THE IMPACT OF ENERGY CONSUMPTION, AND INDUSTRIAL PERFORMANCE ON CARBON DIOXIDE EMISSIONS IN THREE LARGEST ECONOMIES OF SUB - SAHARAN AFRICA (SSA).

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DEDICATION

This research work is dedicated to Almighty Allah for his faithfulness and protection and my parents, late Sarkin Fulani Shehu Ahmed Bungudu and Hajiya Fatima (Inno), who brought me up in the fear of the Almighty Allah and made me realize early in life that "knowledge is power".

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LIST OF ABBREVIATIONS

ADF:	Augmented Dickey – Fuller
AIC:	Akaike Information Criterion
ARDL:	Autoregressive Distributed Lag
CEF:	Conservation Energy Future
CO_2:	Carbon Dioxide
DOLS:	Dynamic OLS
ECM:	Error Correction Model
EDC:	Environmental Daly Curve
EIA:	Energy Information Administration
EKC:	Environmental Kutznet Curve
ENG:	Energy consumption/use
EU:	European Union
FAO:	Food and Agriculture Organization
FD:	Financial Development
FDI:	Foreign Direct Investment
FIRS:	Federal Inland Revenue Services
FMOLS:	Fully Modified Ordinary Least Square
GHG:	Greenhouse Gas
GMM:	Generalise Method of Moment
GWP:	Global Warming Potential
HDI:	Human Development Index
IND:	Industrial Performance
INTERPOL:	International Criminal Police Organization
MCO:	Mining Cadastre Office
MENA:	Middle East North Africa
MNCs:	Multinational Companies
NDC:	Nationally Determine Contribution
NDIC:	Nigerian Deposit Insurance Corporation
NGSA:	Nigerian Geological Survey Agency
NIPSS:	National Institute for Policy and Strategic Studies
mni:	Member National Institute
OECD	Organisation for Economic Co-operation and Development
OLS:	Ordinary Least Square
PHH:	Pollution Haven Hypothesis
PP:	Philip – Peron
PSTR:	Panel Smooth Transition Technique
SBIC:	Schwarz's Bayesian Information Criterion
SSA:	Sub Saharan Africa
SSEA:	Southeast Asian
UK:	United Kingdom
UN:	United Nations
UNEP:	United Nations Environment Programme
US:	United States
VAR:	Vector Autoregressive
VEC:	Vector Error Correction
VECM:	Vector Error Correction Model
WDI:	World Development Indicators

ABSTRACT

The debate on global climate change has received increasing attention by researchers, and policymakers in both public and private sectors, as well as other relevant stakeholders. The consensus is that excessive emissions of greenhouse gases, particularly carbon dioxide emission, remain a crucial threat to achieving sustainable environmental quality and development across the world. Many influential studies continued to focus on lowering emissions in advanced rich countries, with little attention on developing economies. Although studies have focused on the determinants of carbon dioxide emission in the advanced economies with mixed findings amidst several policy-recommendations, which may not be appropriate for developing economies due to their relative low level of economic subsistence. Hence, this study empirically examines the impact of energy consumption, financial development, foreign direct investment, gross domestic product growth, and industrial performance on carbon dioxide emissions in Nigeria, Ghana, and South Africa by using autoregressive distributive lag (ARDL) model, vector autoregressive and Toda-Yamamoto causality techniques from 1980Q1 to 2017Q1.

The findings reveal the existence of cointegration among the variables in the models of the three studied countries. Similarly, the outcome from the estimated model for Nigeria illustrates a negative and significant relationship between fossil fuel energy consumption, financial development, foreign direct investment, industrial performance, and carbon dioxide emission. The result from the model of Ghana also reveals a negative link among fossil fuel consumption, financial development, foreign direct investment, industrial value, and carbon dioxide discharge. However, the outcome from the South African model shows that financial development, foreign direct investment, economic growth, and industrial value increase the level of carbon dioxide emissions. Moreover, from the impulse response function for Nigeria shows a positive shock among fossil fuel energy consumption and carbon dioxide emission from the short run to longer periods. Similarly, the finding from the impulse response function for Ghana and South Africa also illustrate that shock in energy use accelerates the capacity of carbon dioxide emission in these economies. The estimate from the variance decomposition in Nigeria, Ghana and South Africa reveals a positive and significant shock of fossil fuel energy consumption on carbon dioxide emissions. This means that fossil fuel energy consumption increases the level of carbon dioxide emissions in these countries. Similarly, the result of impulse response for Nigeria, Ghana and South Africa indicates negative shocks of energy consumption, foreign direct investments, credit, and industrial value toward carbon dioxide

emissions. However, domestic credit and economic growth positively influence carbon dioxide emissions in South Africa. Nonetheless, the result from variance decomposition for Nigeria, Ghana and South Africa reveals that fossil fuel use, economic growth, foreign direct investments, and industrial performance forecast positively on the trend of carbon dioxide emissions in long-run quarter in these economies. Lastly, the outcome from the Toda-Yamamoto causality test for Nigeria shows the existence of causality between economic growth, industrial value, credit, fossil fuel and carbon dioxide emissions. In the case of Ghana and South Africa, the result reveals no causality among the variables. However, energy resources have no influence on carbon dioxide discharge in South Africa.

Since the results of fossil fuel energy use, industrial performance, foreign direct investment, and financial development have significant negative impact on the level of carbon dioxide discharge in these countries. It is important for policy makers to emphasize on more appropriate policies that will consider financial reform, sound industrial policies and all avenues that will attract clean foreign investment to stimulate sustainable development in these economies. This could be through further control on high explosion of carbon dioxide emissions by making availability of low emissions technologies, provision of financial incentives that will encourage the use of low carbon dioxide emissions technology and removing trade barriers that will attract foreign investment, human capital development and research. Consequently, policy on the restructuring of financial and industrial sectors should meet up with the designed goals to enhance the level of environmental quality. This entails that it is important to consider policies on mitigation of carbon dioxide emission; especially regarding policies that will promote environmental quality. Based on the findings of the study, energy consumption and financial progress, economic growth and industrial value addition have positive and significant relationship with carbon dioxide discharge. This entails that energy consumption increases the level of carbon dioxide emissions in these countries. Therefore, there is the need for extensive policies on energy use regulations and emphasis should be on other low emission alternatives of energy such as solar, thermal, wind and hydro energy. This will help in mitigation of carbon dioxide discharge and improve the environmental quality in sub-Saharan Africa countries.

From the foregoing, this study recommends the need for relevant stakeholders to implement strategies to reduce carbon emission in the continent to support higher trajectory of environmental quality through adoption of innovative energy technologies to promote intra- and inter-generational equity in the use of natural resources in sustainable manner overtime.

The study accentuates the need for financial system regulators to develop regulatory-incentive strategy to encourage banking credit intermediation for businesses to adopt environmentally friendly energy sources in their productive activities. Moreover, governments of these countries should strengthen their environment-related policy frameworks to counteract the import of pollution-intensive industries in a bid to achieve a non-declining trajectory in environmental quality overtime in the African continent.

CHAPTER ONE

INTRODUCTION

1.1 Background

There is renewed focus by researchers and policymakers in both public and private sectors on the rising detrimental effects of global climate change due, perhaps to its increasing criticality to achieving sustainable environmental quality across the world (Klinsky et al. 2016; Burton and van Aalst, 1999; Klein 2001; Chambers, 1989). Issues around climate change has turn into one of the most significant crises of the present age, as its effects cuts across global countries' boundaries. The trend in emissions continue to fuel the increasing debate and clamor for humans to safeguard the environment to ensure intra- and inter-generational equity in the use of natural resources. Africa's total energy consumption is under 3% of global energy consumption (British Petroleum, 2020), despite having a 17% share of the global population. Investment in sustainable projects is growing globally. Multilateral agencies are promoting sustainable developments and investments like sustainable finance and climate financing. The United Nations Environmental Program (UNEP) defines climate finance as local, national, or transnational financing, which may be drawn from public, private and alternative sources of financing.

Policymakers on the African continent should not ignore the effects of environmental degradation. Despite the evidence of deteriorating environmental quality, economic growth in sub-Saharan Africa depends on investing in the energy industry to accommodate the rising energy demand. Like many developing economies and emerging markets, burning fossil fuels for energy is seen as necessary for economic growth – despite the evidence of climate change. The economies of Ghana, Nigeria, and South Africa have made progress in strengthening their macroeconomic policies since the turn of the century. Ghana, Nigeria, and South Africa are among the three largest economies in sub–Saharan Africa. They are endowed with vast mineral resources. For example, Ghana is Africa's largest gold miner, and the world's second largest cocoa producer and it is an emerging petroleum and natural gas economy. South Africa is also a mining jurisdiction with sector that comprises of platinum and lignite, coal, gold, iron ore, uranium, and manganese. Nigeria on the other hand, due to the influence of its vast oil resources, the domestic mining industry is underdeveloped leading to importation of minerals that it could produce domestically such as salt, iron ore, and Bitumen.

In 2020, the output of these three countries accounted for 50% of the sub-Saharan African economy (World Bank, 2022). However, the growth in these economies has relied on traditional energy sources. It seems worrying for policymakers of these countries to be less concerned about environmental impacts. To the best of the researcher's knowledge, this aspect has received little or no empirical attention in the context of selected pooled African countries, including Ghana, Nigeria, and South Africa. Moreover, despite advances in carbon dioxide emissions analysis, agreement on the existence and stability of the Environmental Kuznets Hypothesis and pollution-haven hypothesis remain inconclusive within the African continent. The impact of carbon dioxide emissions is gravely affecting both the ecosystem and humanity, and it is causing several environmental hazards (Asongo, 2018; IPCC, 2014). Recently, some under-developed and developing countries have increased their economic restructuring by carrying out rapid industrialization (Niva, et al. 2020). Nevertheless, this rapid industrialization amongst global economies have resulted in an upsurge in energy-related carbon dioxide emissions and environmental degradation. Moreover, an increase in urbanization and a fast population growth have also created high potential for energy-related carbon dioxide emissions due to enhanced energy consumption (Gasimili, et al. 2019). A rise in carbon dioxide emissions has been witnessed in sub-Saharan Africa countries due to high population, economic growth, and related factors (Hamilton and Kelly, 2017).

