.|. |	5	-0.029	-0.016	5.8545	0.321
.|. |	.|. |	6	-0.020	-0.044	5.9352	0.430
.|. |	.|. |	7	0.007	0.008	5.9464	0.546
.|. |	.|. |	8	0.006	0.010	5.9533	0.652
.|. |	.|. |	9	0.035	0.046	6.2144	0.718
.|. |	.|. |	10	0.017	0.012	6.2750	0.792
.|. |	.|. |	11	0.033	0.033	6.5147	0.837
.|. |	.|. |	12	-0.004	-0.020	6.5188	0.888
.|. |	.|. |	13	0.030	0.032	6.7223	0.916
.|. |	.|. |	14	0.073	0.063	7.8837	0.895
.|. |	.|. |	15	0.009	0.014	7.9004	0.928
.|. |	.|. |	16	0.001	-0.002	7.9006	0.952
.|. |	.|. |	17	0.021	0.002	8.0029	0.966
.|. |	.|. |	18	0.037	0.033	8.3138	0.974
.|. |	.|. |	19	-0.012	-0.009	8.3440	0.983
*|. |	*|. |	20	-0.076	-0.076	9.6613	0.974
.|. |	.|. |	21	-0.006	-0.014	9.6697	0.983
.|. |	.|. |	22	-0.021	-0.028	9.7693	0.988
.|. |	.|. |	23	-0.041	-0.019	10.149	0.990
.|. |	.|. |	24	-0.031	-0.032	10.367	0.993



Forecast: AHTLF
Actual: AHTL
Forecast sample: 29/04/2001 20/05/...
Included observations: 4

Root Mean Squared Error	3.976416
Mean Absolute Error	3.051042
Mean Abs. Percent Error	2.870944
Theil Inequality Coef.	0.019088
Bias Proportion	0.588725
Variance Proportion	0.001704
Covariance Proportion	0.409571
Theil U2 Coefficient	0.962709
Symmetric MAPE	2.943462

Date	close	forecast
29/04/2001	98.23800	97.69851
6/05/2001	104.2870	97.68632
13/05/2001	109.9930	105.6492
20/05/2001	109.7680	109.0478

14. AV.L

Dependent Variable: D(AV_L)
Method: ARMA Maximum Likelihood (OPG - BHHH)
Date: 05/12/20 Time: 12:36
Sample: 8/06/1997 22/04/2001
Included observations: 203
Convergence achieved after 14 iterations
Coefficient covariance computed using outer product of gradients

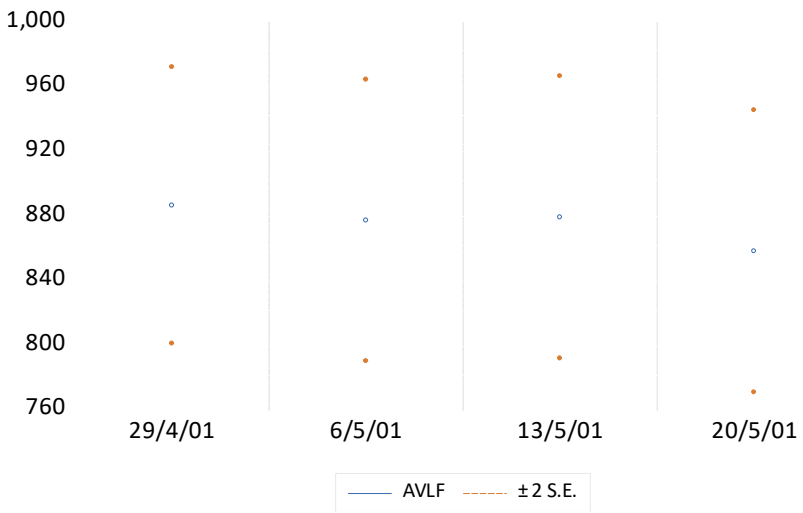
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1.206614	2.270651	0.531396	0.5957
AR(1)	-0.194501	0.079762	-2.438528	0.0156
MA(4)	-0.160080	0.063401	-2.524896	0.0124
SIGMASQ	1789.209	129.5377	13.81226	0.0000

R-squared	0.064028	Mean dependent var	1.177655
Adjusted R-squared	0.049918	S.D. dependent var	43.83001
S.E. of regression	42.72205	Akaike info criterion	10.36751
Sum squared resid	363209.5	Schwarz criterion	10.43280
Log likelihood	-1048.303	Hannan-Quinn criter.	10.39393
F-statistic	4.537756	Durbin-Watson stat	2.011013
Prob(F-statistic)	0.004222		

Inverted AR Roots	-.19			
Inverted MA Roots	.63	-.00+.63i	-.00-.63i	-.63

Date: 05/12/20 Time: 12:39
Sample (adjusted): 8/06/1997 22/04/2001
Included observations: 203 after adjustments

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
.|. |	.|. |	1	-0.063	-0.063	0.8196	0.365
.|* |	.|* |	2	0.149	0.145	5.4045	0.067
.|. |	.|* |	3	0.064	0.083	6.2461	0.100
.|. |	.|. |	4	0.066	0.055	7.1695	0.127
.|. |	.|. |	5	0.020	0.007	7.2549	0.202
.|. |	.|. |	6	-0.036	-0.059	7.5265	0.275
.|. |	.|. |	7	0.033	0.014	7.7575	0.354
.|. |	.|. |	8	-0.053	-0.043	8.3468	0.400
.|. |	.|. |	9	0.021	0.014	8.4420	0.490
.|. |	.|. |	10	-0.037	-0.019	8.7323	0.558
.|. |	.|. |	11	-0.007	-0.011	8.7434	0.646
.|* |	.|* |	12	0.100	0.112	10.920	0.536
.|. |	.|* |	13	0.061	0.087	11.730	0.550
.|. |	*|. |	14	-0.051	-0.075	12.314	0.581
.|* |	.|. |	15	0.097	0.059	14.381	0.497
.|** |	.|** |	16	0.268	0.285	30.306	0.016
.|. |	.|. |	17	0.046	0.072	30.780	0.021
.|* |	.|. |	18	0.113	0.045	33.644	0.014
.|. |	.|. |	19	-0.006	-0.061	33.653	0.020
.|. |	.|. |	20	0.061	-0.007	34.499	0.023
.|. |	.|. |	21	0.036	0.049	34.793	0.030
.|. |	.|. |	22	-0.030	-0.025	35.006	0.039
.|* |	.|* |	23	0.093	0.091	37.007	0.032
*|. |	*|. |	24	-0.087	-0.068	38.777	0.029



Forecast: AVLF
Actual: AVL
Forecast sample: 29/04/2001 20/05/...
Included observations: 4

Root Mean Squared Error	15.94907
Mean Absolute Error	12.11692
Mean Abs. Percent Error	1.413938
Theil Inequality Coef.	0.009176
Bias Proportion	0.577184
Variance Proportion	0.009035
Covariance Proportion	0.413781
Theil U2 Coefficient	1.129999
Symmetric MAPE	1.396757

Date	close	forecast
29/04/2001	873.5040	886.2637
6/05/2001	876.2620	877.0042
13/05/2001	850.5170	879.0187
20/05/2001	851.4360	857.9001

15. BAB.L

Dependent Variable: D(BAB_L)
Method: ARMA Maximum Likelihood (OPG - BHHH)
Date: 05/12/20 Time: 14:13
Sample: 19/05/2013 2/04/2017
Included observations: 203
Convergence achieved after 12 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.636594	2.265983	-0.280935	0.7791
AR(10)	-0.142331	0.070080	-2.030982	0.0436
MA(15)	0.165271	0.069784	2.368322	0.0188
SIGMASQ	929.3382	80.93095	11.48310	0.0000

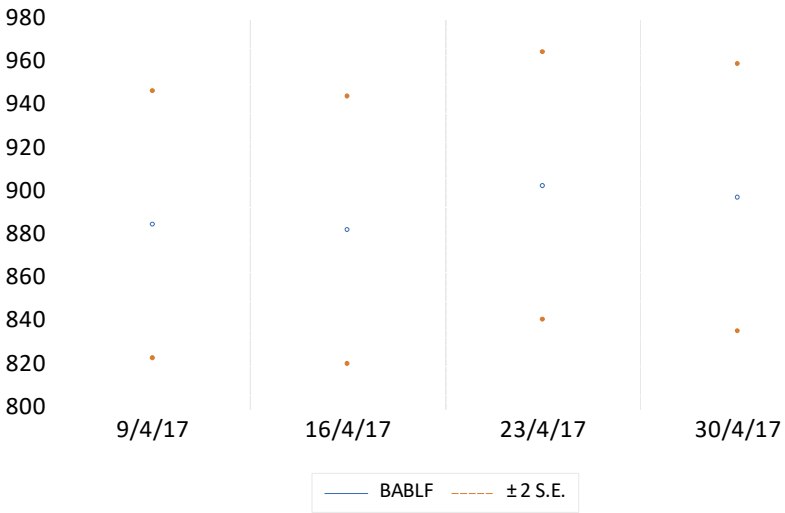
R-squared	0.038401	Mean dependent var	-0.586749
Adjusted R-squared	0.023904	S.D. dependent var	31.16464
S.E. of regression	30.78991	Akaike info criterion	9.714817
Sum squared resid	188655.7	Schwarz criterion	9.780102
Log likelihood	-982.0539	Hannan-Quinn criter.	9.741229
F-statistic	2.648972	Durbin-Watson stat	2.175835
Prob(F-statistic)	0.050065		

Inverted AR Roots	.78+.25i	.78-.25i	.48+.67i	.48-.67i
	.00-.82i	-.00+.82i	-.48+.67i	-.48-.67i
	-.78-.25i	-.78+.25i		
Inverted MA Roots	.87+.18i	.87-.18i	.72+.52i	.72-.52i
	.44-.77i	.44+.77i	.09-.88i	.09+.88i
	-.27+.84i	-.27-.84i	-.59+.66i	-.59-.66i
	-.81-.36i	-.81+.36i	-.89	

Date: 05/12/20 Time: 14:14
Sample (adjusted): 19/05/2013 2/04/2017
Included observations: 203 after adjustments

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
.|. |	.|. |	1	0.062	0.062	0.8047	0.370
.|. |	.|. |	2	0.030	0.026	0.9891	0.610
.|* |	.|* |	3	0.087	0.084	2.5687	0.463
.|* |	.|* |	4	0.099	0.089	4.6302	0.327
*|. |	*|. |	5	-0.095	-0.112	6.5376	0.257
.|. |	.|. |	6	0.001	0.001	6.5378	0.366
.|. |	.|. |	7	0.013	0.003	6.5735	0.475
*|. |	*|. |	8	-0.081	-0.076	7.9626	0.437
*|. |	.|. |	9	-0.071	-0.044	9.0518	0.433
.|. |	.|. |	10	0.008	0.008	9.0670	0.526
*|. |	.|. |	11	-0.074	-0.063	10.246	0.508
.|. |	.|* |	12	0.050	0.087	10.788	0.547
.|. |	.|. |	13	-0.024	-0.035	10.913	0.618
.|* |	.|* |	14	0.144	0.149	15.486	0.346
.|. |	.|. |	15	0.052	0.045	16.093	0.376
*|. |	*|. |	16	-0.079	-0.128	17.484	0.355
.|. |	.|. |	17	0.051	0.056	18.069	0.385
.|. |	*|. |	18	-0.062	-0.119	18.931	0.396
.|. |	.|. |	19	0.026	0.063	19.079	0.452

.|.	|	.|.	|	20	-0.044	-0.023	19.518	0.488
.|.	|	.|.	|	21	0.001	-0.019	19.519	0.552
.|.	|	.|.	|	22	-0.064	-0.023	20.470	0.554
.|.	|	.|*	|	23	0.072	0.103	21.656	0.541
.|.	|	.|.	|	24	0.011	-0.009	21.684	0.598



Forecast: BABLF
Actual: BABL
Forecast sample: 9/04/2017 30/04/2017
Included observations: 4

Root Mean Squared Error	13.63539
Mean Absolute Error	10.60501
Mean Abs. Percent Error	1.168331
Theil Inequality Coef.	0.007604
Bias Proportion	0.390981
Variance Proportion	0.026603
Covariance Proportion	0.582416
Theil U2 Coefficient	1.119051
Symmetric MAPE	1.179186

Date	close	forecast
9/04/2017	885.5000	885.2733
16/04/2017	903.0000	882.7556
23/04/2017	899.0000	903.1580
30/04/2017	915.5000	897.7090

16. BARC.L

Dependent Variable: D(BARC_L)
Method: ARMA Maximum Likelihood (OPG - BHHH)
Date: 06/12/20 Time: 20:00
Sample: 8/10/2000 22/08/2004
Included observations: 203
Convergence achieved after 15 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.226609	1.307478	0.173317	0.8626
AR(4)	-0.215201	0.057213	-3.761397	0.0002
MA(22)	0.172835	0.075263	2.296414	0.0227
SIGMASQ	366.7388	30.31442	12.09783	0.0000

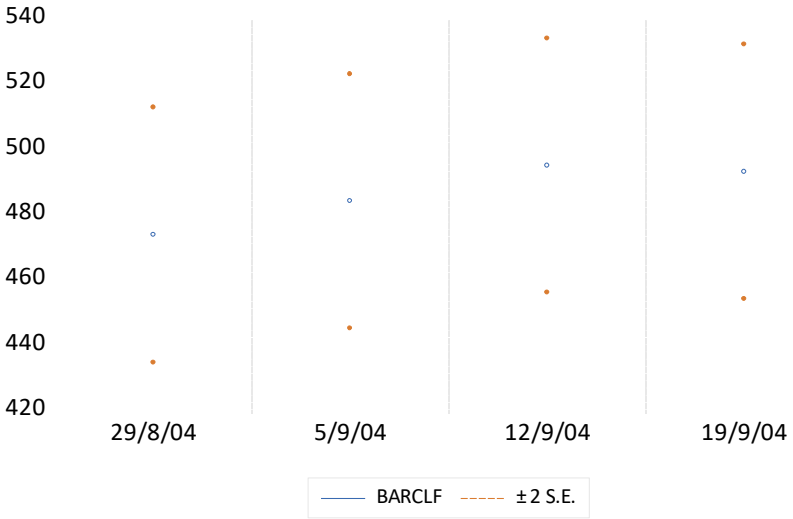
R-squared	0.059915	Mean dependent var	0.230936
Adjusted R-squared	0.045743	S.D. dependent var	19.80009
S.E. of regression	19.34193	Akaike info criterion	8.786157
Sum squared resid	74447.98	Schwarz criterion	8.851442
Log likelihood	-887.7949	Hannan-Quinn criter.	8.812568
F-statistic	4.227648	Durbin-Watson stat	2.102807
Prob(F-statistic)	0.006346		

Inverted AR Roots	.48-.48i	.48+.48i	-.48+.48i	-.48+.48i

Inverted MA Roots	.91+.13i	.91-.13i	.84+.38i	.84-.38i
	.70+.60i	.70-.60i	.50+.78i	.50-.78i
	.26-.89i	.26+.89i	.00-.92i	-.00+.92i
	-.26-.89i	-.26+.89i	-.50-.78i	-.50+.78i
	-.70-.60i	-.70+.60i	-.84-.38i	-.84+.38i
	-.91-.13i	-.91+.13i		

Date: 06/12/20 Time: 20:09
Sample (adjusted): 8/10/2000 22/08/2004
Included observations: 203 after adjustments

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
.|** |	.|** |	1	0.274	0.274	15.520	0.000
.|. |	.|. |	2	0.064	-0.012	16.380	0.000
.|* |	.|* |	3	0.111	0.104	18.929	0.000
.|* |	.|* |	4	0.146	0.097	23.381	0.000
.|. |	.|. |	5	0.020	-0.052	23.462	0.000
.|. |	.|. |	6	0.009	0.008	23.478	0.001
.|. |	.|. |	7	0.054	0.033	24.087	0.001
.|* |	.|. |	8	0.099	0.071	26.183	0.001
.|. |	*|. |	9	-0.037	-0.085	26.472	0.002
.|. |	.|. |	10	-0.014	0.012	26.512	0.003
.|. |	.|. |	11	-0.033	-0.058	26.747	0.005
.|. |	.|. |	12	0.029	0.048	26.927	0.008
.|. |	.|. |	13	0.041	0.046	27.292	0.011
*|. |	*|. |	14	-0.067	-0.098	28.281	0.013
.|. |	.|. |	15	-0.033	0.010	28.518	0.019
.|. |	.|. |	16	-0.007	-0.022	28.530	0.027
.|. |	.|. |	17	0.021	0.049	28.631	0.038
.|. |	.|. |	18	0.023	0.030	28.751	0.052
.|. |	.|. |	19	0.009	0.002	28.771	0.070
.|. |	*|. |	20	-0.050	-0.082	29.334	0.081
.|. |	.|. |	21	-0.012	0.012	29.365	0.106
.|. |	.|. |	22	-0.015	0.002	29.419	0.133
.|. |	.|. |	23	0.049	0.066	29.972	0.150
.|. |	.|. |	24	0.041	0.033	30.354	0.173



Forecast: BARCLF
Actual: BARCL
Forecast sample: 29/08/2004 19/09/...
Included observations: 4

Root Mean Squared Error	8.460138
Mean Absolute Error	7.314886
Mean Abs. Percent Error	1.487715
Theil Inequality Coef.	0.008628
Bias Proportion	0.527611
Variance Proportion	0.302345
Covariance Proportion	0.170044
Theil U2 Coefficient	1.362048
Symmetric MAPE	1.502219

Date	close	forecast
29/08/2004	488.1990	474.4189
5/09/2004	492.8180	484.7310
12/09/2004	493.2800	495.6194
19/09/2004	498.8220	493.7689

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17. AZN.L

Dependent Variable: D(AZN_L)
Method: ARMA Maximum Likelihood (OPG - BHHH)
Date: 06/12/20 Time: 21:05
Sample: 11/01/2010 25/11/2013
Included observations: 203
Convergence achieved after 19 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	2.534412	3.871714	0.654597	0.5135
AR(12)	0.614034	0.350291	1.752927	0.0812
MA(12)	-0.725463	0.297548	-2.438141	0.0156
SIGMASQ	4716.655	425.7687	11.07797	0.0000

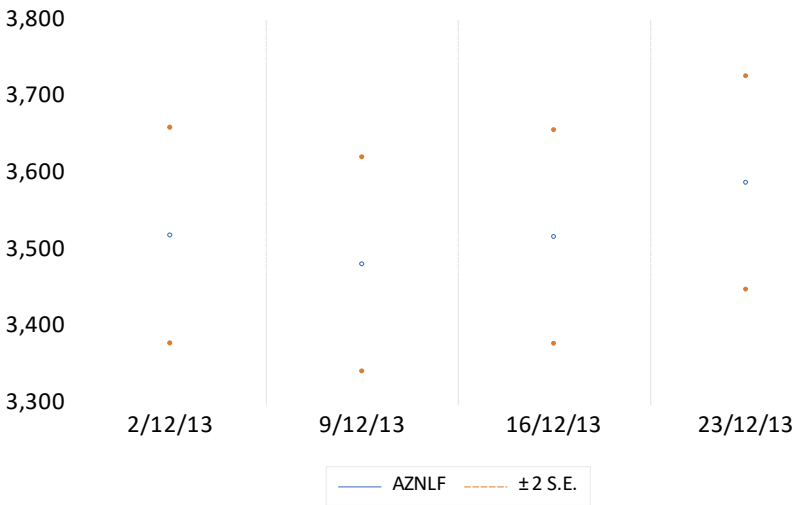
R-squared	0.018980	Mean dependent var	2.980296
Adjusted R-squared	0.004191	S.D. dependent var	69.51052
S.E. of regression	69.36470	Akaike info criterion	11.33858
Sum squared resid	957480.9	Schwarz criterion	11.40386
Log likelihood	-1146.866	Hannan-Quinn criter.	11.36499
F-statistic	1.283398	Durbin-Watson stat	1.990500
Prob(F-statistic)	0.281226		

Inverted AR Roots	.96	.83+.48i	.83-.48i	.48+.83i
	.48-.83i	.00+.96i	-.00-.96i	-.48+.83i
	-.48-.83i	-.83-.48i	-.83+.48i	-.96
Inverted MA Roots	.97	.84+.49i	.84-.49i	.49+.84i
	.49-.84i	-.00-.97i	-.00+.97i	-.49-.84i
	-.49+.84i	-.84+.49i	-.84-.49i	-.97

Date: 06/12/20 Time: 21:06
Sample (adjusted): 11/01/2010 25/11/2013
Included observations: 203 after adjustments

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
.|* |	.|* |	1	0.074	0.074	1.1227	0.289
*|. |	*|. |	2	-0.080	-0.086	2.4628	0.292
.|. |	.|. |	3	-0.050	-0.037	2.9746	0.396
.|. |	.|. |	4	-0.062	-0.063	3.7889	0.435
*|. |	*|. |	5	-0.072	-0.071	4.8704	0.432
.|. |	.|. |	6	-0.043	-0.046	5.2567	0.511
.|. |	.|. |	7	-0.027	-0.040	5.4135	0.610
.|. |	.|. |	8	0.018	0.004	5.4801	0.705
.|. |	.|. |	9	-0.019	-0.040	5.5564	0.783

.|. |	.|. |	10	-0.033	-0.042	5.7946	0.832
.|. |	*|. |	11	-0.062	-0.074	6.6227	0.829
.|. |	.|. |	12	-0.042	-0.051	7.0043	0.857
.|. |	.|. |	13	0.059	0.044	7.7556	0.859
.|. |	.|. |	14	0.061	0.031	8.5731	0.857
.|. |	.|. |	15	-0.024	-0.042	8.6982	0.893
.|. |	.|. |	16	0.051	0.049	9.2728	0.902
.|* |	.|. |	17	0.083	0.070	10.819	0.866
.|. |	.|. |	18	-0.023	-0.023	10.939	0.897
*|. |	.|. |	19	-0.081	-0.059	12.426	0.867
.|. |	.|* |	20	0.072	0.095	13.596	0.850
.|. |	.|. |	21	0.039	0.027	13.939	0.872
.|. |	.|. |	22	0.017	0.027	14.005	0.901
*|. |	.|. |	23	-0.067	-0.059	15.045	0.893
.|. |	.|. |	24	-0.023	0.003	15.166	0.916



Forecast: AZNLF
Actual: AZNL
Forecast sample: 2/12/2013 23/12/2013
Included observations: 4
Root Mean Squared Error 43.97337
Mean Absolute Error 39.12068
Mean Abs. Percent Error 1.100702
Theil Inequality Coef. 0.006214
Bias Proportion 0.302208
Variance Proportion 0.047761
Covariance Proportion 0.650030
Theil U2 Coefficient 1.064539
Symmetric MAPE 1.106539

Date	close	forecast
2/12/2013	3489.000	3518.894
9/12/2013	3518.500	3481.288
16/12/2013	3588.500	3516.773
23/12/2013	3605.000	3587.350

18. GSK.L

Dependent Variable: D(GSK_L)
Method: ARMA Maximum Likelihood (OPG - BHHH)
Date: 06/12/20 Time: 21:37
Sample: 8/06/1997 22/04/2001
Included observations: 203
Convergence achieved after 11 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	3.008853	2.662826	1.129947	0.2599
AR(1)	0.782065	0.112403	6.957694	0.0000
MA(1)	-0.900019	0.083000	-10.84362	0.0000

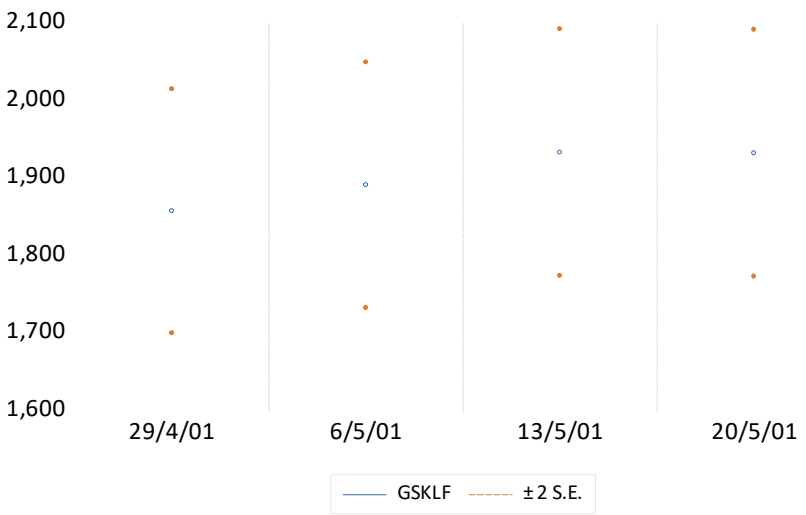
SIGMASQ	5968.542	489.8837	12.18359	0.0000

R-squared	0.035310	Mean dependent var	3.128079
Adjusted R-squared	0.020767	S.D. dependent var	78.85196
S.E. of regression	78.02892	Akaike info criterion	11.57239
Sum squared resid	1211614.	Schwarz criterion	11.63768
Log likelihood	-1170.598	Hannan-Quinn criter.	11.59881
F-statistic	2.427939	Durbin-Watson stat	2.008131
Prob(F-statistic)	0.066626		

Inverted AR Roots	.78
Inverted MA Roots	.90

Date: 06/12/20 Time: 21:38
Sample (adjusted): 8/06/1997 22/04/2001
Included observations: 203 after adjustments

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
.|. |	.|. |	1	0.009	0.009	0.0180	0.893
.|. |	.|. |	2	0.000	0.000	0.0181	0.991
.|. |	.|. |	3	0.013	0.013	0.0507	0.997
.|. |	.|. |	4	-0.034	-0.035	0.2975	0.990
.|. |	.|. |	5	-0.023	-0.022	0.4041	0.995
*|. |	*|. |	6	-0.099	-0.099	2.4687	0.872
*|. |	*|. |	7	-0.086	-0.085	4.0453	0.775
.|* |	.|* |	8	0.127	0.129	7.4727	0.487
.|. |	.|. |	9	-0.017	-0.018	7.5345	0.582
.|. |	.|. |	10	-0.023	-0.029	7.6491	0.663
.|. |	.|. |	11	0.055	0.045	8.3164	0.685
.|* |	.|* |	12	0.164	0.165	14.187	0.289
.|. |	.|. |	13	-0.029	-0.047	14.366	0.349
.|. |	.|. |	14	0.032	0.045	14.584	0.407
.|. |	.|. |	15	-0.020	-0.002	14.675	0.475
.|. |	.|. |	16	-0.029	-0.042	14.857	0.535
.|. |	.|. |	17	-0.061	-0.054	15.690	0.546
*|. |	.|. |	18	-0.089	-0.042	17.490	0.490
.|. |	.|. |	19	-0.043	-0.037	17.911	0.528
.|. |	*|. |	20	-0.037	-0.085	18.228	0.572
*|. |	*|. |	21	-0.089	-0.074	20.020	0.520
*|. |	*|. |	22	-0.074	-0.099	21.271	0.504
.|. |	.|. |	23	0.036	0.004	21.574	0.546
.|. |	*|. |	24	-0.024	-0.069	21.709	0.597



Forecast: GSKLF
Actual: GSKL
Forecast sample: 29/04/2001 20/05/...
Included observations: 4

Root Mean Squared Error	38.85497
Mean Absolute Error	33.56586
Mean Abs. Percent Error	1.764622
Theil Inequality Coef.	0.010188
Bias Proportion	0.032239
Variance Proportion	0.020254
Covariance Proportion	0.947507
Theil U2 Coefficient	0.963569
Symmetric MAPE	1.765746

Date	close	forecast
29/04/2001	1890.0	1857.193
6/05/2001	1937.0	1890.847
13/05/2001	1935.0	1932.875
20/05/2001	1879.0	1932.179

19. SHP.L

Dependent Variable: D(SHPL)
Method: ARMA Maximum Likelihood (OPG - BHHH)
Date: 06/12/20 Time: 22:59
Sample: 8/10/2006 22/08/2010
Included observations: 203
Convergence achieved after 15 iterations
Coefficient covariance computed using outer product of gradients

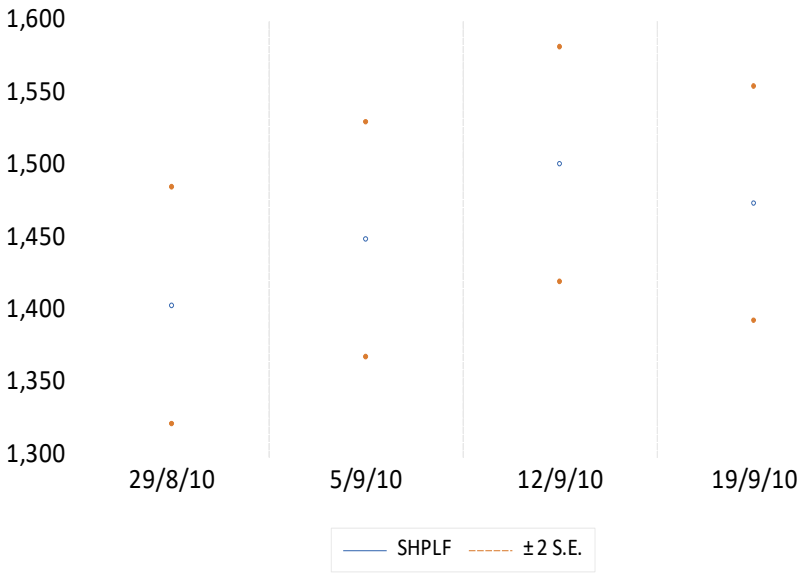
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	2.630879	3.102002	0.848123	0.3974
AR(8)	-0.141579	0.057342	-2.469006	0.0144
MA(14)	0.199888	0.077572	2.576806	0.0107
SIGMASQ	1595.180	120.3386	13.25577	0.0000

R-squared	0.062899	Mean dependent var	2.586207
Adjusted R-squared	0.048772	S.D. dependent var	41.36033
S.E. of regression	40.33911	Akaike info criterion	10.25564
Sum squared resid	323821.6	Schwarz criterion	10.32092
Log likelihood	-1036.947	Hannan-Quinn criter.	10.28205
F-statistic	4.452349	Durbin-Watson stat	2.175035
Prob(F-statistic)	0.004724		

Inverted AR Roots	.72+.30i	.72-.30i	.30-.72i	.30+.72i
	-.30+.72i	-.30-.72i	-.72-.30i	-.72+.30i
Inverted MA Roots	.87+.20i	.87-.20i	.70+.56i	.70-.56i
	.39-.80i	.39+.80i	.00+.89i	-.00-.89i
	-.39+.80i	-.39-.80i	-.70+.56i	-.70-.56i
	-.87+.20i	-.87-.20i		

Date: 06/12/20 Time: 23:00
Sample: 8/10/2006 22/08/2010
Included observations: 203

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
.|. |	.|. |	1	-0.020	-0.020	0.0824	0.774
.|. |	.|. |	2	-0.031	-0.032	0.2860	0.867
*|. |	*|. |	3	-0.068	-0.069	1.2469	0.742
.|. |	.|. |	4	0.000	-0.004	1.2469	0.870
.|. |	.|. |	5	0.034	0.029	1.4869	0.915
.|. |	.|. |	6	0.020	0.017	1.5753	0.954
.|. |	.|. |	7	0.006	0.008	1.5818	0.979
.|* |	.|* |	8	0.159	0.166	6.9798	0.539
.|. |	.|. |	9	-0.019	-0.008	7.0568	0.631
.|. |	.|. |	10	0.043	0.055	7.4565	0.682
.|* |	.|* |	11	0.080	0.106	8.8271	0.638
.|. |	.|. |	12	-0.040	-0.036	9.1693	0.688
.|. |	.|. |	13	0.042	0.044	9.5468	0.731
.|. |	.|. |	14	-0.012	-0.004	9.5773	0.792
.|. |	.|. |	15	-0.012	-0.023	9.6077	0.844
.|. |	*|. |	16	-0.040	-0.073	9.9613	0.869
*|. |	*|. |	17	-0.082	-0.091	11.464	0.831
.|. |	.|. |	18	0.015	-0.019	11.517	0.871
.|** |	.|* |	19	0.229	0.194	23.330	0.223
.|. |	.|. |	20	0.044	0.061	23.767	0.253
.|. |	.|. |	21	-0.059	-0.064	24.567	0.266
.|. |	.|. |	22	-0.057	-0.016	25.304	0.283
.|. |	.|. |	23	-0.016	-0.003	25.364	0.332
.|. |	.|. |	24	0.000	-0.016	25.364	0.386



Forecast: SHPLF
Actual: SHPL
Forecast sample: 29/08/2010 19/09/...
Included observations: 4

Root Mean Squared Error	38.09709
Mean Absolute Error	33.10405
Mean Abs. Percent Error	2.246899
Theil Inequality Coef.	0.013001
Bias Proportion	0.161144
Variance Proportion	0.240607
Covariance Proportion	0.598250
Theil U2 Coefficient	1.043464
Symmetric MAPE	2.267844

Date	close	forecast
29/08/2010	1451.000	1403.785
5/09/2010	1499.000	1449.420
12/09/2010	1468.000	1501.363
19/09/2010	1472.000	1474.259

20. SGE.L

Dependent Variable: D(SGE_L)
Method: ARMA Maximum Likelihood (OPG - BHHH)
Date: 08/12/20 Time: 12:04
Sample: 8/06/1997 22/04/2001
Included observations: 203
Convergence achieved after 36 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1.188283	2.005916	0.592389	0.5543
AR(1)	-0.219753	0.039956	-5.499890	0.0000
MA(15)	-0.191772	0.049833	-3.848319	0.0002
SIGMASQ	1594.398	85.62906	18.61982	0.0000

R-squared	0.090478	Mean dependent var	1.046897
Adjusted R-squared	0.076766	S.D. dependent var	41.97241
S.E. of regression	40.32922	Akaike info criterion	10.25455
Sum squared resid	323662.7	Schwarz criterion	10.31983
Log likelihood	-1036.837	Hannan-Quinn criter.	10.28096
F-statistic	6.598720	Durbin-Watson stat	2.000239
Prob(F-statistic)	0.000284		

Inverted AR Roots	-.22			
Inverted MA Roots	.90	.82+.36i	.82-.36i	.60-.67i
	.60+.67i	.28-.85i	.28+.85i	-.09-.89i
	-.09+.89i	-.45-.78i	-.45+.78i	-.72+.53i
	-.72-.53i	-.88-.19i	-.88+.19i	

Date: 08/12/20 Time: 12:22
Sample (adjusted): 8/06/1997 22/04/2001
Included observations: 203 after adjustments

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
.|** |	.|** |	1	0.273	0.273	15.350	0.000
.|* |	.|* |	2	0.197	0.132	23.344	0.000
.|* |	.|* |	3	0.151	0.075	28.063	0.000
.|* |	.|* |	4	0.196	0.131	36.084	0.000
.|** |	.|** |	5	0.313	0.237	56.691	0.000
.|* |	.|. |	6	0.207	0.057	65.781	0.000
.|* |	.|. |	7	0.180	0.051	72.683	0.000
.|* |	.|. |	8	0.172	0.059	78.974	0.000
.|** |	.|* |	9	0.216	0.095	89.015	0.000
.|* |	.|. |	10	0.127	-0.054	92.487	0.000
.|* |	.|. |	11	0.118	-0.009	95.521	0.000
.|* |	.|. |	12	0.166	0.066	101.51	0.000
.|** |	.|* |	13	0.294	0.193	120.47	0.000
.|* |	.|. |	14	0.166	-0.031	126.56	0.000
.|* |	.|. |	15	0.138	0.016	130.77	0.000
.|* |	.|. |	16	0.124	0.026	134.19	0.000
.|* |	.|. |	17	0.120	-0.016	137.39	0.000
.|* |	.|. |	18	0.159	-0.022	143.08	0.000
.|* |	.|. |	19	0.094	-0.033	145.07	0.000

.|** |	.|** |	20	0.308	0.262	166.59	0.000
.|** |	.|* |	21	0.252	0.106	181.14	0.000
.|* |	*|. |	22	0.105	-0.122	183.66	0.000
.|* |	.|. |	23	0.098	0.001	185.86	0.000
.|. |	.|. |	24	0.031	-0.058	186.08	0.000

Dependent Variable: D(SGE_L)
Method: ARMA Maximum Likelihood (OPG - BHHH)
Date: 08/12/20 Time: 12:25
Sample: 8/06/1997 22/04/2001
Included observations: 203
Convergence achieved after 32 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1.125840	1.973586	0.570454	0.5690
AR(15)	-0.195902	0.049134	-3.987109	0.0001
MA(1)	-0.200433	0.040941	-4.895614	0.0000
SIGMASQ	1596.105	85.58891	18.64851	0.0000

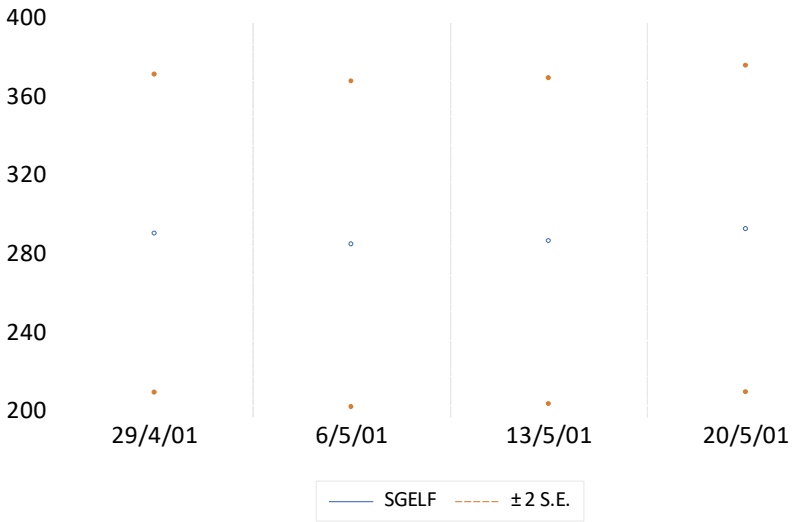
R-squared	0.089504	Mean dependent var	1.046897
Adjusted R-squared	0.075777	S.D. dependent var	41.97241
S.E. of regression	40.35081	Akaike info criterion	10.25570
Sum squared resid	324009.4	Schwarz criterion	10.32099
Log likelihood	-1036.954	Hannan-Quinn criter.	10.28211
F-statistic	6.520691	Durbin-Watson stat	2.024503
Prob(F-statistic)	0.000315		

Inverted AR Roots	.88+.19i	.88-.19i	.73+.53i	.73-.53i
	.45-.78i	.45+.78i	.09-.89i	.09+.89i
	-.28-.85i	-.28+.85i	-.60+.67i	-.60-.67i
	-.82-.36i	-.82+.36i	-.90	
Inverted MA Roots	.20			