Since the industrial revolution of the 1860s, a rise in the earth's carbon dioxide emissions levels has been clearly visible. Before this landmark phase, the concentration of atmospheric carbon dioxide was just below 280 parts per million (ppm) which did remain consistent for about 700 years (Intergovernmental panel on climate change (IPCC), 2018). Ever since the industrialisation drive that started in the United Kingdom, there has been exponential growth in carbon dioxide concentrations (Ayoade, 2003). A recent National Oceanic and Atmospheric Administration (NOAA) Research (2021) study, based on initial analysis, indicated the mean amount of atmospheric carbon dioxide stood at 412.5 ppm in 2020, rising by 2.6ppm above the 2019 levels, and the jump was considered the 5th highest yearly rise in NOAA's 63-year records, following increases recorded in 1987, 1998, 2015 and 2016. Meanwhile, the world's atmospheric carbon dioxide level has risen by 43.5ppm, representing a 12% increase, since 2000, when it was nearly 370 ppm, and have grown by 47% since the start of the industrial age. The emission of carbon dioxide growth rate in the atmosphere is predicted to jump to 450 ppm by 2050 (Botkin and Keller, 1997). The commercial development of different countries globally has also contributed to the increase in emissions of carbon dioxide (Shah and Zeeshan, 2016), and a higher density of population and faster economic growth both moderately increase the environmental price of economic growth (Panayotou, 1997).

Globally, Africa's Human Development Index (HDI) is lowest, which explains the need to quickly increase the speed of economic development in Africa (Niva, et al. 2020). Head (2009) argues furthermore that Africa must strive hard at all costs in the coming years to stay in pace with other economies of the world. There has been an upsurge in energy-related carbon dioxide emissions around the world and Africa, and due to its stage of development, is most likely to contribute to global warming and greenhouse gases emissions in the coming years. The major source of energy in most emerging and developing countries is fossil fuels usage, often consumed inefficiently, leading to enhanced carbon dioxide emissions and pollution in the region (Samu, et al. 2019). There was a strong emphasis on the subject area of carbon dioxide emission, which was discussed in the first world global climate change and environment in 1979 and in December 1980. Followed by Kyoto protocol in 1997 that was attended by majority of member states. The Kyoto protocol culminated into Paris agreement. Under the 2015 Paris agreement, there is a global commitment to limit the average global temperature rise to 1.5°C above pre-industrial levels. However, the portion of carbon dioxide explosion from emerging economies had increased the level of deteriorating environmental quality due to atmospheric heat and climate alteration (Nejat, et al. 2015). Regions and countries like China, India, sub-Saharan Africa (SSA), North Africa, Asia, and Latin America account for almost 63% of global carbon dioxide discharge. The global trend of carbon dioxide discharge is becoming a threat to all countries' ecosystems and development (Sehrawat, et al. 2015; Abbasi and Riaz, 2016). There is a connection between fossil fuel as an energy source, the level of economic activities and the trajectory of industrial production (Asongu, 2018).

Additionally, there is a direct connection between economic growth and energy usage, which has resulted in an indirect impact on the environment and local ecosystem of sub-Saharan Africa (Yusuf, 2014). Non-renewable energy resources have rapidly depleted all over the world, which has a direct influence on Africa's future economic development (Niva, et al. 2020). Africa's future energy use is expected to intensify due to its growing economy, the pace of economic development, and its rapidly increasing population (USEIA, 2018).The resultant environmental impacts include the vulnerability of the economy to recurrent floods, droughts, and cyclones as well as the spread of diseases, reduction in wildlife, melting of glaciers and the reduction of agricultural productivity (Asongu, 2018; IPCC, 2014). As postulated by Sulaiman and Abdul-Rahim (2018), a higher density of population and faster economic growth moderately increase the environmental value of economic growth. Consequently, carbon dioxide emission levels in the earth's atmosphere have witnessed a continuous rise ever since the time of the industrial revolution (IPCC, 2018). Prior to this landmark phase, the concentration of carbon dioxide emissions was consistent at nearly 280 ppm for about 700 years. However, atmospheric carbon dioxide discharge growth rate is now about 0.5% annually, and its level is predicted to rise to 450 ppm by 2050 (IPCC, 2018). Carbon dioxide emissions contributed to about 76% of the world's total greenhouse gases (Shahzad, et al. 2017). The danger of climatic change owing to increasing heat levels has therefore become a topic of global concern for the attainment of environmental sustainability.

It is widely acknowledged that the rise in carbon dioxide emissions is a key component that contributes to weather variability and the warming of the globe (Heidari, et al. 2015). Global carbon dioxide emissions have rapidly increased recently, and are on course to reach a new record, extending beyond the challenge the world faces in curtailing the effects of climate change (Tiwari, 2011). The world carbon dioxide discharge outflows increased from 19.35mn kilotons in 1980 to 35.84m kilotons in 2013, showing that it increased by around 84% during this period (Banday and Aneja, 2018). In addition, carbon dioxide emissions from both industrialized and emerging countries have grown at 1.3 % annually and are projected to double by the year 2030. This situation will doubtless be attained unless control measures are put in place (IPCC, 2014).

According to Global Carbon Project (2018), carbon dioxide emissions from fossil fuels and industries increased from 33.1% in 2010 to 36.2% by 2017, and are projected to rise by a further 2.7% with China and India accounting for greater portions. While addressing this concern, it is important to make strategies for striking a balance between economic development and climate change. In line with the report from the intergovernmental panel on climate change (2013), forwarding off the catastrophic climatic variation, it is necessary that global warming remains limited to 2ºC and the atmospheric concentration of greenhouse gases to less than 450 ppm carbon dioxide emissions. It is projected that the total world population will hit 9.2 billion people by 2050 and to sustain within this 'carbon budget', the average per capita annual emissions must be limited to about 2.1 to 2.6 tons carbon dioxide by 2050. Recently, it has been documented that most developing countries have increased their carbon dioxide discharge to pursue higher economic performance. This has become an issue of concern to the international community, especially concerning mitigation of carbon dioxide discharge. Similarly, developing countries from the Middle East and North Africa, Latin America, Asia, sub-Saharan Africa, India, and China cumulatively contributed to about 63% of the global carbon dioxide emissions as indicated in figure 1.1.

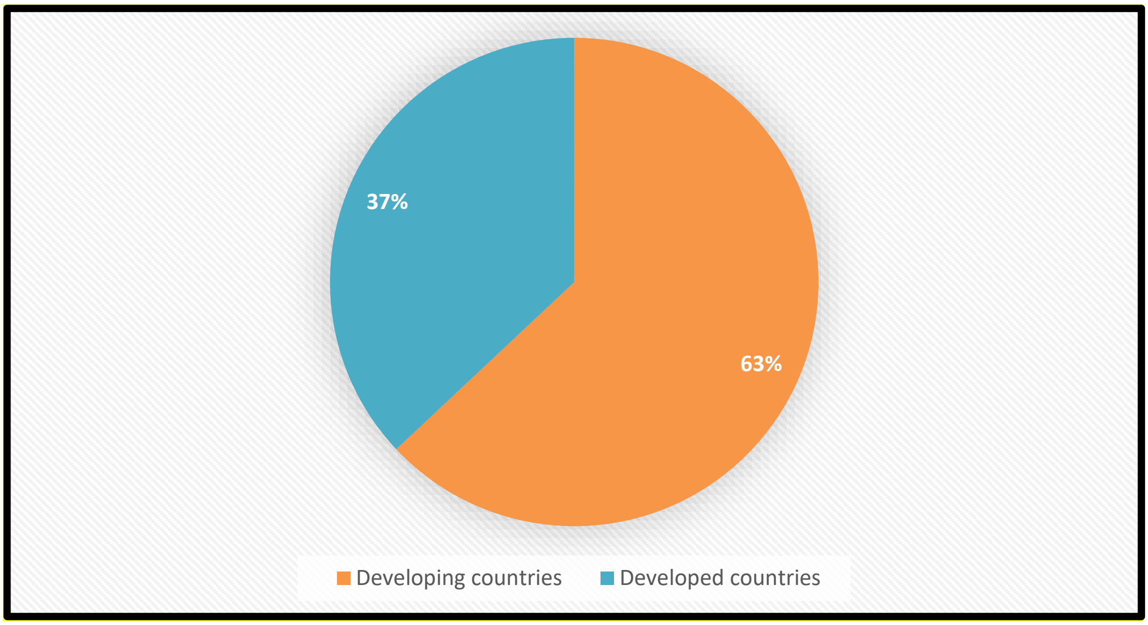


Figure 1. 1: Contribution of Carbon Dioxide Emissions

Source: Intergovernmental panel on climate change (2018)

Among all the continents in the world, Africa is the lowest ranked in terms of human development index, which highlights the significance of accelerating economic development in the continent (Niva, et al. 2020). Indeed, Head, (2009) suggests that it is imperative for the continent to strive hard in the coming years to keep pace with other economies of the world. The major source of energy in developing countries within the continent is fossil fuels, which lowers the efficiency of energy consumption and increases carbon dioxide emissions (Samu, et al. 2019). In response to this situation, SSA countries have set up targets for sustainable development, including the reduction of carbon dioxide emissions to the level of 80% by 2050 (from 1990 period). There is also another target to increase human development index with ecological footprints by 1.44 global hectares (gha) per capita development.

Industrialised and developing countries, especially the sub-Saharan African countries have recently given utmost priority to ecological sustainability and fiscal variables, which clearly indicates that SSA countries are at an important stage of economic expansion. These economies are witnessing swift rise in population with encouraging demographics of young and growing workforce in the urban areas. Although this region has relatively lower per capita echelons of greenhouse gasses releases, the ever-increasing risks of adverse worldwide climatic changes indicate that global economies need to avoid economic growth path based on high-emission models. This atmospheric limitation is in conflict with the growth trend which is witnessing the rapid growth of greenhouse gasses emissions in the SSA region, owing to increased fossil fuel extraction and use, population growth, and, deforestation as well as a steep rise in cattle production (EIA, 2014; Acaravci and Ozturk, 2010; Sehrawat, Giri, and Mohapatra, 2015). Therefore, for sub-Saharan African countries to overcome several developmental challenges such as illiteracy, healthcare, conflicts, lack of energy access and widespread poverty, they must design their economic development in such ways that it does not cause large-scale rise in greenhouse gasses emissions. Niva, et al. (2020) point out that, some under-developed and developing countries within SSA have accelerated their economic restructuring by embarking on rapid industrialisation initiatives.

Figures 1.2 reflects that energy demand due to the urgent need for these countries to accelerate their level of economic development and growth has resulted in higher energy consumption. It has been argued that emissions from fossil fuel energy have increased over a period with solid and liquid fuels with each one currently accounting for 35% and gas fuel 16.9 % of the regional total in SSA countries. For instance, figure 1.2 shows that in Ghana, energy use increased from 1.45 million kg of oil equivalent in 2000 to 1.72 million kg of oil equivalent in 2020. Similarly, in South Africa, the trend in energy consumption grew by 0.1 million kg of oil equivalent from 2000 to 2020. In addition, the trend in consumption of energy resources in Nigeria indicates that fossil fuel energy use increased from 1.2 million kg of oil equivalent in 2000 to 1.26 million kg of oil equivalent in 2020. Hence, in all the three countries, it is evident that for almost a decade, energy consumption possessed an increasing trend.