Date: 08/12/20 Time: 12:24
Sample (adjusted): 8/06/1997 22/04/2001
Included observations: 203 after adjustments

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
.|** |	.|** |	1	0.280	0.280	16.185	0.000
.|* |	.|* |	2	0.198	0.129	24.276	0.000
.|* |	.|* |	3	0.156	0.079	29.320	0.000
.|* |	.|* |	4	0.183	0.114	36.302	0.000
.|** |	.|** |	5	0.300	0.226	55.170	0.000
.|* |	.|. |	6	0.213	0.067	64.720	0.000
.|* |	.|. |	7	0.184	0.054	71.911	0.000
.|* |	.|. |	8	0.173	0.058	78.296	0.000
.|* |	.|* |	9	0.206	0.089	87.414	0.000
.|* |	.|. |	10	0.140	-0.029	91.666	0.000
.|* |	.|. |	11	0.122	-0.010	94.873	0.000
.|* |	.|. |	12	0.168	0.064	100.99	0.000
.|** |	.|* |	13	0.300	0.202	120.69	0.000
.|* |	.|. |	14	0.160	-0.041	126.33	0.000
.|* |	.|. |	15	0.119	-0.017	129.44	0.000
.|* |	.|. |	16	0.118	0.023	132.52	0.000

.|* |	.|. |	17	0.120	-0.003	135.74	0.000
.|* |	.|. |	18	0.149	-0.031	140.71	0.000
.|* |	.|. |	19	0.104	-0.021	143.15	0.000
.|** |	.|** |	20	0.297	0.258	163.23	0.000
.|** |	.|* |	21	0.251	0.110	177.63	0.000
.|* |	*|. |	22	0.100	-0.130	179.92	0.000
.|* |	.|. |	23	0.103	0.003	182.36	0.000
.|. |	.|. |	24	0.034	-0.044	182.63	0.000



Forecast: SGELF
Actual: SGEL
Forecast sample: 29/04/2001 20/05/...
Included observations: 4

Root Mean Squared Error	12.96525
Mean Absolute Error	7.927934
Mean Abs. Percent Error	2.527741
Theil Inequality Coef.	0.022065
Bias Proportion	0.142025
Variance Proportion	0.786356
Covariance Proportion	0.071619
Theil U2 Coefficient	0.763353
Symmetric MAPE	2.608432

Date	close	forecast
29/04/2001	291.3900	292.8947
6/05/2001	284.0260	287.5079
13/05/2001	287.9710	289.0681
20/05/2001	320.8440	295.2159

21. SN.L

Dependent Variable: D(SN_L)
Method: ARMA Maximum Likelihood (OPG - BHHH)
Date: 08/12/20 Time: 12:54
Sample: 11/01/2010 25/11/2013
Included observations: 203
Convergence achieved after 11 iterations
Coefficient covariance computed using outer product of gradients

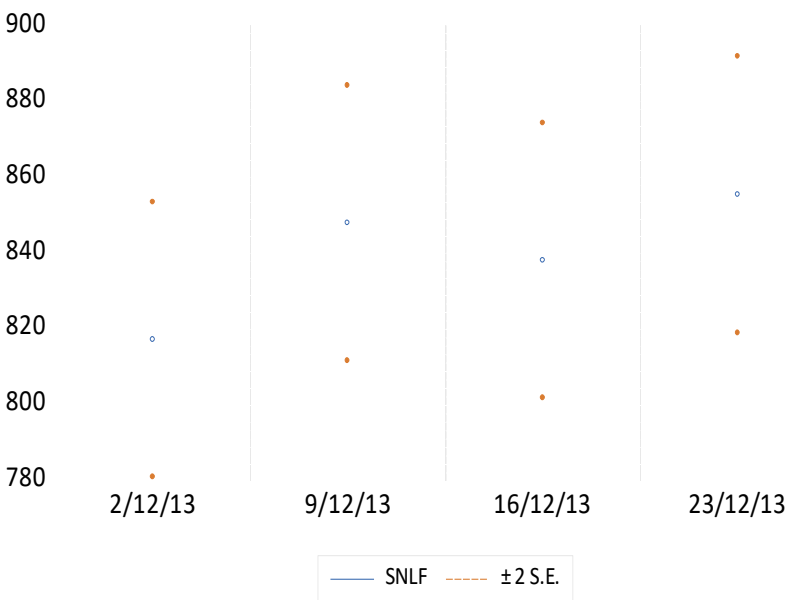
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.931553	1.178649	0.790357	0.4303
AR(4)	-0.645700	0.219865	-2.936796	0.0037
MA(4)	0.471422	0.248335	1.898331	0.0591
SIGMASQ	319.5609	23.88994	13.37638	0.0000

R-squared	0.052021	Mean dependent var	0.899015
Adjusted R-squared	0.037730	S.D. dependent var	18.40559
S.E. of regression	18.05503	Akaike info criterion	8.645511
Sum squared resid	64870.87	Schwarz criterion	8.710796
Log likelihood	-873.5194	Hannan-Quinn criter.	8.671923
F-statistic	3.640065	Durbin-Watson stat	2.220834

Prob(F-statistic)	0.013729			
Inverted AR Roots	.63-.63i	.63-.63i	-.63+.63i	-.63+.63i
Inverted MA Roots	.59+.59i	.59+.59i	-.59-.59i	-.59-.59i

Date: 08/12/20 Time: 12:54
Sample (adjusted): 11/01/2010 25/11/2013
Included observations: 203 after adjustments

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
.|. |	.|. |	1	-0.029	-0.029	0.1716	0.679
.|. |	.|. |	2	0.007	0.006	0.1811	0.913
.|* |	.|* |	3	0.074	0.075	1.3257	0.723
.|. |	.|. |	4	0.049	0.054	1.8358	0.766
.|** |	.|** |	5	0.215	0.219	11.512	0.042
.|. |	.|. |	6	-0.001	0.010	11.512	0.074
.|. |	.|. |	7	-0.027	-0.036	11.663	0.112
.|. |	.|. |	8	0.047	0.010	12.140	0.145
.|. |	.|. |	9	0.055	0.035	12.783	0.173
.|. |	.|. |	10	0.015	-0.025	12.832	0.233
.|. |	.|. |	11	-0.031	-0.035	13.036	0.291
.|. |	.|. |	12	-0.028	-0.030	13.212	0.354
.|* |	.|* |	13	0.100	0.086	15.401	0.283
.|. |	.|. |	14	-0.011	-0.019	15.427	0.350
.|* |	.|* |	15	0.111	0.130	18.168	0.254
.|. |	.|. |	16	-0.019	-0.004	18.248	0.310
.|. |	.|. |	17	0.037	0.043	18.549	0.355
.|. |	*|. |	18	-0.036	-0.100	18.841	0.402
.|. |	.|. |	19	-0.006	-0.015	18.850	0.467
.|* |	.|* |	20	0.179	0.143	26.126	0.162
.|. |	.|. |	21	0.008	0.031	26.139	0.201
.|. |	.|. |	22	0.001	-0.009	26.140	0.246
.|* |	.|* |	23	0.100	0.111	28.445	0.199
.|. |	.|. |	24	0.041	0.036	28.836	0.226



Forecast: SNLF
Actual: SNL
Forecast sample: 2/12/2013 23/12/2013
Included observations: 4

Root Mean Squared Error	18.25925
Mean Absolute Error	16.69459
Mean Abs. Percent Error	1.965597
Theil Inequality Coef.	0.010802
Bias Proportion	0.363556
Variance Proportion	0.040008
Covariance Proportion	0.596436
Theil U2 Coefficient	0.969098
Symmetric MAPE	1.984470

Date	close	forecast
2/12/2013	846.0000	817.1832
9/12/2013	836.5000	847.8701
16/12/2013	854.5000	838.0135
23/12/2013	865.5000	855.3950

(viii) GARCH (1,1) MODEL

1. FTSE-350 General Industrial Index

Dependent Variable: D(FTSE_350_INDUS__INDEX)
Method: ML ARCH - Normal distribution (BFGS / Marquardt steps)
Date: 20/12/20 Time: 19:31
Sample (adjusted): 19/05/2013 26/03/2017
Included observations: 202 after adjustments
Convergence achieved after 32 iterations
Coefficient covariance computed using outer product of gradients
MA Backcast: 16/12/2012 12/05/2013
Presample variance: backcast (parameter = 0.7)
GARCH = C(4) + C(5)*RESID(-1)^2 + C(6)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	14.47899	6.363028	2.275488	0.0229
AR(1)	-0.129078	0.061296	-2.105833	0.0352
MA(22)	0.103034	0.079984	1.288182	0.1977
Variance Equation				
C	2135.516	1065.993	2.003312	0.0451
RESID(-1)^2	-0.111598	0.036043	-3.096280	0.0020
GARCH(-1)	0.872549	0.098978	8.815557	0.0000

R-squared	0.029055	Mean dependent var	9.145891
Adjusted R-squared	0.019297	S.D. dependent var	96.11659
S.E. of regression	95.18471	Akaike info criterion	11.96153
Sum squared resid	1802966.	Schwarz criterion	12.05979
Log likelihood	-1202.114	Hannan-Quinn criter.	12.00128
Durbin-Watson stat	1.998335		

Inverted AR Roots	-.13			
Inverted MA Roots	.89-.13i	.89+.13i	.82-.37i	.82+.37i
	.68-.59i	.68+.59i	.49+.76i	.49-.76i
	.25+.87i	.25-.87i	.00+.90i	-.00-.90i
	-.25+.87i	-.25-.87i	-.49+.76i	-.49-.76i
	-.68-.59i	-.68+.59i	-.82+.37i	-.82-.37i
	-.89+.13i	-.89-.13i		

Date: 20/12/20 Time: 19:42
Sample (adjusted): 19/05/2013 26/03/2017
Q-statistic probabilities adjusted for 2 ARMA terms

Autocorrelation	Partial Correlation	AC	PAC	Q-Stat	Prob*

.|. |	.|. |	1	0.036	0.036	0.2588	
.|* |	.|* |	2	0.095	0.094	2.1335	
.|. |	.|. |	3	-0.048	-0.055	2.6175	0.106
.|. |	.|. |	4	-0.017	-0.023	2.6780	0.262
.|. |	.|. |	5	-0.065	-0.054	3.5579	0.313
.|. |	.|. |	6	-0.014	-0.009	3.6020	0.463
.|. |	.|. |	7	0.032	0.043	3.8195	0.576
.|. |	.|. |	8	-0.027	-0.034	3.9710	0.681
.|. |	.|. |	9	0.073	0.066	5.1049	0.647
*|. |	*|. |	10	-0.099	-0.101	7.2059	0.515
*|. |	*|. |	11	-0.102	-0.114	9.4525	0.397
.|. |	.|. |	12	-0.049	-0.013	9.9822	0.442
.|. |	.|. |	13	-0.030	-0.018	10.180	0.514
.|* |	.|* |	14	0.075	0.081	11.401	0.495
.|. |	.|. |	15	0.074	0.062	12.592	0.480
.|. |	.|. |	16	0.050	0.007	13.151	0.515
.|. |	.|. |	17	0.006	0.001	13.158	0.590
*|. |	*|. |	18	-0.075	-0.089	14.414	0.568
.|. |	.|. |	19	-0.009	0.019	14.431	0.636
.|. |	.|. |	20	-0.011	0.024	14.459	0.699
.|. |	.|. |	21	0.043	0.023	14.889	0.730
.|. |	.|. |	22	0.002	-0.011	14.890	0.783
.|. |	.|. |	23	0.043	0.003	15.306	0.807
.|. |	.|. |	24	0.025	0.025	15.445	0.842

*Probabilities may not be valid for this equation specification.

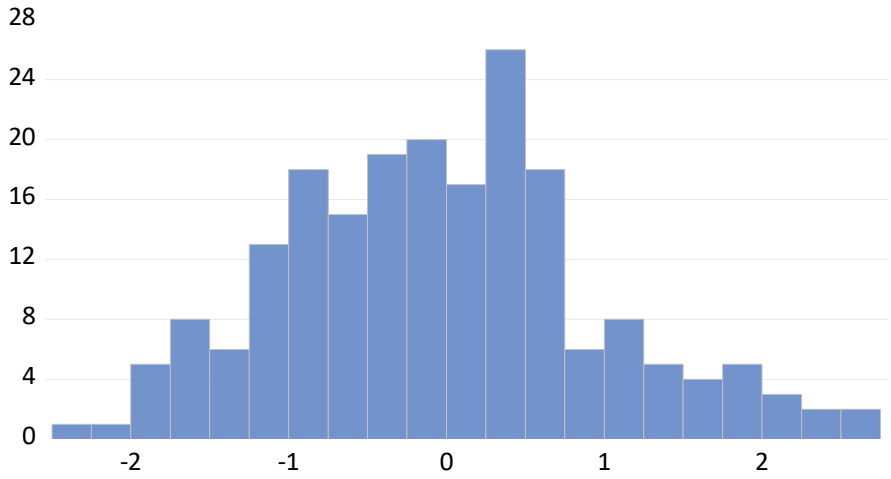
Heteroskedasticity Test: ARCH

F-statistic	0.016630	Prob. F(1,199)	0.8975
Obs*R-squared	0.016796	Prob. Chi-Square(1)	0.8969

Test Equation:
Dependent Variable: WGT_RESID^2
Method: Least Squares
Date: 20/12/20 Time: 19:46
Sample (adjusted): 26/05/2013 26/03/2017
Included observations: 201 after adjustments

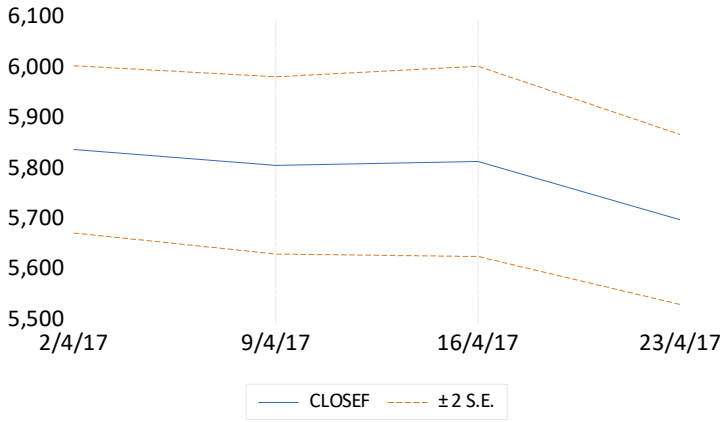
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.993524	0.119792	8.293752	0.0000
WGT_RESID^2(-1)	0.009136	0.070846	0.128957	0.8975

R-squared	0.000084	Mean dependent var	1.002606
Adjusted R-squared	-0.004941	S.D. dependent var	1.370526
S.E. of regression	1.373908	Akaike info criterion	3.483096
Sum squared resid	375.6371	Schwarz criterion	3.515965
Log likelihood	-348.0512	Hannan-Quinn criter.	3.496396
F-statistic	0.016630	Durbin-Watson stat	2.001507
Prob(F-statistic)	0.897522		



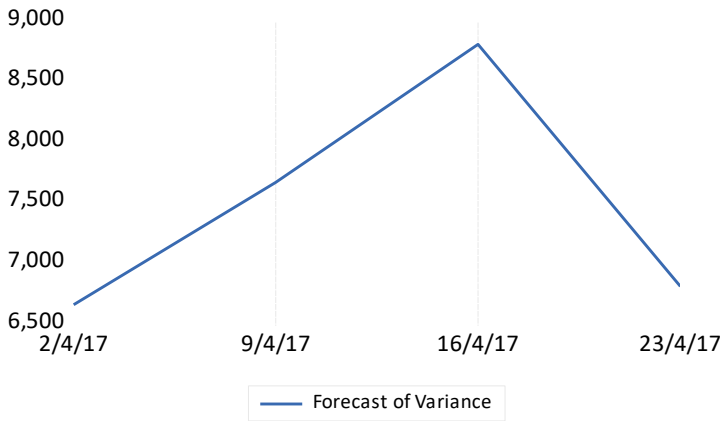
Series: Standardized Residuals
Sample 19/05/2013 26/03/2017
Observations 202

Mean	-0.035989
Median	-0.078828
Maximum	2.739865
Minimum	-2.305944
Std. Dev.	1.000681
Skewness	0.311617
Kurtosis	2.917799
Jarque-Bera	3.326087
Probability	0.189561



Forecast: CLOSEF
Actual: CLOSE
Forecast sample: 2/04/2017 23/04/2017
Included observations: 4

Root Mean Squared Error	113.0058
Mean Absolute Error	93.16987
Mean Abs. Percent Error	1.618699
Theil Inequality Coef.	0.009764
Bias Proportion	0.030916
Variance Proportion	0.027658
Covariance Proportion	0.941426
Theil U2 Coefficient	0.903659
Symmetric MAPE	1.615288



Date	close	forecast
2/04/2017	5795.67	5845.266
9/04/2017	5801.53	5813.756
16/04/2017	5657.35	5821.607
23/04/2017	5852.57	5705.970

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2. ANTO.L

Dependent Variable: D(ANTO_L)
Method: ML ARCH - Normal distribution (BFGS / Marquardt

steps)
Date: 09/12/20 Time: 13:51
Sample (adjusted): 3/06/2013 27/03/2017
Included observations: 200 after adjustments
Convergence achieved after 62 iterations
Coefficient covariance computed using outer product of gradients
MA Backcast: 20/05/2013 27/05/2013
Presample variance: backcast (parameter = 0.7)
GARCH = C(4) + C(5)*RESID(-1)^2 + C(6)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.636424	2.580939	-0.246586	0.8052
AR(3)	-0.155967	0.083769	-1.861865	0.0626
MA(2)	0.135732	0.078039	1.739276	0.0820
Variance Equation				
C	91.05168	433.4963	0.210040	0.8336
RESID(-1)^2	0.011497	0.033675	0.341413	0.7328
GARCH(-1)	0.910910	0.403102	2.259753	0.0238

R-squared	0.044608	Mean dependent var	-0.555000
Adjusted R-squared	0.034909	S.D. dependent var	35.02099
S.E. of regression	34.40429	Akaike info criterion	9.957035
Sum squared resid	233180.1	Schwarz criterion	10.05598
Log likelihood	-989.7035	Hannan-Quinn criter.	9.997078
Durbin-Watson stat	2.165774		

Inverted AR Roots	.27-.47i	.27+.47i	-.54
Inverted MA Roots	-.00+.37i	-.00-.37i	

Date: 09/12/20 Time: 13:53
Sample (adjusted): 3/06/2013 27/03/2017
Q-statistic probabilities adjusted for 2 ARMA terms

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob*
*|. |	*|. |	1	-0.079	-0.079	1.2708	
.|. |	.|. |	2	-0.006	-0.013	1.2792	
.|. |	.|. |	3	-0.000	-0.002	1.2793	0.258
*|. |	*|. |	4	-0.068	-0.069	2.2357	0.327
.|. |	.|. |	5	-0.037	-0.048	2.5129	0.473
.|. |	.|. |	6	0.005	-0.004	2.5172	0.642
.|. |	.|. |	7	0.004	0.002	2.5199	0.773
.|. |	.|. |	8	-0.054	-0.059	3.1311	0.792
.|* |	.|. |	9	0.081	0.067	4.5201	0.718
.|. |	.|. |	10	-0.022	-0.013	4.6216	0.797
.|. |	.|. |	11	0.045	0.044	5.0453	0.830
.|. |	.|. |	12	0.011	0.011	5.0709	0.886
*|. |	*|. |	13	-0.085	-0.078	6.6462	0.827
.|. |	.|. |	14	-0.019	-0.028	6.7253	0.875
.|. |	.|. |	15	-0.009	-0.010	6.7421	0.915
.|. |	.|. |	16	0.039	0.039	7.0785	0.932
.|. |	.|. |	17	0.050	0.055	7.6321	0.938
.|. |	.|. |	18	0.051	0.045	8.2147	0.942
.|. |	.|. |	19	-0.008	0.005	8.2299	0.961

.|.	|	.|.	|	20	0.016	0.017	8.2885	0.974
.|*	|	.|*	|	21	0.089	0.097	10.066	0.951
.|.	|	.|.	|	22	-0.059	-0.027	10.867	0.950
.|.	|	.|.	|	23	0.062	0.063	11.745	0.946
.|*	|	.|*	|	24	0.083	0.112	13.331	0.924

*Probabilities may not be valid for this equation specification.

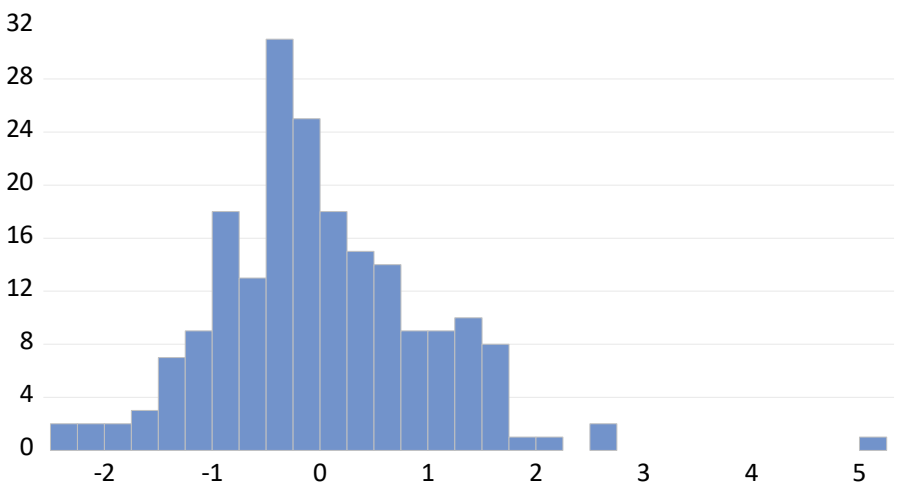
Heteroskedasticity Test: ARCH

F-statistic	0.223288	Prob. F(1,197)	0.6371
Obs*R-squared	0.225299	Prob. Chi-Square(1)	0.6350

Test Equation:
Dependent Variable: WGT_RESID^2
Method: Least Squares
Date: 09/12/20 Time: 13:53
Sample (adjusted): 10/06/2013 27/03/2017
Included observations: 199 after adjustments

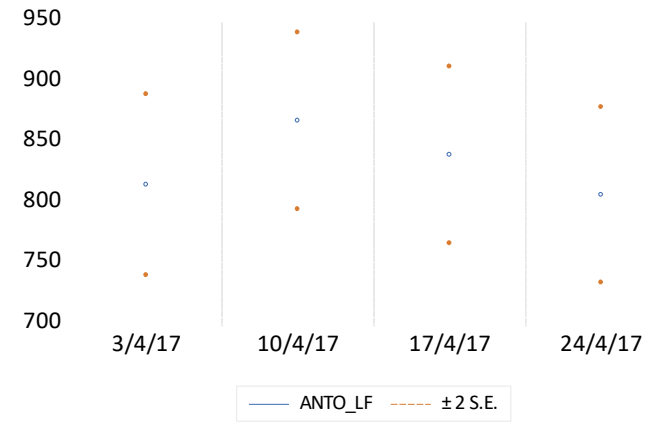
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1.038637	0.175366	5.922676	0.0000
WGT_RESID^2(-1)	-0.033648	0.071208	-0.472533	0.6371

R-squared	0.001132	Mean dependent var	1.004823
Adjusted R-squared	-0.003938	S.D. dependent var	2.254073
S.E. of regression	2.258507	Akaike info criterion	4.477284
Sum squared resid	1004.868	Schwarz criterion	4.510383
Log likelihood	-443.4898	Hannan-Quinn criter.	4.490680
F-statistic	0.223288	Durbin-Watson stat	1.998938
Prob(F-statistic)	0.637069		



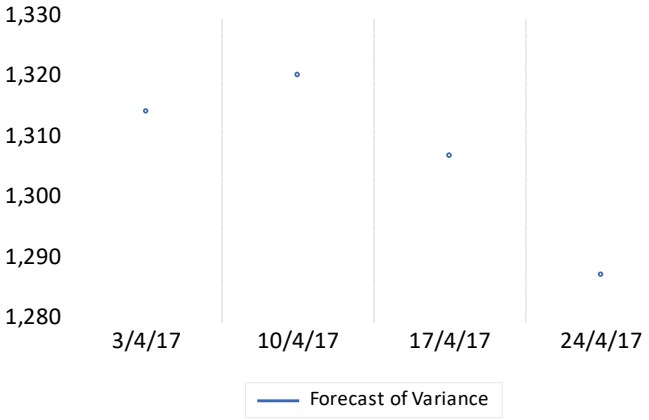
Series: Standardized Residuals
Sample 3/06/2013 27/03/2017
Observations 200

Mean	0.000898
Median	-0.145121
Maximum	5.225486
Minimum	-2.496795
Std. Dev.	1.003198
Skewness	0.827761
Kurtosis	6.015616
Jarque-Bera	98.62246
Probability	0.000000



Forecast: ANTO_LF
Actual: ANTO_L
Forecast sample: 3/04/2017 24/04/2017
Included observations: 4

Root Mean Squared Error	36.61553
Mean Absolute Error	34.85524
Mean Abs. Percent Error	4.122595
Theil Inequality Coef.	0.021872
Bias Proportion	0.033364
Variance Proportion	0.023535
Covariance Proportion	0.943100
Theil U2 Coefficient	1.204551
Symmetric MAPE	4.157353



Date	close	forecast
3/04/2017	869.0000	816.1473
10/04/2017	835.0000	869.0199
17/04/2017	818.5000	840.8142
24/04/2017	838.0000	807.7659

3. BP.L

Dependent Variable: D(BP_L)
Method: ML ARCH - Normal distribution (BFGS / Marquardt steps)
Date: 10/12/20 Time: 11:38
Sample (adjusted): 7/05/2006 22/02/2010
Included observations: 199 after adjustments
Convergence achieved after 25 iterations
Coefficient covariance computed using outer product of gradients
MA Backcast: 31/03/2006 30/04/2006
Presample variance: backcast (parameter = 0.7)
GARCH = C(4) + C(5)*RESID(-1)^2 + C(6)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.181035	0.983711	-0.184033	0.8540
AR(4)	-0.158259	0.073512	-2.152846	0.0313
MA(7)	-0.178078	0.074093	-2.403427	0.0162
Variance Equation				
C	36.66766	27.60071	1.328504	0.1840

RESID(-1)^2	0.125813	0.063930	1.967972	0.0491
GARCH(-1)	0.773537	0.124833	6.196567	0.0000

R-squared	0.069505	Mean dependent var	-0.531658
Adjusted R-squared	0.060010	S.D. dependent var	20.17593
S.E. of regression	19.56119	Akaike info criterion	8.722716
Sum squared resid	74997.47	Schwarz criterion	8.822012
Log likelihood	-861.9102	Hannan-Quinn criter.	8.762903
Durbin-Watson stat	2.120929		

Inverted AR Roots	.45-.45i	.45+.45i	-.45+.45i	-.45-.45i
Inverted MA Roots	.78	.49-.61i	.49+.61i	-.17-.76i
	-.17+.76i	-.70-.34i	-.70+.34i	

Date: 10/12/20 Time: 11:36
Sample (adjusted): 7/05/2006 22/02/2010
Q-statistic probabilities adjusted for 2 ARMA terms

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob*
.|. |	.|. |	1	0.010	0.010	0.0196	
.|. |	.|. |	2	0.055	0.055	0.6397	
*|. |	*|. |	3	-0.074	-0.075	1.7600	0.185
.|. |	.|. |	4	0.028	0.026	1.9159	0.384
.|. |	.|. |	5	0.016	0.024	1.9688	0.579
.|. |	.|. |	6	-0.010	-0.020	1.9916	0.737
.|. |	.|. |	7	0.027	0.030	2.1426	0.829
.|. |	.|. |	8	0.033	0.036	2.3690	0.883
.|. |	.|. |	9	-0.044	-0.052	2.7783	0.905
.|. |	.|. |	10	-0.014	-0.012	2.8188	0.945
.|. |	.|. |	11	0.034	0.045	3.0615	0.962
*|. |	*|. |	12	-0.103	-0.115	5.3109	0.869
.|. |	.|. |	13	0.028	0.029	5.4811	0.906
.|. |	.|. |	14	-0.038	-0.017	5.7926	0.926
.|. |	.|. |	15	0.034	0.008	6.0412	0.945
.|. |	.|. |	16	-0.001	0.013	6.0413	0.965
.|. |	.|. |	17	-0.015	-0.014	6.0937	0.978
.|. |	.|. |	18	0.051	0.048	6.6696	0.979
.|. |	.|. |	19	0.042	0.048	7.0685	0.983
.|. |	.|. |	20	-0.030	-0.034	7.2698	0.988
.|. |	.|. |	21	-0.020	-0.026	7.3616	0.992
.|. |	.|. |	22	-0.036	-0.026	7.6506	0.994
.|. |	.|. |	23	0.031	0.028	7.8716	0.996
.|. |	.|. |	24	0.015	0.004	7.9197	0.997

*Probabilities may not be valid for this equation specification.

Heteroskedasticity Test: ARCH

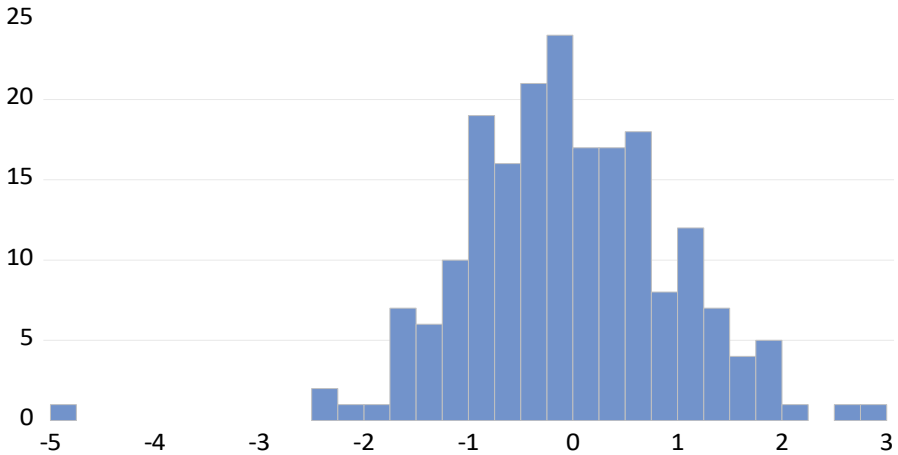
F-statistic	0.226614	Prob. F(1,196)	0.6346
Obs*R-squared	0.228662	Prob. Chi-Square(1)	0.6325

Test Equation:
Dependent Variable: WGT_RESID^2
Method: Least Squares
Date: 10/12/20 Time: 11:37

Sample (adjusted): 14/05/2006 22/02/2010
Included observations: 198 after adjustments

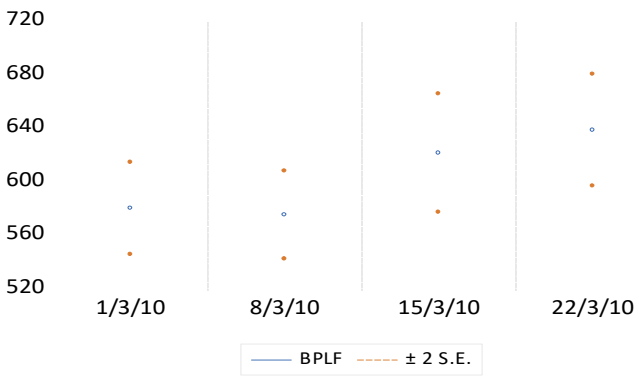
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.965200	0.159999	6.032543	0.0000
WGT_RESID^2(-1)	0.034004	0.071431	0.476040	0.6346

R-squared	0.001155	Mean dependent var	0.999373
Adjusted R-squared	-0.003941	S.D. dependent var	2.008107
S.E. of regression	2.012061	Akaike info criterion	4.246245
Sum squared resid	793.4840	Schwarz criterion	4.279460
Log likelihood	-418.3783	Hannan-Quinn criter.	4.259690
F-statistic	0.226614	Durbin-Watson stat	1.994886
Prob(F-statistic)	0.634576		



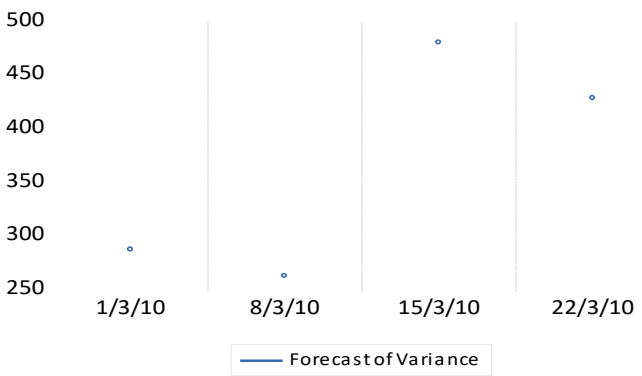
Series: Standardized Residuals
Sample 7/05/2006 22/02/2010
Observations 199

Mean	-0.037930
Median	-0.060951
Maximum	2.840816
Minimum	-4.811789
Std. Dev.	1.001785
Skewness	-0.277327
Kurtosis	4.955922
Jarque-Bera	34.27172
Probability	0.000000



Forecast: BPLF
Actual: BPL
Forecast sample: 1/03/2010 22/03/2010
Included observations: 4

Root Mean Squared Error	23.29032
Mean Absolute Error	17.48291
Mean Abs. Percent Error	2.819547
Theil Inequality Coef.	0.019070
Bias Proportion	0.214931
Variance Proportion	0.017281
Covariance Proportion	0.767789
Theil U2 Coefficient	0.982496
Symmetric MAPE	2.886161



Date	close	forecast
1/03/2010	575.5000	581.1042
8/03/2010	619.9000	576.1525
15/03/2010	635.1000	622.2866
22/03/2010	631.6000	639.3665

4. CNA.L

Dependent Variable: D(CNA_L)
Method: ML ARCH - Normal distribution (BFGS / Marquardt steps)
Date: 10/12/20 Time: 12:09
Sample (adjusted): 12/09/2010 1/06/2014
Included observations: 195 after adjustments
Convergence achieved after 68 iterations
Coefficient covariance computed using outer product of gradients
MA Backcast: 18/07/2010 5/09/2010
Presample variance: backcast (parameter = 0.7)
GARCH = C(4) + C(5)*RESID(-1)^2 + C(6)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.355664	1.166878	-0.304800	0.7605
AR(8)	0.895262	0.062124	14.41093	0.0000
MA(8)	-0.839482	0.074020	-11.34125	0.0000
Variance Equation				
C	11.48895	9.165352	1.253520	0.2100
RESID(-1)^2	-0.041122	0.024811	-1.657389	0.0974
GARCH(-1)	0.827201	0.163749	5.051633	0.0000

R-squared	0.074163	Mean dependent var	-0.040513
Adjusted R-squared	0.064519	S.D. dependent var	7.577709
S.E. of regression	7.329179	Akaike info criterion	6.851697
Sum squared resid	10313.64	Schwarz criterion	6.952405
Log likelihood	-662.0405	Hannan-Quinn criter.	6.892472
Durbin-Watson stat	2.321459		

Inverted AR Roots	.99	.70+.70i	.70-.70i	-.00+.99i
	-.00-.99i	-.70+.70i	-.70+.70i	-.99
Inverted MA Roots	.98	.69-.69i	.69+.69i	-.00-.98i
	-.00+.98i	-.69+.69i	-.69+.69i	-.98

Date: 10/12/20 Time: 12:15
Sample (adjusted): 12/09/2010 1/06/2014
Q-statistic probabilities adjusted for 2 ARMA terms

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob*
*|. |	*|. |	1	-0.137	-0.137	3.7422	
.|. |	.|. |	2	0.026	0.007	3.8785	
.|. |	.|. |	3	-0.029	-0.025	4.0520	0.044
.|. |	.|. |	4	-0.009	-0.017	4.0679	0.131
.|* |	.|. |	5	0.074	0.073	5.1895	0.158
.|. |	.|. |	6	-0.029	-0.009	5.3561	0.253

.|. |	.|. |	7	0.016	0.008	5.4082	0.368
.|. |	.|. |	8	0.009	0.017	5.4257	0.490
.|. |	.|. |	9	-0.039	-0.037	5.7440	0.570
.|. |	*|. |	10	-0.057	-0.074	6.4161	0.601
.|. |	.|. |	11	0.057	0.046	7.1047	0.626
*|. |	*|. |	12	-0.082	-0.073	8.5257	0.578
*|. |	*|. |	13	-0.093	-0.125	10.337	0.500
.|* |	.|* |	14	0.112	0.100	12.976	0.371
.|. |	.|. |	15	0.001	0.037	12.977	0.450
.|* |	.|* |	16	0.167	0.159	18.927	0.168
.|* |	.|* |	17	0.107	0.190	21.391	0.125
*|. |	.|. |	18	-0.095	-0.050	23.349	0.105
*|. |	*|. |	19	-0.072	-0.129	24.479	0.107
.|. |	.|. |	20	-0.019	-0.038	24.559	0.138
.|. |	.|. |	21	0.030	-0.015	24.762	0.169
.|* |	.|* |	22	0.120	0.090	27.985	0.110
.|. |	.|* |	23	0.011	0.081	28.015	0.140
.|. |	.|. |	24	-0.060	-0.035	28.824	0.150

*Probabilities may not be valid for this equation specification.

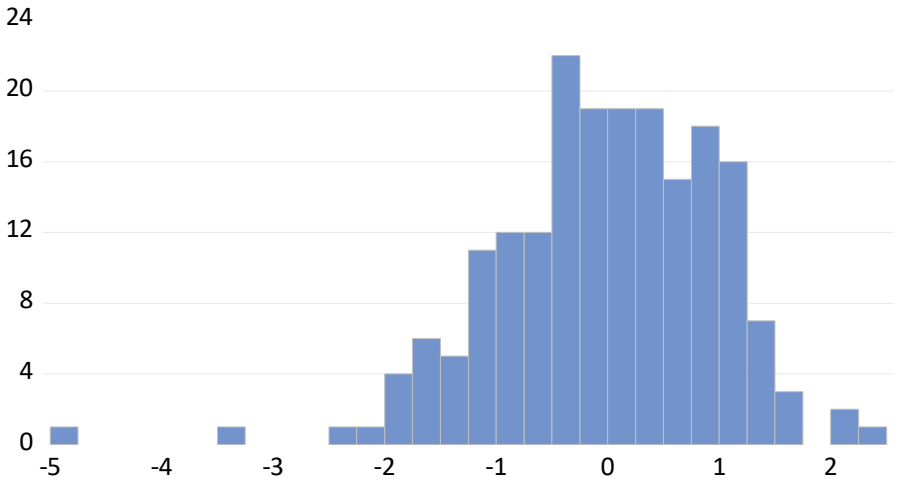
Heteroskedasticity Test: ARCH

F-statistic	0.102473	Prob. F(1,192)	0.7492
Obs*R-squared	0.103485	Prob. Chi-Square(1)	0.7477

Test Equation:
Dependent Variable: WGT_RESID^2
Method: Least Squares
Date: 10/12/20 Time: 12:16
Sample (adjusted): 19/09/2010 1/06/2014
Included observations: 194 after adjustments

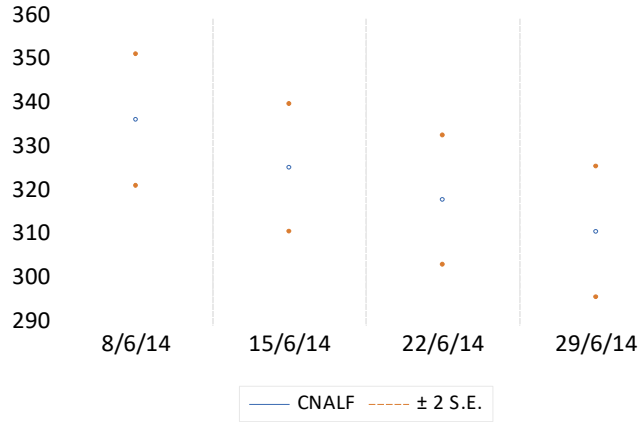
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.975877	0.165745	5.887831	0.0000
WGT_RESID^2(-1)	0.023100	0.072163	0.320114	0.7492

R-squared	0.000533	Mean dependent var	0.998975
Adjusted R-squared	-0.004672	S.D. dependent var	2.073487
S.E. of regression	2.078326	Akaike info criterion	4.311258
Sum squared resid	829.3320	Schwarz criterion	4.344947
Log likelihood	-416.1920	Hannan-Quinn criter.	4.324900
F-statistic	0.102473	Durbin-Watson stat	1.999845
Prob(F-statistic)	0.749230		



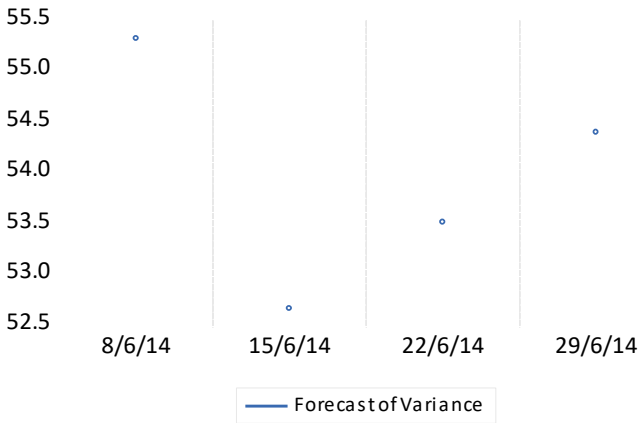
Series: Standardized Residuals
Sample 12/09/2010 1/06/2014
Observations 195

Mean	-0.023039
Median	0.012119
Maximum	2.367108
Minimum	-4.857981
Std. Dev.	0.999756
Skewness	-0.783031
Kurtosis	5.232169
Jarque-Bera	60.41041
Probability	0.000000



Forecast: CNALF
Actual: CNAL
Forecast sample: 8/06/2014 29/06/2014
Included observations: 4

Root Mean Squared Error	6.963172
Mean Absolute Error	6.475086
Mean Abs. Percent Error	2.022766
Theil Inequality Coef.	0.010851
Bias Proportion	0.462099
Variance Proportion	0.371376
Covariance Proportion	0.166524
Theil U2 Coefficient	0.935223
Symmetric MAPE	2.002728



Date	close	forecast
8/06/2014	326.3000	336.8529
15/06/2014	319.8000	325.9158
22/06/2014	312.8000	318.5483
29/06/2014	314.7000	311.2167

5. SVT.L

Dependent Variable: SVT_L
Method: ML ARCH - Normal distribution (BFGS / Marquardt

steps)
Date: 10/12/20 Time: 12:43
Sample (adjusted): 26/05/2013 2/04/2017
Included observations: 202 after adjustments
Convergence achieved after 35 iterations
Coefficient covariance computed using outer product of gradients
MA Backcast: 12/05/2013 19/05/2013
Presample variance: backcast (parameter = 0.7)
GARCH = C(4) + C(5)*RESID(-1)^2 + C(6)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	2423.887	284.9047	8.507712	0.0000
AR(2)	0.977078	0.017133	57.02773	0.0000
MA(2)	-0.283676	0.088147	-3.218206	0.0013
Variance Equation				
C	1269.593	406.5940	3.122508	0.0018
RESID(-1)^2	0.208092	0.065547	3.174716	0.0015
GARCH(-1)	0.521092	0.069721	7.473917	0.0000

R-squared	0.872415	Mean dependent var	2060.441
Adjusted R-squared	0.871133	S.D. dependent var	215.6284
S.E. of regression	77.40649	Akaike info criterion	11.35752
Sum squared resid	1192361.	Schwarz criterion	11.45578
Log likelihood	-1141.109	Hannan-Quinn criter.	11.39727
Durbin-Watson stat	0.871362		

Inverted AR Roots	.99	-.99
Inverted MA Roots	.53	-.53

Date: 10/12/20 Time: 12:49
Sample (adjusted): 26/05/2013 2/04/2017
Q-statistic probabilities adjusted for 2 ARMA terms

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob*
.|*** |	.|*** |	1	0.473	0.473	45.857	
.|. |	**|. |	2	-0.008	-0.299	45.871	
.|. |	.|* |	3	-0.002	0.204	45.871	0.000
.|. |	*|. |	4	0.035	-0.093	46.128	0.000
*|. |	*|. |	5	-0.099	-0.116	48.165	0.000
**|. |	*|. |	6	-0.231	-0.141	59.405	0.000
*|. |	.|. |	7	-0.144	0.038	63.817	0.000
.|. |	.|. |	8	-0.045	-0.062	64.249	0.000
.|. |	.|* |	9	0.062	0.164	65.080	0.000
.|. |	*|. |	10	0.029	-0.132	65.264	0.000
.|. |	.|* |	11	0.039	0.136	65.587	0.000
.|. |	*|. |	12	0.057	-0.111	66.282	0.000
.|. |	.|* |	13	0.042	0.078	66.664	0.000
.|. |	*|. |	14	0.013	-0.070	66.699	0.000
*|. |	*|. |	15	-0.099	-0.066	68.865	0.000
*|. |	.|. |	16	-0.121	-0.044	72.109	0.000
*|. |	.|. |	17	-0.075	0.019	73.352	0.000
*|. |	*|. |	18	-0.075	-0.122	74.603	0.000
*|. |	.|. |	19	-0.127	-0.011	78.222	0.000
*|. |	.|. |	20	-0.068	-0.017	79.267	0.000

.|. |	.|. |	21	0.004	-0.036	79.271	0.000
.|. |	*|. |	22	-0.059	-0.126	80.081	0.000
.|. |	.|* |	23	-0.031	0.091	80.299	0.000
.|. |	.|. |	24	0.072	-0.003	81.487	0.000

*Probabilities may not be valid for this equation specification.

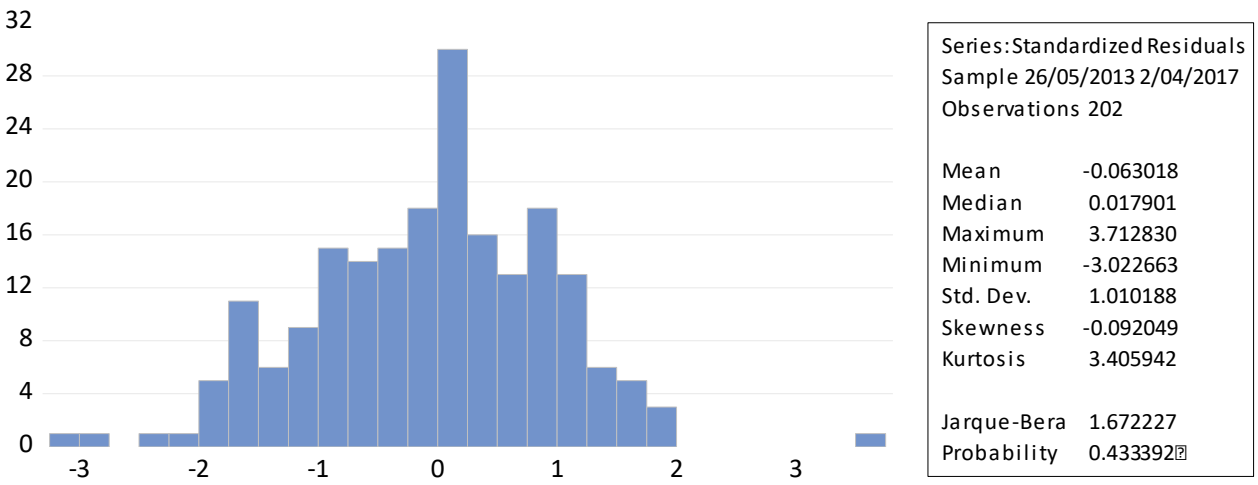
Heteroskedasticity Test: ARCH

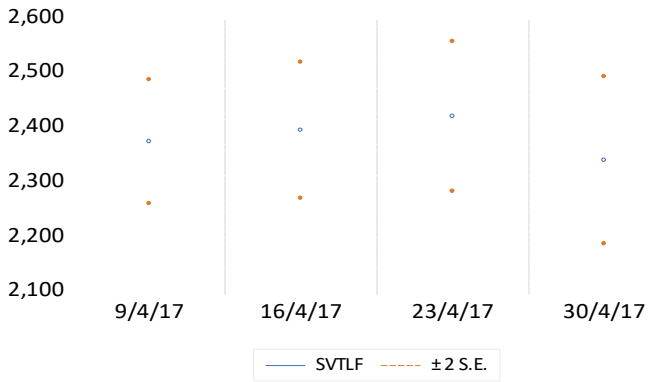
F-statistic	4.638718	Prob. F(1,199)	0.0325
Obs*R-squared	4.578610	Prob. Chi-Square(1)	0.0324

Test Equation:
Dependent Variable: WGT_RESID^2
Method: Least Squares
Date: 10/12/20 Time: 12:50
Sample (adjusted): 2/06/2013 2/04/2017
Included observations: 201 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.869902	0.132531	6.563758	0.0000
WGT_RESID^2(-1)	0.150913	0.070069	2.153768	0.0325

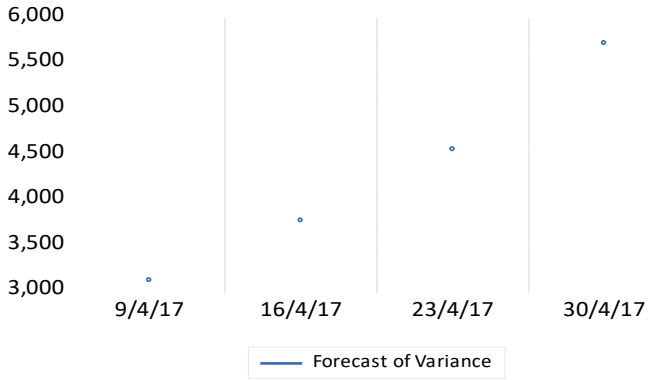
R-squared	0.022779	Mean dependent var	1.024471
Adjusted R-squared	0.017868	S.D. dependent var	1.593930
S.E. of regression	1.579626	Akaike info criterion	3.762153
Sum squared resid	496.5482	Schwarz criterion	3.795022
Log likelihood	-376.0964	Hannan-Quinn criter.	3.775453
F-statistic	4.638718	Durbin-Watson stat	1.985829
Prob(F-statistic)	0.032461		





Forecast: SVTLF
Actual: SVTL
Forecast sample: 9/04/2017 30/04/2017
Included observations: 4

Root Mean Squared Error	73.15062
Mean Absolute Error	68.24784
Mean Abs. Percent Error	2.897015
Theil Inequality Coef.	0.015389
Bias Proportion	0.087602
Variance Proportion	0.078488
Covariance Proportion	0.833910
Theil U2 Coefficient	1.010646
Symmetric MAPE	2.870602



Date	SVT.L	GARCH
09/04/2017	2444	2378.8
16/04/2017	2320	2399.754
23/04/2017	2325	2425.043
30/04/2017	2373	2345.006

6. JMAT.L

Dependent Variable: D(JMAT_L)
Method: ML ARCH - Normal distribution (BFGS / Marquardt steps)
Date: 10/12/20 Time: 13:07
Sample (adjusted): 25/06/2006 22/02/2010
Included observations: 192 after adjustments
Convergence achieved after 41 iterations
Coefficient covariance computed using outer product of gradients
MA Backcast: 9/04/2006 18/06/2006
Presample variance: backcast (parameter = 0.7)
GARCH = C(4) + C(5)*RESID(-1)^2 + C(6)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	5.929358	3.502387	1.692948	0.0905
AR(11)	0.396304	0.193790	2.045012	0.0409
MA(11)	-0.608726	0.170697	-3.566120	0.0004
Variance Equation				
C	89.52856	67.25247	1.331231	0.1831
RESID(-1)^2	0.091556	0.044314	2.066058	0.0388

GARCH(-1)	0.896584	0.043074	20.81478	0.0000

R-squared	0.002909	Mean dependent var	1.609636
Adjusted R-squared	-0.007642	S.D. dependent var	72.68764
S.E. of regression	72.96486	Akaike info criterion	11.27515
Sum squared resid	1006211.	Schwarz criterion	11.37695
Log likelihood	-1076.414	Hannan-Quinn criter.	11.31638
Durbin-Watson stat	2.173975		

Inverted AR Roots	.92	.77+.50i	.77-.50i	.38-.84i
	.38+.84i	-.13-.91i	-.13+.91i	-.60+.69i
	-.60-.69i	-.88+.26i	-.88-.26i	
Inverted MA Roots	.96	.80+.52i	.80-.52i	.40+.87i
	.40-.87i	-.14-.95i	-.14+.95i	-.63+.72i
	-.63-.72i	-.92-.27i	-.92+.27i	

Date: 10/12/20 Time: 13:12
Sample (adjusted): 25/06/2006 22/02/2010
Q-statistic probabilities adjusted for 2 ARMA terms

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob*
*|. |	*|. |	1	-0.116	-0.116	2.6301	
.|. |	.|. |	2	-0.014	-0.028	2.6694	
.|. |	.|. |	3	-0.011	-0.016	2.6942	0.101
.|. |	.|. |	4	0.022	0.019	2.7895	0.248
.|. |	.|. |	5	0.052	0.058	3.3381	0.342
.|. |	.|. |	6	0.023	0.038	3.4471	0.486
*|. |	*|. |	7	-0.115	-0.107	6.1043	0.296
.|* |	.|* |	8	0.130	0.109	9.5219	0.146
.|. |	.|. |	9	-0.007	0.014	9.5327	0.217
.|. |	.|. |	10	-0.035	-0.038	9.7767	0.281
.|. |	.|. |	11	0.066	0.066	10.667	0.299
.|. |	.|. |	12	-0.044	-0.026	11.060	0.353
.|. |	.|. |	13	0.053	0.040	11.635	0.392
.|* |	.|* |	14	0.121	0.123	14.696	0.258
.|. |	.|. |	15	-0.004	0.049	14.700	0.326
.|* |	.|* |	16	0.131	0.133	18.325	0.192
.|. |	.|* |	17	0.067	0.103	19.281	0.201
*|. |	.|. |	18	-0.076	-0.042	20.526	0.197
.|* |	.|. |	19	0.078	0.044	21.840	0.191
.|. |	.|. |	20	0.022	0.043	21.940	0.235
*|. |	*|. |	21	-0.079	-0.082	23.312	0.224
.|. |	*|. |	22	-0.017	-0.073	23.374	0.271
.|. |	.|. |	23	0.048	0.068	23.875	0.299
.|. |	.|. |	24	0.023	0.008	23.995	0.347

*Probabilities may not be valid for this equation specification.

Heteroskedasticity Test: ARCH

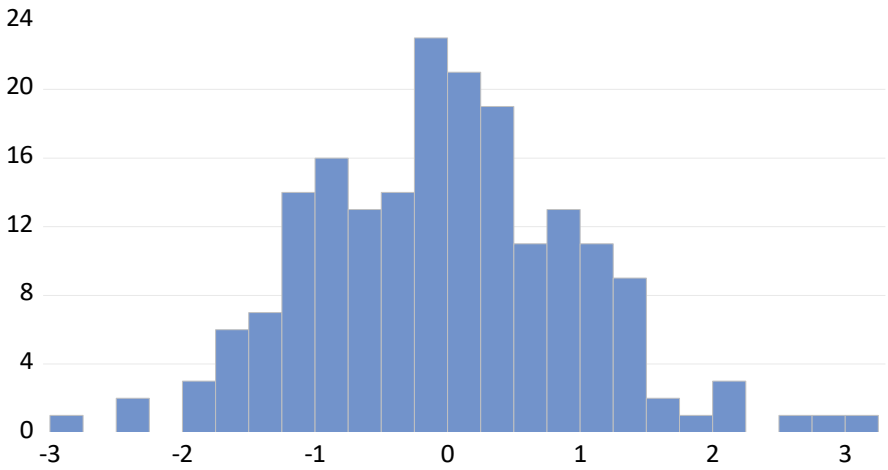
F-statistic	0.016140	Prob. F(1,189)	0.8990
Obs*R-squared	0.016309	Prob. Chi-Square(1)	0.8984

Test Equation:
Dependent Variable: WGT_RESID^2

Method: Least Squares
Date: 10/12/20 Time: 13:12
Sample (adjusted): 2/07/2006 22/02/2010
Included observations: 191 after adjustments

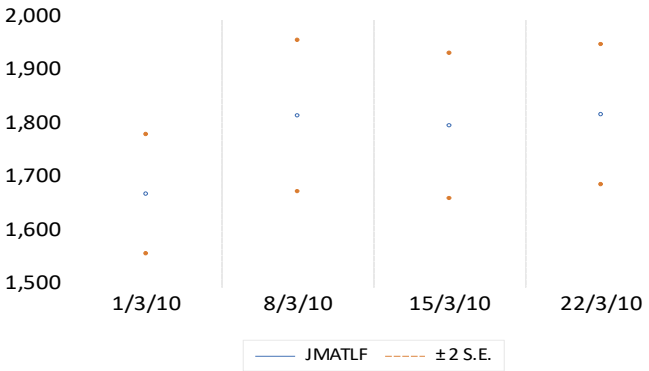
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.999156	0.131055	7.623940	0.0000
WGT_RESID^2(-1)	-0.009244	0.072762	-0.127042	0.8990

R-squared	0.000085	Mean dependent var	0.989952
Adjusted R-squared	-0.005205	S.D. dependent var	1.505390
S.E. of regression	1.509303	Akaike info criterion	3.671589
Sum squared resid	430.5413	Schwarz criterion	3.705645
Log likelihood	-348.6368	Hannan-Quinn criter.	3.685383
F-statistic	0.016140	Durbin-Watson stat	1.997699
Prob(F-statistic)	0.899043		



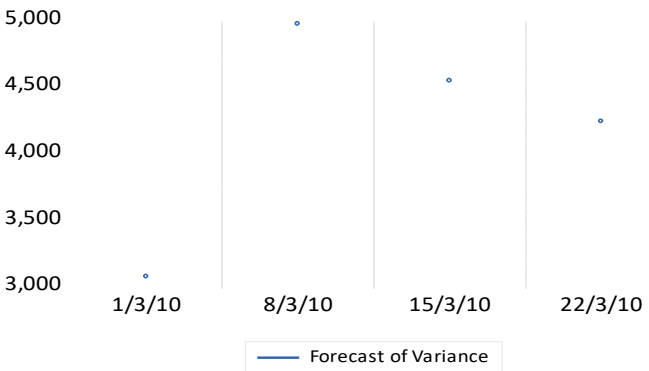
Series: Standardized Residuals
Sample 25/06/2006 22/02/2010
Observations 192

Mean	-0.038513
Median	-0.053640
Maximum	3.103006
Minimum	-2.820992
Std. Dev.	0.997898
Skewness	0.206251
Kurtosis	3.312123
Jarque-Bera	2.140628
Probability	0.342901



Forecast: JMATLF
Actual: JMATL
Forecast sample: 1/03/2010 22/03/2010
Included observations: 4

Root Mean Squared Error	77.88602
Mean Absolute Error	49.33588
Mean Abs. Percent Error	2.699760
Theil Inequality Coef.	0.021583
Bias Proportion	0.389640
Variance Proportion	0.495633
Covariance Proportion	0.114727
Theil U2 Coefficient	2.086932
Symmetric MAPE	2.794506



Date	close	forecast
1/03/2010	1826.000	1673.616
8/03/2010	1818.670	1820.107
15/03/2010	1830.190	1801.543
22/03/2010	1837.520	1822.644

The manufacturing industry

7. ABF.L

Dependent Variable: D(ABF_L)
Method: ML ARCH - Normal distribution (BFGS / Marquardt steps)
Date: 10/12/20 Time: 13:38
Sample (adjusted): 20/03/2006 23/11/2009
Included observations: 193 after adjustments
Convergence achieved after 31 iterations
Coefficient covariance computed using outer product of gradients
MA Backcast: 9/01/2006 13/03/2006
Presample variance: backcast (parameter = 0.7)
GARCH = C(4) + C(5)*RESID(-1)^2 + C(6)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.088998	1.637189	-0.054360	0.9566
AR(10)	-0.745122	0.124762	-5.972352	0.0000
MA(10)	0.667463	0.149733	4.457679	0.0000
Variance Equation				
C	30.54358	30.90600	0.988274	0.3230
RESID(-1)^2	0.067567	0.055850	1.209792	0.2264
GARCH(-1)	0.880973	0.088948	9.904394	0.0000

R-squared	0.055128	Mean dependent var	-0.295337
Adjusted R-squared	0.045182	S.D. dependent var	24.75849
S.E. of regression	24.19271	Akaike info criterion	9.171712
Sum squared resid	111204.6	Schwarz criterion	9.273142
Log likelihood	-879.0702	Hannan-Quinn criter.	9.212788
Durbin-Watson stat	2.114517		

Inverted AR Roots	.92-.30i	.92+.30i	.57+.79i	.57-.79i
	.00-.97i	.00+.97i	-.57+.79i	-.57-.79i
	-.92+.30i	-.92-.30i		
Inverted MA Roots	.91+.30i	.91-.30i	.56+.78i	.56-.78i
	.00+.96i	-.00-.96i	-.56-.78i	-.56+.78i
	-.91-.30i	-.91+.30i		

Date: 10/12/20 Time: 13:42
Sample (adjusted): 20/03/2006 23/11/2009
Q-statistic probabilities adjusted for 2 ARMA terms

Autocorrelation	Partial Correlation	AC	PAC	Q-Stat	Prob*

.|. |	.|. |	1	0.008	0.008	0.0133	
.|. |	.|. |	2	-0.014	-0.014	0.0500	
.|. |	.|. |	3	-0.064	-0.064	0.8622	0.353
.|* |	.|* |	4	0.100	0.101	2.8569	0.240
.|. |	.|. |	5	-0.020	-0.025	2.9397	0.401
.|. |	.|. |	6	-0.014	-0.015	2.9805	0.561
*|. |	*|. |	7	-0.083	-0.071	4.3612	0.499
.|* |	.|* |	8	0.128	0.120	7.7140	0.260
.|. |	.|. |	9	-0.056	-0.063	8.3656	0.301
.|. |	.|. |	10	-0.001	-0.002	8.3658	0.399
*|. |	*|. |	11	-0.118	-0.094	11.221	0.261
.|. |	.|. |	12	-0.002	-0.030	11.222	0.341
.|. |	.|. |	13	-0.025	-0.017	11.356	0.414
*|. |	*|. |	14	-0.080	-0.099	12.691	0.392
.|. |	.|. |	15	0.018	0.058	12.759	0.467
.|* |	.|. |	16	0.087	0.058	14.385	0.421
.|. |	.|. |	17	0.040	0.046	14.734	0.471
.|. |	.|. |	18	0.051	0.054	15.302	0.503
.|. |	.|. |	19	-0.036	-0.016	15.588	0.553
.|. |	.|. |	20	0.004	-0.014	15.591	0.621
.|. |	.|. |	21	0.016	0.005	15.647	0.681
.|. |	.|. |	22	-0.045	-0.045	16.091	0.711
.|. |	*|. |	23	-0.060	-0.069	16.897	0.717
.|* |	.|* |	24	0.112	0.113	19.690	0.602

*Probabilities may not be valid for this equation specification.

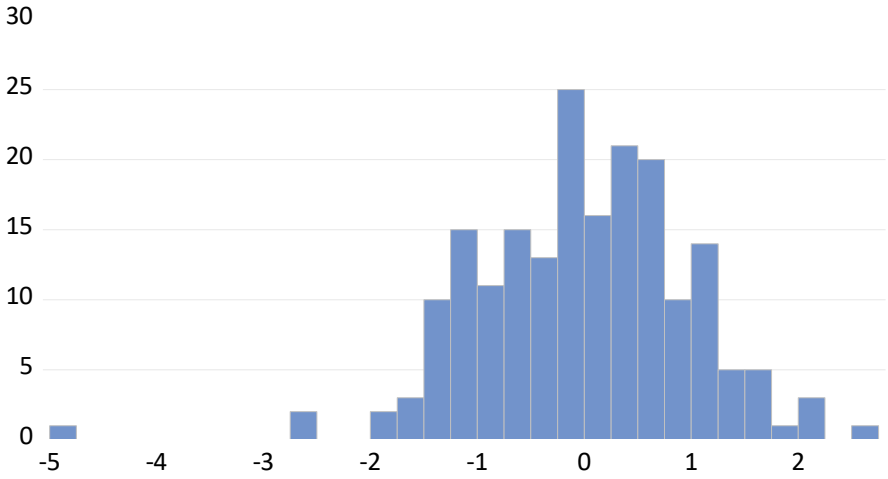
Heteroskedasticity Test: ARCH

F-statistic	0.037583	Prob. F(1,190)	0.8465
Obs*R-squared	0.037971	Prob. Chi-Square(1)	0.8455

Test Equation:
Dependent Variable: WGT_RESID^2
Method: Least Squares
Date: 10/12/20 Time: 13:43
Sample (adjusted): 26/03/2006 23/11/2009
Included observations: 192 after adjustments

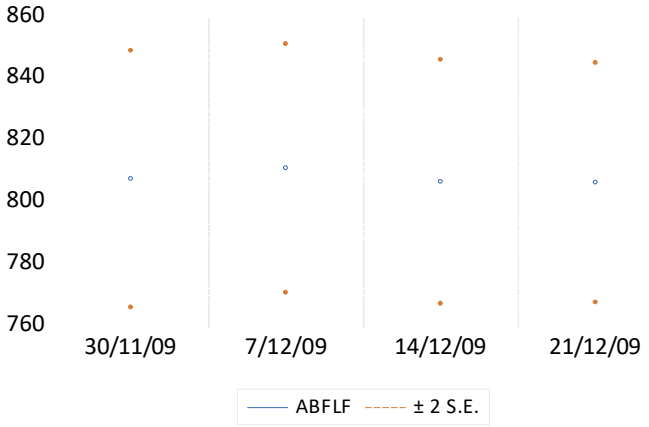
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.978565	0.162244	6.031436	0.0000
WGT_RESID^2(-1)	0.014064	0.072544	0.193863	0.8465

R-squared	0.000198	Mean dependent var	0.992556
Adjusted R-squared	-0.005064	S.D. dependent var	2.008406
S.E. of regression	2.013485	Akaike info criterion	4.247973
Sum squared resid	770.2829	Schwarz criterion	4.281905
Log likelihood	-405.8054	Hannan-Quinn criter.	4.261716
F-statistic	0.037583	Durbin-Watson stat	2.001767
Prob(F-statistic)	0.846491		



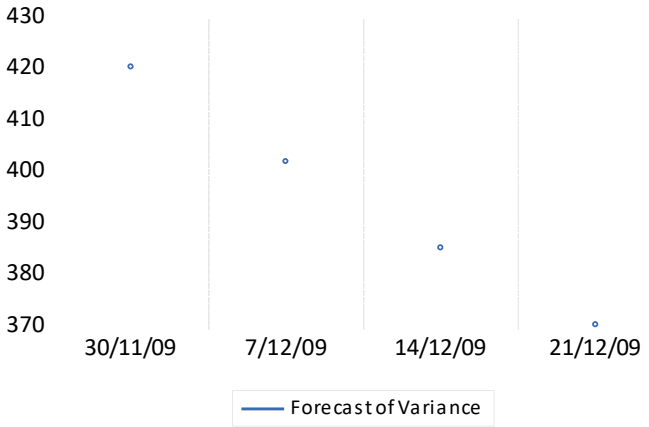
Series: Standardized Residuals
Sample 20/03/2006 23/11/2009
Observations 193

Mean	-0.010333
Median	-0.000507
Maximum	2.629408
Minimum	-4.801708
Std. Dev.	0.999117
Skewness	-0.528286
Kurtosis	5.025600
Jarque-Bera	41.97265
Probability	0.000000



Forecast: ABFLF
Actual: ABFL
Forecast sample: 30/11/2009 21/12/...
Included observations: 4

Root Mean Squared Error	6.724357
Mean Absolute Error	5.439030
Mean Abs. Percent Error	0.667737
Theil Inequality Coef.	0.004153
Bias Proportion	0.161225
Variance Proportion	0.265528
Covariance Proportion	0.573247
Theil U2 Coefficient	0.830336
Symmetric MAPE	0.670564



Date	close	forecast
30/11/2009	812.0000	807.9412
7/12/2009	808.5000	811.4373
14/12/2009	804.5000	807.0407
21/12/2009	819.0000	806.7807

1. BATS.L

Dependent Variable: D(BATS_L)
Method: ML ARCH - Normal distribution (BFGS / Marquardt steps)

Date: 11/12/20 Time: 11:39
Sample (adjusted): 16/04/2006 22/02/2010
Included observations: 202 after adjustments
Convergence achieved after 24 iterations
Coefficient covariance computed using outer product of gradients
MA Backcast: 23/03/2006 9/04/2006
Presample variance: backcast (parameter = 0.7)
GARCH = C(4) + C(5)*RESID(-1)^2 + C(6)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	3.566638	2.382577	1.496966	0.1344
AR(1)	-0.321932	0.087137	-3.694554	0.0002
MA(12)	-0.139064	0.049566	-2.805614	0.0050
Variance Equation				
C	684.2641	277.7351	2.463729	0.0138
RESID(-1)^2	0.620982	0.116285	5.340160	0.0000
GARCH(-1)	0.344502	0.107096	3.216760	0.0013

R-squared	0.135220	Mean dependent var	4.190594
Adjusted R-squared	0.126529	S.D. dependent var	62.87660
S.E. of regression	58.76427	Akaike info criterion	10.81631
Sum squared resid	687194.7	Schwarz criterion	10.91458
Log likelihood	-1086.447	Hannan-Quinn criter.	10.85607
Durbin-Watson stat	2.047774		

Inverted AR Roots	-.32			
Inverted MA Roots	.85	.73+.42i	.73-.42i	.42-.73i
	.42+.73i	.00+.85i	-.00-.85i	-.42-.73i
	-.42+.73i	-.73+.42i	-.73-.42i	-.85

Date: 11/12/20 Time: 11:44
Sample (adjusted): 16/04/2006 22/02/2010
Q-statistic probabilities adjusted for 2 ARMA terms

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob*
.|. |	.|. |	1	0.031	0.031	0.1974	
*|. |	*|. |	2	-0.085	-0.086	1.6873	
.|. |	.|. |	3	0.042	0.048	2.0535	0.152
.|. |	.|. |	4	0.004	-0.007	2.0569	0.358
.|. |	.|. |	5	0.031	0.039	2.2532	0.522
*|. |	*|. |	6	-0.103	-0.109	4.4791	0.345
*|. |	.|. |	7	-0.068	-0.055	5.4645	0.362
.|. |	.|. |	8	-0.006	-0.024	5.4722	0.485
.|. |	.|. |	9	-0.014	-0.013	5.5113	0.598
*|. |	*|. |	10	-0.072	-0.071	6.6147	0.579
.|. |	.|. |	11	-0.043	-0.034	7.0208	0.635
.|. |	.|. |	12	-0.034	-0.051	7.2665	0.700
.|. |	.|. |	13	0.038	0.030	7.5855	0.750
.|. |	.|. |	14	0.008	-0.006	7.6004	0.816
.|. |	.|. |	15	-0.035	-0.027	7.8716	0.852
.|. |	.|. |	16	0.067	0.052	8.8581	0.840
.|* |	.|* |	17	0.098	0.078	11.006	0.752
.|. |	.|. |	18	-0.014	-0.025	11.052	0.806

.|. |	.|. |	19	-0.019	-0.010	11.133	0.850
.|* |	.|* |	20	0.113	0.108	14.004	0.729
.|* |	.|* |	21	0.130	0.118	17.867	0.531
.|. |	.|. |	22	-0.035	-0.026	18.150	0.578
.|. |	.|. |	23	0.012	0.055	18.183	0.637
.|* |	.|* |	24	0.075	0.079	19.498	0.614

*Probabilities may not be valid for this equation specification.

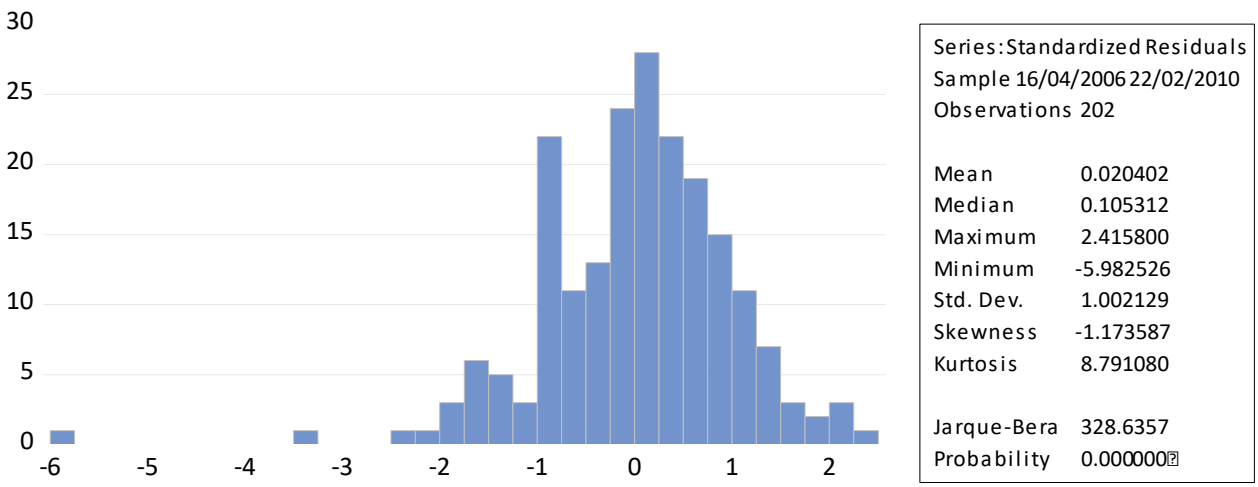
Heteroskedasticity Test: ARCH

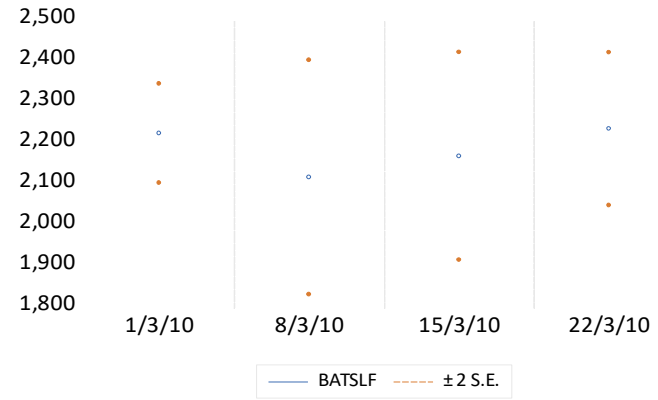
F-statistic	0.009721	Prob. F(1,199)	0.9216
Obs*R-squared	0.009818	Prob. Chi-Square(1)	0.9211

Test Equation:
Dependent Variable: WGT_RESID^2
Method: Least Squares
Date: 11/12/20 Time: 11:44
Sample (adjusted): 23/04/2006 22/02/2010
Included observations: 201 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1.006744	0.209477	4.805982	0.0000
WGT_RESID^2(-1)	-0.006991	0.070903	-0.098595	0.9216

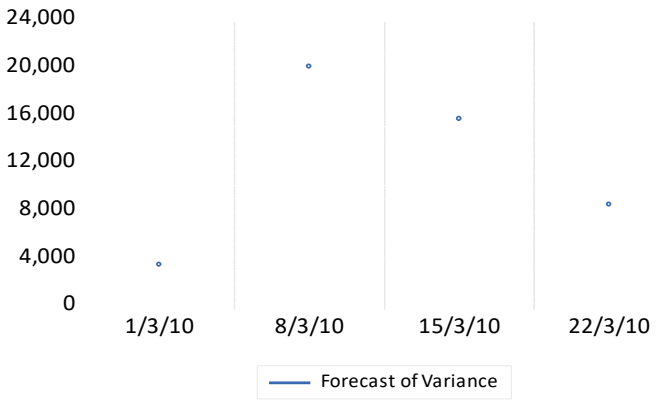
R-squared	0.000049	Mean dependent var	0.999725
Adjusted R-squared	-0.004976	S.D. dependent var	2.786198
S.E. of regression	2.793122	Akaike info criterion	4.902097
Sum squared resid	1552.505	Schwarz criterion	4.934966
Log likelihood	-490.6608	Hannan-Quinn criter.	4.915397
F-statistic	0.009721	Durbin-Watson stat	1.999645
Prob(F-statistic)	0.921559		





Forecast: BATSLF
Actual: BATSL
Forecast sample: 1/03/2010 22/03/2010
Included observations: 4

Root Mean Squared Error	110.0675
Mean Absolute Error	97.81319
Mean Abs. Percent Error	4.538673
Theil Inequality Coef.	0.025077
Bias Proportion	0.011797
Variance Proportion	0.122675
Covariance Proportion	0.865528
Theil U2 Coefficient	0.731332
Symmetric MAPE	4.503261



Date	close	forecast
1/03/2010	2054.000	2225.717
8/03/2010	2233.500	2118.422
15/03/2010	2233.500	2169.563
22/03/2010	2277.000	2236.479

9. BDEV.L

Dependent Variable: D(BDEV_L)
Method: ML ARCH - Normal distribution (BFGS / Marquardt steps)
Date: 11/12/20 Time: 12:01
Sample (adjusted): 16/06/2013 2/04/2017
Included observations: 199 after adjustments
Convergence achieved after 25 iterations
Coefficient covariance computed using outer product of gradients
MA Backcast: 26/05/2013 9/06/2013
Presample variance: backcast (parameter = 0.7)
GARCH = C(4) + C(5)*RESID(-1)^2 + C(6)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	1.723350	1.512795	1.139183	0.2546
AR(4)	0.201794	0.076540	2.636458	0.0084
MA(3)	-0.112057	0.084778	-1.321775	0.1862
Variance Equation				
C	24.86923	31.38399	0.792418	0.4281
RESID(-1)^2	0.086018	0.065464	1.313979	0.1889

GARCH(-1)	0.846723	0.137220	6.170575	0.0000

R-squared	0.047083	Mean dependent var	1.248744
Adjusted R-squared	0.037359	S.D. dependent var	19.57116
S.E. of regression	19.20210	Akaike info criterion	8.744581
Sum squared resid	72269.23	Schwarz criterion	8.843877
Log likelihood	-864.0858	Hannan-Quinn criter.	8.784769
Durbin-Watson stat	1.858766		

Inverted AR Roots	.67	-.00+.67i	-.00-.67i	-.67
Inverted MA Roots	.48	-.24-.42i	-.24+.42i	

Date: 11/12/20 Time: 12:06
Sample (adjusted): 16/06/2013 2/04/2017
Q-statistic probabilities adjusted for 2 ARMA terms

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob*
.|. |	.|. |	1	0.010	0.010	0.0210	
.|. |	.|. |	2	-0.058	-0.059	0.7145	
.|. |	.|. |	3	-0.011	-0.010	0.7384	0.390
.|. |	.|. |	4	-0.011	-0.014	0.7623	0.683
*|. |	*|. |	5	-0.093	-0.094	2.5286	0.470
.|. |	.|. |	6	-0.027	-0.027	2.6774	0.613
*|. |	*|. |	7	-0.105	-0.118	4.9917	0.417
.|. |	.|. |	8	-0.040	-0.046	5.3230	0.503
.|. |	.|. |	9	-0.023	-0.042	5.4317	0.607
.|. |	.|. |	10	0.046	0.027	5.8806	0.661
.|. |	.|. |	11	0.038	0.024	6.1893	0.721
.|. |	.|. |	12	0.071	0.054	7.2747	0.699
.|* |	.|* |	13	0.106	0.101	9.6976	0.558
.|. |	.|. |	14	-0.026	-0.035	9.8385	0.630
.|. |	.|. |	15	-0.041	-0.028	10.210	0.677
.|* |	.|* |	16	0.077	0.080	11.509	0.646
.|. |	.|. |	17	-0.006	0.011	11.516	0.715
.|. |	.|* |	18	0.061	0.107	12.332	0.721
*|. |	*|. |	19	-0.108	-0.092	14.907	0.602
.|. |	.|. |	20	-0.005	0.031	14.912	0.668
.|. |	.|. |	21	-0.005	-0.002	14.918	0.728
.|. |	.|. |	22	-0.036	-0.045	15.213	0.764
.|. |	.|. |	23	0.032	0.050	15.450	0.800
.|* |	.|* |	24	0.101	0.079	17.789	0.718

*Probabilities may not be valid for this equation specification.