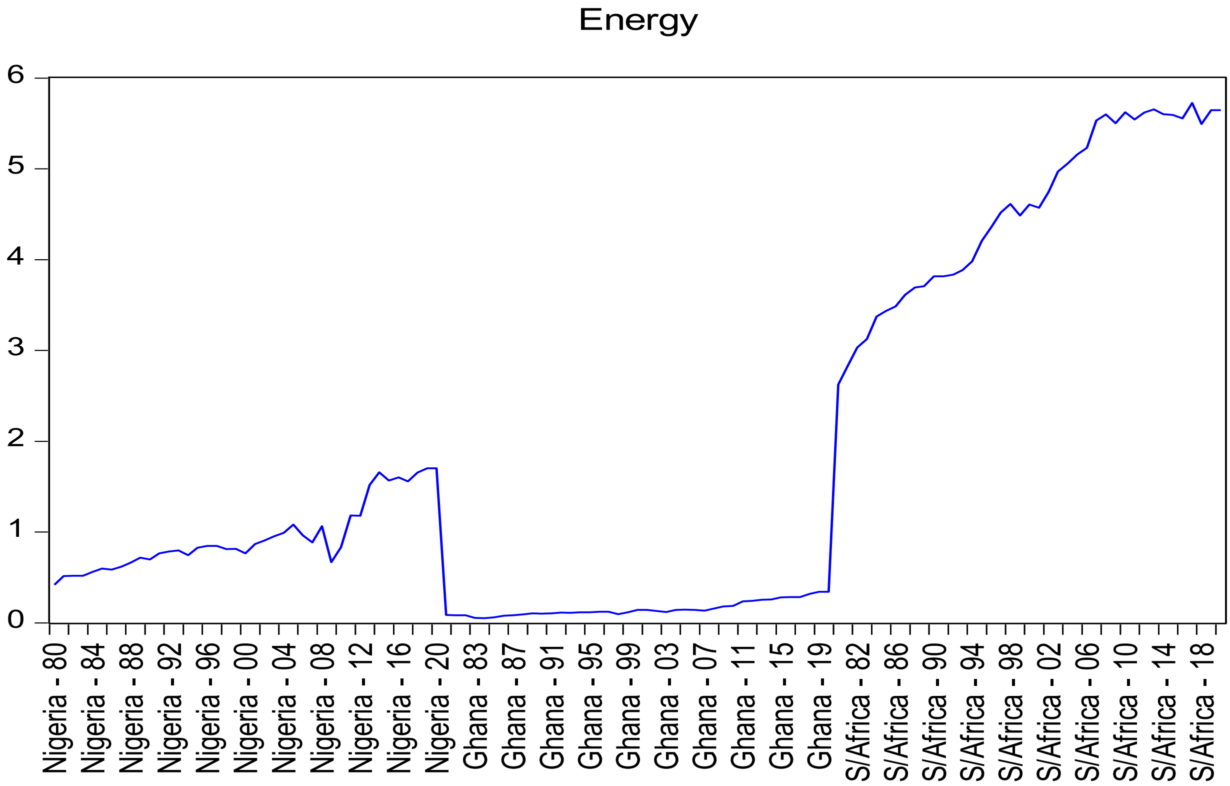


Figure 1. 2: Energy Consumption in Nigeria, Ghana, and South Africa.

Source: (WDI, 2020).

Similarly, SSA countries have recorded rapid growth in industrial performance for almost a decade. The annual growth in value of the output in 2012 for the region was 4.6%, which is projected to increase in the coming years, (World Bank, 2020). The value of industrial performance in SSA apparently remains in a growing trend as the oil and non-oil producing countries have shown improvements in recent times. Nigeria is among the strongest economy in sub-Saharan Africa, with her output increasing at an average of 5.7% annually between 2006 and 2020. In the case of South Africa, the country's output increased to almost triple peak at $400 billion in 2011, while Ghana had an annual growth increase, which averaged 8.6% from 2000 to 2020. Between 2000 and 2020, these countries' gross domestic product (GDP) growth has moved in an upward direction, which also indicates an improvement in economic performance. For example, in all the countries, output increased significantly between 2000 and 2020. Specifically, the total monetary value of output in Nigeria was worth $568.49 billion, in South Africa was $351.30 billion, and $126.77 billion in Ghana. Figure 1.3 shows that the trend of output in Ghana, South Africa, and Nigeria from 2000 to 2020 moved on a positive track. This implies that since the value of industrial performance has been growing, it will directly affect the level of energy demand and cause high carbon dioxide emissions' discharge.

Consequently, based on these situations, energy consumption and industrial performance might be linked with the increasing level of carbon dioxide discharge in these countries.

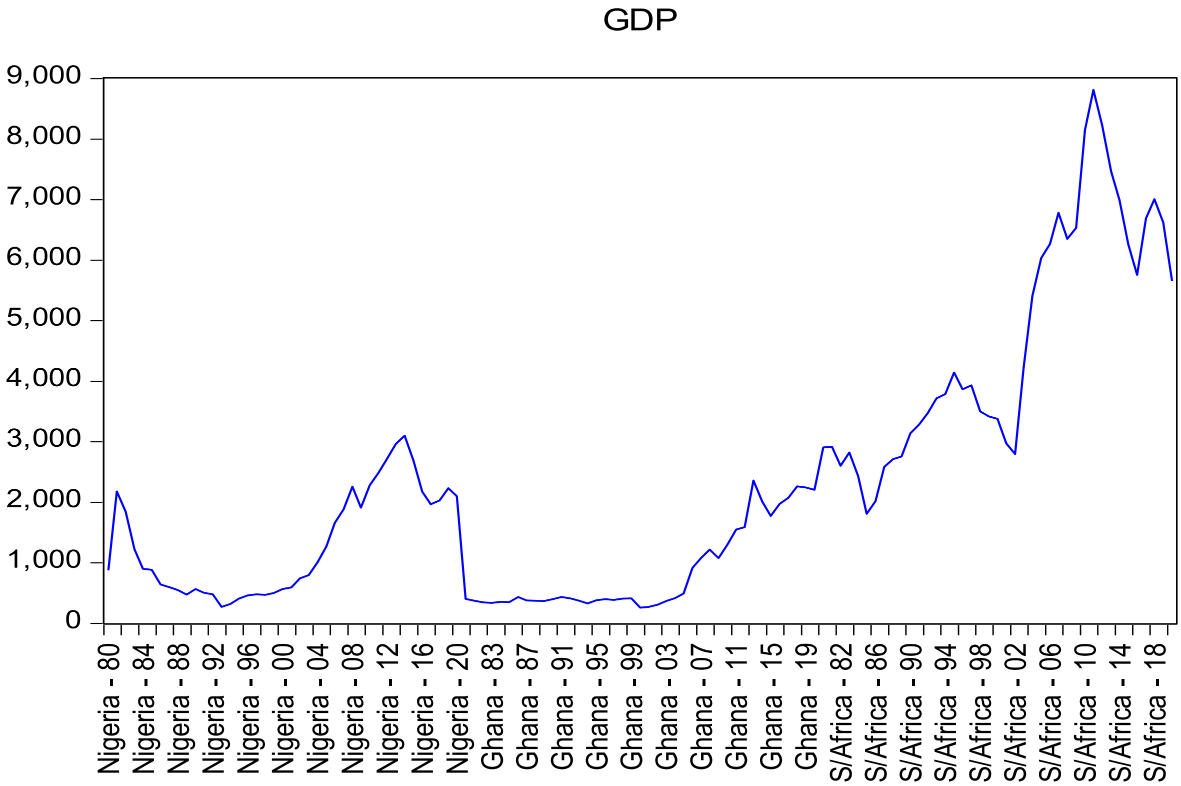


Figure 1. 3: Output Growth in Nigeria, Ghana, and South Africa1980 – 2020

Source: World Development Indicators 2022

This study highlights the conditions of the three largest economies of SSA countries and studied the relationship between energy consumption and energy-supporting economic activities, viz-a-viz carbon dioxide emissions, using econometric analysis, with a view to entrenching environmental sustainability perspective. Thus, the main aim of this study is to investigate the impact of energy consumption, financial development, foreign direct investment, growth rate of gross domestic product, and industrial performance on carbon dioxide emissions in the three largest SSA economies.

1.2 Motivation and Objectives of the Study

The matter of global warming does not have same significance in the developing economies as it has in the developed economies, and so is the case of countries of SSA region. The SSA region has higher dependence on the environmental and natural resources and this region suffers significantly from the climate change and natural disasters due to financial constraints in adapting to these scenarios. In addition, Ghana, Nigeria, and South Africa being the largest economies in SSA are going through rapid urbanisation, population growth and economic growth that can further intensify the pollution levels. Therefore, environmental challenges have become global issues in the present time. The consequences of increased carbon dioxide emissions such as global heat and climate change that affect all communities in the world have prompted policymakers to embark on policies aimed at mitigating the carbon dioxide discharge (Danlami, Applanaidu, and Islam, 2018).

The increasing level of greenhouse gases and carbon dioxide emissions have become a threat to the environment, causing an overall rise in temperature and accelerating global warming. The main cause of the rise in temperature and the noticeable change in the weather across the globe can be attributed to the upsurge in levels of carbon dioxide emissions in the atmosphere (Heidari, et al. 2015). Global climate change is increasingly gaining momentum among researchers, policymakers (public and private), and other interested parties. Excessive greenhouse gas emissions, particularly carbon dioxide emissions, are widely acknowledged as a major obstacle to having sustainable environmental quality and growth. However, much notable research continued to focus on studies motivated to reducing emissions in advanced rich countries, while relatively few have been carried-out in SSA economies. More so, these studies on the drivers of carbon dioxide emissions in advanced economies have yielded conflicting results with policy recommendations that may not be applicable for developing economies due to the relatively wide divergence in stages of economic development.

The conflicting findings have remarkable implications on the design and implementation of emissions-reducing initiatives in SSA. As a result, this study focuses on finding the determinants of carbon dioxide emissions, using data of the three largest economies in sub-Saharan Africa. Although the African region has relatively lower per capita levels of emitted greenhouse gasses, the ever-increasing risks of adverse worldwide climatic changes indicate that global economies need to avoid economic growth paths based on high-emission models. While the SSA countries are trying to overcome several developmental challenges, it is essential to design their economic development in such manners that will not cause a large-scale rise in greenhouse gasses emissions. In fact, despite relative advances in economic growth and carbon dioxide emissions literature, empirical findings on the applicability of the environmental kuznets hypothesis within the African continent remains inconclusive and unresolved. In other words, it remains unclear to what extent the environmental kuznets hypothesis holds true in SSA. Thus, this study further ascertains the extent to which the

Environmental Kuznets Hypothesis holds in the three largest economies of African countries. This is useful for regulators to develop and implement effective policies aimed at safeguarding the quality of the environment. Moreover, very few studies have attempted to examine these linkages using a combination of both specific country analysis and pooled data analysis, while explaining the causality among financial development, output growth, energy consumption, industrial performance, and foreign direct investment. Adopting these diverse modelling techniques would further shed light on the nature of the fossil fuels emissions and its macroeconomic determinants, with a smaller number of studies, analysing the transmission path of carbon dioxide emissions, using impulse response and variance decomposition techniques, within a VAR model context, to circumvent any possible specification bias. Although some studies have been conducted on the issue of energy consumption and carbon dioxide emissions, only a limited number have focused on the evaluation of industrial performance in Ghana, South Africa, and Nigeria.

The contradicting findings of prior studies of the interrelationships between energy usage and environmental pollution have highlighted the need for further investigating this nexus, and this is precisely what the present study aims to carry out. It strives to provide evidence-based information to policymakers for an informed appropriate environmental policy that are effective in mitigating carbon dioxide emissions and maintaining the environmental quality of the SSA countries. It is believed that, investigating the nature of these relationships would further elevate the trajectory of policy making for informed strategy to effectively and efficiently stimulate the consumption of improved environmental quality that considers the intra- and inter-generational equity in the use of natural resources, while also delivering non-declining consumption for the current generation in the production process among sampled SSA countries.

1.2.1 Objectives of the Study

The overall aim of this study is to investigate the impact, causal order and transmission path of energy consumption, financial development, foreign direct investment, gross domestic product growth, and industrial performance on carbon dioxide emissions in the three largest SSA economies.

The specific objectives of this study are:

1 to empirically examine, the impact of fossil fuel energy consumption, foreign direct investment, financial development, gross domestic product growth and industrial performance on carbon dioxide emissions in three largest economies of sub-Saharan Africa.

2 to analyse how the dynamics and transmission channels of fossil fuel energy consumption affect carbon dioxide discharges in the three largest economies of SSA countries.

3 to carry out the forecast of future dynamic behaviour of fossil fuel energy consumption, foreign direct investment, financial development, gross domestic product growth, and industrial performance as they influence carbon dioxide emissions in the three largest economies of SSA countries.

1.3 Research Questions

Based on the above motivation and objectives of the study and considering the unsettled debate on the energy-demand factors and carbon dioxide emissions nexus in SSA, the following are the specific questions this study seeks to answer:

1. Do fossil fuel energy consumption, foreign direct investment, financial development, gross domestic product growth, and industrial performance promote carbon dioxide emissions in the three largest economies of sub-Saharan Africa?
2. What is the dynamic nature of the transmission channel between fossil fuel energy consumption and carbon dioxide emissions in the three largest economies of SSA countries?
3. What is the causal relationship among fossil fuel energy consumption, foreign direct investment, financial development, gross domestic product growth and industrial performance and carbon dioxide emissions, and to what extent do these macroeconomic-energy demand factors explain the future forecast variations of carbon dioxide emissions in the three largest economies of sub-Saharan African countries?

1.4 Contributions of the study

The study brings together different strand of macro – economic factors of energy demand and environmental degradation metrics, which includes energy consumption, foreign direct investment, financial development, industrial performance, and gross domestic product growth on carbon dioxide discharge. The study also contributes to the empirical literature on energy consumption and emission nexus, providing further empirical relationship between energy demand because of economic activities and carbon dioxide emissions using data obtained for the three selected largest economies in sub – Saharan African countries, since extant studies across global regions have failed to agree and ascertain a clear transmission path of impact and casual relationship. Furthermore, the study offers insight into macro-economic variables that ascertains the impulse response dynamics and forecast error variance decomposition of carbon dioxide emissions and granger causality within a vector autoregressive (VAR) framework, Toda Yamamoto in VAR framework, and autoregressive distributive lag bounds (ARDL) model technique using quarterly data.

1.5 Structure of the study

The study is organised in six main chapters. The first chapter, which dwells on the general introduction, provides the background of the study, problem statement, research objectives, and significance of the study. Chapter two provides the synopsis of evolutions, and current trends of carbon dioxide emissions. The third chapter illuminates empirical evidence on the impact of energy consumption, financial development, foreign direct investment, gross domestic product growth, and industrial performance on carbon dioxide emissions in three largest sub-Saharan African economies. The fourth chapter presents an evaluation of energy use and carbon dioxide emissions nexus using a variance decomposition and impulse response analysis. The fifth chapter examines the extent to which energy consumption, financial development, foreign direct investment, industrial performance, and gross domestic product growth in three largest economies of sub-Saharan African countries explain systematic dynamism in carbon dioxide emissions. Finally, chapter six summarises and concludes the study by articulating the major findings, outlining policy recommendations based on the findings, limitations of the study, and agenda for future research.

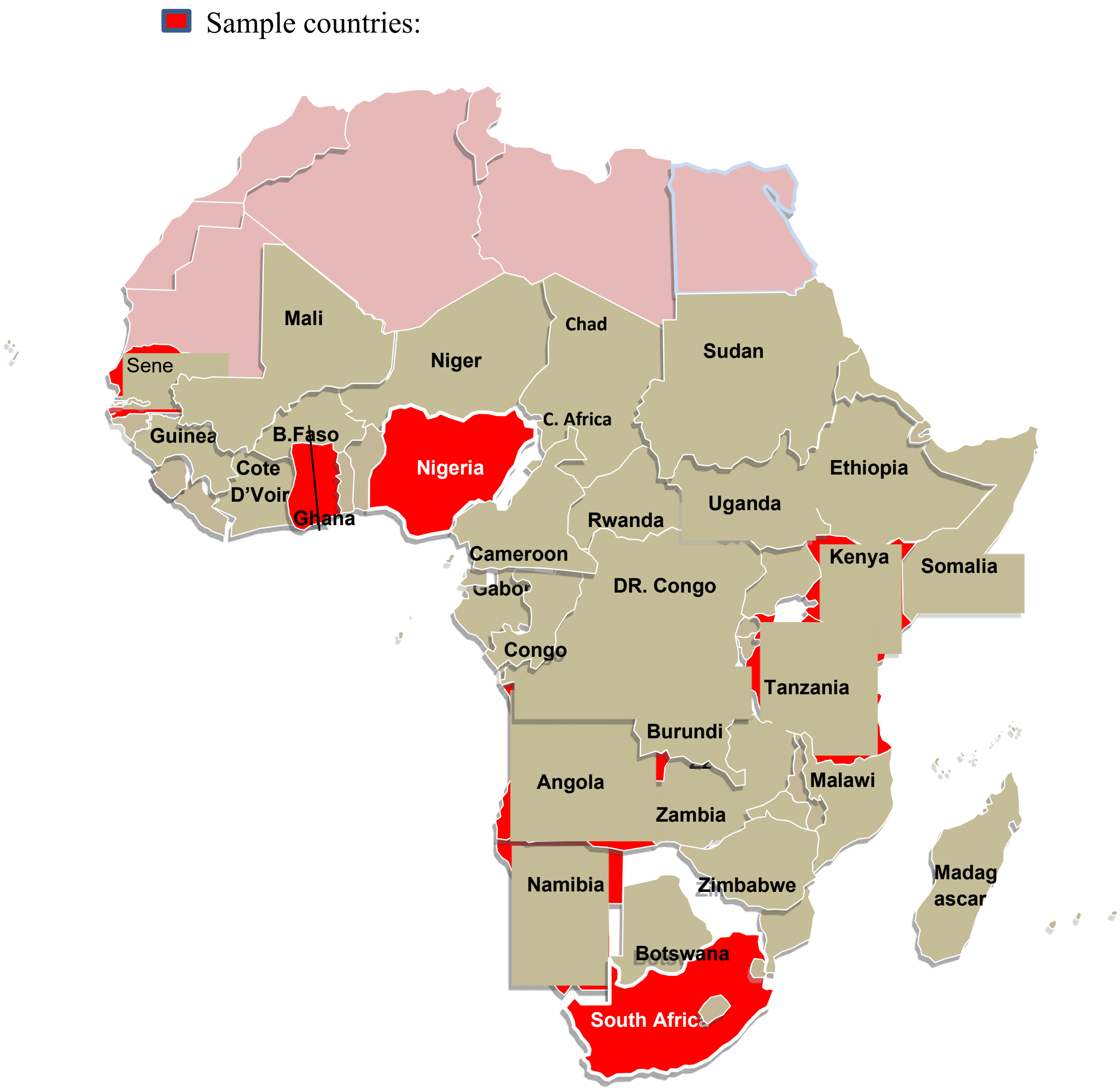


Figure 1. 4: Countries in the Sub-Saharan African Region.

Source: Brewminate (2020)

CHAPTER TWO

TRENDS AND EVOLUTIONS OF CARBON DIOXIDE

2.1 Introduction

The second chapter of the study discusses the synopsis of evolutions, and current trends of carbon dioxide emission. Section 2.2 dwells on carbon dioxide emission looking at the specific evolution and current trends. Section 2.3 focuses on the global annual emission, while 2.4 discusses the share of annual carbon dioxide emissions. Section 2.5 considers an examination of the global and regional trend of carbon dioxide emission. Next, section 2.6 highlights the impact of emissions on atmospheric concentration, and section 2.7 outlines an overview of greenhouse gas emission sources, focusing on the global warming potential of greenhouse gases. In addition, section 2.8 examines the future emission scenarios, and section 2.9 illuminates the linkage of carbon dioxide emissions to Industrial performance and fossil fuel energy consumption through a model of multi-variate analysis. Finally, section 2.10 presents conclusion of the chapter.

2.2 Evolutions of Carbon Dioxide Emissions

Carbon dioxide is a greenhouse gas (GHG) as it creates the 'greenhouse effect' by absorbing and emitting thermal radiation. Carbon dioxide along with the other greenhouse gases such as methane and nitrous oxide, is crucial in maintaining a habitable global temperature as without the greenhouse gases, the earth would be too cold. According to Qiancheng Ma (1998), the average surface temperature of the Earth without the GHGs would be approximately -18 degrees Celsius. There has been rapid rise in the level of carbon dioxide emissions since the industrial revolution due to the increased consumption of fossil fuels for generating energy, this has caused disruption in the global carbon cycle and is further causing the global warming. There are potential ecological, health and physical effects of climate change and global warming such as rise in sea- level, disruption in water systems, altered crop growth and extreme weather conditions like storms, floods, heat waves, draughts etc.