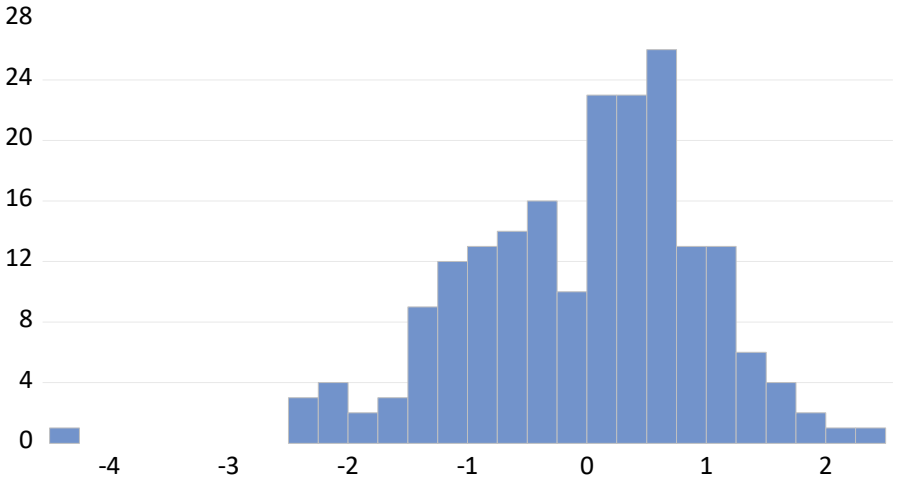
Heteroskedasticity Test: ARCH

F-statistic	0.004895	Prob. F(1,196)	0.9443
Obs*R-squared	0.004945	Prob. Chi-Square(1)	0.9439

Test Equation:
Dependent Variable: WGT_RESID^2
Method: Least Squares
Date: 11/12/20 Time: 12:07
Sample (adjusted): 23/06/2013 2/04/2017
Included observations: 198 after adjustments

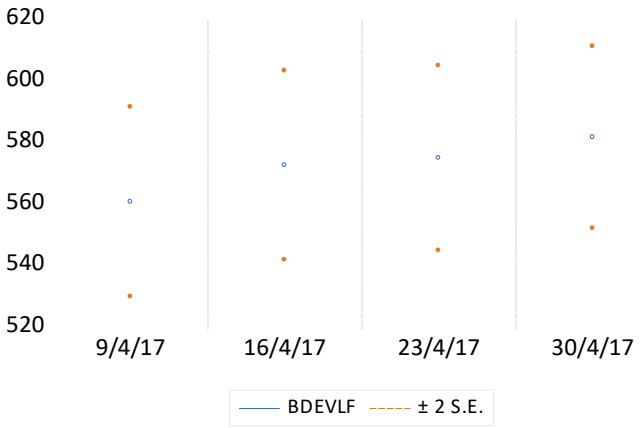
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.994787	0.144929	6.863950	0.0000
WGT_RESID^2(-1)	0.004999	0.071457	0.069965	0.9443

R-squared	0.000025	Mean dependent var	0.999798
Adjusted R-squared	-0.005077	S.D. dependent var	1.768422
S.E. of regression	1.772905	Akaike info criterion	3.993166
Sum squared resid	616.0658	Schwarz criterion	4.026381
Log likelihood	-393.3234	Hannan-Quinn criter.	4.006610
F-statistic	0.004895	Durbin-Watson stat	1.999031
Prob(F-statistic)	0.944293		



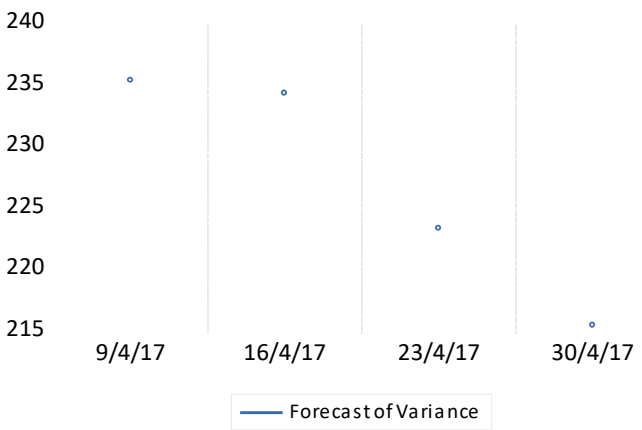
Series: Standardized Residuals
Sample 16/06/2013 2/04/2017
Observations 199

Mean	-0.016322
Median	0.120648
Maximum	2.367555
Minimum	-4.384725
Std. Dev.	1.001664
Skewness	-0.611438
Kurtosis	4.065792
Jarque-Bera	21.81817
Probability	0.000018



Forecast: BDEVLF
Actual: BDEVL
Forecast sample: 9/04/2017 30/04/2017
Included observations: 4

Root Mean Squared Error	7.207350
Mean Absolute Error	6.122466
Mean Abs. Percent Error	1.056305
Theil Inequality Coef.	0.006257
Bias Proportion	0.721608
Variance Proportion	0.002725
Covariance Proportion	0.275666
Theil U2 Coefficient	0.759193
Symmetric MAPE	1.064123



Date	close	forecast
9/04/2017	572.0000	561.1248
16/04/2017	574.0000	573.0014
23/04/2017	579.5000	575.3055
30/04/2017	590.5000	582.0785

10. BKG.L

Dependent Variable: D(BKG_L)
Method: ML ARCH - Normal distribution (BFGS / Marquardt steps)
Date: 11/12/20 Time: 12:23
Sample (adjusted): 15/09/2013 2/04/2017
Included observations: 186 after adjustments
Failure to improve likelihood (singular hessian) after 175 iterations
Coefficient covariance computed using outer product of gradients
MA Backcast: 6/05/2013 8/09/2013
Presample variance: backcast (parameter = 0.7)
GARCH = C(4) + C(5)*RESID(-1)^2 + C(6)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	8.421730	10.33282	0.815047	0.4150
AR(17)	0.049918	0.086259	0.578695	0.5628
MA(24)	0.208263	0.053223	3.913004	0.0001
Variance Equation				
C	-52.43440	173.8458	-0.301614	0.7629
RESID(-1)^2	-0.049266	0.017185	-2.866852	0.0041
GARCH(-1)	1.054375	0.030584	34.47511	0.0000

R-squared	0.026212	Mean dependent var	5.080645
Adjusted R-squared	0.015569	S.D. dependent var	111.1054
S.E. of regression	110.2371	Akaike info criterion	12.14513
Sum squared resid	2223858.	Schwarz criterion	12.24918
Log likelihood	-1123.497	Hannan-Quinn criter.	12.18729
Durbin-Watson stat	1.951301		

Inverted AR Roots	.84	.78+.30i	.78-.30i	.62+.56i
	.62-.56i	.37-.75i	.37+.75i	.08-.83i
	.08+.83i	-.23+.81i	-.23-.81i	-.51-.67i
	-.51+.67i	-.71+.44i	-.71-.44i	-.82+.15i
	-.82-.15i			
Inverted MA Roots	.93+.12i	.93-.12i	.87-.36i	.87+.36i
	.74-.57i	.74+.57i	.57+.74i	.57-.74i
	.36-.87i	.36+.87i	.12-.93i	.12+.93i
	-.12-.93i	-.12+.93i	-.36-.87i	-.36+.87i
	-.57-.74i	-.57+.74i	-.74-.57i	-.74+.57i
	-.87-.36i	-.87+.36i	-.93-.12i	-.93+.12i

Date: 11/12/20 Time: 12:27
Sample (adjusted): 15/09/2013 2/04/2017
Q-statistic probabilities adjusted for 2 ARMA terms

Autocorrelation	Partial Correlation	AC	PAC	Q-Stat	Prob*

.|. |	.|. |	1	0.002	0.002	0.0009	
*|. |	*|. |	2	-0.089	-0.089	1.4931	
.|. |	.|. |	3	-0.059	-0.059	2.1631	0.141
.|. |	.|. |	4	0.012	0.004	2.1898	0.335
.|. |	.|. |	5	0.029	0.018	2.3488	0.503
.|. |	.|. |	6	-0.049	-0.052	2.8214	0.588
.|. |	.|. |	7	-0.059	-0.055	3.4967	0.624
.|. |	.|. |	8	-0.031	-0.039	3.6909	0.718
*|. |	*|. |	9	-0.079	-0.097	4.9210	0.670
.|. |	.|. |	10	0.060	0.047	5.6353	0.688
.|. |	.|. |	11	-0.003	-0.020	5.6372	0.776
.|. |	.|. |	12	0.028	0.028	5.7994	0.832
.|. |	.|. |	13	0.025	0.026	5.9248	0.878
.|. |	.|. |	14	0.003	0.003	5.9272	0.920
.|. |	.|. |	15	0.034	0.028	6.1695	0.940
.|. |	.|* |	16	0.073	0.074	7.2691	0.924
.|. |	.|. |	17	0.019	0.026	7.3463	0.947
.|. |	.|. |	18	0.051	0.068	7.8780	0.952
.|. |	.|. |	19	-0.015	0.015	7.9271	0.968
*|. |	*|. |	20	-0.081	-0.071	9.3069	0.952
.|. |	.|. |	21	-0.010	0.006	9.3267	0.968
.|. |	.|. |	22	0.011	0.009	9.3532	0.978
*|. |	*|. |	23	-0.077	-0.082	10.616	0.970
*|. |	*|. |	24	-0.092	-0.078	12.461	0.947

*Probabilities may not be valid for this equation specification.

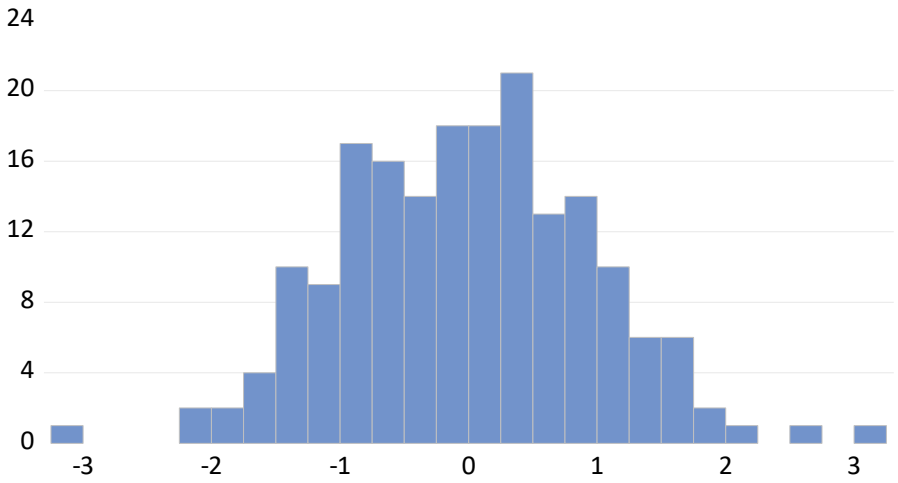
Heteroskedasticity Test: ARCH

F-statistic	0.028540	Prob. F(1,183)	0.8660
Obs*R-squared	0.028847	Prob. Chi-Square(1)	0.8651

Test Equation:
Dependent Variable: WGT_RESID^2
Method: Least Squares
Date: 11/12/20 Time: 12:28
Sample (adjusted): 22/09/2013 2/04/2017
Included observations: 185 after adjustments

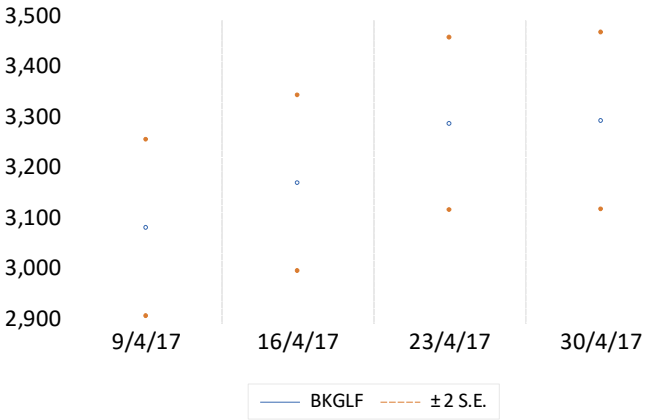
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.952087	0.125360	7.594844	0.0000
WGT_RESID^2(-1)	-0.012496	0.073967	-0.168937	0.8660

R-squared	0.000156	Mean dependent var	0.940355
Adjusted R-squared	-0.005308	S.D. dependent var	1.415795
S.E. of regression	1.419547	Akaike info criterion	3.549305
Sum squared resid	368.7658	Schwarz criterion	3.584119
Log likelihood	-326.3107	Hannan-Quinn criter.	3.563414
F-statistic	0.028540	Durbin-Watson stat	1.989955
Prob(F-statistic)	0.866033		



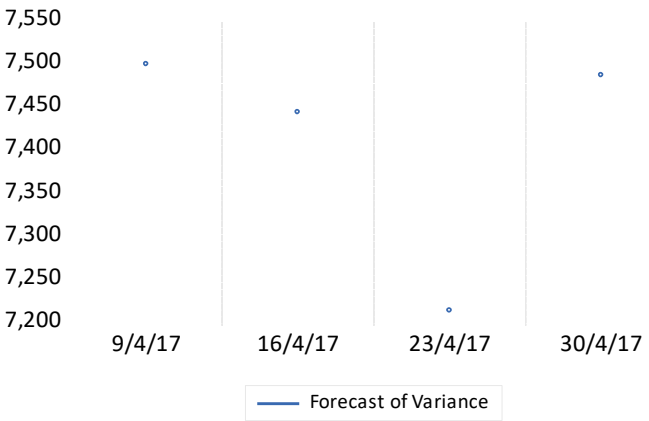
Series: Standardized Residuals
Sample 15/09/2013 2/04/2017
Observations 186

Mean	-0.005623
Median	0.007048
Maximum	3.055681
Minimum	-3.158369
Std. Dev.	0.974460
Skewness	0.047537
Kurtosis	3.227490
Jarque-Bera	0.471131
Probability	0.790124



Forecast: BKGLF
Actual: BKGL
Forecast sample: 9/04/2017 30/04/2017
Included observations: 4

Root Mean Squared Error	73.53948
Mean Absolute Error	61.82565
Mean Abs. Percent Error	1.906488
Theil Inequality Coef.	0.011356
Bias Proportion	0.346391
Variance Proportion	0.282303
Covariance Proportion	0.371307
Theil U2 Coefficient	0.949258
Symmetric MAPE	1.929361



Date	close	forecast
9/04/2017	3180.000	3088.664
16/04/2017	3286.000	3177.325
23/04/2017	3258.000	3295.088
30/04/2017	3311.000	3300.797

11. DGE.L

Dependent Variable: D(DGE_L)
Method: ML ARCH - Normal distribution (BFGS / Marquardt

steps)
Date: 12/12/20 Time: 11:24
Sample (adjusted): 2/06/2013 2/04/2017
Included observations: 201 after adjustments
Convergence achieved after 63 iterations
Coefficient covariance computed using outer product of gradients
MA Backcast: 19/05/2013 26/05/2013
Presample variance: backcast (parameter = 0.7)
GARCH = C(4) + C(5)*RESID(-1)^2 + C(6)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	1.280838	1.663288	0.770064	0.4413
AR(2)	0.621434	0.147554	4.211568	0.0000
MA(2)	-0.827042	0.114506	-7.222683	0.0000
Variance Equation				
C	1775.629	1280.296	1.386889	0.1655
RESID(-1)^2	0.131251	0.059212	2.216637	0.0266
GARCH(-1)	0.084123	0.574366	0.146462	0.8836

R-squared	0.069816	Mean dependent var	1.644279
Adjusted R-squared	0.060420	S.D. dependent var	49.33061
S.E. of regression	47.81712	Akaike info criterion	10.60298
Sum squared resid	452722.4	Schwarz criterion	10.70159
Log likelihood	-1059.600	Hannan-Quinn criter.	10.64288
Durbin-Watson stat	1.954762		

Inverted AR Roots	.79	-.79
Inverted MA Roots	.91	-.91

Date: 12/12/20 Time: 11:28
Sample (adjusted): 2/06/2013 2/04/2017
Q-statistic probabilities adjusted for 2 ARMA terms

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob*
.|. |	.|. |	1	0.004	0.004	0.0033	
.|. |	.|. |	2	-0.019	-0.019	0.0759	
.|. |	.|. |	3	-0.045	-0.045	0.4961	0.481
.|* |	.|* |	4	0.099	0.099	2.5146	0.284
.|. |	.|. |	5	0.026	0.023	2.6506	0.449
*|. |	*|. |	6	-0.112	-0.112	5.2599	0.262
.|. |	.|. |	7	-0.008	0.004	5.2724	0.384
.|. |	.|. |	8	-0.019	-0.030	5.3487	0.500
.|. |	.|. |	9	0.063	0.050	6.2049	0.516
*|. |	*|. |	10	-0.120	-0.103	9.2875	0.319
.|. |	.|. |	11	0.045	0.054	9.7260	0.373
.|. |	.|. |	12	0.054	0.050	10.351	0.410
.|. |	.|. |	13	-0.010	-0.032	10.371	0.497
.|. |	.|. |	14	0.022	0.043	10.478	0.574
*|. |	*|. |	15	-0.112	-0.106	13.215	0.431
.|. |	.|. |	16	0.054	0.024	13.856	0.461
*|. |	*|. |	17	-0.087	-0.079	15.516	0.415
.|. |	.|. |	18	0.034	0.028	15.767	0.469
.|. |	.|. |	19	-0.031	-0.000	15.976	0.526

.|*	|	.|*	|	20	0.131	0.120	19.845	0.342
.|.	|	.|.	|	21	-0.039	-0.048	20.185	0.384
.|.	|	.|.	|	22	-0.027	-0.007	20.350	0.436
.|.	|	.|.	|	23	0.066	0.047	21.338	0.438
.|.	|	.|.	|	24	0.068	0.066	22.395	0.437

*Probabilities may not be valid for this equation specification.

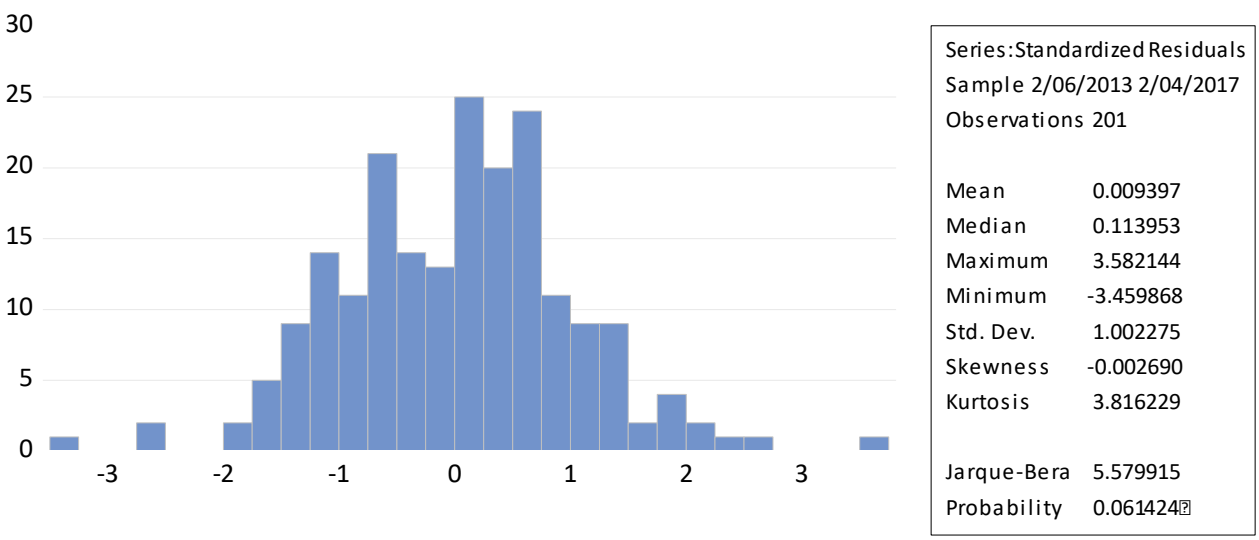
Heteroskedasticity Test: ARCH

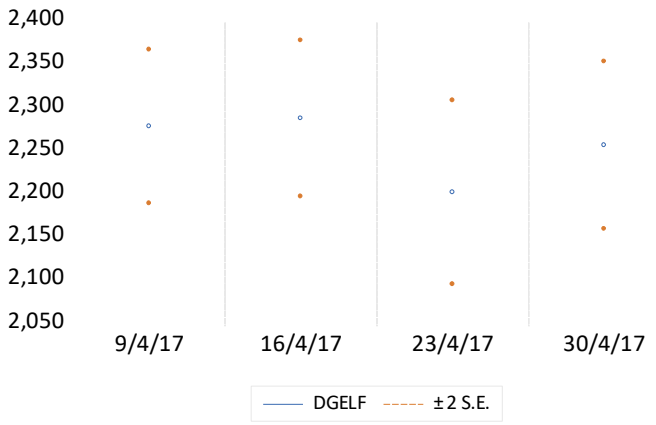
F-statistic	0.021121	Prob. F(1,198)	0.8846
Obs*R-squared	0.021332	Prob. Chi-Square(1)	0.8839

Test Equation:
Dependent Variable: WGT_RESID^2
Method: Least Squares
Date: 12/12/20 Time: 11:29
Sample (adjusted): 9/06/2013 2/04/2017
Included observations: 200 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1.014887	0.139110	7.295552	0.0000
WGT_RESID^2(-1)	-0.010327	0.071060	-0.145330	0.8846

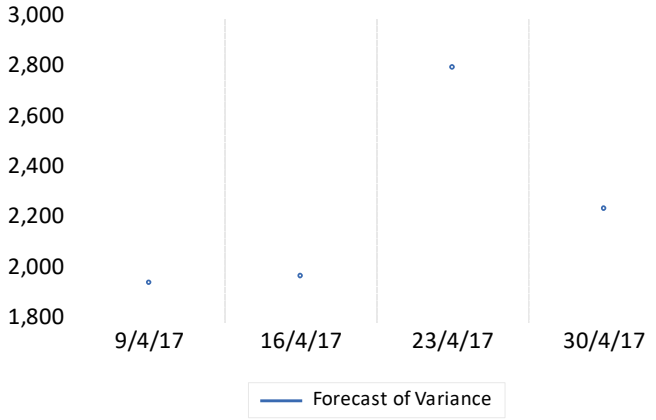
R-squared	0.000107	Mean dependent var	1.004515
Adjusted R-squared	-0.004943	S.D. dependent var	1.684481
S.E. of regression	1.688640	Akaike info criterion	3.895673
Sum squared resid	564.5977	Schwarz criterion	3.928656
Log likelihood	-387.5673	Hannan-Quinn criter.	3.909021
F-statistic	0.021121	Durbin-Watson stat	1.998412
Prob(F-statistic)	0.884598		





Forecast: DGELF
Actual: DGEL
Forecast sample: 9/04/2017 30/04/2017
Included observations: 4

Root Mean Squared Error	47.68980
Mean Absolute Error	40.21729
Mean Abs. Percent Error	1.798614
Theil Inequality Coef.	0.010560
Bias Proportion	0.000071
Variance Proportion	0.000313
Covariance Proportion	0.999616
Theil U2 Coefficient	0.913910
Symmetric MAPE	1.788176



Date	close	forecast
9/04/2017	2298.000	2280.150
16/04/2017	2208.000	2289.237
23/04/2017	2246.500	2203.976
30/04/2017	2277.500	2258.242

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12. ADN.L

Dependent Variable: D(ADN_L)
Method: ML ARCH - Normal distribution (BFGS / Marquardt steps)
Date: 12/12/20 Time: 12:19
Sample (adjusted): 9/06/2013 2/04/2017
Included observations: 200 after adjustments
Convergence achieved after 26 iterations
Coefficient covariance computed using outer product of gradients
MA Backcast: 28/04/2013 2/06/2013
Presample variance: backcast (parameter = 0.7)
GARCH = C(4) + C(5)*RESID(-1)^2 + C(6)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.656150	0.959706	-0.683700	0.4942
AR(3)	-0.150214	0.073958	-2.031078	0.0422
MA(18)	-0.119889	0.065819	-1.821505	0.0685

Variance Equation

C	109.6910	245.3070	0.447158	0.6548
RESID(-1)^2	-0.032814	0.047374	-0.692654	0.4885
GARCH(-1)	0.666302	0.802444	0.830341	0.4063

R-squared	0.041408	Mean dependent var	-0.686500
Adjusted R-squared	0.031676	S.D. dependent var	17.75164
S.E. of regression	17.46822	Akaike info criterion	8.599935
Sum squared resid	60112.34	Schwarz criterion	8.698884
Log likelihood	-853.9935	Hannan-Quinn criter.	8.639978
Durbin-Watson stat	2.071353		

Inverted AR Roots	.27+.46i	.27-.46i	-.53	
Inverted MA Roots	.89	.84-.30i	.84+.30i	.68-.57i
	.68+.57i	.44+.77i	.44-.77i	.15+.88i
	.15-.88i	-.15+.88i	-.15-.88i	-.44+.77i
	-.44-.77i	-.68-.57i	-.68+.57i	-.84+.30i
	-.84-.30i	-.89		

Date: 12/12/20 Time: 12:24
Sample (adjusted): 9/06/2013 2/04/2017
Q-statistic probabilities adjusted for 2 ARMA terms

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob*
.|. |	.|. |	1	-0.046	-0.046	0.4253	
*|. |	*|. |	2	-0.074	-0.076	1.5364	
.|. |	.|. |	3	-0.001	-0.008	1.5365	0.215
.|* |	.|* |	4	0.122	0.117	4.6116	0.100
.|. |	.|* |	5	0.062	0.074	5.3967	0.145
.|. |	.|. |	6	-0.004	0.020	5.4007	0.249
.|. |	.|. |	7	-0.019	-0.009	5.4743	0.361
*|. |	*|. |	8	-0.072	-0.090	6.5676	0.363
.|. |	.|. |	9	-0.028	-0.058	6.7327	0.457
.|. |	*|. |	10	-0.061	-0.087	7.5351	0.480
.|. |	.|. |	11	0.014	0.003	7.5787	0.577
*|. |	*|. |	12	-0.097	-0.086	9.6127	0.475
*|. |	*|. |	13	-0.090	-0.080	11.364	0.413
*|. |	*|. |	14	-0.072	-0.076	12.496	0.407
.|* |	.|* |	15	0.092	0.081	14.354	0.349
.|. |	.|. |	16	-0.027	-0.010	14.518	0.412
*|. |	*|. |	17	-0.115	-0.083	17.432	0.294
.|. |	.|. |	18	0.019	0.021	17.513	0.353
.|* |	.|. |	19	0.090	0.067	19.317	0.311
.|. |	.|. |	20	0.033	0.022	19.563	0.358
.|. |	.|. |	21	0.010	0.029	19.584	0.420
.|. |	.|. |	22	0.050	0.041	20.159	0.448
.|. |	.|. |	23	0.073	0.064	21.382	0.436
.|. |	*|. |	24	-0.040	-0.066	21.755	0.475

*Probabilities may not be valid for this equation specification.

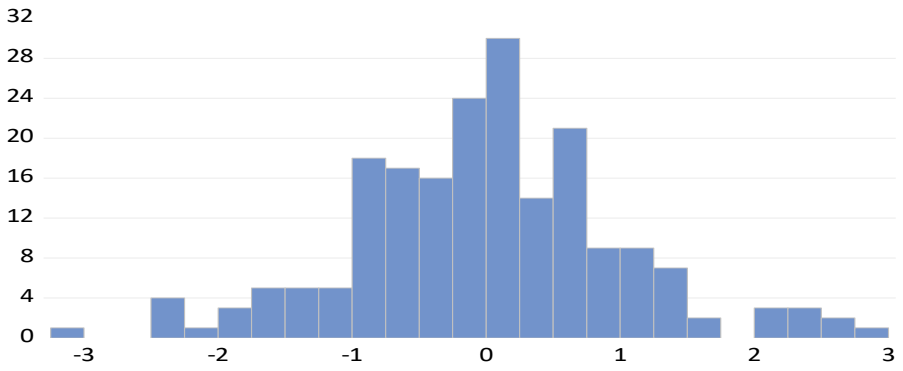
Heteroskedasticity Test: ARCH

F-statistic	0.151280	Prob. F(1,197)	0.6977
Obs*R-squared	0.152699	Prob. Chi-Square(1)	0.6960

Test Equation:
Dependent Variable: WGT_RESID^2
Method: Least Squares
Date: 12/12/20 Time: 12:25
Sample (adjusted): 16/06/2013 2/04/2017
Included observations: 199 after adjustments

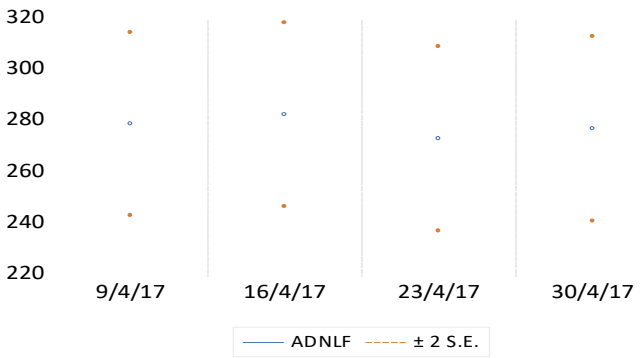
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.975045	0.137065	7.113735	0.0000
WGT_RESID^2(-1)	0.027712	0.071249	0.388948	0.6977

R-squared	0.000767	Mean dependent var	1.002909
Adjusted R-squared	-0.004305	S.D. dependent var	1.644884
S.E. of regression	1.648420	Akaike info criterion	3.847511
Sum squared resid	535.3060	Schwarz criterion	3.880610
Log likelihood	-380.8274	Hannan-Quinn criter.	3.860907
F-statistic	0.151280	Durbin-Watson stat	1.985518
Prob(F-statistic)	0.697735		



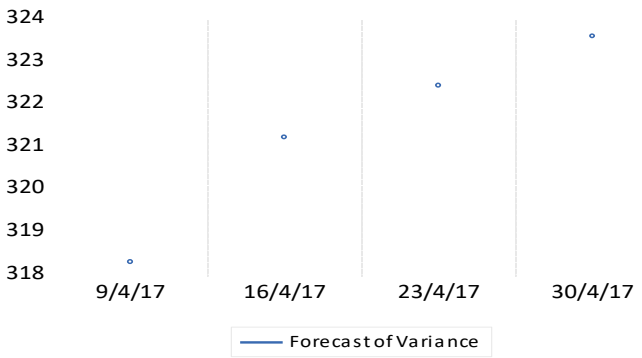
Series: Standardized Residuals
Sample 9/06/2013 2/04/2017
Observations 200

Mean	-0.006584
Median	0.009414
Maximum	2.815146
Minimum	-3.117883
Std. Dev.	1.003492
Skewness	0.065747
Kurtosis	3.669834
Jarque-Bera	3.883067
Probability	0.143484



Forecast: ADNLF
Actual: ADNL
Forecast sample: 9/04/2017 30/04/2017
Included observations: 4

Root Mean Squared Error	9.808768
Mean Absolute Error	8.244693
Mean Abs. Percent Error	2.869895
Theil Inequality Coef.	0.017451
Bias Proportion	0.273520
Variance Proportion	0.135479
Covariance Proportion	0.591001
Theil U2 Coefficient	1.104559
Symmetric MAPE	2.915420



Date	close	forecast
9/04/2017	283.5000	279.4264
16/04/2017	276.8000	283.0296
23/04/2017	279.0000	273.6770
30/04/2017	294.9000	277.5474

13. AHT.L

Dependent Variable: D(AHT_L)
Method: ML ARCH - Normal distribution (BFGS / Marquardt steps)
Date: 12/12/20 Time: 12:40
Sample (adjusted): 7/09/1997 22/04/2001
Included observations: 190 after adjustments
Convergence achieved after 25 iterations
Coefficient covariance computed using outer product of gradients
MA Backcast: 30/05/1997 31/08/1997
Presample variance: backcast (parameter = 0.7)
GARCH = C(4) + C(5)*RESID(-1)^2 + C(6)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.677534	0.576537	1.175179	0.2399
AR(13)	0.205290	0.051713	3.969767	0.0001
MA(16)	-0.206872	0.065685	-3.149472	0.0016
Variance Equation				
C	27.74433	8.004080	3.466273	0.0005
RESID(-1)^2	0.542314	0.123222	4.401110	0.0000
GARCH(-1)	0.352301	0.087607	4.021388	0.0001

R-squared	0.065073	Mean dependent var	-0.202689
Adjusted R-squared	0.055073	S.D. dependent var	10.45628
S.E. of regression	10.16427	Akaike info criterion	7.467580
Sum squared resid	19319.43	Schwarz criterion	7.570118
Log likelihood	-703.4201	Hannan-Quinn criter.	7.509117
Durbin-Watson stat	1.870483		

Inverted AR Roots	.89	.78+.41i	.78-.41i	.50-.73i
	.50+.73i	.11+.88i	.11-.88i	-.31+.83i
	-.31-.83i	-.66-.59i	-.66+.59i	-.86-.21i
	-.86+.21i			
Inverted MA Roots	.91	.84-.35i	.84+.35i	.64+.64i
	.64+.64i	.35-.84i	.35+.84i	.00+.91i
	-.00-.91i	-.35-.84i	-.35+.84i	-.64+.64i
	-.64+.64i	-.84+.35i	-.84-.35i	-.91

Date: 12/12/20 Time: 12:44
Sample (adjusted): 7/09/1997 22/04/2001
Q-statistic probabilities adjusted for 2 ARMA terms

Autocorrelation	Partial Correlation	AC	PAC	Q-Stat	Prob*

.|. |	.|. |	1	0.033	0.033	0.2103	
.|. |	.|. |	2	0.016	0.015	0.2575	
*|. |	*|. |	3	-0.097	-0.098	2.1037	0.147
.|. |	.|. |	4	-0.023	-0.017	2.2070	0.332
.|* |	.|* |	5	0.119	0.125	4.9960	0.172
.|. |	.|. |	6	-0.007	-0.025	5.0063	0.287
.|. |	.|. |	7	-0.027	-0.037	5.1568	0.397
.|. |	.|. |	8	0.030	0.058	5.3325	0.502
.|. |	.|. |	9	0.065	0.069	6.1969	0.517
.|. |	.|. |	10	-0.023	-0.055	6.3027	0.613
.|* |	.|* |	11	0.087	0.100	7.8535	0.549
.|. |	.|. |	12	0.047	0.071	8.3152	0.598
*|. |	*|. |	13	-0.081	-0.115	9.6585	0.561
*|. |	*|. |	14	-0.072	-0.072	10.721	0.553
.|. |	.|* |	15	0.033	0.088	10.949	0.615
.|. |	.|. |	16	0.046	0.007	11.397	0.655
.|. |	*|. |	17	-0.054	-0.118	12.007	0.679
*|. |	.|. |	18	-0.091	-0.045	13.750	0.617
*|. |	*|. |	19	-0.114	-0.073	16.527	0.487
.|. |	.|. |	20	0.023	-0.034	16.637	0.548
.|* |	.|. |	21	0.077	0.068	17.929	0.527
*|. |	*|. |	22	-0.114	-0.105	20.744	0.412
.|. |	*|. |	23	-0.062	-0.077	21.593	0.423
.|. |	.|* |	24	0.052	0.111	22.195	0.448

*Probabilities may not be valid for this equation specification.

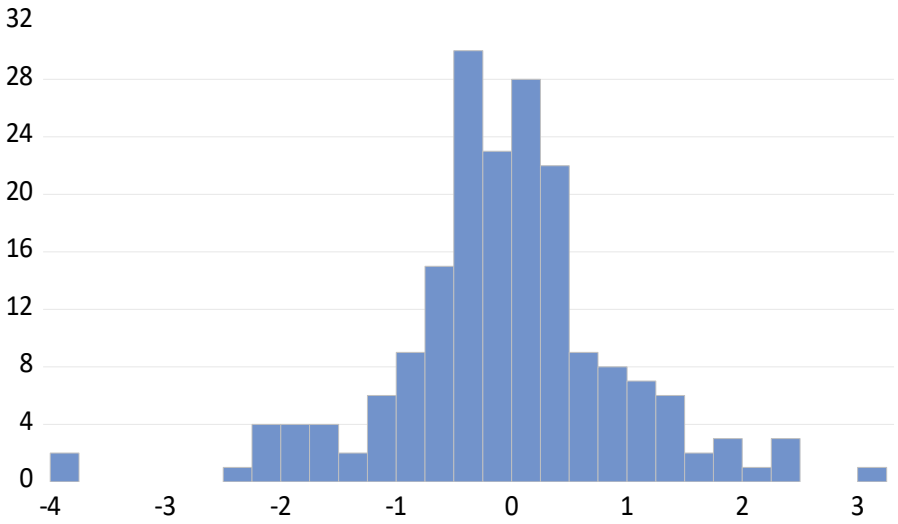
Heteroskedasticity Test: ARCH

F-statistic	0.006755	Prob. F(1,187)	0.9346
Obs*R-squared	0.006827	Prob. Chi-Square(1)	0.9341

Test Equation:
Dependent Variable: WGT_RESID^2
Method: Least Squares
Date: 12/12/20 Time: 12:45
Sample (adjusted): 14/09/1997 22/04/2001
Included observations: 189 after adjustments

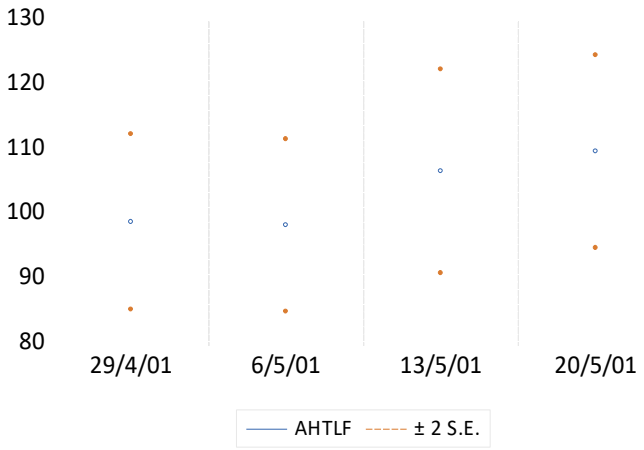
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1.009724	0.169412	5.960175	0.0000
WGT_RESID^2(-1)	-0.006011	0.073135	-0.082190	0.9346

R-squared	0.000036	Mean dependent var	1.003687
Adjusted R-squared	-0.005311	S.D. dependent var	2.093205
S.E. of regression	2.098756	Akaike info criterion	4.331092
Sum squared resid	823.6933	Schwarz criterion	4.365397
Log likelihood	-407.2882	Hannan-Quinn criter.	4.344990
F-statistic	0.006755	Durbin-Watson stat	1.999117
Prob(F-statistic)	0.934583		



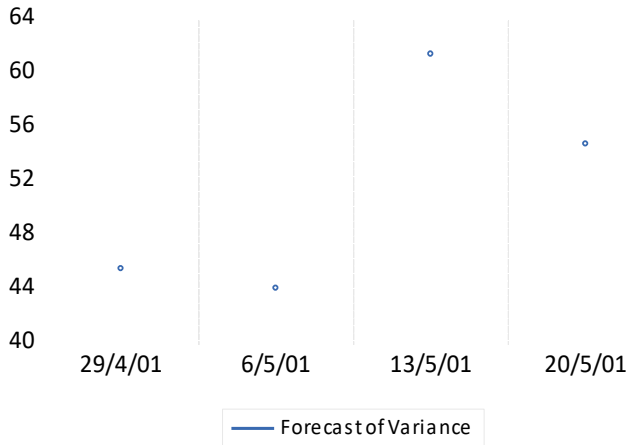
Series: Standardized Residuals
Sample 7/09/1997 22/04/2001
Observations 190

Mean	-0.061121
Median	-0.054594
Maximum	3.057899
Minimum	-3.983686
Std. Dev.	1.000376
Skewness	-0.370481
Kurtosis	5.272803
Jarque-Bera	45.24104
Probability	0.000000



Forecast: AHTLF
Actual: AHTL
Forecast sample: 29/04/2001 20/05/...
Included observations: 4

Root Mean Squared Error	3.324223
Mean Absolute Error	2.466071
Mean Abs. Percent Error	2.335542
Theil Inequality Coef.	0.015878
Bias Proportion	0.366108
Variance Proportion	0.001188
Covariance Proportion	0.632705
Theil U2 Coefficient	0.804961
Symmetric MAPE	2.384897



Date	close	forecast
29/04/2001	98.23800	99.02450
6/05/2001	104.2870	98.49179
13/05/2001	109.9930	106.8333
20/05/2001	109.7680	109.8909

14. AV.L

Dependent Variable: D(AV_L)
Method: ML ARCH - Normal distribution (BFGS / Marquardt steps)
Date: 12/12/20 Time: 13:01
Sample (adjusted): 15/06/1997 22/04/2001
Included observations: 202 after adjustments
Convergence achieved after 28 iterations
Coefficient covariance computed using outer product of gradients
MA Backcast: 30/05/1997 8/06/1997
Presample variance: backcast (parameter = 0.7)
GARCH = C(4) + C(5)*RESID(-1)^2 + C(6)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.830220	2.216315	0.374595	0.7080
AR(1)	-0.139151	0.091015	-1.528880	0.1263
MA(4)	-0.194806	0.076829	-2.535580	0.0112
Variance Equation				
C	66.31557	48.26044	1.374118	0.1694
RESID(-1)^2	0.058670	0.035379	1.658332	0.0973
GARCH(-1)	0.907280	0.046694	19.43053	0.0000

R-squared	0.060603	Mean dependent var	1.156173
Adjusted R-squared	0.051162	S.D. dependent var	43.93783
S.E. of regression	42.79911	Akaike info criterion	10.34275
Sum squared resid	364521.0	Schwarz criterion	10.44102
Log likelihood	-1038.618	Hannan-Quinn criter.	10.38251
Durbin-Watson stat	2.108357		

Inverted AR Roots	-.14			
Inverted MA Roots	.66	-.00+.66i	-.00-.66i	-.66

Date: 12/12/20 Time: 13:05
Sample (adjusted): 15/06/1997 22/04/2001
Q-statistic probabilities adjusted for 2 ARMA terms

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob*
.|. |	.|. |	1	-0.017	-0.017	0.0575	
.|. |	.|. |	2	-0.009	-0.010	0.0760	
.|. |	.|. |	3	0.028	0.028	0.2363	0.627
.|. |	.|. |	4	0.036	0.037	0.5049	0.777
.|. |	.|. |	5	0.012	0.014	0.5347	0.911
.|. |	.|. |	6	-0.000	0.000	0.5348	0.970
.|* |	.|* |	7	0.084	0.082	2.0203	0.846
.|. |	.|. |	8	-0.040	-0.039	2.3616	0.884
.|. |	.|. |	9	-0.063	-0.064	3.2095	0.865
.|* |	.|. |	10	0.078	0.071	4.5046	0.809
*|. |	*|. |	11	-0.094	-0.098	6.4067	0.699
.|. |	.|. |	12	-0.033	-0.031	6.6393	0.759
.|. |	.|. |	13	0.063	0.065	7.4958	0.758

*|. |	*|. |	14	-0.107	-0.118	10.013	0.615
.|. |	.|. |	15	0.039	0.055	10.350	0.665
.|* |	.|* |	16	0.083	0.100	11.878	0.616
.|* |	.|. |	17	0.075	0.057	13.128	0.592
.|. |	.|. |	18	-0.056	-0.030	13.823	0.612
.|. |	.|. |	19	0.012	0.019	13.855	0.677
.|. |	*|. |	20	-0.039	-0.089	14.194	0.716
.|. |	.|. |	21	-0.035	-0.010	14.468	0.756
.|. |	.|. |	22	0.025	0.016	14.606	0.798
.|. |	.|. |	23	0.066	0.025	15.603	0.792
.|. |	.|. |	24	-0.014	0.022	15.646	0.833

*Probabilities may not be valid for this equation specification.

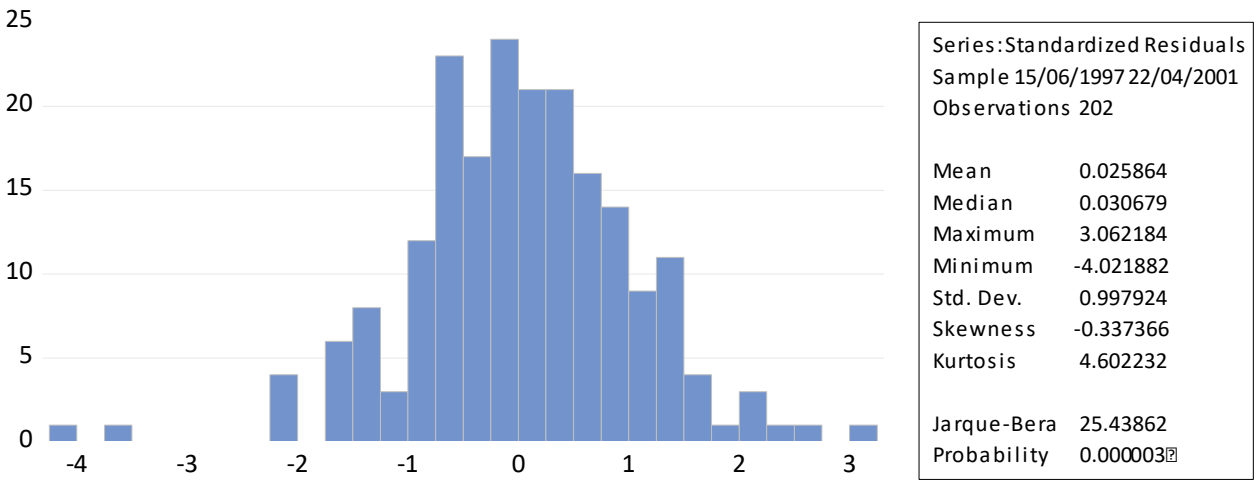
Heteroskedasticity Test: ARCH

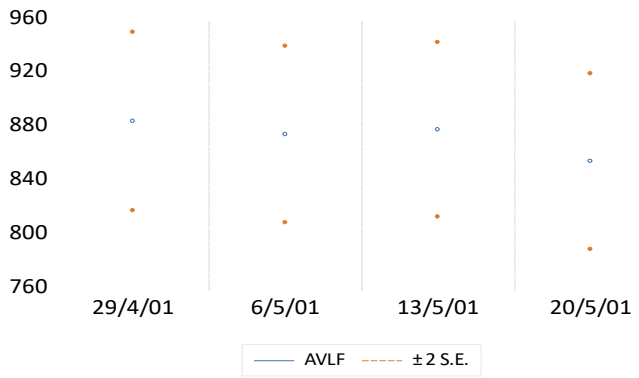
F-statistic	1.923418	Prob. F(1,199)	0.1670
Obs*R-squared	1.924151	Prob. Chi-Square(1)	0.1654

Test Equation:
Dependent Variable: WGT_RESID^2
Method: Least Squares
Date: 12/12/20 Time: 13:06
Sample (adjusted): 22/06/1997 22/04/2001
Included observations: 201 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1.082476	0.149754	7.228344	0.0000
WGT_RESID^2(-1)	-0.097787	0.070509	-1.386874	0.1670

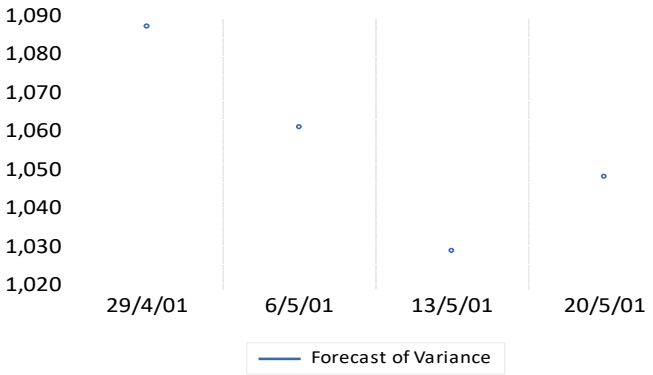
R-squared	0.009573	Mean dependent var	0.985033
Adjusted R-squared	0.004596	S.D. dependent var	1.879275
S.E. of regression	1.874952	Akaike info criterion	4.104943
Sum squared resid	699.5733	Schwarz criterion	4.137812
Log likelihood	-410.5468	Hannan-Quinn criter.	4.118243
F-statistic	1.923418	Durbin-Watson stat	1.987153
Prob(F-statistic)	0.167032		





Forecast: AVLF
Actual: AVL
Forecast sample: 29/04/2001 20/05/...
Included observations: 4

Root Mean Squared Error	15.71057
Mean Absolute Error	11.36087
Mean Abs. Percent Error	1.325929
Theil Inequality Coef.	0.009044
Bias Proportion	0.500525
Variance Proportion	0.002803
Covariance Proportion	0.496672
Theil U2 Coefficient	1.121699
Symmetric MAPE	1.309260



Date	close	forecast
29/04/2001	873.5040	885.4909
6/05/2001	876.2620	875.7700
13/05/2001	850.5170	879.2473
20/05/2001	851.4360	855.6702

15. BAB.L

Dependent Variable: D(BAB_L)
Method: ML ARCH - Normal distribution (BFGS / Marquardt steps)
Date: 12/12/20 Time: 13:21
Sample (adjusted): 28/07/2013 2/04/2017
Included observations: 193 after adjustments
Convergence achieved after 46 iterations
Coefficient covariance computed using outer product of gradients
MA Backcast: 8/05/2013 21/07/2013
Presample variance: backcast (parameter = 0.7)
GARCH = C(4) + C(5)*RESID(-1)^2 + C(6)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.292831	2.415027	-0.121254	0.9035
AR(10)	-0.140459	0.067918	-2.068069	0.0386
MA(15)	0.237734	0.071322	3.333236	0.0009
Variance Equation				
C	227.2326	282.2471	0.805084	0.4208

RESID(-1)^2	0.080861	0.060066	1.346203	0.1782
GARCH(-1)	0.681628	0.326967	2.084701	0.0371

R-squared	0.035992	Mean dependent var	-0.822746
Adjusted R-squared	0.025845	S.D. dependent var	31.47896
S.E. of regression	31.06951	Akaike info criterion	9.742286
Sum squared resid	183409.8	Schwarz criterion	9.843717
Log likelihood	-934.1306	Hannan-Quinn criter.	9.783362
Durbin-Watson stat	2.186189		

Inverted AR Roots	.78-.25i	.78+.25i	.48+.66i	.48-.66i
	.00-.82i	.00+.82i	-.48+.66i	-.48-.66i
	-.78+.25i	-.78-.25i		
Inverted MA Roots	.89-.19i	.89+.19i	.74-.53i	.74+.53i
	.45+.79i	.45-.79i	.09+.90i	.09-.90i
	-.28+.86i	-.28-.86i	-.61+.68i	-.61-.68i
	-.83-.37i	-.83+.37i	-.91	

Date: 12/12/20 Time: 13:30
Sample (adjusted): 28/07/2013 2/04/2017
Q-statistic probabilities adjusted for 2 ARMA terms

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob*
*|. |	*|. |	1	-0.071	-0.071	0.9860	
.|. |	.|. |	2	-0.015	-0.020	1.0291	
.|. |	.|. |	3	-0.023	-0.026	1.1358	0.287
.|. |	.|. |	4	-0.017	-0.021	1.1935	0.551
.|. |	.|. |	5	0.054	0.050	1.7709	0.621
*|. |	*|. |	6	-0.133	-0.128	5.3415	0.254
.|* |	.|. |	7	0.085	0.069	6.7931	0.236
.|. |	.|. |	8	-0.032	-0.026	7.0031	0.321
.|. |	.|. |	9	0.023	0.018	7.1092	0.418
.|. |	.|. |	10	-0.024	-0.026	7.2240	0.513
*|. |	*|. |	11	-0.154	-0.146	12.108	0.207
.|. |	.|. |	12	0.037	-0.005	12.387	0.260
.|. |	.|. |	13	0.051	0.070	12.924	0.298
.|. |	.|. |	14	0.005	-0.011	12.929	0.374
*|. |	*|. |	15	-0.086	-0.081	14.499	0.340
.|. |	.|. |	16	-0.037	-0.045	14.795	0.392
.|. |	*|. |	17	-0.044	-0.088	15.201	0.437
*|. |	*|. |	18	-0.159	-0.163	20.622	0.194
.|. |	.|. |	19	0.035	0.012	20.889	0.231
.|. |	.|. |	20	-0.010	-0.020	20.910	0.284
.|. |	.|. |	21	0.053	0.019	21.536	0.308
.|. |	.|. |	22	0.011	-0.008	21.562	0.365
.|. |	.|. |	23	-0.007	-0.005	21.572	0.425
.|* |	.|* |	24	0.098	0.092	23.732	0.361

*Probabilities may not be valid for this equation specification.

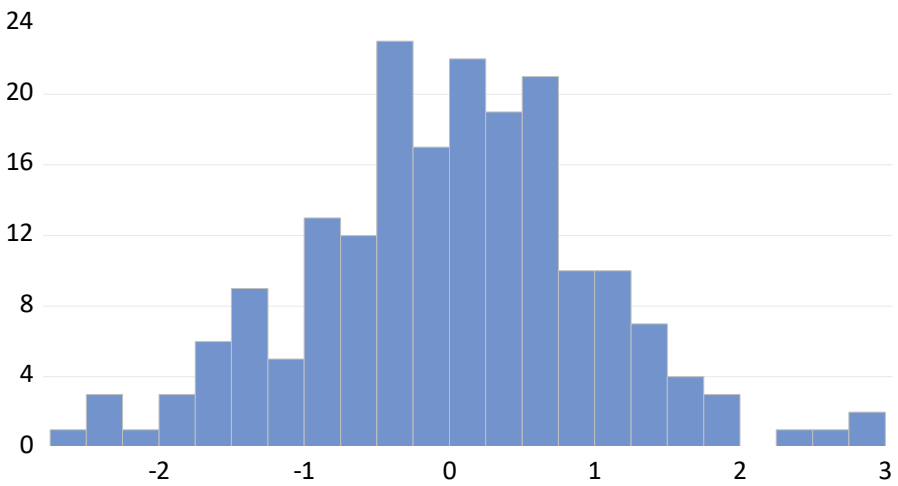
Heteroskedasticity Test: ARCH

F-statistic	0.046923	Prob. F(1,190)	0.8287
Obs*R-squared	0.047405	Prob. Chi-Square(1)	0.8276

Test Equation:
Dependent Variable: WGT_RESID^2
Method: Least Squares
Date: 12/12/20 Time: 13:30
Sample (adjusted): 4/08/2013 2/04/2017
Included observations: 192 after adjustments

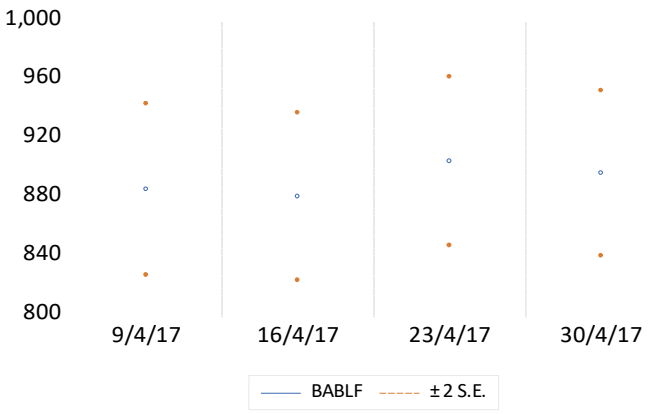
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1.019330	0.130992	7.781630	0.0000
WGT_RESID^2(-1)	-0.015713	0.072539	-0.216617	0.8287

R-squared	0.000247	Mean dependent var	1.003561
Adjusted R-squared	-0.005015	S.D. dependent var	1.505211
S.E. of regression	1.508981	Akaike info criterion	3.671108
Sum squared resid	432.6344	Schwarz criterion	3.705040
Log likelihood	-350.4264	Hannan-Quinn criter.	3.684851
F-statistic	0.046923	Durbin-Watson stat	2.000426
Prob(F-statistic)	0.828739		



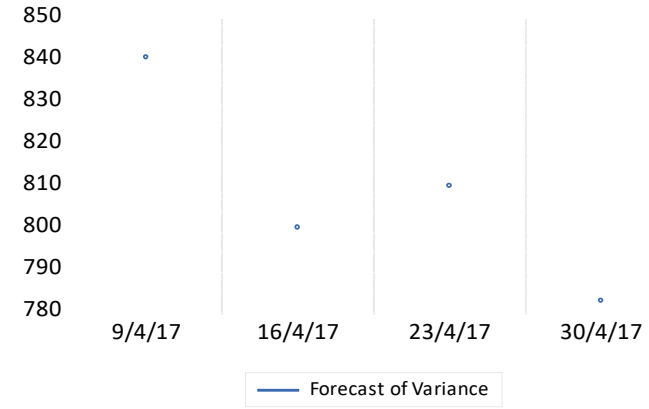
Series: Standardized Residuals
Sample 28/07/2013 2/04/2017
Observations 193

Mean	-0.007631
Median	0.023092
Maximum	2.868683
Minimum	-2.678704
Std. Dev.	1.001806
Skewness	-0.000833
Kurtosis	3.254026
Jarque-Bera	0.518945
Probability	0.771458



Forecast: BABLF
Actual: BABL
Forecast sample: 9/04/2017 30/04/2017
Included observations: 4

Root Mean Squared Error	14.47354
Mean Absolute Error	11.76175
Mean Abs. Percent Error	1.296876
Theil Inequality Coef.	0.008070
Bias Proportion	0.313628
Variance Proportion	0.008340
Covariance Proportion	0.678032
Theil U2 Coefficient	1.187320
Symmetric MAPE	1.308396



Date	close	forecast
9/04/2017	885.5000	886.3021
16/04/2017	903.0000	881.4763
23/04/2017	899.0000	905.5103
30/04/2017	915.5000	897.2891

16. BARC.L

Dependent Variable: D(BARC_L)
Method: ML ARCH - Normal distribution (BFGS / Marquardt steps)
Date: 12/12/20 Time: 14:17
Sample (adjusted): 6/11/2000 22/08/2004
Included observations: 199 after adjustments
Convergence achieved after 24 iterations
Coefficient covariance computed using outer product of gradients
MA Backcast: 14/09/2000 30/10/2000
Presample variance: backcast (parameter = 0.7)
GARCH = C(4) + C(5)*RESID(-1)^2 + C(6)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	1.234806	1.235534	0.999411	0.3176
AR(4)	-0.178292	0.072004	-2.476159	0.0133
MA(22)	0.233280	0.072776	3.205475	0.0013
Variance Equation				
C	57.74995	49.94801	1.156201	0.2476

RESID(-1)^2	0.161804	0.076944	2.102873	0.0355
GARCH(-1)	0.682077	0.193870	3.518217	0.0004

R-squared	0.055893	Mean dependent var	0.118367
Adjusted R-squared	0.046259	S.D. dependent var	19.82149
S.E. of regression	19.35760	Akaike info criterion	8.715950
Sum squared resid	73444.47	Schwarz criterion	8.815245
Log likelihood	-861.2370	Hannan-Quinn criter.	8.756137
Durbin-Watson stat	2.076508		

Inverted AR Roots	.46-.46i	.46+.46i	-.46+.46i	-.46+.46i
Inverted MA Roots	.93-.13i	.93+.13i	.85-.39i	.85+.39i
	.71-.61i	.71+.61i	.51+.79i	.51-.79i
	.26+.90i	.26-.90i	.00+.94i	-.00-.94i
	-.26+.90i	-.26-.90i	-.51+.79i	-.51-.79i
	-.71-.61i	-.71+.61i	-.85+.39i	-.85-.39i
	-.93+.13i	-.93-.13i		

Date: 12/12/20 Time: 14:22
Sample (adjusted): 6/11/2000 22/08/2004
Q-statistic probabilities adjusted for 2 ARMA terms

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob*
.|. |	.|. |	1	-0.030	-0.030	0.1774	
.|. |	.|. |	2	-0.062	-0.063	0.9562	
.|. |	.|. |	3	0.036	0.032	1.2190	0.270
.|. |	.|. |	4	-0.021	-0.023	1.3080	0.520
*|. |	*|. |	5	-0.133	-0.131	4.9757	0.174
.|* |	.|* |	6	0.089	0.079	6.6183	0.157
.|. |	.|. |	7	-0.031	-0.042	6.8159	0.235
.|. |	.|. |	8	0.047	0.065	7.2867	0.295
.|. |	*|. |	9	-0.063	-0.078	8.1137	0.323
.|. |	.|. |	10	0.012	0.006	8.1449	0.419
.|. |	.|. |	11	-0.037	-0.030	8.4359	0.491
.|* |	.|* |	12	0.116	0.112	11.330	0.332
*|. |	.|. |	13	-0.070	-0.059	12.394	0.335
*|. |	*|. |	14	-0.138	-0.158	16.512	0.169
.|. |	.|. |	15	0.035	0.035	16.783	0.209
.|* |	.|. |	16	0.088	0.069	18.473	0.186
.|. |	.|. |	17	0.008	0.071	18.489	0.238
.|* |	.|* |	18	0.155	0.117	23.791	0.094
*|. |	*|. |	19	-0.093	-0.119	25.727	0.080
.|. |	.|. |	20	-0.022	0.004	25.835	0.104
.|. |	.|. |	21	-0.034	-0.024	26.090	0.128
*|. |	*|. |	22	-0.100	-0.089	28.336	0.102
*|. |	*|. |	23	-0.067	-0.070	29.344	0.106
.|* |	.|. |	24	0.085	0.014	31.013	0.096

*Probabilities may not be valid for this equation specification.

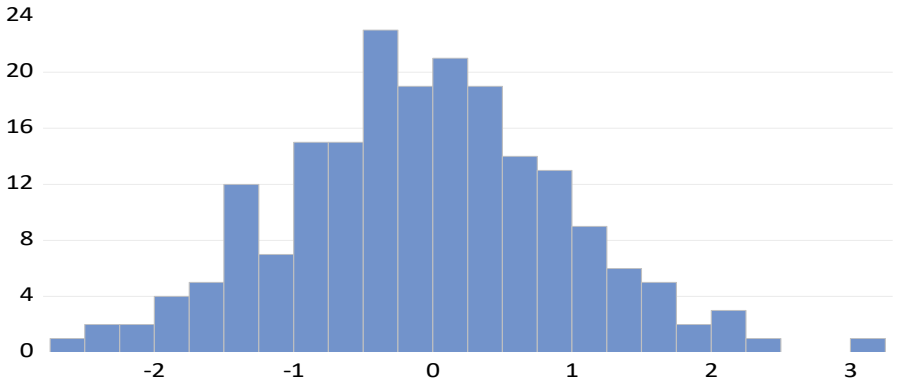
Heteroskedasticity Test: ARCH

F-statistic	0.188633	Prob. F(1,196)	0.6645
Obs*R-squared	0.190375	Prob. Chi-Square(1)	0.6626

Test Equation:
Dependent Variable: WGT_RESID^2
Method: Least Squares
Date: 12/12/20 Time: 14:23
Sample (adjusted): 13/11/2000 22/08/2004
Included observations: 198 after adjustments

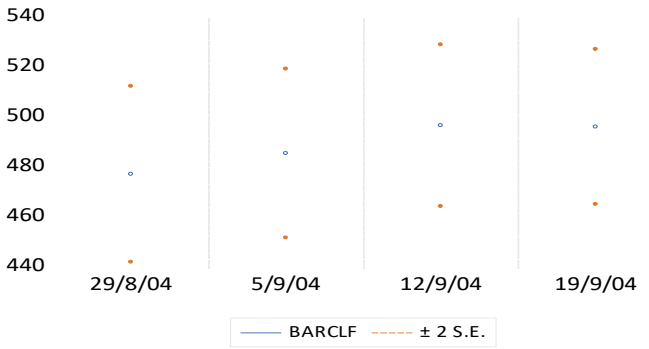
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.970657	0.124179	7.816590	0.0000
WGT_RESID^2(-1)	0.030974	0.071317	0.434319	0.6645

R-squared	0.000961	Mean dependent var	1.001571
Adjusted R-squared	-0.004136	S.D. dependent var	1.428885
S.E. of regression	1.431837	Akaike info criterion	3.565843
Sum squared resid	401.8305	Schwarz criterion	3.599057
Log likelihood	-351.0184	Hannan-Quinn criter.	3.579287
F-statistic	0.188633	Durbin-Watson stat	2.000537
Prob(F-statistic)	0.664534		



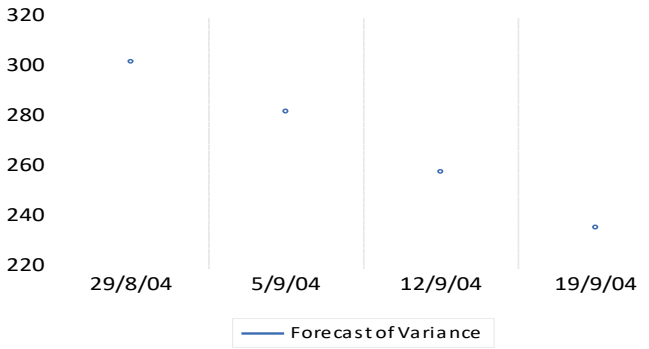
Series: Standardized Residuals
Sample 6/11/2000 22/08/2004
Observations 199

Mean	-0.057564
Median	-0.048681
Maximum	3.013945
Minimum	-2.680495
Std. Dev.	0.999182
Skewness	0.079529
Kurtosis	3.058217
Jarque-Bera	0.237874
Probability	0.887864



Forecast: BARCLF
Actual: BARCL
Forecast sample: 29/08/2004 19/09/...
Included observations: 4

Root Mean Squared Error	6.773533
Mean Absolute Error	5.954520
Mean Abs. Percent Error	1.211768
Theil Inequality Coef.	0.006894
Bias Proportion	0.368841
Variance Proportion	0.406476
Covariance Proportion	0.224684
Theil U2 Coefficient	1.149752
Symmetric MAPE	1.220014



Date	close	forecast
29/08/2004	488.1990	477.4797
5/09/2004	492.8180	485.7938
12/09/2004	493.2800	496.9616
19/09/2004	498.8220	496.4290

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17. AZN.L

Dependent Variable: D(AZN_L)
Method: ML ARCH - Normal distribution (BFGS / Marquardt steps)
Date: 13/12/20 Time: 22:05
Sample (adjusted): 4/04/2010 25/11/2013
Included observations: 191 after adjustments
Convergence achieved after 39 iterations
Coefficient covariance computed using outer product of gradients
MA Backcast: 11/01/2010 28/03/2010
Presample variance: backcast (parameter = 0.7)
GARCH = C(4) + C(5)*RESID(-1)^2 + C(6)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	3.366298	3.972018	0.847503	0.3967
AR(12)	0.683051	0.051065	13.37615	0.0000
MA(12)	-0.917028	0.018917	-48.47556	0.0000
Variance Equation				
C	454.7001	266.2821	1.707588	0.0877
RESID(-1)^2	-0.043707	0.013914	-3.141188	0.0017
GARCH(-1)	0.935456	0.063420	14.75010	0.0000

R-squared	0.103736	Mean dependent var	2.971204
Adjusted R-squared	0.094201	S.D. dependent var	68.02510
S.E. of regression	64.74183	Akaike info criterion	11.19218
Sum squared resid	788002.8	Schwarz criterion	11.29435
Log likelihood	-1062.854	Hannan-Quinn criter.	11.23357
Durbin-Watson stat	1.996672		

Inverted AR Roots	.97	.84-.48i	.84+.48i	.48+.84i
	.48-.84i	.00+.97i	-.00-.97i	-.48+.84i
	-.48-.84i	-.84-.48i	-.84+.48i	-.97
Inverted MA Roots	.99	.86-.50i	.86+.50i	.50-.86i
	.50+.86i	.00+.99i	-.00-.99i	-.50+.86i
	-.50-.86i	-.86+.50i	-.86-.50i	-.99

Date: 13/12/20 Time: 22:10
Sample (adjusted): 4/04/2010 25/11/2013
Q-statistic probabilities adjusted for 2 ARMA terms

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob*
.|. |	.|. |	1	-0.038	-0.038	0.2835	

.|. |	.|. |	2	0.054	0.053	0.8531	
.|. |	.|. |	3	-0.035	-0.032	1.0997	0.294
*|. |	*|. |	4	-0.076	-0.081	2.2294	0.328
.|. |	.|. |	5	0.016	0.014	2.2802	0.516
.|. |	.|. |	6	-0.065	-0.057	3.1153	0.539
.|. |	.|. |	7	0.003	-0.008	3.1173	0.682
*|. |	*|. |	8	-0.079	-0.079	4.3701	0.627
.|. |	.|. |	9	-0.047	-0.056	4.8241	0.681
*|. |	*|. |	10	-0.075	-0.083	5.9687	0.651
.|. |	.|. |	11	0.015	0.009	6.0178	0.738
.|. |	.|. |	12	0.012	0.000	6.0489	0.811
.|. |	.|. |	13	0.008	-0.006	6.0623	0.869
.|* |	.|. |	14	0.080	0.061	7.3879	0.831
.|. |	.|. |	15	-0.004	-0.001	7.3907	0.881
.|. |	.|. |	16	0.024	0.003	7.5171	0.913
.|. |	.|. |	17	-0.015	-0.016	7.5663	0.940
*|. |	*|. |	18	-0.121	-0.131	10.680	0.829
.|. |	.|. |	19	0.027	0.011	10.840	0.865
.|. |	.|. |	20	-0.062	-0.046	11.669	0.864
*|. |	*|. |	21	-0.130	-0.154	15.327	0.702
*|. |	*|. |	22	-0.084	-0.105	16.875	0.661
.|. |	.|. |	23	0.014	0.022	16.919	0.716
.|. |	.|. |	24	0.004	-0.014	16.922	0.768

*Probabilities may not be valid for this equation specification.