The fifth Intergovernmental Panel on Climate Change (IPCC) report provides the most detailed analysis about the potential effects of climate change and presents an extensive coverage on all effects (Barros, et al. 2014). Considering this report, the members of United Nations member countries have decided a target to limit the average global warming to 2 degrees Celsius above the pre-industrial temperatures. This section attempts to present a perspective about the evolution of carbon dioxide emissions, distribution of these emissions, the associated key factors driving both these trends and the factors holding key to mitigate the climate change. To better understand the global warming situation, we need to know how the temperature on earth started rising since the industrial revolution. Figure 2.1 presents the global temperature anomaly with x-axis presenting the period from 1850-2017 and the y-axis presents the average global temperature going below or above the baseline temperature of 1860-2017. Therefore, we are using the average temperature during the period 1860-2017 as a baseline for the measurement of annual changes in temperature.

In figure 2.1 below, the red line represents the average annual temperature throughout the period and the light grey line represents the upper and lower temperature range. Here we can clearly see that there has been sharp rise in the global temperatures during last few decades, which is about 0.8 degrees Celsius higher than the baseline temperature of 1860-2017. If we extend back to the period of 1850, the temperatures during those times were 0.4 degrees colder than the baseline temperature of 1860-2017. Therefore, when we calculate the overall rise in temperature since the pre- industrial era, it is a rise of 1.2 degrees Celsius approximately. Since we have already crossed the one-degree mark, we are more than halfway close to the global threshold to limit the average global warming to 2 degrees Celsius above the pre-industrial temperatures.

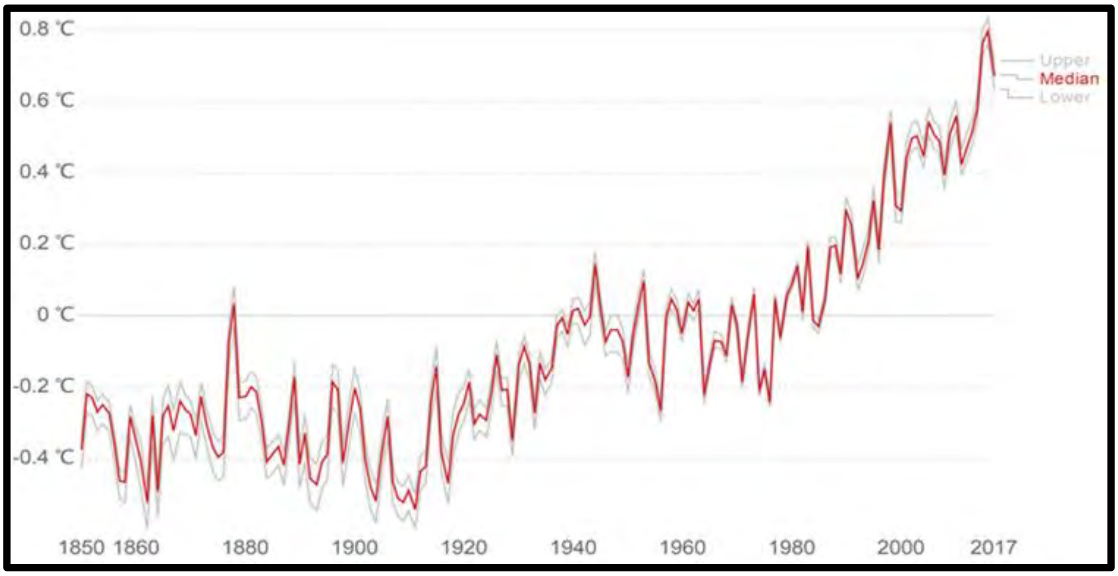


Figure 2.1: Temperature Anomaly from 1850-2017.

Source: Hadley Centre

Figure 2.1 above presents these trends both by the tropics (30 degrees above and below the equator), as well as by hemisphere (Northern hemisphere and Southern hemisphere). We notice that the average temperature rise is higher in the Northern hemisphere (about 1.4 degrees Celsius since 1850) as compared to the southern hemisphere (about 0.8 degrees Celsius). According to Delworth, et al. (2016), this distribution has a strong association with the ocean circulation patterns (North Atlantic Oscillation) which causes higher temperature in the northern hemisphere.

The Long-Run History of Cumulative Carbon Dioxide Emissions

By extending back our timeline to 1750 and calculating the carbon dioxide emission of each country until date, we can arrive at the cumulative emissions of each country. Figure 2.2 presents the cumulative emission of each country plotted from the period 1750 to 2016. According to this chart, the United Kingdom (UK) was the earliest industrial-scale carbon dioxide emitting country of the world. The emissions in North America and the other European countries that produced carbon dioxide during most of this period shortly followed it. Other Asian, African, and Latin American countries started causing worldwide carbon dioxide releases after quite some time during the 20th and 21st centuries.

Today, Europe and the United States (US) have the heaviest cumulative emissions. Although the rapid rise of emissions in China during the last few decades has made it the second biggest cumulative emitter in the world, its contribution is still less than half of the US' cumulative emission. In figure 2.2, the amount of collective carbon dioxide emanations is shown as a percentage portion of the total worldwide emissions. Therefore, we can see the occurrences of major shifts and transitions in global emissions. Europe had dominated global cumulative emissions during the 19th century firstly it was the United Kingdom and later there were other european countries (which are now a part of European Union (EU)). During the latter half of 19th century, the cumulative emissions of US started rising, its contribution peaked at 40% during 1950, and since then, it has been on a decline. Although it now stands at 26%, it is still the highest in the universe. By 2015, India was accountable for 3% of overall global accumulative emanations, while China accounted for 12%.

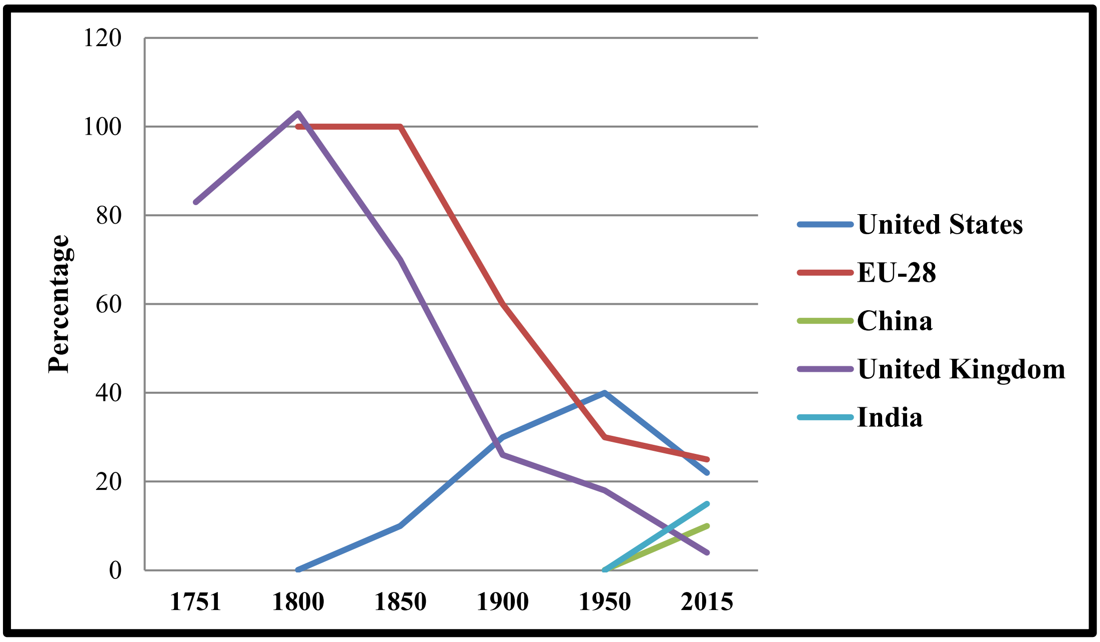


Figure 2.2: Share of Global Cumulative Carbon Dioxide Emissions

Source: Global Carbon Project (2017)

By sparing the accumulative time measurement and just focusing on yearly discharges, we can compare the recent trends of annual emissions of the countries. Figure 2.3 presents the country-wise annual carbon dioxide emissions data. In line with the above cumulative emissions chart, North American and European countries have grown much earlier compared to other countries. Over the last few decades, emission levels have been rapidly rising in developing economies. We could notice that some middle- and low-earning countries have become topmost worldwide emitters.

Now, China is the leading emitter, and just behind it, we can find the USA, EU-28, India, Russia, Indonesia, Brazil, Japan, Canada, and Mexico. It is also to be noted that these countries, which are already top emitters, might persist to augment productions as they are undergoing rapid progress. However, contrary to the growth of carbon dioxide discharges in developing countries, we can see stabilisation in the emission trends of high-income countries and in many cases, a reduction in emanations level was witnessed during the 19th century. Despite, the downward curve in some countries, the global trend is being dominated by the transition economies and therefore, global annual emissions have been continuously rising over this period.

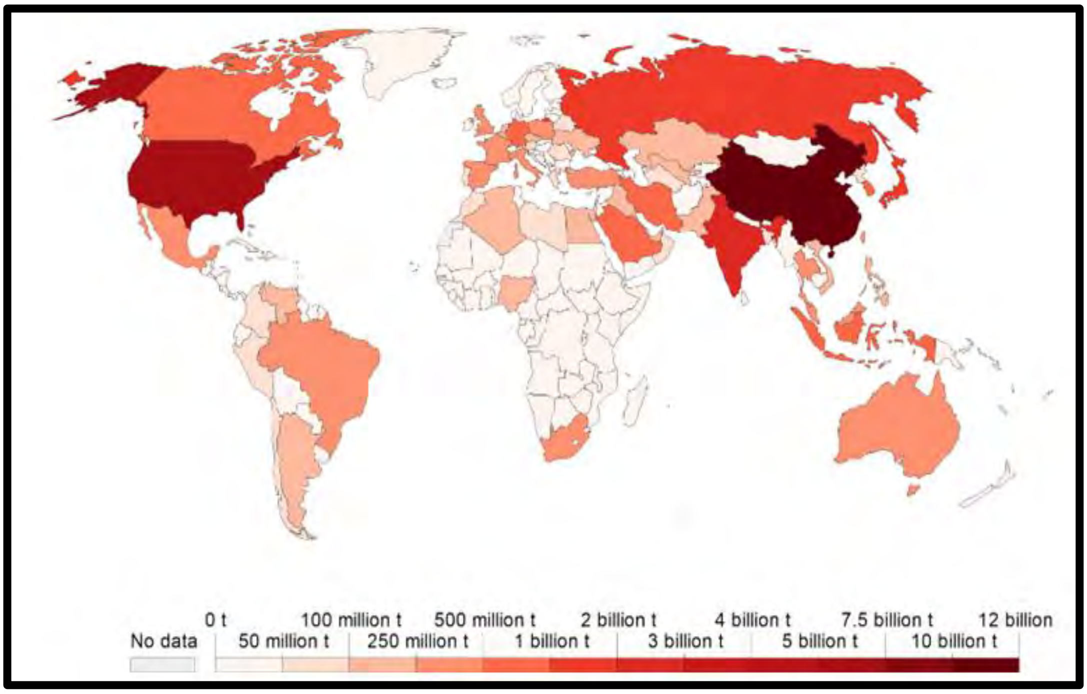


Figure 2. 3: Annual Carbon Dioxide Emissions, 2016

Source: Global Carbon Project (2016).