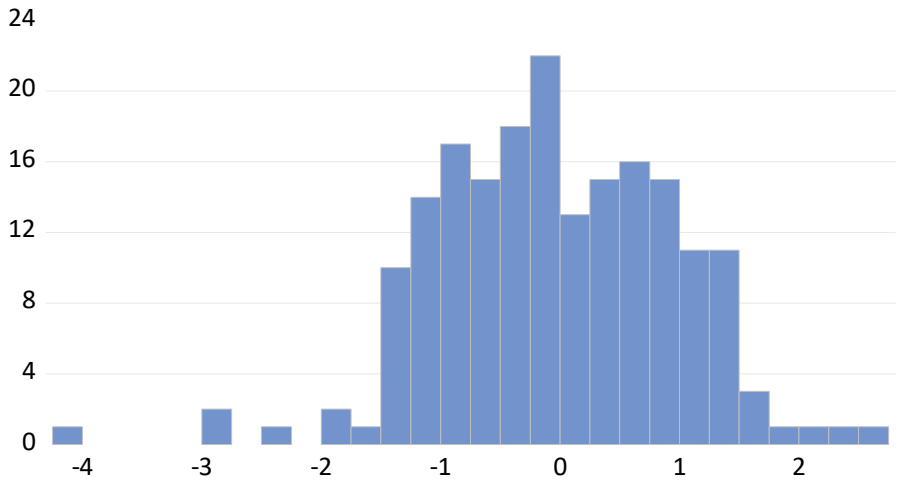
Heteroskedasticity Test: ARCH

F-statistic	1.346898	Prob. F(1,188)	0.2473
Obs*R-squared	1.351543	Prob. Chi-Square(1)	0.2450

Test Equation:
Dependent Variable: WGT_RESID^2
Method: Least Squares
Date: 13/12/20 Time: 22:12
Sample (adjusted): 11/04/2010 25/11/2013
Included observations: 190 after adjustments

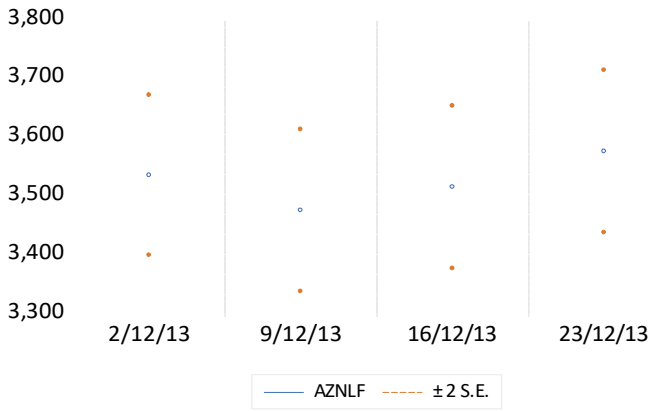
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.909169	0.147808	6.151020	0.0000
WGT_RESID^2(-1)	0.084339	0.072671	1.160559	0.2473

R-squared	0.007113	Mean dependent var	0.993198
Adjusted R-squared	0.001832	S.D. dependent var	1.777840
S.E. of regression	1.776211	Akaike info criterion	3.997312
Sum squared resid	593.1257	Schwarz criterion	4.031491
Log likelihood	-377.7446	Hannan-Quinn criter.	4.011158
F-statistic	1.346898	Durbin-Watson stat	1.987038
Prob(F-statistic)	0.247293		



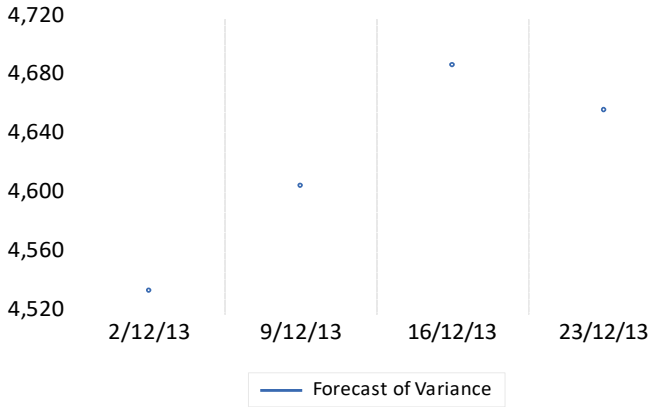
Series: Standardized Residuals
Sample 4/04/2010 25/11/2013
Observations 191

Mean	-0.046780
Median	-0.037938
Maximum	2.738663
Minimum	-4.129740
Std. Dev.	0.998963
Skewness	-0.355166
Kurtosis	4.098804
Jarque-Bera	13.62419
Probability	0.001100



Forecast: AZNLF
Actual: AZNL
Forecast sample: 2/12/2013 23/12/2013
Included observations: 4

Root Mean Squared Error	49.19855
Mean Absolute Error	46.50343
Mean Abs. Percent Error	1.310470
Theil Inequality Coef.	0.006950
Bias Proportion	0.194686
Variance Proportion	0.057394
Covariance Proportion	0.747920
Theil U2 Coefficient	1.092987
Symmetric MAPE	1.315089



Date	AZN.L	GARCH
02/12/2013	3489	3538.591
09/12/2013	3518.5	3478.466
16/12/2013	3588.5	3518.231
23/12/2013	3605	3578.88

18. GSK.L

Dependent Variable: D(GSK_L)
Method: ML ARCH - Normal distribution (BFGS / Marquardt steps)

Date: 13/12/20 Time: 23:07
Sample (adjusted): 15/06/1997 22/04/2001
Included observations: 202 after adjustments
Convergence achieved after 54 iterations
Coefficient covariance computed using outer product of gradients
MA Backcast: 8/06/1997
Presample variance: backcast (parameter = 0.7)
GARCH = C(4) + C(5)*RESID(-1)^2 + C(6)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	2.798635	5.564174	0.502974	0.6150
AR(1)	-0.210996	0.645404	-0.326922	0.7437
MA(1)	0.120410	0.665075	0.181046	0.8563
Variance Equation				
C	448.2714	342.5574	1.308602	0.1907
RESID(-1)^2	-0.017790	0.015830	-1.123847	0.2611
GARCH(-1)	0.948733	0.053762	17.64698	0.0000

R-squared	0.008422	Mean dependent var	2.811881
Adjusted R-squared	-0.001544	S.D. dependent var	78.91875
S.E. of regression	78.97965	Akaike info criterion	11.59605
Sum squared resid	1241319.	Schwarz criterion	11.69431
Log likelihood	-1165.201	Hannan-Quinn criter.	11.63581
Durbin-Watson stat	2.007223		

Inverted AR Roots	-.21
Inverted MA Roots	-.12

Date: 13/12/20 Time: 23:13
Sample (adjusted): 15/06/1997 22/04/2001
Q-statistic probabilities adjusted for 2 ARMA terms

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob*
.|. |	.|. |	1	-0.009	-0.009	0.0157	
*|. |	*|. |	2	-0.072	-0.072	1.0842	
*|. |	*|. |	3	-0.139	-0.141	5.0703	0.024
.|. |	.|. |	4	-0.010	-0.020	5.0920	0.078
.|. |	.|. |	5	-0.028	-0.050	5.2515	0.154
.|. |	.|. |	6	0.000	-0.024	5.2515	0.262
.|. |	.|. |	7	-0.017	-0.029	5.3122	0.379
.|. |	*|. |	8	-0.063	-0.079	6.1511	0.406
.|. |	.|. |	9	0.051	0.041	6.7150	0.459
.|. |	.|. |	10	-0.017	-0.036	6.7738	0.561
.|. |	.|. |	11	-0.015	-0.032	6.8233	0.656
.|. |	.|. |	12	0.022	0.027	6.9287	0.732
.|. |	.|. |	13	0.032	0.018	7.1582	0.786
*|. |	*|. |	14	-0.099	-0.104	9.3209	0.675
*|. |	*|. |	15	-0.077	-0.079	10.632	0.642
*|. |	*|. |	16	-0.138	-0.164	14.822	0.390
.|. |	*|. |	17	-0.020	-0.071	14.911	0.458
.|. |	.|. |	18	0.052	-0.011	15.525	0.487
.|* |	.|. |	19	0.119	0.059	18.713	0.345
.|. |	.|. |	20	0.042	0.032	19.107	0.385

.|.	|	.|.	|	21	0.021	0.027	19.205	0.444
.|.	|	.|.	|	22	0.038	0.049	19.530	0.488
.|.	|	.|.	|	23	0.029	0.050	19.721	0.539
.|.	|	.|.	|	24	0.018	0.028	19.796	0.596

*Probabilities may not be valid for this equation specification.

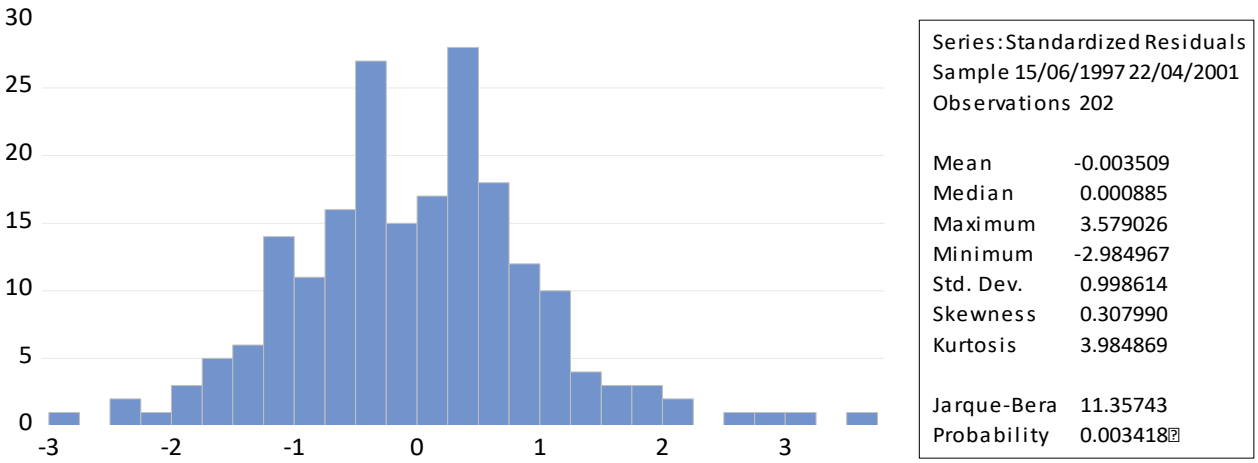
Heteroskedasticity Test: ARCH

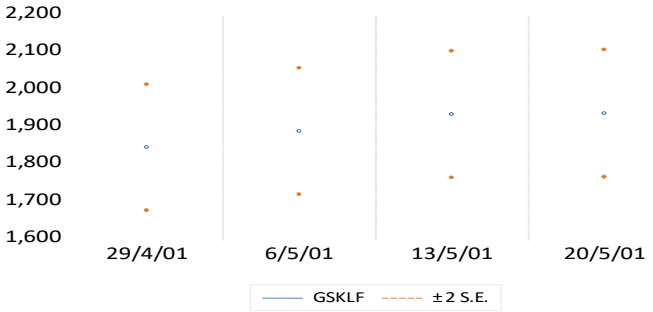
F-statistic	0.010335	Prob. F(1,199)	0.9191
Obs*R-squared	0.010438	Prob. Chi-Square(1)	0.9186

Test Equation:
Dependent Variable: WGT_RESID^2
Method: Least Squares
Date: 13/12/20 Time: 23:16
Sample (adjusted): 22/06/1997 22/04/2001
Included observations: 201 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.989251	0.140569	7.037458	0.0000
WGT_RESID^2(-1)	0.007203	0.070850	0.101661	0.9191

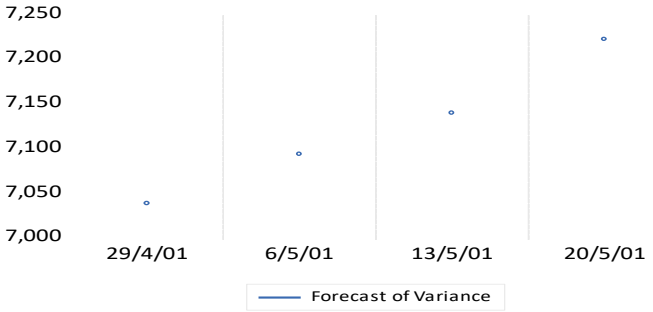
R-squared	0.000052	Mean dependent var	0.996408
Adjusted R-squared	-0.004973	S.D. dependent var	1.720683
S.E. of regression	1.724957	Akaike info criterion	3.938181
Sum squared resid	592.1195	Schwarz criterion	3.971050
Log likelihood	-393.7872	Hannan-Quinn criter.	3.951481
F-statistic	0.010335	Durbin-Watson stat	2.001045
Prob(F-statistic)	0.919128		





Forecast: GSKLF
Actual: GSKL
Forecast sample: 29/04/2001 20/05/...
Included observations: 4

Root Mean Squared Error	43.44172
Mean Absolute Error	37.48850
Mean Abs. Percent Error	1.972891
Theil Inequality Coef.	0.011390
Bias Proportion	0.026806
Variance Proportion	0.069531
Covariance Proportion	0.903663
Theil U2 Coefficient	1.033593
Symmetric MAPE	1.974219



Date	GSK.L	GARCH
29/04/2001	1890	1847.283
06/05/2001	1937	1890.515
13/05/2001	1935	1936.07
20/05/2001	1879	1938.682

19. SHP.L

Dependent Variable: D(SHP_L)
Method: ML ARCH - Normal distribution (BFGS / Marquardt steps)
Date: 14/12/20 Time: 21:01
Sample (adjusted): 4/12/2006 22/08/2010
Included observations: 195 after adjustments
Convergence achieved after 39 iterations
Coefficient covariance computed using outer product of gradients
MA Backcast: 26/09/2006 27/11/2006
Presample variance: backcast (parameter = 0.7)
GARCH = C(4) + C(5)*RESID(-1)^2 + C(6)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	2.689962	3.239751	0.830299	0.4064
AR(8)	-0.145335	0.060543	-2.400518	0.0164
MA(14)	0.232444	0.084973	2.735510	0.0062
Variance Equation				
C	90.88614	76.32720	1.190744	0.2338
RESID(-1)^2	-0.003078	0.014176	-0.217111	0.8281
GARCH(-1)	0.949676	0.048997	19.38239	0.0000

R-squared	0.059138	Mean dependent var	1.925641
Adjusted R-squared	0.049338	S.D. dependent var	41.31153
S.E. of regression	40.27954	Akaike info criterion	10.25376

Sum squared resid	311508.7	Schwarz criterion	10.35447
Log likelihood	-993.7417	Hannan-Quinn criter.	10.29454
Durbin-Watson stat	2.191729		

Inverted AR Roots	.73+.30i	.73-.30i	.30+.73i	.30-.73i
	-.30-.73i	-.30+.73i	-.73-.30i	-.73+.30i
Inverted MA Roots	.88-.20i	.88+.20i	.70-.56i	.70+.56i
	.39+.81i	.39-.81i	.00+.90i	-.00-.90i
	-.39+.81i	-.39-.81i	-.70+.56i	-.70-.56i
	-.88+.20i	-.88-.20i		

Date: 14/12/20 Time: 21:05
Sample (adjusted): 4/12/2006 22/08/2010
Q-statistic probabilities adjusted for 2 ARMA terms

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob*
*|. |	*|. |	1	-0.104	-0.104	2.1339	
.|. |	.|. |	2	0.055	0.045	2.7439	
.|. |	.|. |	3	-0.063	-0.053	3.5312	0.060
.|. |	.|. |	4	0.055	0.042	4.1330	0.127
.|. |	.|. |	5	-0.000	0.015	4.1331	0.247
.|. |	.|. |	6	-0.034	-0.041	4.3708	0.358
.|. |	.|. |	7	-0.003	-0.006	4.3728	0.497
.|. |	.|. |	8	0.022	0.023	4.4694	0.613
.|. |	.|. |	9	0.001	0.001	4.4697	0.724
.|. |	.|. |	10	-0.004	-0.003	4.4736	0.812
*|. |	*|. |	11	-0.143	-0.143	8.7363	0.462
.|. |	.|. |	12	0.038	0.008	9.0362	0.529
.|. |	.|. |	13	0.031	0.049	9.2392	0.600
.|. |	.|. |	14	-0.025	-0.035	9.3756	0.671
.|. |	.|. |	15	-0.021	-0.015	9.4725	0.736
.|* |	.|* |	16	0.102	0.108	11.696	0.631
.|. |	.|. |	17	-0.052	-0.052	12.279	0.658
.|* |	.|* |	18	0.124	0.113	15.610	0.480
.|. |	.|* |	19	0.028	0.081	15.783	0.539
.|* |	.|. |	20	0.079	0.062	17.136	0.514
.|. |	.|. |	21	0.005	0.028	17.143	0.580
.|. |	.|. |	22	-0.017	-0.038	17.209	0.639
.|. |	.|. |	23	0.003	0.001	17.210	0.698
.|. |	.|. |	24	0.014	0.032	17.255	0.749

*Probabilities may not be valid for this equation specification.

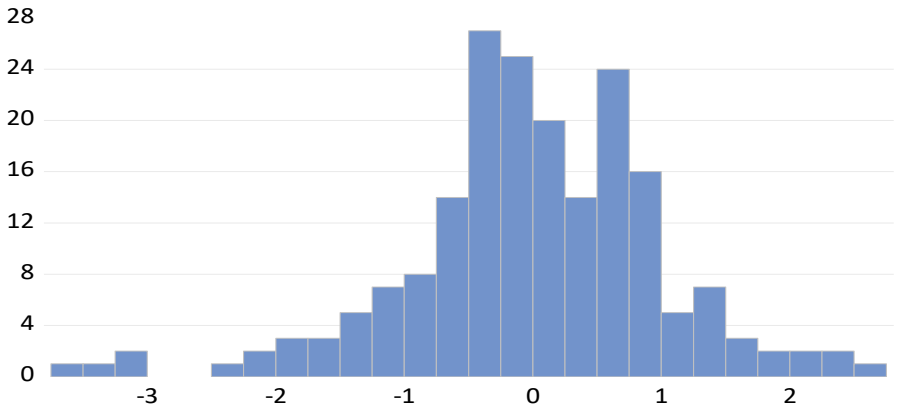
Heteroskedasticity Test: ARCH

F-statistic	0.131199	Prob. F(1,192)	0.7176
Obs*R-squared	0.132475	Prob. Chi-Square(1)	0.7159

Test Equation:
Dependent Variable: WGT_RESID^2
Method: Least Squares
Date: 14/12/20 Time: 21:05
Sample (adjusted): 11/12/2006 22/08/2010
Included observations: 194 after adjustments

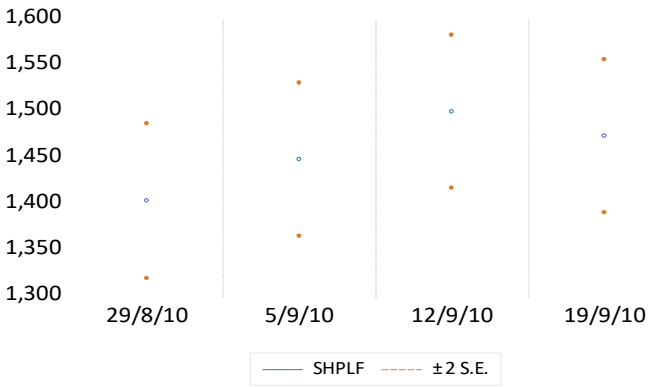
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1.020517	0.154326	6.612720	0.0000
WGT_RESID^2(-1)	-0.026138	0.072163	-0.362214	0.7176

R-squared	0.000683	Mean dependent var	0.994494
Adjusted R-squared	-0.004522	S.D. dependent var	1.898102
S.E. of regression	1.902388	Akaike info criterion	4.134353
Sum squared resid	694.8636	Schwarz criterion	4.168042
Log likelihood	-399.0322	Hannan-Quinn criter.	4.147995
F-statistic	0.131199	Durbin-Watson stat	1.999472
Prob(F-statistic)	0.717591		



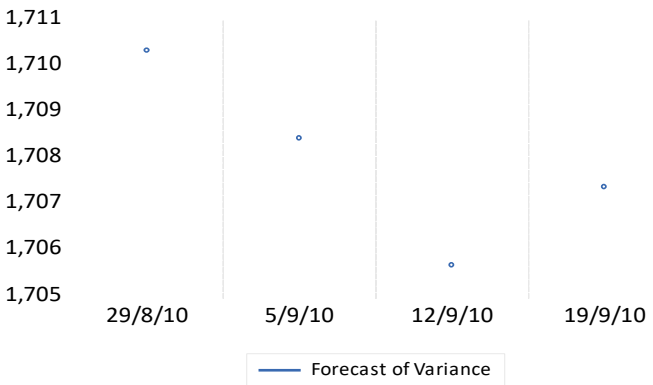
Series:Standardized Residuals
Sample 4/12/2006 22/08/2010
Observations 195

Mean	-0.013927
Median	-0.027003
Maximum	2.502798
Minimum	-3.652039
Std. Dev.	0.997823
Skewness	-0.551939
Kurtosis	4.605346
Jarque-Bera	30.83991
Probability	0.000000



Forecast: SHPLF
Actual: SHPL
Forecast sample: 29/08/2010 19/09/...
Included observations: 4

Root Mean Squared Error	37.96141
Mean Absolute Error	33.03201
Mean Abs. Percent Error	2.241766
Theil Inequality Coef.	0.012955
Bias Proportion	0.161451
Variance Proportion	0.235827
Covariance Proportion	0.602723
Theil U2 Coefficient	1.044898
Symmetric MAPE	2.262707



Date	close	forecast
29/08/2010	1451.000	1404.312
5/09/2010	1499.000	1449.117
12/09/2010	1468.000	1501.011
19/09/2010	1472.000	1474.546

20. SGE.L

Dependent Variable: D(SGE_L)
Method: ML ARCH - Normal distribution (BFGS / Marquardt steps)
Date: 14/12/20 Time: 21:33
Sample (adjusted): 15/06/1997 22/04/2001
Included observations: 202 after adjustments
Convergence achieved after 31 iterations
Coefficient covariance computed using outer product of gradients
MA Backcast: 19/05/1997 8/06/1997
Presample variance: backcast (parameter = 0.7)
GARCH = C(4) + C(5)*RESID(-1)^2 + C(6)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.896293	0.466096	1.922980	0.0545
AR(1)	-0.178646	0.077458	-2.306360	0.0211
MA(15)	-0.104057	0.086079	-1.208858	0.2267
Variance Equation				
C	0.659555	0.532054	1.239640	0.2151
RESID(-1)^2	0.222174	0.066785	3.326737	0.0009
GARCH(-1)	0.840416	0.050693	16.57861	0.0000

R-squared	0.078970	Mean dependent var	1.052079
Adjusted R-squared	0.069714	S.D. dependent var	42.07663
S.E. of regression	40.58348	Akaike info criterion	8.891079
Sum squared resid	327756.7	Schwarz criterion	8.989344
Log likelihood	-891.9989	Hannan-Quinn criter.	8.930837
Durbin-Watson stat	2.084946		

Inverted AR Roots	-.18			
Inverted MA Roots	.86	.79+.35i	.79-.35i	.58-.64i
	.58+.64i	.27-.82i	.27+.82i	-.09-.86i
	-.09+.86i	-.43+.74i	-.43-.74i	-.70-.51i
	-.70+.51i	-.84-.18i	-.84+.18i	

Date: 14/12/20 Time: 21:37
Sample (adjusted): 15/06/1997 22/04/2001
Q-statistic probabilities adjusted for 2 ARMA terms

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob*
.|* |	.|* |	1	0.085	0.085	1.4673	
.|. |	.|. |	2	0.052	0.045	2.0222	
.|* |	.|* |	3	0.109	0.102	4.4911	0.034
.|. |	.|. |	4	0.007	-0.012	4.5007	0.105
.|* |	.|* |	5	0.147	0.141	9.0020	0.029
.|* |	.|* |	6	0.141	0.113	13.203	0.010
.|. |	.|. |	7	-0.007	-0.035	13.212	0.021
.|. |	.|. |	8	0.045	0.012	13.647	0.034
.|. |	.|. |	9	0.041	0.018	14.006	0.051
*|. |	*|. |	10	-0.071	-0.095	15.096	0.057
*|. |	*|. |	11	-0.067	-0.104	16.053	0.066

.|.	|	.|.	|	12	0.040	0.045	16.406	0.089
.|.	|	.|.	|	13	-0.011	0.003	16.431	0.126
.|*	|	.|*	|	14	0.097	0.098	18.489	0.102
.|.	|	.|.	|	15	0.056	0.058	19.179	0.118
.|.	|	.|.	|	16	0.026	0.067	19.332	0.153
*|.	|	*|.	|	17	-0.081	-0.111	20.802	0.143
.|.	|	.|.	|	18	0.034	0.027	21.054	0.176
*|.	|	*|.	|	19	-0.110	-0.146	23.755	0.126
.|.	|	.|.	|	20	0.064	0.055	24.670	0.134
.|.	|	.|.	|	21	0.007	-0.048	24.682	0.171
.|.	|	.|.	|	22	-0.019	0.026	24.768	0.210
.|.	|	.|.	|	23	0.006	0.008	24.775	0.257
*|.	|	*|.	|	24	-0.101	-0.066	27.138	0.206

*Probabilities may not be valid for this equation specification.

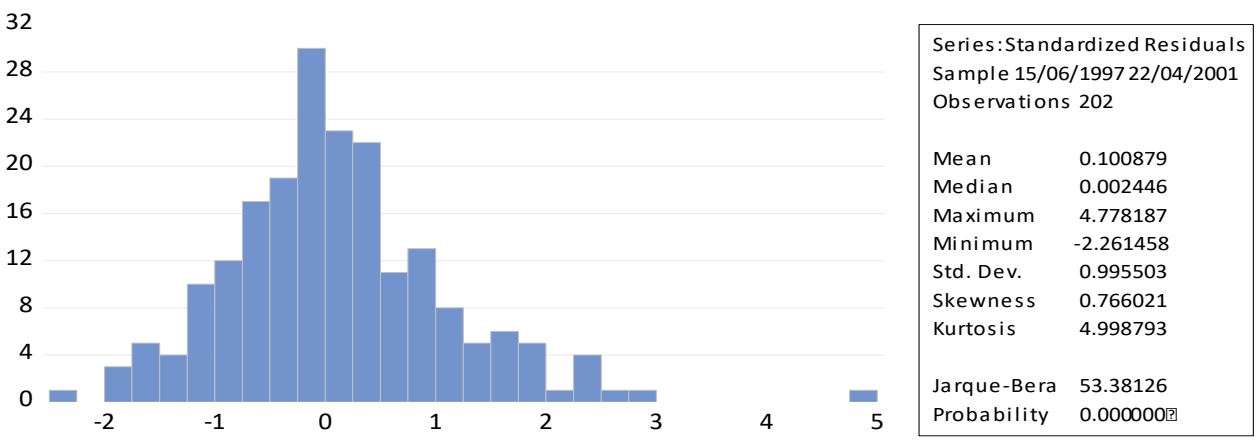
Heteroskedasticity Test: ARCH

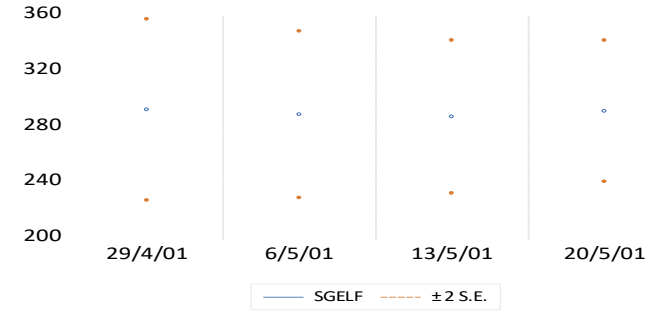
F-statistic	0.002634	Prob. F(1,199)	0.9591
Obs*R-squared	0.002660	Prob. Chi-Square(1)	0.9589

Test Equation:
Dependent Variable: WGT_RESID^2
Method: Least Squares
Date: 14/12/20 Time: 21:40
Sample (adjusted): 22/06/1997 22/04/2001
Included observations: 201 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1.004021	0.162452	6.180408	0.0000
WGT_RESID^2(-1)	-0.003638	0.070900	-0.051318	0.9591

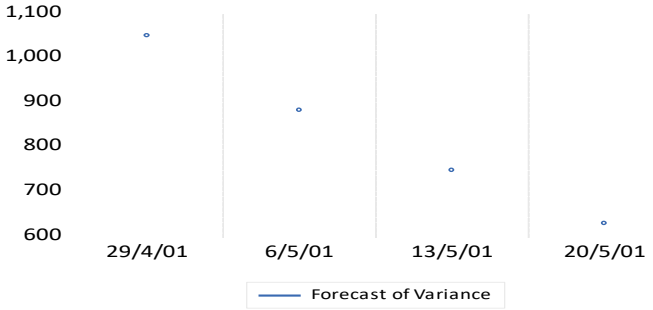
R-squared	0.000013	Mean dependent var	1.000378
Adjusted R-squared	-0.005012	S.D. dependent var	2.066477
S.E. of regression	2.071649	Akaike info criterion	4.304467
Sum squared resid	854.0539	Schwarz criterion	4.337336
Log likelihood	-430.5989	Hannan-Quinn criter.	4.317767
F-statistic	0.002634	Durbin-Watson stat	2.000296
Prob(F-statistic)	0.959123		





Forecast: SGELF
Actual: SGEL
Forecast sample: 29/04/2001 20/05/...
Included observations: 4

Root Mean Squared Error	14.80453
Mean Absolute Error	8.955972
Mean Abs. Percent Error	2.856003
Theil Inequality Coef.	0.025231
Bias Proportion	0.149420
Variance Proportion	0.723311
Covariance Proportion	0.127269
Theil U2 Coefficient	0.872170
Symmetric MAPE	2.959479



Date	close	forecast
29/04/2001	291.3900	292.6516
6/05/2001	284.0260	289.2310
13/05/2001	287.9710	287.7334
20/05/2001	320.8440	291.7243

21.SN.L

Dependent Variable: D(SN_L)
Method: ML ARCH - Normal distribution (BFGS / Marquardt steps)
Date: 14/12/20 Time: 21:58
Sample (adjusted): 8/02/2010 25/11/2013
Included observations: 199 after adjustments
Convergence achieved after 45 iterations
Coefficient covariance computed using outer product of gradients
MA Backcast: 11/01/2010 1/02/2010
Presample variance: backcast (parameter = 0.7)
GARCH = C(4) + C(5)*RESID(-1)^2 + C(6)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	1.519089	1.314225	1.155882	0.2477
AR(4)	-0.875559	0.059980	-14.59755	0.0000
MA(4)	0.819321	0.075126	10.90594	0.0000
Variance Equation				
C	17.78774	13.78584	1.290291	0.1969
RESID(-1)^2	0.088410	0.047189	1.873520	0.0610
GARCH(-1)	0.862104	0.066910	12.88450	0.0000

R-squared	0.070636	Mean dependent var	0.959799
Adjusted R-squared	0.061153	S.D. dependent var	18.56910
S.E. of regression	17.99237	Akaike info criterion	8.603679
Sum squared resid	63450.18	Schwarz criterion	8.702975

Log likelihood	-850.0661	Hannan-Quinn criter.	8.643867
Durbin-Watson stat	2.202150		

Inverted AR Roots	.68+.68i	.68+.68i	-.68-.68i	-.68-.68i
Inverted MA Roots	.67-.67i	.67-.67i	-.67+.67i	-.67+.67i

Date: 14/12/20 Time: 22:01
Sample (adjusted): 8/02/2010 25/11/2013
Q-statistic probabilities adjusted for 2 ARMA terms

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob*
*|. |	*|. |	1	-0.105	-0.105	2.2179	
.|. |	.|. |	2	0.027	0.016	2.3654	
.|. |	.|. |	3	-0.013	-0.009	2.4005	0.121
*|. |	*|. |	4	-0.103	-0.106	4.5574	0.102
.|. |	.|. |	5	0.025	0.004	4.6873	0.196
.|. |	.|. |	6	0.009	0.017	4.7060	0.319
.|* |	.|* |	7	0.088	0.089	6.3185	0.276
.|. |	.|. |	8	-0.008	-0.001	6.3325	0.387
.|* |	.|* |	9	0.101	0.103	8.4898	0.291
.|. |	.|. |	10	-0.046	-0.020	8.9324	0.348
.|. |	.|. |	11	-0.021	-0.015	9.0303	0.434
.|. |	.|. |	12	-0.012	-0.016	9.0595	0.526
.|. |	.|. |	13	-0.010	0.005	9.0793	0.615
.|. |	.|. |	14	0.011	-0.009	9.1036	0.694
*|. |	*|. |	15	-0.086	-0.097	10.730	0.633
.|. |	.|. |	16	0.047	0.011	11.217	0.669
.|. |	.|. |	17	-0.021	-0.006	11.314	0.730
*|. |	*|. |	18	-0.100	-0.118	13.527	0.634
*|. |	*|. |	19	-0.086	-0.124	15.183	0.582
.|. |	.|. |	20	0.052	0.050	15.782	0.608
.|. |	.|. |	21	-0.027	-0.015	15.945	0.661
.|. |	.|. |	22	0.069	0.053	17.030	0.651
.|. |	.|. |	23	-0.016	-0.022	17.089	0.706
*|. |	*|. |	24	-0.108	-0.079	19.751	0.599

*Probabilities may not be valid for this equation specification.

Heteroskedasticity Test: ARCH

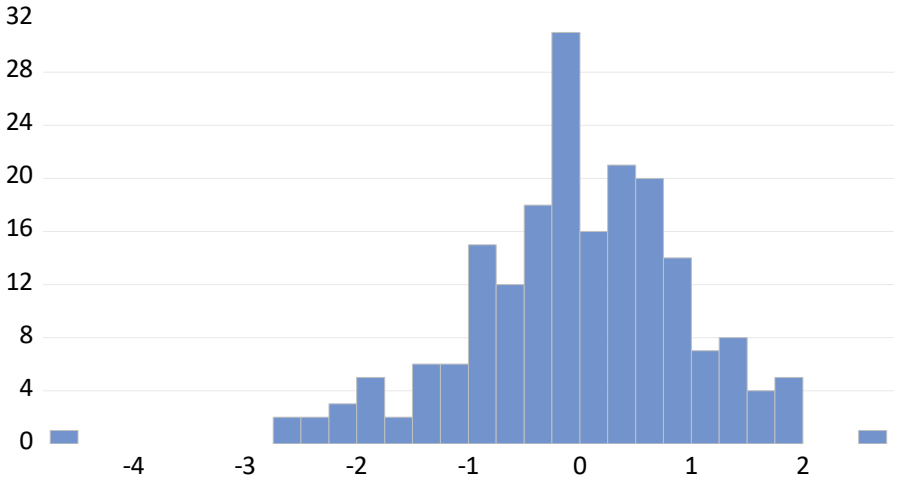
F-statistic	0.569836	Prob. F(1,196)	0.4512
Obs*R-squared	0.573982	Prob. Chi-Square(1)	0.4487

Test Equation:
Dependent Variable: WGT_RESID^2
Method: Least Squares
Date: 14/12/20 Time: 22:01
Sample (adjusted): 15/02/2010 25/11/2013
Included observations: 198 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1.051483	0.154022	6.826815	0.0000
WGT_RESID^2(-1)	-0.053838	0.071320	-0.754875	0.4512

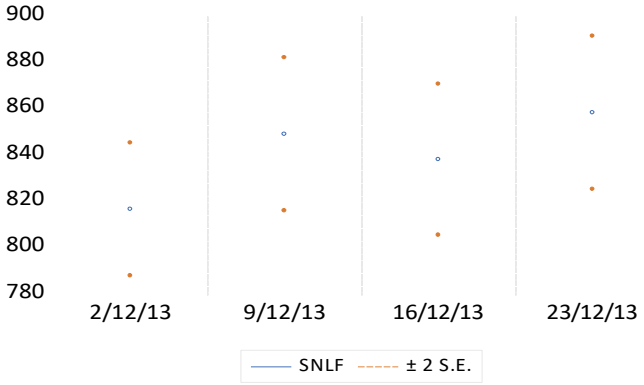
R-squared	0.002899	Mean dependent var	0.997808

Adjusted R-squared	-0.002188	S.D. dependent var	1.920424
S.E. of regression	1.922525	Akaike info criterion	4.155205
Sum squared resid	724.4357	Schwarz criterion	4.188420
Log likelihood	-409.3653	Hannan-Quinn criter.	4.168649
F-statistic	0.569836	Durbin-Watson stat	2.003195
Prob(F-statistic)	0.451230		



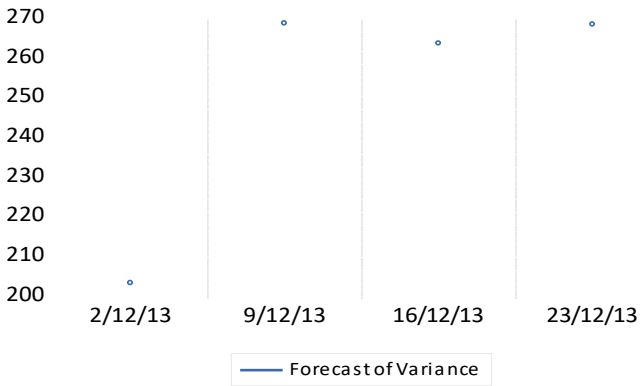
Series: Standardized Residuals
Sample 8/02/2010 25/11/2013
Observations 199

Mean	-0.040296
Median	-0.026251
Maximum	2.733875
Minimum	-4.500184
Std. Dev.	0.999670
Skewness	-0.636687
Kurtosis	4.584057
Jarque-Bera	34.25054
Probability	0.000000



Forecast: SNLF
Actual: SNL
Forecast sample: 2/12/2013 23/12/2013
Included observations: 4

Root Mean Squared Error	18.24706
Mean Absolute Error	16.31609
Mean Abs. Percent Error	1.923406
Theil Inequality Coef.	0.010788
Bias Proportion	0.298631
Variance Proportion	0.071113
Covariance Proportion	0.630256
Theil U2 Coefficient	0.942978
Symmetric MAPE	1.941180



Date	close	forecast
2/12/2013	846.0000	816.7341
9/12/2013	836.5000	849.1892
16/12/2013	854.5000	838.2273
23/12/2013	865.5000	858.4634

(ix) Double exponential smoothing technique

1. FTSE-All Share Index

Date	FTSE-All	Smooth	Level	Trend	Fits	Residuals	Forecast	Upper	Lower
03/04/2017	4010.28	4045.68	4045.68	12.87	4054.53	-44.2495	4054.53	4227.892	3881.167
10/04/2017	4012.3	4049.3	4049.3	11.02002	4058.55	-46.2496	4069.17	4246.144	3892.195
17/04/2017	3912.58	4030.772	4030.772	5.110435	4060.32	-147.74	4083.809	4264.674	3902.945
24/04/2017	3962.49	4021.204	4021.204	2.174745	4035.882	-73.3922	4098.449	4283.464	3913.435

2. FTSE-350 General Industrial Index

Date	FTSE-350	Smooth	Level	Trend	Fits	Resid	Forecast	Upper	Lower
42827.00	5795.67	6033.81	6033.81	9.44	6093.35	-297.68	6093.35	6390.76	5795.93
42834.00	5801.53	5994.91	5994.91	-0.23	6043.25	-241.72	6114.69	6418.31	5811.08
42841.00	5657.35	5927.21	5927.21	-13.72	5994.68	-337.33	6136.04	6446.33	5825.76
42848.00	5852.57	5901.31	5901.31	-16.16	5913.49	-60.92	6157.39	6474.80	5839.98

The primary industry

3. ANTO.L

Date	ANTO.L	Smooth	Level	Trend	Fits	Resid	Forecast	Upper	Lower
03/04/2017	869	866.5734	866.5734	6.856193	865.9667	3.033305	865.9667	968.8763	763.0571
10/04/2017	835	865.7436	865.7436	5.319011	873.4295	-38.4295	872.7016	977.7553	767.6478
17/04/2017	818.5	860.5501	860.5501	3.216505	871.0627	-52.5627	879.4364	986.7993	772.0735
24/04/2017	838	858.6133	858.6133	2.18584	863.7666	-25.7666	886.1713	995.9979	776.3447

Series	RMSE	MAE	MAPE	Theil U1	Theil U2
ANTO.L	43.19817	37.46064	4.514366	0.025168	2.070696

4. BP.L

Date	BP.L	Smooth	Level	Trend	Fits	Resid	Forecast	Upper
01/03/2010	575.5	586.3932	586.3932	-2.64162	589.1164	-13.6164	589.1164	650.199
08/03/2010	619.900024	590.9812	590.9812	-1.19568	583.7515	36.14849	587.0195	649.3747
15/03/2010	635.099976	598.8484	598.8484	0.616896	589.7856	45.31442	584.9225	648.6483
22/03/2010	631.599976	605.8923	605.8923	1.902281	599.4653	32.13464	582.8256	648.0137

Series	RMSE	MAE	MAPE	Theil U1	Theil U2
BP.L	39.25321	36.36221	5.823316	0.032658	1.544930

5. **CNA.L**

Date	CNA.L	Smooth	Level	Trend	Fits	Resid	Forecast	Upper	Lower
08/06/2014	326.299988	333.7322	333.7322	0.482682	335.5902	-9.29021	335.5902	356.1665	315.0139
15/06/2014	319.799988	331.3319	331.3319	-0.09391	334.2148	-14.4148	336.4445	357.4495	315.4395
22/06/2014	312.799988	327.5504	327.5504	-0.83143	331.238	-18.438	337.2988	358.7655	315.8321
29/06/2014	314.700012	324.3151	324.3151	-1.31219	326.7189	-12.0189	338.1531	360.1124	316.1938

Series	RMSE	MAE	MAPE	Theil U1	Theil U2
CNA.L	19.45240	18.47164	5.834100	0.029684	3.929118

6. **SVT.L**

Date	SVT.L	Smooth	Level	Trend	Fits	Resid	Forecast	Upper	Lower
09/04/2017	2444	2434.245	2434.245	21.98814	2431.806	12.19358	2431.806	2594.964	2268.649
16/04/2017	2320	2428.987	2428.987	16.53881	2456.233	-136.233	2453.307	2619.864	2286.75
23/04/2017	2325	2421.42	2421.42	11.71779	2445.525	-120.525	2474.807	2645.025	2304.589
30/04/2017	2373	2421.111	2421.111	9.312268	2433.138	-60.1381	2496.308	2670.431	2322.184

Series	RMSE	MAE	MAPE	Theil U1	Theil U2
SVT.L	117.8626	104.6538	4.471125	0.024401	1.820317