2.3 Per Capita Emissions of Carbon Dioxide Emissions

One of the major shortcomings of evaluating the overall discharges of a country is that it does not take into consideration the population size of that country. Although the Chinese Republic is currently the topmost emitter in the universe, we must note that it has the world's largest population, and this fact must be given due weightage. Therefore, for a fair comparison of the country-wise emission contribution, the emissions must be compared about per capita carbon dioxide emissions. It is observed that for most countries, the per capita emission continues to increase with development. However, large global inequalities were found in the per capita emissions distribution in the year 2014.

It is worthy to note that there are many other greenhouse gasses besides the bad goon carbon dioxide contribute to climatic variation. These other greenhouse gasses such as methane and nitrous oxide are also responsible but have not been considered here. The food production industry, particularly, the intensive rearing of livestock for dairy and meat also has major contribution in producing non-carbon dioxide greenhouse gases. As the per capita meat consumption is strongly related with the level of output, there is a much higher per capita emission level of methane and nitrous oxide in high-income countries. Consequently, if these gases were also accounted with the carbon dioxide emissions, there would be even greater global inequalities.

In addition, a significant north-south divide has been found in per-capita emissions. While the annual per-capita discharges of most of the republics in South Asia, South America and sub-Saharan Africa are lower than 5 tons, the annual per capita emissions in the north are above 5 tons, with North America exceeding the annual per capita emissions by over 15 tons. The monthly per capita emission of wealthy states is generally greater in comparison to the poorer states. Qatar is the largest emitter with annual per capita emissions of 50 tons, which is 1243 multiple of Chad, the bottommost emitter.

2.3.1 Carbon Dioxide Emissions by Fuel

The carbon dioxide emissions related to the industrial production and energy can arise from various types of fuel. Over the time, the contribution of each fuel type has significantly changed, and the consumption of a certain fuel type largely varies from region to region. Figure 2.4 presents an absolute and relative contribution of these sources of fuel to the carbon dioxide emissions. Looking at the global picture, we can see that solid fuel was the dominant fuel type in the initial industrialisation phase. Europe and North America had first started the industrial-scale use of coal-fired power during the 1700s, according to Zilio and Recalde (2011). The issue of carbon dioxide emissions due to oil and gas production only started arising from the late-1800s, and the emissions from cement production as well as flaring started rising only in the late-1900s. Presently, there is dominant contribution of solid and liquid fuels in the emission levels. However, there is a notable contribution from gas production as well. The contribution of flaring and cement production to global emissions remains comparatively small.

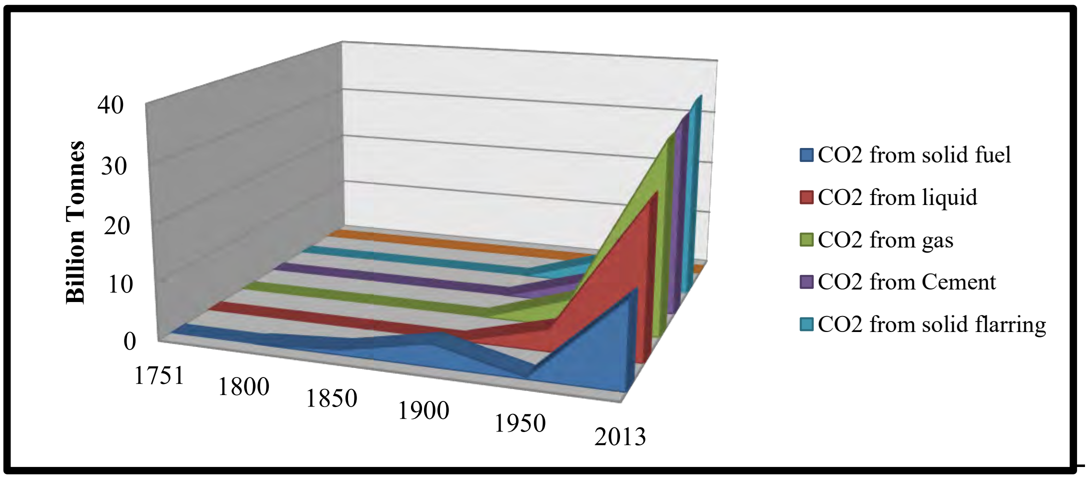


Figure 2.4: Carbon Dioxide Emissions by Source across the World

Source: Carbon Dioxide Information Analysis Centre

A critical question therefore is which factor is the biggest contributor of carbon dioxide emissions – electricity, residential, transport or manufacturing? Figure 2.5 presents the percentage share of carbon dioxide emissions that arise due to fuel combustion done in these sectors. In 2018, about 28% of global emissions were due to building operations. About 23% contribution was by the transportation sector, 22.7% contribution was by the concrete, steel, and aluminum industries, 20.3% was due to the industry sector and 6% was contributed by the remaining sectors.

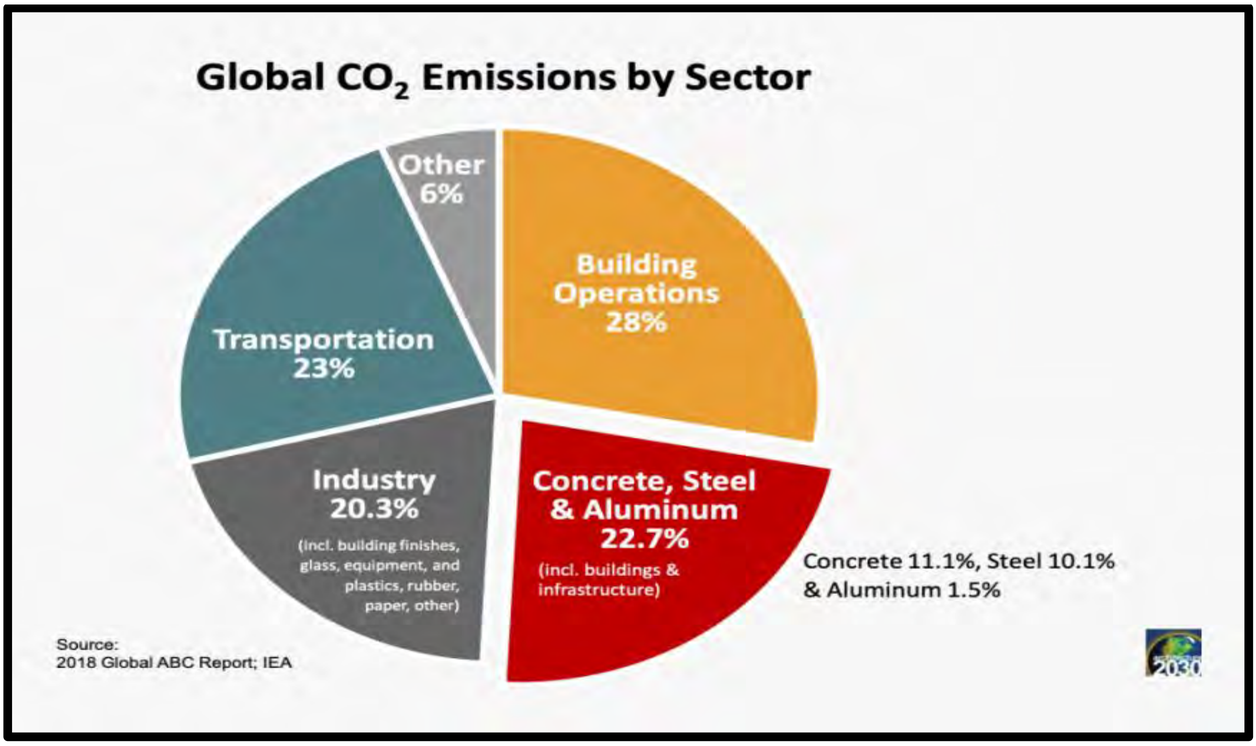


Figure 2.5: Carbon Dioxide Emissions by Sector, World

Source: Global ABC Report IEA (2018)

2.4 Geographical Distribution of Carbon Dioxide Emissions

Figure 2.6 below shows each country's share in the global carbon dioxide emissions from the period 1970 to 2021. It was calculated by dividing each country's emissions with the total of all countries' emissions each year. However, it does not include the emissions caused by international shipping and aviation and the 'statistical differences'.

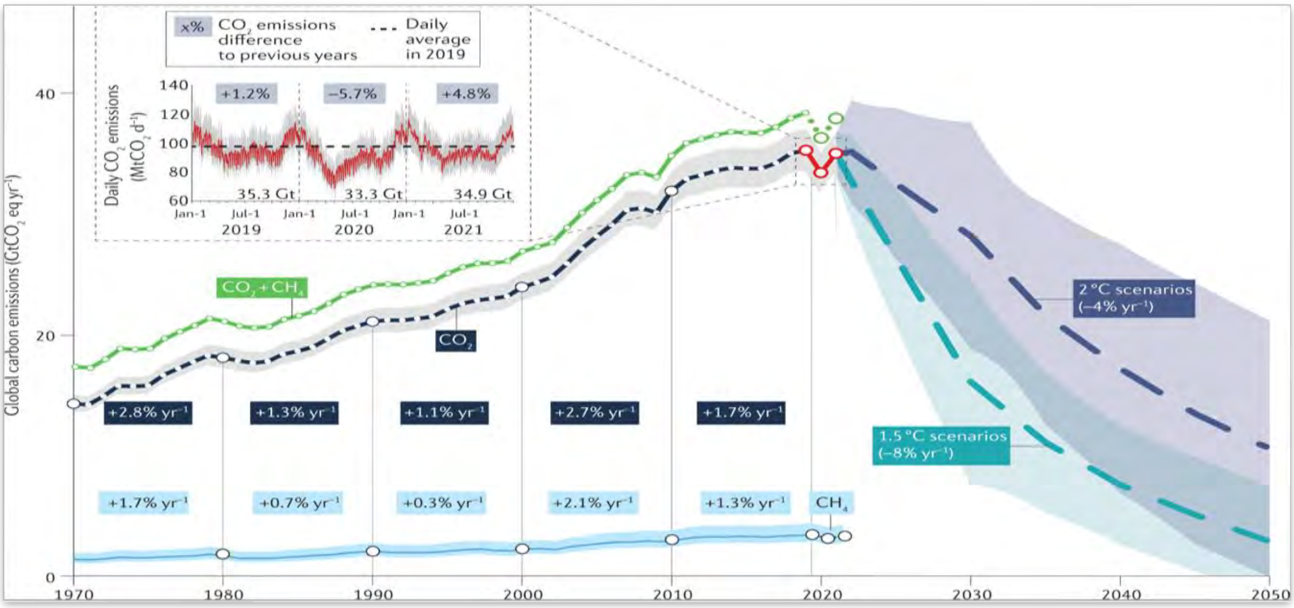


Figure 2.6: Annual Share of Global Carbon Dioxide Emissions, 2021
Source: Global Carbon Project

2.5 Global and Regional Trends

Figure 2.7 shows the long-term outlook on worldwide carbon dioxide productions. Since 1900, the overall discharges soared up from two (2) billion tonnes of carbon dioxide to over 36 gigatonnes in 2015. While data for the period 2014-2017 indicates the stabilisation of the global annual emissions, data from the global carbon project (2019) reports an increase of 2.7% in global annual emissions level in 2019.