7. JMAT.L

Date	JMAT.L	Smooth	Level	Trend	Fits	Resid	Forecast	Upper	Lower
01/03/2010	1826	1679.86	1679.86	10.95416	1643.325	182.675	1643.325	1831.029	1455.621
08/03/2010	1818.67	1716.385	1716.385	16.06839	1690.814	127.8559	1646.972	1838.587	1455.358
15/03/2010	1830.19	1752.001	1752.001	19.97784	1732.454	97.73623	1650.619	1846.446	1454.793
22/03/2010	1837.52	1785.087	1785.087	22.59949	1771.979	65.54122	1654.266	1854.587	1453.946

Series	RMSE	MAE	MAPE	Theil U1	Theil U2
JMAT.L	179.3585	179.2993	9.807355	0.051586	19.89782

The Manufacturing industry:

8. **ABF.L**

Date	ABF.L	Smooth	Level	Trend	Fits	Resid	Forecast	Upper	Lower
30/11/2009	812	831.1507	831.1507	-2.86051	835.9383	-23.9383	835.9383	917.2846	754.5921
07/12/2009	808.5	824.3321	824.3321	-3.65212	828.2902	-19.7902	834.0354	917.0765	750.9942
14/12/2009	804.5	817.444	817.444	-4.29932	820.68	-16.18	832.1324	916.9988	747.2659
21/12/2009	819	814.3158	814.3158	-4.0651	813.1447	5.855312	830.2294	917.0433	743.4155

Series	RMSE	MAE	MAPE	Theil U1	Theil U2
ABF.L	22.99318	22.08387	2.728067	0.013985	2.528351

9. BATS.L

Date	close	Smooth	Level	Trend	Fits	Resid	Forecast	Upper	Lower
01/03/2010	2054	2151.586	2151.586	18.32683	2175.982	-121.982	2175.982	2329.87	2022.095
08/03/2010	2233.5	2182.63	2182.63	20.87032	2169.913	63.58739	2199.188	2356.282	2042.095
15/03/2010	2233.5	2209.5	2209.5	22.07031	2203.5	29.99959	2222.394	2382.941	2061.848
22/03/2010	2277	2240.657	2240.657	23.88748	2231.571	45.42937	2245.601	2409.831	2081.37

Series	RMSE	MAE	MAPE	Theil U1	Theil U2
BATS.L	65.50994	49.69971	2.337800	0.014848	0.250096

10. BDEV.L

Date	BDEV.L	Smooth	Level	Trend	Fits	Resid	Forecast	Upper	Lower
09/04/2017	572	560.5978	560.5978	7.061162	557.7472	14.25281	557.7472	613.0632	502.4312
16/04/2017	574	568.9271	568.9271	7.314805	567.6589	6.341088	564.2382	620.7068	507.7697
23/04/2017	579.5	576.8935	576.8935	7.445128	576.2419	3.258065	570.7293	628.439	513.0195
30/04/2017	590.5	585.5709	585.5709	7.691581	584.3387	6.161324	577.2203	636.2544	518.1863

Series	RMSE	MAE	MAPE	Theil U1	Theil U2
BDEV.L	11.74425	11.51624	1.988697	0.010243	1.503635

11. BKG.L

Date	BKG.L	Smooth	Level	Trend	Fits	Resid	Forecast	Upper	Lower
09/04/2017	3180	3196.958	3196.958	29.96031	3201.198	-21.198	3201.198	3518.28	2884.116
16/04/2017	3286	3238.735	3238.735	32.32356	3226.919	59.08129	3232.006	3555.694	2908.318
23/04/2017	3258	3268.447	3268.447	31.80122	3271.059	-13.0585	3262.814	3593.617	2932.011
30/04/2017	3311	3302.398	3302.398	32.2313	3300.248	10.75196	3293.623	3632.017	2955.229

Series	RMSE	MAE	MAPE	Theil U1	Theil U2
BKG.L	30.37200	24.34589	0.745590	0.004668	0.469225

12. DGE.L

Date	DGE.L	Smooth	Level	Trend	Fits	Residuals	Forecast	Upper	Lower
09/04/2017	2298	2343.358	2343.358	14.06765	2354.698	-56.6981	2354.698	2505.996	2203.4
16/04/2017	2208	2327.541	2327.541	8.090602	2357.426	-149.426	2371.034	2525.484	2216.583
23/04/2017	2246.5	2317.805	2317.805	4.525342	2335.632	-89.1315	2387.369	2545.215	2229.524
30/04/2017	2277.5	2313.364	2313.364	2.73212	2322.331	-44.8305	2403.705	2565.172	2242.237

Series	RMSE	MAE	MAPE	Theil U1	Theil U2
DGE.L	128.0297	121.7015	5.415759	0.027610	2.458514

The service industry

13. ADN.L

Date	ADN.L	Smooth	Level	Trend	Fits	Resid	Forecast	Upper	Lower
09/04/2017	283.5	273.7819	273.7819	2.188404	271.3523	12.14767	271.3523	329.3677	213.337
16/04/2017	276.799988	276.1362	276.1362	2.221592	275.9703	0.829723	273.0548	332.279	213.8307
23/04/2017	279	278.4862	278.4862	2.24728	278.3578	0.642198	274.7573	335.2832	214.2314
30/04/2017	294.899994	283.5668	283.5668	2.813939	280.7335	14.16647	276.4598	338.3747	214.545

Series	RMSE	MAE	MAPE	Theil U1	Theil U2
ADN.L	11.39773	9.643923	3.352904	0.020443	1.111195

14. AHT.L

Date	AHT.L	Smooth	Level	Trend	Fits	Resid	Forecast	Upper	Lower
29/04/2001	98.237999	93.91531	93.91531	-1.84704	92.83464	5.403358	92.83464	124.4579	61.21134
06/05/2001	104.287003	94.51202	94.51202	-1.35829	92.06827	12.21873	90.77147	123.0537	58.48927
13/05/2001	109.992996	96.52158	96.52158	-0.68472	93.15373	16.83927	88.70829	121.7001	55.71651
20/05/2001	109.767998	98.62309	98.62309	-0.12747	95.83686	13.93114	86.64512	120.394	52.89626

Series	RMSE	MAE	MAPE	Theil U1	Theil U2
AHT.L	17.31742	15.83162	14.71910	0.088603	3.928435

15. AV.L

Date	AV.L	Smooth	Level	Trend	Fits	Resid	Forecast	Upper	Lower
29/04/2001	873.504	869.538	869.538	-2.63432	868.5465	4.957499	868.5465	997.7411	739.352
06/05/2001	876.262	868.7754	868.7754	-2.25998	866.9037	9.358312	865.7139	997.6003	733.8275
13/05/2001	850.517	863.3157	863.3157	-2.89992	866.5154	-15.9984	862.8813	997.6666	728.0959
20/05/2001	851.436	858.6198	858.6198	-3.25911	860.4158	-8.97982	860.0487	997.927	722.1703

Series	RMSE	MAE	MAPE	Theil U1	Theil U2
AV.L	9.524878	9.120645	1.059147	0.005514	0.715380

16. BAB.L

Date	BAB.L	Smooth	Level	Trend	Fits	residual	Forecast	Upper	Lower
09/04/2017	885.5	883.6234	883.6234	-1.45579	883.1542	2.345774	883.1542	984.8992	781.4093
16/04/2017	903	886.3341	886.3341	-0.62249	882.1676	20.83241	881.6046	985.4695	777.7398
23/04/2017	899	888.3693	888.3693	-0.09095	885.7116	13.28841	880.055	986.2029	773.9071
30/04/2017	915.5	893.7227	893.7227	0.997914	888.2783	27.22168	878.5054	987.0891	769.9217

Series	RMSE	MAE	MAPE	Theil U1	Theil U2
BAB.L	23.40289	19.92020	2.195635	0.013136	1.907208

17. BARC.L

Date	BARC.L	Smooth	Level	Trend	Fits	residual	Forecast	Upper	Lower
29/08/2004	488.199	459.5365	459.5365	4.147502	452.3709	35.82807	452.3709	509.8896	394.8523
05/09/2004	492.818	469.5108	469.5108	5.31286	463.6841	29.13394	455.0853	513.8024	396.3682
12/09/2004	493.28	478.515	478.515	6.051112	474.8237	18.4563	457.7997	517.8074	397.792
19/09/2004	498.822	487.4173	487.4173	6.621348	484.5661	14.25592	460.5141	521.8988	399.1293

Series	RMSE	MAE	MAPE	Theil U1	Theil U2
BARC.L	36.85700	36.83724	7.466937	0.038807	8.907646

The quaternary industry

18. AZN.L

Date	AZN.L	Smooth	Level	Trend	Fits	residual	Forecast	Upper	Lower
02/12/2013	3489	3393.001	3393.001	30.65985	3369.002	119.9982	3369.002	3590.143	3147.86
09/12/2013	3518.5	3442.629	3442.629	34.4534	3423.661	94.83871	3394.862	3620.611	3169.113
16/12/2013	3588.5	3499.366	3499.366	38.9101	3477.082	111.4176	3420.722	3651.433	3190.011
23/12/2013	3605	3551.621	3551.621	41.57906	3538.276	66.72396	3446.582	3682.587	3210.576

Series	RMSE	MAE	MAPE	Theil U1	Theil U2
AZN.L	143.9896	142.4583	4.005783	0.020693	3.349079

19. GSK.L

Date	GSK.L	Smooth	Level	Trend	Fits	residual	Forecast	Upper	Lower
29/04/2001	1890	1815.846	1815.846	3.03852	1797.307	92.69266	1797.307	2031.966	1562.648
06/05/2001	1937	1842.508	1842.508	7.763144	1818.884	118.1156	1796.638	2036.187	1557.09
13/05/2001	1935	1867.217	1867.217	11.15232	1850.271	84.72934	1795.969	2040.783	1551.155
20/05/2001	1879	1878.495	1878.495	11.17756	1878.369	0.631156	1795.3	2045.731	1544.868

Series	RMSE	MAE	MAPE	Theil U1	Theil U2
GSK.L	116.8640	113.9464	5.947575	0.031527	2.933498

20. SHP.L

Date	SHP.L	Smooth	Level	Trend	Fits	residual	Forecast	Upper	Lower
29/08/2010	1451	1436.575	1436.575	0.003296	1432.968	18.03176	1432.968	1553.379	1312.557
05/09/2010	1499	1449.062	1449.062	2.50018	1436.578	62.42211	1432.25	1555.17	1309.331
12/09/2010	1468	1454.85	1454.85	3.157681	1451.562	16.43751	1431.532	1557.154	1305.911
19/09/2010	1472	1460.806	1460.806	3.717374	1458.008	13.99233	1430.814	1559.318	1302.31

Series	RMSE	MAE	MAPE	Theil U1	Theil U2
SHP.L	44.17812	40.60872	2.744445	0.015210	1.511719

21. SGE.L

Date	SGE.L	Smooth	Level	Trend	Fits	residual	Forecast	Upper	Lower
29/04/2001	291.39	262.743	262.743	-2.19209	255.5813	35.80875	255.5813	339.093	172.0695
06/05/2001	284.026	265.2459	265.2459	-1.25309	260.5509	23.47508	251.9568	337.2086	166.7051
13/05/2001	287.971	268.7885	268.7885	-0.29396	263.9929	23.97816	248.3324	335.458	161.2067
20/05/2001	320.844	278.9644	278.9644	1.800018	268.4945	52.34947	244.7079	333.8329	155.583

Series	RMSE	MAE	MAPE	Theil U1	Theil U2
SGE.L	49.18998	45.91315	15.26865	0.089994	2.705754

22. SN.L

Date	SN.L	Smooth	Level	Trend	Fits	residual	Forecast	Upper	Lower
02/12/2013	846	816.4392	816.4392	5.087239	809.049	36.95103	809.049	860.4102	757.6878
09/12/2013	836.5	824.5211	824.5211	5.686183	821.5264	14.97358	812.6582	865.0895	760.2268
16/12/2013	854.5	835.0659	835.0659	6.65789	830.2073	24.29269	816.2674	869.8512	762.6836
23/12/2013	865.5	846.479	846.479	7.60894	841.7237	23.77626	819.8766	874.69	765.0632

Series	RMSE	MAE	MAPE	Theil U1	Theil U2
SN.L	37.00353	36.16223	4.240883	0.022222	2.756107

(x) Triple exponential smoothing technique:

1. FTSE-All Share Index

Date	FTSE-All	Smooth	Level	Trend	Seasonal	Fits	Residuals	Forecast	Upper	Lower
03/04/2017	4010.28	4030.19	4007.13	11.26	23.93	4042.75	-32.47	4042.75	4213.55	3871.95
10/04/2017	4012.30	4038.25	4010.95	9.77	25.16	4049.51	-37.21	4057.30	4230.77	3883.82

17/04/2017	3912.58	4036.68	3993.95	4.42	4.31	4046.45	-133.87	4064.47	4240.93	3888.01
24/04/2017	3962.49	4017.88	3986.40	2.02	14.36	4022.29	-59.80	4080.43	4260.16	3900.69

2. FTSE-350 General Industrial Index

Date	FTSE-350	Smooth	Level	Trend	Season	Fits	Resid	Forecast	Upper	Lower
02/04/2017	5795.67	6037.997	6002.578	7.422022	-40.4083	6055.825	-260.155	6055.825	6336.555	5775.095
09/04/2017	5801.53	5987.474	5971.327	-0.31262	-46.0422	5994.896	-193.366	6057.333	6342.462	5772.205
16/04/2017	5657.35	5949.585	5912.629	-11.9895	-68.4488	5949.273	-291.923	6068.524	6358.556	5778.492
23/04/2017	5852.57	5872.221	5899.108	-12.296	-41.6342	5860.232	-7.66152	6109.31	6404.727	5813.893

The Primary Industry

3. ANTO.L

Date	ANTO.L	Smooth	Level	Trend	Seasonal	Fits	Resid	Forecast	Upper	Lower
2017-04-03	869.00	857.36	866.51	7.74	-0.12	864.93	4.07	864.93	963.93	765.94
2017-04-10	835.00	866.62	866.38	6.17	-6.19	874.36	-39.36	873.38	973.93	772.84
2017-04-17	818.50	847.88	865.44	4.74	-24.19	854.04	-35.54	862.35	964.63	760.07
2017-04-24	838.00	865.33	863.77	3.46	-5.25	870.07	-32.07	887.67	991.84	783.49

Series	RMSE	MAE	MAPE	Theil U1	Theil U2
ANTO.L	38.33910	33.99165	4.087236	0.022388	1.836150

4. BP.L

Date	BP.L	Smooth	Level	Trend	Season	Fits	Resid	Forecast	Upper	Lower
01/03/2010	575.5	585.185	586.111	-1.92577	-5.43819	583.5825	-8.08248	583.5825	638.8025	528.3624
08/03/2010	619.90002	583.9189	591.7666	-0.409493	.872984	581.993	137.90694	583.9329	640.018	527.8477
15/03/2010	635.09997	588.0906	600.8409	1.4872643	.910988	587.681	147.41891	580.8465	637.8963	523.7967
22/03/2010	631.59997	595.4027	609.2702	2.8756650	.115412	596.893	4.71001	578.7751	636.884	520.6661

Series	RMSE	MAE	MAPE	Theil U1	Theil U2
BP.L	42.10960	37.78200	6.028173	0.035157	1.675553

5. CNA.L

Date	CNA.L	Smooth	Level	Trend	Season	Fits	Resid	Forecast	Upper	Lower
08/06/2014	326.29998	332.7863	333.9923	0.296894	-3.1701	333.3659	-7.06588	333.3659	353.1474	313.5844
15/06/2014	319.79998	332.704	331.649	-0.23114	-3.40036	333.0009	-13.201	334.6968	354.7882	314.6053

22/06/2014312.799988329.8933328.0454 -0.90563 -4.45363329.6621 -16.8621334.8088355.2458314.3718

29/06/2014314.700012324.8753325.2858 -1.27642 -4.65325323.9696 -9.26964335.1045355.9208314.2881

Series	RMSE	MAE	MAPE	Theil U1	Theil U2
CNA.L	17.12140	16.09397	5.085861	0.026222	3.483295

6. SVT.L

Date	SVT.L	Smooth	Level	Trend	Season	Fits	Resid	Forecast	Upper	Lower
09/04/2017	2444	2408.999841	2411.133	17.21904	21.0128	2425.478	18.522	2425.478	2575.453	2275.503
16/04/2017	2320	2426.012988	2403.706	12.28976	-4.83726	2443.232	-123.232	2438.787	2591.111	2286.463
23/04/2017	2325	2420.250444	2394.487	7.988151	-0.66175	2432.54	-107.54	2456.93	2611.874	2301.986
30/04/2017	2373	2415.500273	2392.378	5.968614	12.93465	2423.488	-50.4884	2474.912	2632.733	2317.092

Series	RMSE	MAE	MAPE	Theil U1	Theil U2
SVT.L	102.7679	92.78774	3.961760	0.021343	1.581641

7. JMAT.L

Date	JMAT.L	Smooth	Level	Trend	Season	Fits	Resid	Forecast	Upper	Lower
01/03/2010	1826	1634.403	1673.152	12.26201	33.29108	1639.193	186.8073	1639.193	1821.332	1457.053
08/03/2010	1818.67	1683.167	1710.063	17.19167	29.733	1695.429	123.2414	1650.595	1835.588	1465.602
15/03/2010	1830.19	1727.08	1744.438	20.62838	30.7648	1744.272	85.91779	1662.388	1850.563	1474.213
22/03/2010	1837.52	1777.729	1772.899	22.1949	39.55712	1798.357	39.1628	1653.562	1845.23	1461.893

Series	RMSE	MAE	MAPE	Theil U1	Theil U2
JMAT.L	176.8787	176.6606	9.662958	0.050834	19.35932

The manufacturing industry

8. ABF.L

Date	ABF.L	Smooth	Level	Trend	Season	Fits	Resid	Forecast	Upper	Lower
30/11/2009	812	837.6088	819.4439	-1.93766	8.3369	836.6574	-24.6574	836.6574	912.993	760.3219
07/12/2009	808.5	831.3769	813.3183	-2.77523	8.582799	829.4393	-20.9393	835.3571	912.8886	757.8256
14/12/2009	804.5	814.0924	809.1797	-3.04792	-0.31672	811.3171	-6.81713	823.2466	902.1116	744.3817
21/12/2009	819	817.5166	807.038	-2.86666	9.061913	814.4687	4.531328	833.8034	914.1325	753.4742

Series	RMSE	MAE	MAPE	Theil U1	Theil U2
ABF.L	21.79374	21.26613	2.624046	0.013262	2.314116

9. BATS.L

Date	close	Smooth	Level	Trend	Season	Fits	Resid	Forecast	Upper	Lower
01/03/2010	2054	2174.094	2153.685	16.42386	-8.67267	2196.206	-142.206	2196.206	2336.539	2055.874
08/03/2010	2233.5	2167.331	2180.058	18.41366	21.60555	2183.755	49.74508	2217.884	2360.416	2075.353
15/03/2010	2233.5	2199.93	2201.502	19.0199	22.29779	2218.344	15.15588	2246.223	2391.206	2101.241
22/03/2010	2277	2192.83	2233.552	21.62591	1.751382	2211.85	65.15034	2262.543	2410.217	2114.869

Series	RMSE	MAE	MAPE	Theil U1	Theil U2
BATS.L	72.17579	46.25057	2.206778	0.016285	0.128392

10. BDEV.L

Date	BDEV.L	Smooth	Level	Trend	Season	Fits	Resid	Forecast	Upper	Lower
09/04/2017	572	550.5444	541.0516	6.453354	20.94688	556.3727	15.62731	556.3727	609.6395	503.1059
16/04/2017	574	560.4635	548.9216	6.73668	20.54517	566.9169	7.083145	563.1663	617.2676	509.065
23/04/2017	579.5	572.6854	555.6739	6.739796	23.77627	579.4221	0.077895	573.3465	628.3783	518.3147
30/04/2017	590.5	576.6208	563.8416	7.025374	22.08919	583.3606	7.139443	573.8575	629.911	517.804

Series	RMSE	MAE	MAPE	Theil U1	Theil U2
BDEV.L	13.00405	12.31426	2.124924	0.011350	1.672187

11. BKG.L

Date	BKG.L	Smooth	Level	Trend	Season	Fits	Resid	Forecast	Upper	Lower
09/04/2017	3180	3167.645	3130.844	30.52621	61.27057	3198.928	-18.9283	3198.928	3499.864	2897.993
16/04/2017	3286	3193.325	3173.799	33.01215	72.42545	3223.851	62.14855	3228.394	3534.045	2922.744
23/04/2017	3258	3239.404	3203.928	32.43549	63.29815	3272.416	-14.4164	3262.801	3573.708	2951.893
30/04/2017	3311	3265.199	3239.037	32.97012	63.40906	3297.634	13.3656	3292.778	3609.458	2976.099

Series	RMSE	MAE	MAPE	Theil U1	Theil U2
BKG.L	31.74815	24.88910	0.761496	0.004881	0.499641

12. DGE.L

Date	DGE.L	Smooth	Level	Trend	Season	Fits	Resid	Forecast	Upper	Lower
09/04/2017	2298	2326.574	2273.501	10.81587	50.7588	2339.031	-41.0314	2339.031	2482.631	2195.432
16/04/2017	2208	2329.599	2257.834	5.51927	34.91145	2340.415	-132.415	2350.263	2496.112	2204.413
23/04/2017	2246.5	2307.337	2250.082	2.865023	38.88576	2312.856	-66.3562	2356.125	2504.482	2207.767
30/04/2017	2277.5	2300.841	2247.706	1.816782	46.56584	2303.706	-26.206	2376.403	2527.515	2225.291

Series	RMSE	MAE	MAPE	Theil U1	Theil U2
DGE.L	104.5485	97.95534	4.362744	0.022663	2.015039

The service industry

13. ADN.L

Date	ADN.L	Smooth	Level	Trend	Season	Fits	Resid	Forecast	Upper	Lower
09/04/2017	283.5	271.5089	249.4308	1.248604	26.90754	272.3099	11.19006	272.3099	326.8068	217.8131
16/04/2017	276.8	275.3618	250.7173	1.256187	25.96132	276.6104	0.189574	273.9248	329.2754	218.5742
23/04/2017	279	273.2671	252.8689	1.435257	23.266	274.5232	4.476754	271.3445	327.6471	215.0419
30/04/2017	294.9	279.7764	257.0418	1.98279	29.09768	281.2117	13.68832	274.7129	332.0608	217.3651

Series	RMSE	MAE	MAPE	Theil U1	Theil U2
ADN.L	12.24344	10.47694	3.643779	0.021992	1.255875

14. AHT.L

Date	AHT.L	Smooth	Level	Trend	Season	Fits	Resid	Forecast	Upper	Lower
29/04/2001	98.238	93.825433	891.95886	-1.56059	2.297038	92.01596	6.222038	92.01596	119.0295	65.00239
06/05/2001	104.287	94.126375	592.74251	-1.09174	4.042913	92.56578	11.72122	91.0725	118.5093	63.63571
13/05/2001	109.993	95.230991	294.82152	-0.45759	5.025081	94.13925	15.85375	89.58399	117.4927	61.67531
20/05/2001	109.768	97.118554	796.98533	0.066689	4.394164	96.66096	13.10704	86.58754	115.0143	58.16074

Series	RMSE	MAE	MAPE	Theil U1	Theil U2
AHT.L	17.08214	15.75650	14.66936	0.087368	3.853282

15. AV.L

Date	AV.L	Smooth	Level	Trend	Season	Fits	Resid	Forecast	Upper	Lower
29/04/2001	873.504	873.5405	854.1819	-1.95576	18.04258	871.5048	1.99922	871.5048	988.2884	754.7212
06/05/2001	876.262	877.8857	852.2926	-1.94248	23.7569	875.93	0.332062	875.4501	994.0634	756.8369
13/05/2001	850.517	874.477	845.9466	-2.82318	18.6616	872.5345	-22.0175	871.895	992.5483	751.2418
20/05/2001	851.436	863.9892	841.1774	-3.21238	16.48577	861.166	-9.73005	865.3976	988.2909	742.5044

Series	RMSE	MAE	MAPE	Theil U1	Theil U2
AV.L	12.81213	9.537687	1.118708	00.007388	0.994948

16. BAB.L

Date	BAB.L	Smooth	Level	Trend	Season	Fits	Residual	Forecast	Upper	Lower
09/04/2017	885.5	893.3145	881.8367	-2.6008	7.139126	890.9309	-5.43093	890.9309	980.4261	801.4357

16/04/2017	903	878.3769	884.6806	-1.51184	0.896098	875.7762	27.22385	877.0796	967.9769	786.1823
23/04/2017	899	888.6011	885.5509	-1.03541	5.826179	887.0893	11.91074	882.0762	974.5368	789.6156
30/04/2017	915.5	892.6901	889.2846	-0.0816	10.95438	891.6547	23.84534	883.7803	977.9574	789.6031

Series	RMSE	MAE	MAPE	Theil U1	Theil U2
BAB.L	22.32667	19.99873	2.207764	0.012513	1.812073

17. BARC.L

Date	BARC.L	Smooth	Level	Trend	Season	Fits	Residual	Forecast	Upper	Lower
29/08/2004	488.199	457.4705	468.6783	4.022321	1.716628	460.3801	27.8189	460.3801	512.5342	408.226
05/09/2004	492.818	461.7154	478.1167	5.105532	-2.63003	465.7377	27.08027	459.0612	512.0324	406.09
12/09/2004	493.28	477.9303	485.271	5.5153	1.452688	483.0358	10.24419	468.7473	522.6295	414.865
19/09/2004	498.822	486.9877	492.0501	5.768061	2.727674	492.503	6.319037	469.1088	523.9914	414.2262

Series	RMSE	MAE	MAPE	Theil U1	Theil U2
BARC.L	29.14679	28.95541	5.869521	0.030436	7.089522

The quaternary industry

18. AZN.L

Date	AZN.L	Smooth	Level	Trend	Season	Fits	Residual	Forecast	Upper	Lower
02/12/2013	3489	3368.942	3397.371	27.64943	30.0232	3392.741	96.25915	3392.741	3598.283	3187.199
09/12/2013	3518.5	3429.63	3437.264	30.09825	42.05433	3457.279	61.22059	3434.177	3642.939	3225.415
16/12/2013	3588.5	3457.977	3487.448	34.11526	36.78015	3488.075	100.4251	3446.429	3658.782	3234.077
23/12/2013	3605	3517.471	3532.246	36.25181	38.56941	3551.586	53.41377	3464.138	3680.433	3247.843

Series	RMSE	MAE	MAPE	Theil U1	Theil U2
AZN.L	118.7459	115.8786	3.255487	0.017000	2.772819

19. GSK.L

Date	GSK.L	Smooth	Level	Trend	Season	Fits	Residual	Forecast	Upper	Lower
29/04/2001	1890	1801.13	1826.872	1.502662	4.883203	1798.992	91.00806	1798.992	2014.796	1583.188
06/05/2001	1937	1823.203	1850.833	5.994426	14.29866	1824.706	112.2941	1802.864	2022.049	1583.679
13/05/2001	1935	1841.1	1874.409	9.51063	4.332172	1847.095	87.9051	1794.662	2017.617	1571.708
20/05/2001	1879	1879.292	1881.959	9.118534	3.31482	1888.802	-9.8024	1792.579	2019.673	1565.485

Series	RMSE	MAE	MAPE	Theil U1	Theil U2
GSK.L	115.5836	112.9758	5.898024	0.031174	2.903220

20. SHP.L

Date	SHP.L	Smooth	Level	Trend	Season	Fits	Residual	Forecast	Upper	Lower
29/08/2010	1451	1435.646	1476.191	0.095924	-35.3637	1435.106	15.89432	1435.106	1551.425	1318.786
05/09/2010	1499	1442.207	1487.627	2.363819	-24.9131	1442.303	56.69738	1438.488	1556.63	1320.346
12/09/2010	1468	1450.953	1492.927	2.951149	-34.3245	1453.317	14.68325	1435.259	1555.433	1315.085
19/09/2010	1472	1457.564	1498.175	3.410563	-33.526	1460.515	11.48535	1433.486	1555.891	1311.081

Series	RMSE	MAE	MAPE	Theil U1	Theil U2
BAB.L	40.21700	36.91531	2.494744	0.013829	1.378084

21. SGE.L

Date	SGE.L	Smooth	Level	Trend	Season	Fits	Residual	Forecast	Upper	Lower
29/04/2001	291.39	256.6162	271.8759	-2.96986	-5.64839	252.0736	39.31637	252.0736	327.7556	176.3917
06/05/2001	284.026	273.3306	271.6391	-2.42325	3.641091	270.3607	13.66529	260.9248	337.7924	184.0572
13/05/2001	287.971	263.8259	274.5296	-1.36051	-3.56233	261.4026	26.5684	247.1144	325.304	168.9247
20/05/2001	320.844	268.8812	283.8337	0.772423	2.883341	267.5207	53.32333	238.4461	318.0874	158.8048

Series	RMSE	MAE	MAPE	Theil U1	Theil U2
SGE.L	51.32768	46.41803	15.37389	0.093975	2.802137

22. SN.L

Date	SN.L	Smooth	Level	Trend	Season	Fits	Residual	Forecast	Upper	Lower
02/12/2013	846	809.6343	813.0793	4.747999	11.84222	813.0649	32.93514	813.0649	860.9495	765.1802
09/12/2013	836.5	816.6129	820.8551	5.353563	5.955862	821.3609	15.1391	813.4565	862.0913	764.8216
16/12/2013	854.5	827.0427	830.6294	6.237714	9.724156	832.3962	22.10377	819.541	869.0123	770.0697
23/12/2013	865.5	842.4716	840.2253	6.909339	14.52872	848.7094	16.79064	823.3566	873.7464	772.9669

Series	RMSE	MAE	MAPE	Theil U1	Theil U2
SN.L	33.96292	33.27025	3.902053	0.020361	2.553244

(xi) Forecast encompassing test of Fair-Shiller

1. FTSE-ALL INDUSTRIAL INDEX

Dependent Variable: FTSE_ALL
Method: Least Squares
Date: 26/01/21 Time: 10:56
Sample: 3/04/2017 24/04/2017
Included observations: 4

Variable	Coefficient	Std. Error	t-Statistic	Prob.

C	-2695.466	2392.696	-1.126539	0.4622
ARIMA	198.1257	63.18721	3.135534	0.1965
GARCH01	-196.4468	62.65519	-3.135363	0.1966

R-squared	0.907686	Mean dependent var	3974.413
Adjusted R-squared	0.723057	S.D. dependent var	47.21350
S.E. of regression	24.84629	Akaike info criterion	9.377000
Sum squared resid	617.3384	Schwarz criterion	8.916721
Log likelihood	-15.75400	Hannan-Quinn criter.	8.366951
F-statistic	4.916271	Durbin-Watson stat	3.035486
Prob(F-statistic)	0.303833		

2. FTSE-350 General Industrial Index

Dependent Variable: FTSE_350
Method: Least Squares
Date: 26/01/21 Time: 11:08
Sample: 2/04/2017 23/04/2017
Included observations: 4

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	4054.640	32074.94	0.126411	0.9199
ARIMA	37.71797	197.1521	0.191314	0.8797
GARCH01	-37.39626	191.6058	-0.195173	0.8773

R-squared	0.324970	Mean dependent var	5776.780
Adjusted R-squared	-1.025089	S.D. dependent var	83.62026
S.E. of regression	118.9963	Akaike info criterion	12.50977
Sum squared resid	14160.13	Schwarz criterion	12.04949
Log likelihood	-22.01954	Hannan-Quinn criter.	11.49972
F-statistic	0.240708	Durbin-Watson stat	2.392168
Prob(F-statistic)	0.821602		

The primary industry

3. ANTO.L

Dependent Variable: ANTO_L
Method: Least Squares
Date: 26/01/21 Time: 11:14
Sample: 3/04/2017 24/04/2017
Included observations: 4

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1157.876	636.2624	1.819809	0.3199
ARIMA	-50.88258	492.8797	-0.103235	0.9345
GARCH01	50.51296	492.6439	0.102534	0.9350

R-squared	0.212229	Mean dependent var	840.1250
Adjusted R-squared	-1.363314	S.D. dependent var	21.07279
S.E. of regression	32.39536	Akaike info criterion	9.907613
Sum squared resid	1049.459	Schwarz criterion	9.447334
Log likelihood	-16.81523	Hannan-Quinn criter.	8.897564
F-statistic	0.134702	Durbin-Watson stat	0.812732

Prob(F-statistic)	0.887565

4. BP.L

Dependent Variable: PB_L
Method: Least Squares
Date: 26/01/21 Time: 11:18
Sample: 1/03/2010 22/03/2010
Included observations: 4

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1549.254	881.5247	1.757471	0.3293
GARCH01	-142.0134	94.07462	-1.509582	0.3725
ARIMA	140.4348	92.63878	1.515940	0.3712

R-squared	0.834477	Mean dependent var	615.5250
Adjusted R-squared	0.503430	S.D. dependent var	27.46348
S.E. of regression	19.35289	Akaike info criterion	8.877267
Sum squared resid	374.5345	Schwarz criterion	8.416987
Log likelihood	-14.75453	Hannan-Quinn criter.	7.867218
F-statistic	2.520720	Durbin-Watson stat	3.157530
Prob(F-statistic)	0.406846		

5. CNA.L

Dependent Variable: CNA_L
Method: Least Squares
Date: 26/01/21 Time: 11:22
Sample: 8/06/2014 29/06/2014
Included observations: 4

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	142.0894	116.5174	1.219470	0.4373
GARCH01	1.107658	4.500762	0.246105	0.8464
ARIMA	-0.562190	4.208358	-0.133589	0.9155

R-squared	0.846430	Mean dependent var	318.4000
Adjusted R-squared	0.539291	S.D. dependent var	6.039316
S.E. of regression	4.099218	Akaike info criterion	5.773175
Sum squared resid	16.80359	Schwarz criterion	5.312896
Log likelihood	-8.546351	Hannan-Quinn criter.	4.763127
F-statistic	2.755852	Durbin-Watson stat	2.349269
Prob(F-statistic)	0.391880		

6. SVT.L

Dependent Variable: SVT_L
Method: Least Squares
Date: 26/01/21 Time: 11:34
Sample: 9/04/2017 30/04/2017
Included observations: 4

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	13878.60	2866.541	4.841583	0.1297
ARIMA	26.99460	7.781616	3.469023	0.1787
GARCH01	-31.65448	8.875883	-3.566347	0.1740

R-squared	0.944579	Mean dependent var	2365.500
Adjusted R-squared	0.833738	S.D. dependent var	57.52970
S.E. of regression	23.45789	Akaike info criterion	9.261997
Sum squared resid	550.2728	Schwarz criterion	8.801718
Log likelihood	-15.52399	Hannan-Quinn criter.	8.251948
F-statistic	8.521889	Durbin-Watson stat	2.710070
Prob(F-statistic)	0.235416		

7. JMAT.L

Dependent Variable: JMAT_L
Method: Least Squares
Date: 26/01/21 Time: 11:38
Sample: 1/03/2010 22/03/2010
Included observations: 4

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1866.853	224.7175	8.307558	0.0763
ARIMA	0.496519	0.976113	0.508670	0.7004
GARCH01	-0.516960	1.058506	-0.488386	0.7108

R-squared	0.229435	Mean dependent var	1828.095
Adjusted R-squared	-1.311694	S.D. dependent var	7.883301
S.E. of regression	11.98597	Akaike info criterion	7.919057
Sum squared resid	143.6635	Schwarz criterion	7.458778
Log likelihood	-12.83811	Hannan-Quinn criter.	6.909008
F-statistic	0.148875	Durbin-Watson stat	1.559128
Prob(F-statistic)	0.877818		

The manufacturing industry

8. ABF.L

Dependent Variable: ABF_L
Method: Least Squares
Date: 26/01/21 Time: 11:59
Sample: 30/11/2009 21/12/2009
Included observations: 4

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1492.346	1880.988	0.793384	0.5730
ARIMA	3.039281	4.995591	0.608393	0.6520
GARCH01	-3.883761	5.461129	-0.711164	0.6065

R-squared	0.338848	Mean dependent var	811.0000
Adjusted R-squared	-0.983455	S.D. dependent var	6.150881
S.E. of regression	8.662604	Akaike info criterion	7.269613
Sum squared resid	75.04071	Schwarz criterion	6.809334

Log likelihood	-11.53923	Hannan-Quinn criter.	6.259565
F-statistic	0.256256	Durbin-Watson stat	2.251686
Prob(F-statistic)	0.813112		

9. BATS.L

Dependent Variable: BATS_L
Method: Least Squares
Date: 26/01/21 Time: 12:04
Sample: 1/03/2010 22/03/2010
Included observations: 4

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-4105.224	3750.622	-1.094545	0.4713
TRIPLE	-1.059427	16.95967	-0.062467	0.9603
DOUBLE	3.920769	16.69417	0.234859	0.8531

R-squared	0.759811	Mean dependent var	2199.500
Adjusted R-squared	0.279433	S.D. dependent var	99.14383
S.E. of regression	84.15944	Akaike info criterion	11.81701
Sum squared resid	7082.812	Schwarz criterion	11.35673
Log likelihood	-20.63402	Hannan-Quinn criter.	10.80696
F-statistic	1.581695	Durbin-Watson stat	2.408116
Prob(F-statistic)	0.490091		

10. BDEV.L

Dependent Variable: BDEV_L
Method: Least Squares
Date: 26/01/21 Time: 19:41
Sample: 9/04/2017 30/04/2017
Included observations: 4

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	408.3642	96.61598	4.226674	0.1479
GARCH01	24.24889	5.656171	4.287156	0.1459
ARIMA	-23.99105	5.792018	-4.142089	0.1508

R-squared	0.986440	Mean dependent var	579.0000
Adjusted R-squared	0.959320	S.D. dependent var	8.296586
S.E. of regression	1.673362	Akaike info criterion	3.981252
Sum squared resid	2.800140	Schwarz criterion	3.520973
Log likelihood	-4.962505	Hannan-Quinn criter.	2.971204
F-statistic	36.37315	Durbin-Watson stat	2.936479
Prob(F-statistic)	0.116447		

11. BKG.L

Dependent Variable: BKG_L
Method: Least Squares
Date: 26/01/21 Time: 19:45

Sample: 9/04/2017 30/04/2017
Included observations: 4

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-2632.248	1267.591	-2.076576	0.2857
DOUBLE	25.93383	9.954033	2.605359	0.2333
TRIPLE	-24.13229	9.701633	-2.487446	0.2433

R-squared	0.956663	Mean dependent var	3258.750
Adjusted R-squared	0.869989	S.D. dependent var	56.78835
S.E. of regression	20.47623	Akaike info criterion	8.990112
Sum squared resid	419.2761	Schwarz criterion	8.529833
Log likelihood	-14.98022	Hannan-Quinn criter.	7.980064
F-statistic	11.03745	Durbin-Watson stat	2.020576
Prob(F-statistic)	0.208176		

12. DGE

Dependent Variable: DGE_L
Method: Least Squares
Date: 26/01/21 Time: 19:51
Sample: 9/04/2017 30/04/2017
Included observations: 4

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1082.394	1601.125	0.676021	0.6216
ARIMA	-149.7584	107.4222	-1.394111	0.3961
GARCH01	150.3238	107.8376	1.393983	0.3962

R-squared	0.660316	Mean dependent var	2257.500
Adjusted R-squared	-0.019053	S.D. dependent var	39.20672
S.E. of regression	39.57846	Akaike info criterion	10.30815
Sum squared resid	1566.455	Schwarz criterion	9.847874
Log likelihood	-17.61631	Hannan-Quinn criter.	9.298104
F-statistic	0.971955	Durbin-Watson stat	1.447156
Prob(F-statistic)	0.582825		

The service industry

13. ADN.L

Dependent Variable: ADN_L
Method: Least Squares
Date: 26/01/21 Time: 19:55
Sample: 9/04/2017 30/04/2017
Included observations: 4

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	470.2888	918.0787	0.512253	0.6986
GARCH01	-15.55523	162.6960	-0.095609	0.9393
ARIMA	14.90096	160.2516	0.092985	0.9410

R-squared	0.050975	Mean dependent var	283.5500
Adjusted R-squared	-1.847076	S.D. dependent var	8.064118
S.E. of regression	13.60681	Akaike info criterion	8.172724
Sum squared resid	185.1454	Schwarz criterion	7.712445
Log likelihood	-13.34545	Hannan-Quinn criter.	7.162675
F-statistic	0.026856	Durbin-Watson stat	1.761632
Prob(F-statistic)	0.974179		

14. AHT.L

Dependent Variable: AHT_L
Method: Least Squares
Date: 26/01/21 Time: 19:59
Sample: 29/04/2001 20/05/2001
Included observations: 4

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	32.49719	47.31325	0.686852	0.6169
GARCH01	-5.864837	9.599615	-0.610945	0.6509
ARIMA	6.637091	9.503981	0.698348	0.6119

R-squared	0.816317	Mean dependent var	105.5715
Adjusted R-squared	0.448950	S.D. dependent var	5.555491
S.E. of regression	4.123992	Akaike info criterion	5.785226
Sum squared resid	17.00731	Schwarz criterion	5.324947
Log likelihood	-8.570452	Hannan-Quinn criter.	4.775178
F-statistic	2.222077	Durbin-Watson stat	2.099689
Prob(F-statistic)	0.428583		

15. AV.L

Dependent Variable: AV_L
Method: Least Squares
Date: 26/01/21 Time: 20:03
Sample: 29/04/2001 20/05/2001
Included observations: 4

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-2067.613	1690.854	-1.222822	0.4364
DOUBLE	2.771968	2.558960	1.083240	0.4746
TRIPLE	0.613891	2.242703	0.273728	0.8299

R-squared	0.752758	Mean dependent var	862.9298
Adjusted R-squared	0.258273	S.D. dependent var	13.85337
S.E. of regression	11.93102	Akaike info criterion	7.909866
Sum squared resid	142.3492	Schwarz criterion	7.449587
Log likelihood	-12.81973	Hannan-Quinn criter.	6.899817
F-statistic	1.522306	Durbin-Watson stat	3.348612
Prob(F-statistic)	0.497235		

16. BAB.L

Dependent Variable: BAB_L
Method: Least Squares
Date: 26/01/21 Time: 20:07
Sample: 9/04/2017 30/04/2017
Included observations: 4

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-328.8799	34.86937	-9.431770	0.0672
ARIMA	10.23028	0.264755	38.64063	0.0165
GARCH01	-8.847952	0.239294	-36.97518	0.0172

R-squared	0.999388	Mean dependent var	900.7500
Adjusted R-squared	0.998164	S.D. dependent var	12.35921
S.E. of regression	0.529548	Akaike info criterion	1.680119
Sum squared resid	0.280421	Schwarz criterion	1.219840
Log likelihood	-0.360239	Hannan-Quinn criter.	0.670071
F-statistic	816.5751	Durbin-Watson stat	2.006692
Prob(F-statistic)	0.024737		

17. BARC.L

Dependent Variable: BARC_L
Method: Least Squares
Date: 26/01/21 Time: 20:11
Sample: 29/08/2004 19/09/2004
Included observations: 4

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	284.9279	128.0879	2.224472	0.2690
GARCH01	1.377159	2.565607	0.536777	0.6864
ARIMA	-0.955193	2.464001	-0.387659	0.7646

R-squared	0.730605	Mean dependent var	493.2798
Adjusted R-squared	0.191814	S.D. dependent var	4.349091
S.E. of regression	3.909796	Akaike info criterion	5.678553
Sum squared resid	15.28651	Schwarz criterion	5.218274
Log likelihood	-8.357106	Hannan-Quinn criter.	4.668505
F-statistic	1.356009	Durbin-Watson stat	3.260575
Prob(F-statistic)	0.519033		

The quaternary industry

18. AZN.L

Dependent Variable: AZN_L
Method: Least Squares
Date: 26/01/21 Time: 20:15
Sample: 2/12/2013 23/12/2013
Included observations: 4

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1541.753	2338.613	0.659260	0.6289
ARIMA	3.291776	2.274495	1.447256	0.3849
GARCH01	-2.720261	2.411173	-1.128190	0.4617

R-squared	0.751163	Mean dependent var	3550.250
Adjusted R-squared	0.253488	S.D. dependent var	55.43840
S.E. of regression	47.89930	Akaike info criterion	10.68978
Sum squared resid	2294.342	Schwarz criterion	10.22951
Log likelihood	-18.37957	Hannan-Quinn criter.	9.679736
F-statistic	1.509345	Durbin-Watson stat	2.813746
Prob(F-statistic)	0.498836		

19. GSK.L

Dependent Variable: GSK_L
Method: Least Squares
Date: 26/01/21 Time: 20:19
Sample: 29/04/2001 20/05/2001
Included observations: 4

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1343.727	5450.131	0.246549	0.8461
ARIMA	1.316219	17.48923	0.075259	0.9522
GARCH01	-1.018634	14.72640	-0.069171	0.9560

R-squared	0.021757	Mean dependent var	1910.250
Adjusted R-squared	-1.934729	S.D. dependent var	30.08183
S.E. of regression	51.53334	Akaike info criterion	10.83604
Sum squared resid	2655.685	Schwarz criterion	10.37576
Log likelihood	-18.67208	Hannan-Quinn criter.	9.825992
F-statistic	0.011120	Durbin-Watson stat	1.902368
Prob(F-statistic)	0.989062		

20. SHP.L

Dependent Variable: SHP_L
Method: Least Squares
Date: 26/01/21 Time: 20:23
Sample: 29/08/2010 19/09/2010
Included observations: 4

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1686.645	650.9021	2.591242	0.2345
GARCH01	-40.79860	42.41684	-0.961849	0.5124
ARIMA	40.65276	42.11828	0.965205	0.5113

R-squared	0.526496	Mean dependent var	1472.500
Adjusted R-squared	-0.420512	S.D. dependent var	19.87461
S.E. of regression	23.68760	Akaike info criterion	9.281486
Sum squared resid	561.1023	Schwarz criterion	8.821207

Log likelihood	-15.56297	Hannan-Quinn criter.	8.271437
F-statistic	0.555957	Durbin-Watson stat	3.138135
Prob(F-statistic)	0.688116		

21. SGE.L

Dependent Variable: SGE_L
Method: Least Squares
Date: 26/01/21 Time: 20:26
Sample: 29/04/2001 20/05/2001
Included observations: 4

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-364.1178	888.6445	-0.409745	0.7524
ARIMA	6.103257	3.177663	1.920675	0.3056
GARCH01	-3.847003	4.955679	-0.776282	0.5798

R-squared	0.842092	Mean dependent var	296.0578
Adjusted R-squared	0.526275	S.D. dependent var	16.79588
S.E. of regression	11.56022	Akaike info criterion	7.846722
Sum squared resid	133.6387	Schwarz criterion	7.386443
Log likelihood	-12.69344	Hannan-Quinn criter.	6.836674
F-statistic	2.666391	Durbin-Watson stat	2.961477
Prob(F-statistic)	0.397377		

22. SN.L

Dependent Variable: SN_L
Method: Least Squares
Date: 26/01/21 Time: 20:29
Sample: 2/12/2013 23/12/2013
Included observations: 4

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1261.603	1156.404	1.090971	0.4723
GARCH01	9.092241	15.01583	0.605510	0.6534
ARIMA	-9.592966	16.28654	-0.589012	0.6611

R-squared	0.358741	Mean dependent var	850.6250
Adjusted R-squared	-0.923777	S.D. dependent var	12.34487
S.E. of regression	17.12237	Akaike info criterion	8.632354
Sum squared resid	293.1756	Schwarz criterion	8.172075
Log likelihood	-14.26471	Hannan-Quinn criter.	7.622306
F-statistic	0.279716	Durbin-Watson stat	2.311294
Prob(F-statistic)	0.800786		

(xii) Forecast encompassing test of Chong and Hendry

1. FTSE-ALL SHARE INDEX

Dependent Variable: E1
Method: Least Squares
Date: 19/01/21 Time: 21:04
Sample: 3/04/2017 24/04/2017
Included observations: 4

Variable	Coefficient	Std. Error	t-Statistic	Prob.
GARCH01	-0.001959	0.008632	-0.226884	0.8351

R-squared	0.002059	Mean dependent var	-7.315000
Adjusted R-squared	0.002059	S.D. dependent var	68.81866
S.E. of regression	68.74777	Akaike info criterion	11.51108
Sum squared resid	14178.77	Schwarz criterion	11.35766
Log likelihood	-22.02217	Hannan-Quinn criter.	11.17440
Durbin-Watson stat	2.595333		

Dependent Variable: E2
Method: Least Squares
Date: 19/01/21 Time: 21:17
Sample: 3/04/2017 24/04/2017
Included observations: 4

Variable	Coefficient	Std. Error	t-Statistic	Prob.
ARIMA	-0.001977	0.008691	-0.227509	0.8347

R-squared	0.002044	Mean dependent var	-7.391000
Adjusted R-squared	0.002044	S.D. dependent var	69.28146
S.E. of regression	69.21062	Akaike info criterion	11.52450
Sum squared resid	14370.33	Schwarz criterion	11.37108
Log likelihood	-22.04901	Hannan-Quinn criter.	11.18782
Durbin-Watson stat	2.593260		

2. FTSE-350 GENERAL INDUSTRIAL INDEX

Dependent Variable: E1
Method: Least Squares
Date: 19/01/21 Time: 21:24
Sample: 2/04/2017 23/04/2017
Included observations: 4

Variable	Coefficient	Std. Error	t-Statistic	Prob.
GARCH01	-0.002922	0.010938	-0.267100	0.8067

R-squared	0.002318	Mean dependent var	-16.08750
Adjusted R-squared	0.002318	S.D. dependent var	126.9609
S.E. of regression	126.8137	Akaike info criterion	12.73563
Sum squared resid	48245.15	Schwarz criterion	12.58221

Log likelihood	-24.47127	Hannan-Quinn criter.	12.39895
Durbin-Watson stat	2.463129		

Dependent Variable: E2
Method: Least Squares
Date: 19/01/21 Time: 21:26
Sample: 2/04/2017 23/04/2017
Included observations: 4

Variable	Coefficient	Std. Error	t-Statistic	Prob.
ARIMA	-0.003575	0.011072	-0.322856	0.7680

R-squared	0.002748	Mean dependent var	-19.86975
Adjusted R-squared	0.002748	S.D. dependent var	128.4548
S.E. of regression	128.2782	Akaike info criterion	12.75860
Sum squared resid	49365.92	Schwarz criterion	12.60517
Log likelihood	-24.51720	Hannan-Quinn criter.	12.42192
Durbin-Watson stat	2.448567		

The primary industry

3. ANTO.L

Dependent Variable: E1
Method: Least Squares
Date: 19/01/21 Time: 21:30
Sample: 3/04/2017 24/04/2017
Included observations: 4

Variable	Coefficient	Std. Error	t-Statistic	Prob.
GARCH01	0.006688	0.025029	0.267207	0.8066

R-squared	-0.008588	Mean dependent var	6.497550
Adjusted R-squared	-0.008588	S.D. dependent var	41.55865
S.E. of regression	41.73672	Akaike info criterion	10.51296
Sum squared resid	5225.862	Schwarz criterion	10.35953
Log likelihood	-20.02592	Hannan-Quinn criter.	10.17627
Durbin-Watson stat	2.014425		

Dependent Variable: E2
Method: Least Squares
Date: 19/01/21 Time: 21:32
Sample: 3/04/2017 24/04/2017
Included observations: 4

Variable	Coefficient	Std. Error	t-Statistic	Prob.
ARIMA	0.006915	0.025032	0.276248	0.8003

R-squared	-0.008853	Mean dependent var	6.688175
Adjusted R-squared	-0.008853	S.D. dependent var	41.56865
S.E. of regression	41.75226	Akaike info criterion	10.51370

Sum squared resid	5229.753	Schwarz criterion	10.36028
Log likelihood	-20.02740	Hannan-Quinn criter.	10.17702
Durbin-Watson stat	2.014909		

4. BP.L

Dependent Variable: E1
Method: Least Squares
Date: 19/01/21 Time: 21:38
Sample: 1/03/2010 22/03/2010
Included observations: 4

Variable	Coefficient	Std. Error	t-Statistic	Prob.
ARIMA	0.017014	0.019917	0.854256	0.4558

R-squared	-0.024551	Mean dependent var	10.79755
Adjusted R-squared	-0.024551	S.D. dependent var	23.82858
S.E. of regression	24.11932	Akaike info criterion	9.416221
Sum squared resid	1745.225	Schwarz criterion	9.262795
Log likelihood	-17.83244	Hannan-Quinn criter.	9.079538
Durbin-Watson stat	2.226804		

Dependent Variable: E2
Method: Least Squares
Date: 19/01/21 Time: 21:41
Sample: 1/03/2010 22/03/2010
Included observations: 4

Variable	Coefficient	Std. Error	t-Statistic	Prob.
GARCH01	0.016752	0.020065	0.834879	0.4650

R-squared	-0.024482	Mean dependent var	10.64880
Adjusted R-squared	-0.024482	S.D. dependent var	23.99914
S.E. of regression	24.29115	Akaike info criterion	9.430419
Sum squared resid	1770.179	Schwarz criterion	9.276992
Log likelihood	-17.86084	Hannan-Quinn criter.	9.093736
Durbin-Watson stat	2.217475		

5. CNA.L

Dependent Variable: E1
Method: Least Squares
Date: 19/01/21 Time: 22:23
Sample: 8/06/2014 29/06/2014
Included observations: 4

Variable	Coefficient	Std. Error	t-Statistic	Prob.
ARIMA	-0.015092	0.008877	-1.700146	0.1877

R-squared	0.053177	Mean dependent var	-4.733425
Adjusted R-squared	0.053177	S.D. dependent var	5.896942
S.E. of regression	5.738009	Akaike info criterion	6.544419
Sum squared resid	98.77423	Schwarz criterion	6.390993
Log likelihood	-12.08884	Hannan-Quinn criter.	6.207737
Durbin-Watson stat	1.023128		

Dependent Variable: E2
Method: Least Squares
Date: 19/01/21 Time: 22:25
Sample: 8/06/2014 29/06/2014
Included observations: 4

Variable	Coefficient	Std. Error	t-Statistic	Prob.
GARCH01	-0.014833	0.010038	-1.477719	0.2360

R-squared	0.043925	Mean dependent var	-4.641325
Adjusted R-squared	0.043925	S.D. dependent var	6.637304
S.E. of regression	6.489897	Akaike info criterion	6.790688
Sum squared resid	126.3563	Schwarz criterion	6.637262
Log likelihood	-12.58138	Hannan-Quinn criter.	6.454005
Durbin-Watson stat	1.077776		

6. SVT.L

Dependent Variable: E1
Method: Least Squares
Date: 19/01/21 Time: 22:29
Sample: 9/04/2017 30/04/2017
Included observations: 4

Variable	Coefficient	Std. Error	t-Statistic	Prob.
GARCH01	-0.003336	0.017476	-0.190859	0.8608

R-squared	0.002127	Mean dependent var	-7.230500
Adjusted R-squared	0.002127	S.D. dependent var	83.53254
S.E. of regression	83.44367	Akaike info criterion	11.89854
Sum squared resid	20888.54	Schwarz criterion	11.74511
Log likelihood	-22.79708	Hannan-Quinn criter.	11.56186
Durbin-Watson stat	1.960901		

Dependent Variable: E2
Method: Least Squares
Date: 19/01/21 Time: 22:32
Sample: 9/04/2017 30/04/2017
Included observations: 4

Variable	Coefficient	Std. Error	t-Statistic	Prob.
ARIMA	-0.009442	0.016942	-0.557300	0.6162

R-squared	0.006811	Mean dependent var	-21.65075

Adjusted R-squared	0.006811	S.D. dependent var	80.68248
S.E. of regression	80.40726	Akaike info criterion	11.82440
Sum squared resid	19395.98	Schwarz criterion	11.67098
Log likelihood	-22.64881	Hannan-Quinn criter.	11.48772
Durbin-Watson stat	1.934827		

7. JMAT.L

Dependent Variable: E1
Method: Least Squares
Date: 19/01/21 Time: 22:37
Sample: 1/03/2010 22/03/2010
Included observations: 4

Variable	Coefficient	Std. Error	t-Statistic	Prob.
GARCH01	0.028712	0.021902	1.310910	0.2812

R-squared	-0.055550	Mean dependent var	53.41950
Adjusted R-squared	-0.055550	S.D. dependent var	75.91577
S.E. of regression	77.99582	Akaike info criterion	11.76351
Sum squared resid	18250.04	Schwarz criterion	11.61008
Log likelihood	-22.52701	Hannan-Quinn criter.	11.42682
Durbin-Watson stat	1.487076		

Dependent Variable: E2
Method: Least Squares
Date: 19/01/21 Time: 22:38
Sample: 1/03/2010 22/03/2010
Included observations: 4

Variable	Coefficient	Std. Error	t-Statistic	Prob.
ARIMA	0.026086	0.020355	1.281560	0.2901

R-squared	-0.058754	Mean dependent var	48.61750
Adjusted R-squared	-0.058754	S.D. dependent var	70.26201
S.E. of regression	72.29663	Akaike info criterion	11.61175
Sum squared resid	15680.41	Schwarz criterion	11.45832
Log likelihood	-22.22350	Hannan-Quinn criter.	11.27507
Durbin-Watson stat	1.658624		

The manufacturing industry

8. ABF.L

Dependent Variable: E1
Method: Least Squares
Date: 19/01/21 Time: 23:30
Sample: 30/11/2009 21/12/2009
Included observations: 4

Variable	Coefficient	Std. Error	t-Statistic	Prob.

GARCH01	0.002823	0.004165	0.677727	0.5465

R-squared	-0.001078	Mean dependent var	2.289700
Adjusted R-squared	-0.001078	S.D. dependent var	6.729724
S.E. of regression	6.733351	Akaike info criterion	6.864341
Sum squared resid	136.0141	Schwarz criterion	6.710915
Log likelihood	-12.72868	Hannan-Quinn criter.	6.527658
Durbin-Watson stat	1.594432		

Dependent Variable: E2
Method: Least Squares
Date: 19/01/21 Time: 23:32
Sample: 30/11/2009 21/12/2009
Included observations: 4

Variable	Coefficient	Std. Error	t-Statistic	Prob.
ARIMA	0.003332	0.004398	0.757649	0.5037

R-squared	-0.000732	Mean dependent var	2.700025
Adjusted R-squared	-0.000732	S.D. dependent var	7.111200
S.E. of regression	7.113801	Akaike info criterion	6.974268
Sum squared resid	151.8185	Schwarz criterion	6.820842
Log likelihood	-12.94854	Hannan-Quinn criter.	6.637586
Durbin-Watson stat	1.758537		

9. BATS.L

Dependent Variable: E1
Method: Least Squares
Date: 20/01/21 Time: 10:38
Sample: 1/03/2010 22/03/2010
Included observations: 4

Variable	Coefficient	Std. Error	t-Statistic	Prob.
DOUBLE	-0.013855	0.017066	-0.811856	0.4763

R-squared	-0.008493	Mean dependent var	-31.21413
Adjusted R-squared	-0.008493	S.D. dependent var	75.14451
S.E. of regression	75.46295	Akaike info criterion	11.69748
Sum squared resid	17083.97	Schwarz criterion	11.54405
Log likelihood	-22.39496	Hannan-Quinn criter.	11.36080
Durbin-Watson stat	1.554127		

Dependent Variable: E2
Method: Least Squares
Date: 20/01/21 Time: 10:41
Sample: 1/03/2010 22/03/2010
Included observations: 4

Variable	Coefficient	Std. Error	t-Statistic	Prob.

TRIPLE	-0.004813	0.016725	-0.287772	0.7923

R-squared	-0.002933	Mean dependent var	-11.29140
Adjusted R-squared	-0.002933	S.D. dependent var	74.51225
S.E. of regression	74.62144	Akaike info criterion	11.67505
Sum squared resid	16705.08	Schwarz criterion	11.52162
Log likelihood	-22.35010	Hannan-Quinn criter.	11.33837
Durbin-Watson stat	1.520954		

10. BDEV.L

Dependent Variable: E1
Method: Least Squares
Date: 20/01/21 Time: 12:20
Sample: 9/04/2017 30/04/2017
Included observations: 4

Variable	Coefficient	Std. Error	t-Statistic	Prob.
ARIMA	0.010672	0.003868	2.758718	0.0702

R-squared	-0.015611	Mean dependent var	6.122450
Adjusted R-squared	-0.015611	S.D. dependent var	4.391093
S.E. of regression	4.425234	Akaike info criterion	6.024841
Sum squared resid	58.74810	Schwarz criterion	5.871415
Log likelihood	-11.04968	Hannan-Quinn criter.	5.688159
Durbin-Watson stat	2.169321		

Dependent Variable: E2
Method: Least Squares
Date: 20/01/21 Time: 12:23
Sample: 9/04/2017 30/04/2017
Included observations: 4

Variable	Coefficient	Std. Error	t-Statistic	Prob.
GARCH01	0.012327	0.003937	3.130923	0.0520

R-squared	-0.014778	Mean dependent var	7.078150
Adjusted R-squared	-0.014778	S.D. dependent var	4.478434
S.E. of regression	4.511404	Akaike info criterion	6.063412
Sum squared resid	61.05830	Schwarz criterion	5.909985
Log likelihood	-11.12682	Hannan-Quinn criter.	5.726729
Durbin-Watson stat	2.182030		

11. BKG.L

Dependent Variable: E1
Method: Least Squares
Date: 20/01/21 Time: 12:27
Sample: 9/04/2017 30/04/2017
Included observations: 4

Variable	Coefficient	Std. Error	t-Statistic	Prob.
TRIPLE	0.003512	0.005007	0.701398	0.5336

R-squared	0.001727	Mean dependent var	11.33966
Adjusted R-squared	0.001727	S.D. dependent var	32.53450
S.E. of regression	32.50639	Akaike info criterion	10.01307
Sum squared resid	3169.996	Schwarz criterion	9.859642
Log likelihood	-19.02614	Hannan-Quinn criter.	9.676386
Durbin-Watson stat	3.027984		

Dependent Variable: E2
Method: Least Squares
Date: 20/01/21 Time: 12:28
Sample: 9/04/2017 30/04/2017
Included observations: 4

Variable	Coefficient	Std. Error	t-Statistic	Prob.
DOUBLE	0.004028	0.005143	0.783292	0.4906

R-squared	0.001788	Mean dependent var	13.02461
Adjusted R-squared	0.001788	S.D. dependent var	33.43261
S.E. of regression	33.40270	Akaike info criterion	10.06747
Sum squared resid	3347.222	Schwarz criterion	9.914042
Log likelihood	-19.13494	Hannan-Quinn criter.	9.730786
Durbin-Watson stat	3.069077		

12. DGE.L

Dependent Variable: E1
Method: Least Squares
Date: 20/01/21 Time: 12:33
Sample: 9/04/2017 30/04/2017
Included observations: 4

Variable	Coefficient	Std. Error	t-Statistic	Prob.
GARCH01	-0.000696	0.012239	-0.056842	0.9582

R-squared	0.000569	Mean dependent var	-1.078250
Adjusted R-squared	0.000569	S.D. dependent var	55.29198
S.E. of regression	55.27624	Akaike info criterion	11.07488
Sum squared resid	9166.388	Schwarz criterion	10.92145
Log likelihood	-21.14976	Hannan-Quinn criter.	10.73820
Durbin-Watson stat	2.826765		

Dependent Variable: E2
Method: Least Squares
Date: 20/01/21 Time: 12:35
Sample: 9/04/2017 30/04/2017
Included observations: 4

Variable	Coefficient	Std. Error	t-Statistic	Prob.

ARIMA	-0.000397	0.012187	-0.032555	0.9761

R-squared	0.000282	Mean dependent var	-0.401250
Adjusted R-squared	0.000282	S.D. dependent var	55.06538
S.E. of regression	55.05761	Akaike info criterion	11.06696
Sum squared resid	9094.021	Schwarz criterion	10.91353
Log likelihood	-21.13391	Hannan-Quinn criter.	10.73027
Durbin-Watson stat	2.822309		

The service industry

13. ADN.L

Dependent Variable: E1
Method: Least Squares
Date: 20/01/21 Time: 12:39
Sample: 9/04/2017 30/04/2017
Included observations: 4

Variable	Coefficient	Std. Error	t-Statistic	Prob.
ARIMA	0.018230	0.017430	1.045888	0.3725

R-squared	-0.008699	Mean dependent var	5.129900
Adjusted R-squared	-0.008699	S.D. dependent var	9.653768
S.E. of regression	9.695667	Akaike info criterion	7.593553
Sum squared resid	282.0179	Schwarz criterion	7.440127
Log likelihood	-14.18711	Hannan-Quinn criter.	7.256870
Durbin-Watson stat	1.375694		

Dependent Variable: E2
Method: Least Squares
Date: 20/01/21 Time: 12:40
Sample: 9/04/2017 30/04/2017
Included observations: 4

Variable	Coefficient	Std. Error	t-Statistic	Prob.
GARCH01	0.019314	0.017470	1.105555	0.3496

R-squared	-0.009131	Mean dependent var	5.437075
Adjusted R-squared	-0.009131	S.D. dependent var	9.684378
S.E. of regression	9.728490	Akaike info criterion	7.600312
Sum squared resid	283.9305	Schwarz criterion	7.446886
Log likelihood	-14.20062	Hannan-Quinn criter.	7.263629
Durbin-Watson stat	1.368587		

14. AHT.L

Dependent Variable: E1
Method: Least Squares
Date: 20/01/21 Time: 12:44
Sample: 29/04/2001 20/05/2001
Included observations: 4

Variable	Coefficient	Std. Error	t-Statistic	Prob.
ARIMA	0.019214	0.015053	1.276462	0.2916

R-squared	-0.022314	Mean dependent var	2.011378
Adjusted R-squared	-0.022314	S.D. dependent var	3.056103
S.E. of regression	3.090011	Akaike info criterion	5.306544
Sum squared resid	28.64450	Schwarz criterion	5.153118
Log likelihood	-9.613088	Hannan-Quinn criter.	4.969861
Durbin-Watson stat	2.175154		

Dependent Variable: E2
Method: Least Squares
Date: 20/01/21 Time: 12:46
Sample: 29/04/2001 20/05/2001
Included observations: 4

Variable	Coefficient	Std. Error	t-Statistic	Prob.
GARCH01	0.028997	0.014494	2.000657	0.1392

R-squared	-0.041671	Mean dependent var	3.051043
Adjusted R-squared	-0.041671	S.D. dependent var	2.944592
S.E. of regression	3.005318	Akaike info criterion	5.250962
Sum squared resid	27.09582	Schwarz criterion	5.097536
Log likelihood	-9.501924	Hannan-Quinn criter.	4.914279
Durbin-Watson stat	2.101807		

15. AV.L

Dependent Variable: E1
Method: Least Squares
Date: 20/01/21 Time: 12:50
Sample: 29/04/2001 20/05/2001
Included observations: 4

Variable	Coefficient	Std. Error	t-Statistic	Prob.
TRIPLE	-0.001542	0.006250	-0.246657	0.8211

R-squared	-0.000762	Mean dependent var	-1.367840
Adjusted R-squared	-0.000762	S.D. dependent var	10.88438
S.E. of regression	10.88853	Akaike info criterion	7.825614
Sum squared resid	355.6800	Schwarz criterion	7.672188
Log likelihood	-14.65123	Hannan-Quinn criter.	7.488931
Durbin-Watson stat	1.604111		

Dependent Variable: E2
Method: Least Squares
Date: 20/01/21 Time: 12:52
Sample: 29/04/2001 20/05/2001
Included observations: 4

Variable	Coefficient	Std. Error	t-Statistic	Prob.
DOUBLE	-0.009376	0.006629	-1.414294	0.2522

R-squared	-0.004764	Mean dependent var	-8.132140
Adjusted R-squared	-0.004764	S.D. dependent var	11.43206
S.E. of regression	11.45926	Akaike info criterion	7.927791
Sum squared resid	393.9438	Schwarz criterion	7.774365
Log likelihood	-14.85558	Hannan-Quinn criter.	7.591108
Durbin-Watson stat	1.395258		

16. BAB.L

Dependent Variable: E1
Method: Least Squares
Date: 20/01/21 Time: 12:55
Sample: 9/04/2017 30/04/2017
Included observations: 4

Variable	Coefficient	Std. Error	t-Statistic	Prob.
GARCH01	0.009488	0.006911	1.372912	0.2634

R-squared	-0.008410	Mean dependent var	8.526025
Adjusted R-squared	-0.008410	S.D. dependent var	12.28717
S.E. of regression	12.33873	Akaike info criterion	8.075681
Sum squared resid	456.7326	Schwarz criterion	7.922254
Log likelihood	-15.15136	Hannan-Quinn criter.	7.738998
Durbin-Watson stat	3.271917		

Dependent Variable: E2
Method: Least Squares
Date: 20/01/21 Time: 12:57
Sample: 9/04/2017 30/04/2017
Included observations: 4

Variable	Coefficient	Std. Error	t-Statistic	Prob.
ARIMA	0.009031	0.007780	1.160784	0.3297

R-squared	-0.005380	Mean dependent var	8.105550
Adjusted R-squared	-0.005380	S.D. dependent var	13.84599
S.E. of regression	13.88319	Akaike info criterion	8.311552
Sum squared resid	578.2286	Schwarz criterion	8.158126
Log likelihood	-15.62310	Hannan-Quinn criter.	7.974869
Durbin-Watson stat	3.301981		

17. BARC.L

Dependent Variable: E1
Method: Least Squares
Date: 20/01/21 Time: 13:00
Sample: 29/08/2004 19/09/2004
Included observations: 4

Variable	Coefficient	Std. Error	t-Statistic	Prob.
ARIMA	0.008265	0.006455	1.280454	0.2904

R-squared	-0.024485	Mean dependent var	4.113725
Adjusted R-squared	-0.024485	S.D. dependent var	6.213761
S.E. of regression	6.289372	Akaike info criterion	6.727917
Sum squared resid	118.6686	Schwarz criterion	6.574491
Log likelihood	-12.45583	Hannan-Quinn criter.	6.391235
Durbin-Watson stat	1.415090		

Dependent Variable: E2
Method: Least Squares
Date: 20/01/21 Time: 13:02
Sample: 29/08/2004 19/09/2004
Included observations: 4

Variable	Coefficient	Std. Error	t-Statistic	Prob.
GARCH01	0.012382	0.006970	1.776518	0.1737

R-squared	-0.031627	Mean dependent var	6.145200
Adjusted R-squared	-0.031627	S.D. dependent var	6.714249
S.E. of regression	6.819599	Akaike info criterion	6.889796
Sum squared resid	139.5208	Schwarz criterion	6.736370
Log likelihood	-12.77959	Hannan-Quinn criter.	6.553113
Durbin-Watson stat	1.433142		

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18. AZN.L

Dependent Variable: E1
Method: Least Squares
Date: 20/01/21 Time: 13:06
Sample: 2/12/2013 23/12/2013
Included observations: 4

Variable	Coefficient	Std. Error	t-Statistic	Prob.
GARCH01	0.006810	0.006025	1.130163	0.3406

R-squared	-0.005145	Mean dependent var	24.17375
Adjusted R-squared	-0.005145	S.D. dependent var	42.41536
S.E. of regression	42.52434	Akaike info criterion	10.55035
Sum squared resid	5424.959	Schwarz criterion	10.39692
Log likelihood	-20.10070	Hannan-Quinn criter.	10.21367
Durbin-Watson stat	1.603728		

Dependent Variable: E2
Method: Least Squares
Date: 20/01/21 Time: 13:07
Sample: 2/12/2013 23/12/2013
Included observations: 4

Variable	Coefficient	Std. Error	t-Statistic	Prob.
ARIMA	0.006146	0.007232	0.849866	0.4578

R-squared	-0.000802	Mean dependent var	21.70800
Adjusted R-squared	-0.000802	S.D. dependent var	50.98047
S.E. of regression	51.00091	Akaike info criterion	10.91388
Sum squared resid	7803.279	Schwarz criterion	10.76046
Log likelihood	-20.82776	Hannan-Quinn criter.	10.57720
Durbin-Watson stat	1.404891		

19. GSK.L

Dependent Variable: E1
Method: Least Squares
Date: 20/01/21 Time: 13:19
Sample: 29/04/2001 20/05/2001
Included observations: 4

Variable	Coefficient	Std. Error	t-Statistic	Prob.
GARCH01	0.003372	0.011623	0.290122	0.7906

R-squared	-0.005112	Mean dependent var	6.976500
Adjusted R-squared	-0.005112	S.D. dependent var	44.13704
S.E. of regression	44.24971	Akaike info criterion	10.62989
Sum squared resid	5874.111	Schwarz criterion	10.47647
Log likelihood	-20.25979	Hannan-Quinn criter.	10.29321
Durbin-Watson stat	0.882817		

Dependent Variable: E2
Method: Least Squares
Date: 20/01/21 Time: 13:20
Sample: 29/04/2001 20/05/2001
Included observations: 4

Variable	Coefficient	Std. Error	t-Statistic	Prob.
ARIMA	0.003439	0.013026	0.264025	0.8089

R-squared	-0.004210	Mean dependent var	7.112500
Adjusted R-squared	-0.004210	S.D. dependent var	49.48512
S.E. of regression	49.58918	Akaike info criterion	10.85774
Sum squared resid	7377.262	Schwarz criterion	10.70431
Log likelihood	-20.71548	Hannan-Quinn criter.	10.52106
Durbin-Watson stat	0.775853		

20. SHP.L

Dependent Variable: E1
Method: Least Squares
Date: 20/01/21 Time: 13:25
Sample: 29/08/2010 19/09/2010
Included observations: 4

Variable	Coefficient	Std. Error	t-Statistic	Prob.
ARIMA	0.009945	0.013896	0.715693	0.5259

R-squared	-0.018624	Mean dependent var	15.25350
Adjusted R-squared	-0.018624	S.D. dependent var	40.13981
S.E. of regression	40.51187	Akaike info criterion	10.45338
Sum squared resid	4923.635	Schwarz criterion	10.29996
Log likelihood	-19.90677	Hannan-Quinn criter.	10.11670
Durbin-Watson stat	1.606426		

Dependent Variable: E2
Method: Least Squares
Date: 20/01/21 Time: 13:27
Sample: 29/08/2010 19/09/2010
Included observations: 4

Variable	Coefficient	Std. Error	t-Statistic	Prob.
GARCH01	0.009970	0.013948	0.714822	0.5263

R-squared	-0.018605	Mean dependent var	15.29325
Adjusted R-squared	-0.018605	S.D. dependent var	40.29099
S.E. of regression	40.66408	Akaike info criterion	10.46089
Sum squared resid	4960.702	Schwarz criterion	10.30746
Log likelihood	-19.92177	Hannan-Quinn criter.	10.12420
Durbin-Watson stat	1.603254		

21. SGE.L

Dependent Variable: E1
Method: Least Squares
Date: 20/01/21 Time: 13:30
Sample: 29/04/2001 20/05/2001
Included observations: 4

Variable	Coefficient	Std. Error	t-Statistic	Prob.
GARCH01	0.016944	0.023854	0.710310	0.5288

R-squared	0.002265	Mean dependent var	4.886100
Adjusted R-squared	0.002265	S.D. dependent var	13.86717
S.E. of regression	13.85146	Akaike info criterion	8.306976
Sum squared resid	575.5884	Schwarz criterion	8.153549
Log likelihood	-15.61395	Hannan-Quinn criter.	7.970293
Durbin-Watson stat	1.251101		

Dependent Variable: E2
Method: Least Squares
Date: 20/01/21 Time: 13:31
Sample: 29/04/2001 20/05/2001
Included observations: 4

Variable	Coefficient	Std. Error	t-Statistic	Prob.
ARIMA	0.020047	0.026975	0.743175	0.5113

R-squared	0.007123	Mean dependent var	5.722675
Adjusted R-squared	0.007123	S.D. dependent var	15.76601
S.E. of regression	15.70975	Akaike info criterion	8.558759
Sum squared resid	740.3892	Schwarz criterion	8.405332
Log likelihood	-16.11752	Hannan-Quinn criter.	8.222076
Durbin-Watson stat	1.176495		

22. SN.L

Dependent Variable: E1
Method: Least Squares
Date: 20/01/21 Time: 13:34
Sample: 2/12/2013 23/12/2013
Included observations: 4

Variable	Coefficient	Std. Error	t-Statistic	Prob.
ARIMA	0.011633	0.010596	1.097843	0.3525

R-squared	-0.017142	Mean dependent var	9.971500
Adjusted R-squared	-0.017142	S.D. dependent var	17.64558
S.E. of regression	17.79618	Akaike info criterion	8.808163
Sum squared resid	950.1125	Schwarz criterion	8.654737
Log likelihood	-16.61633	Hannan-Quinn criter.	8.471480
Durbin-Watson stat	2.867913		

Dependent Variable: E2
Method: Least Squares
Date: 20/01/21 Time: 13:35
Sample: 2/12/2013 23/12/2013
Included observations: 4

Variable	Coefficient	Std. Error	t-Statistic	Prob.
GARCH01	0.012863	0.010102	1.273361	0.2926

R-squared	-0.019961	Mean dependent var	11.00955
Adjusted R-squared	-0.019961	S.D. dependent var	16.82025
S.E. of regression	16.98730	Akaike info criterion	8.715126
Sum squared resid	865.7046	Schwarz criterion	8.561700
Log likelihood	-16.43025	Hannan-Quinn criter.	8.378444
Durbin-Watson stat	2.860901		