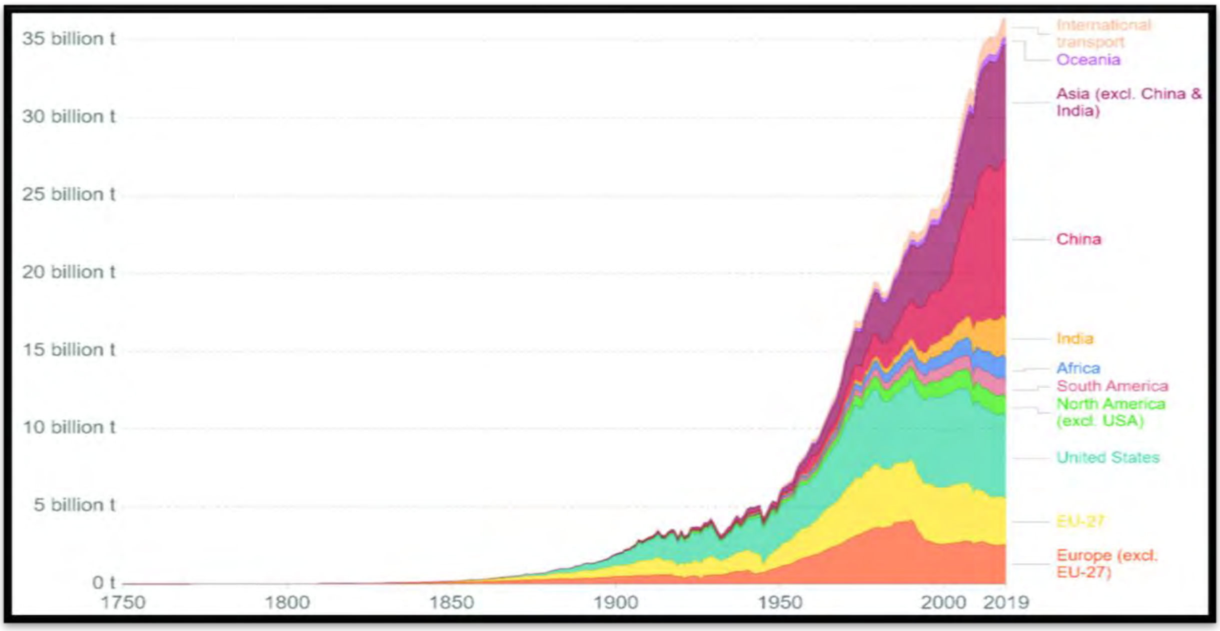


Figure 2.7: Annual Carbon Dioxide Emissions by World Region.
Source: Global Carbon Project (2020)

2.5.1 Cumulative Carbon Dioxide Emissions by Region

Figure 2.8 presents region-wise cumulative carbon dioxide emissions. The cumulative emissions are presented since 1750, show emissions based on production, and do not include emissions related to trade.

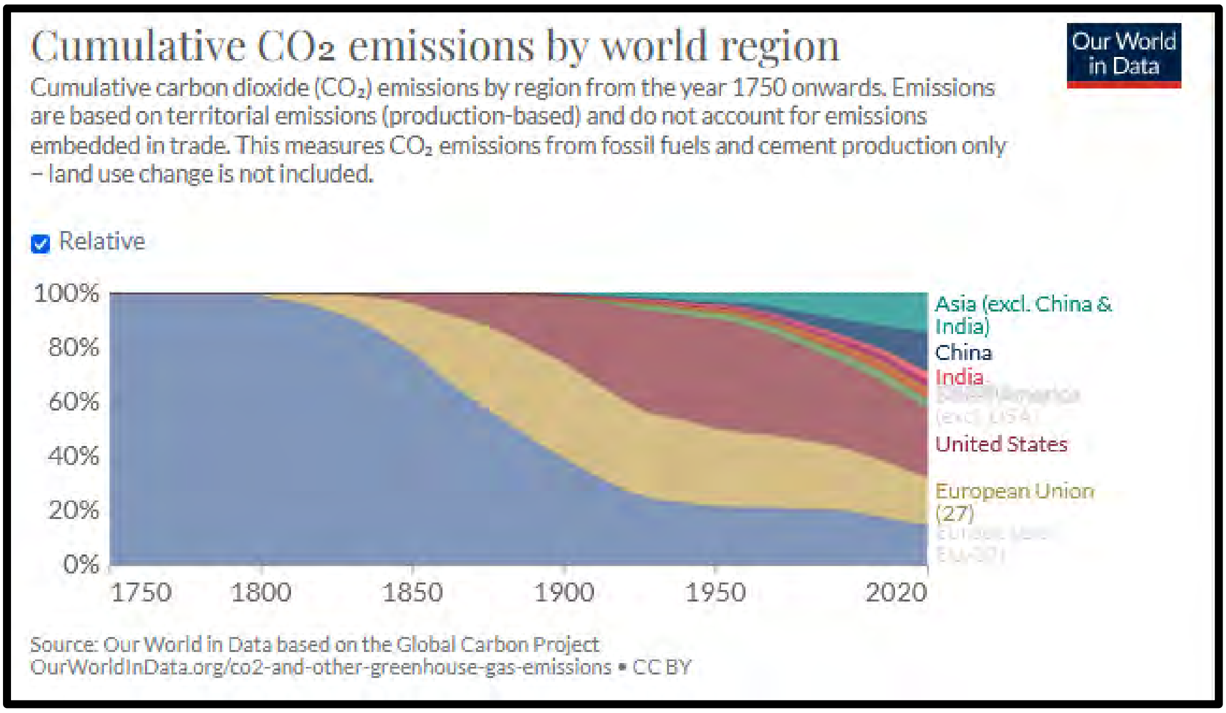


Figure 2.8: **Cumulative Carbon Dioxide Emissions by World Region**

Source: Global Carbon Project (2018)

It is to be noted, that for the past few decades, carbon dioxide emissions in countries of sub-Saharan Africa such as Nigeria, South Africa and Ghana have clearly shown an increasing trend. For example, in Ghana, the explosion of carbon dioxide discharge has been happening since 1990 as specified in figure 2.9. Similarly, figure 2.10 shows that the level of carbon dioxide emission in South Africa increased from 5.5 per capita (metric tons) in 2000 to 5.68 per capita (metric tons) 2017. Accordingly, carbon dioxide discharge in Nigeria has grown by 0.2 million per capita (metric tons) from 2000 to 2017 as shown in figure 2.11. Thus, a general assessment reflects a worrisome growth of the carbon dioxide trend in these countries, intrinsically deteriorating the level of environmental quality and jeopardising human life and development in sub – Saharan African countries.

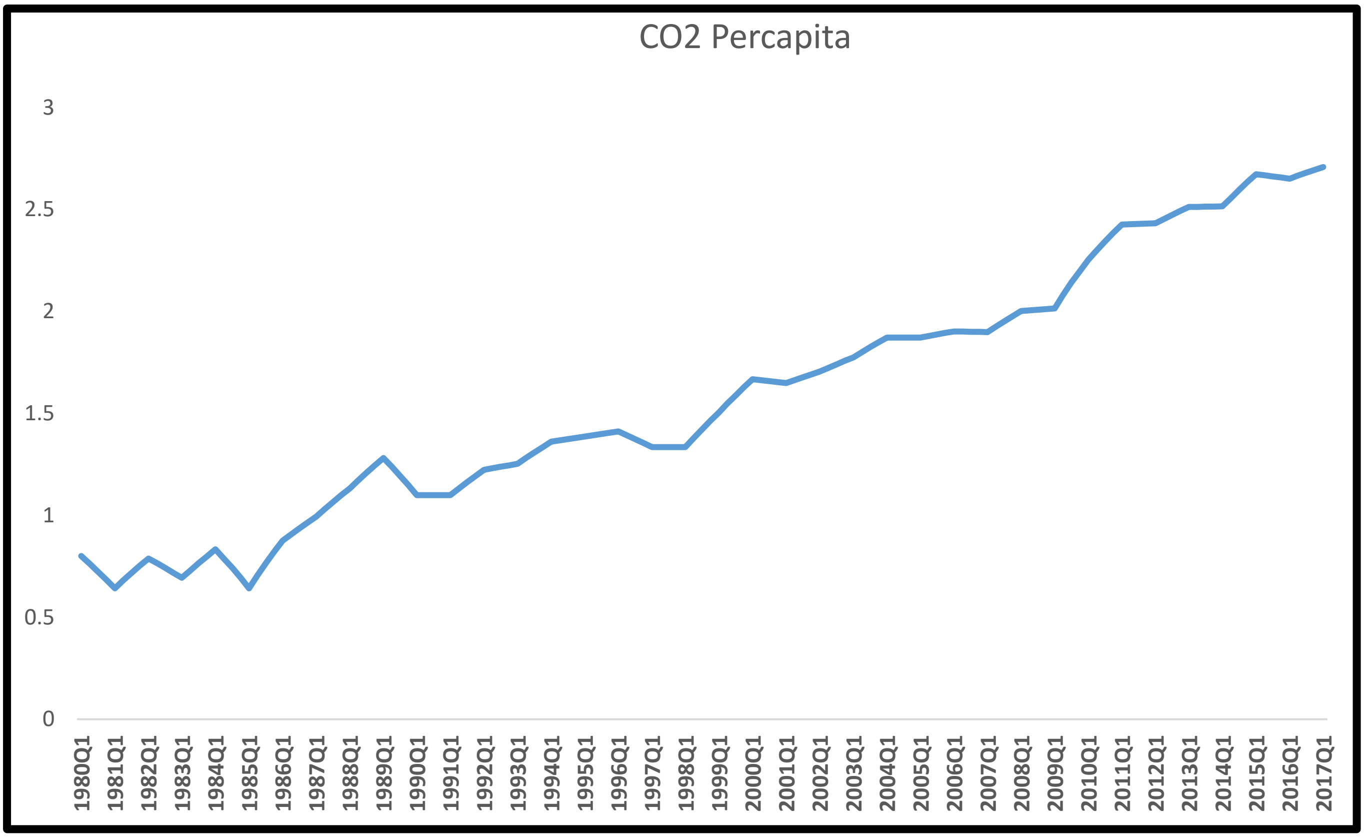


Figure 2.9: Trend of Carbon Dioxide Discharge in Ghana from 1980Q1 to 2017Q1

Source: (EIA, 2017)

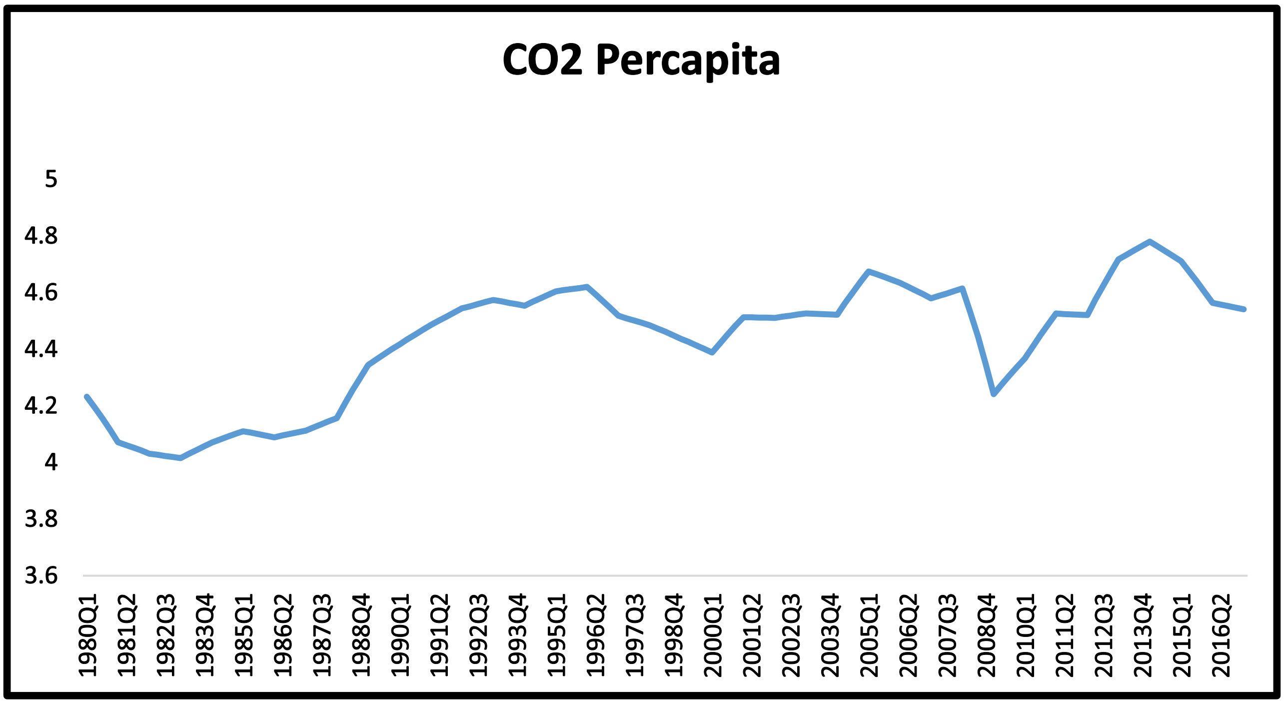


Figure 2.10: Trend of Carbon Dioxide Discharge in Nigeria from 1980Q1 to 2017Q1

Source: (EIA, 2017)

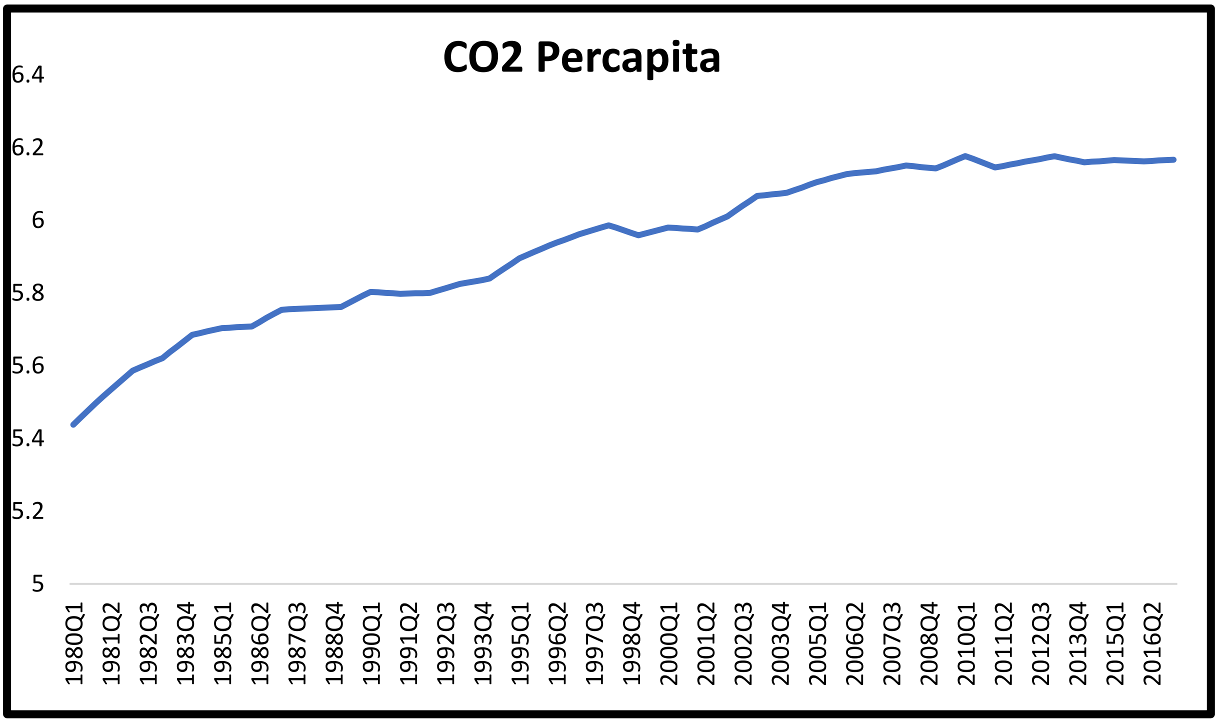


Figure 2.11: Trend of Carbon Dioxide Discharge in South Africa from 1980Q1 to 2017Q1

Source: (EIA, 2017)

2.6 Impact of Emissions on Atmospheric Concentration

The rapid rise in worldwide carbon dioxide productions greatly influences the atmospheric concentration of carbon dioxide on Earth. Considering atmospheric concentrations, figure 2.12 shows that till the 18th century, the intensities were quite unwavering at 270-285 ppm (parts per million). The global carbon dioxide concentrations started rising rapidly since the inception of the industrial revolution. However, carbon dioxide emission is not the only issue; the emissions of methane and nitrous oxide are also escalating due to industrial, energy, and agricultural sources.

There is the need to examine whether the recent stabilisation of worldwide carbon dioxide levels had some effect on global atmospheric concentrations. It is sufficient to state that while some progress is achieved in reducing global emissions, there has been a continuous rise in the global atmospheric concentration. Emissions have surpassed the highest level ever of 400-ppm threshold, and, to reduce or stabilise the atmospheric carbon dioxide concentrations, there must be significant reduction in the carbon dioxide emissions. Another, key issue for debate rests on why the respective efforts at stabilising carbon dioxide emissions does not have immediate impact on atmospheric concentrations. In line with this, Ciais, et al. (2013) stated that it is because the accumulation of carbon dioxide in the atmosphere is based on 'residence time'. This time indicates the interval needed for removing the produced carbon dioxide from the air by the natural procedures of the Earth's carbon cycle. However, this duration varies to a great level: while some carbon dioxide can be removed in as less duration as 5 years by fast cycling processes, the other processes like deep ocean cycling, absorption through soil, vegetation and land might even take hundreds of years. Therefore, even if we completely banish carbon dioxide emissions starting from today, it is still going to take quite a multitude of years to remove most of the mortal discharges from the air (Ciais, et al. 2013).

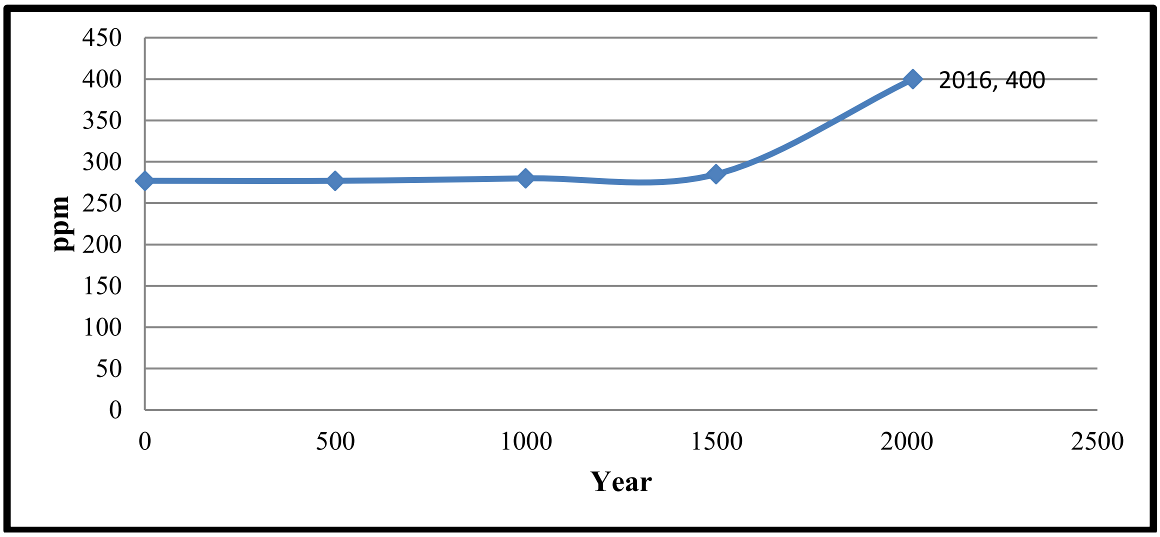


Figure 2.12: Atmospheric Carbon Dioxide Emissions Concentration (ppm)

Source: Global Carbon Project (2018)

2.7 Greenhouse Gas Emission: Global Warming Potential of Greenhouse Gases

As discussed earlier, carbon dioxide is not the only greenhouse gas that raises concerns regarding climatic change and global warming; rather there are a few greenhouse gases including nitrous oxide and methane that are known as the 'F- gases' group. The contribution of all the greenhouse gases to global warming is not the same. One ton of carbon dioxide emission would not affect global warming as much as 1 ton of methane. The Global Warming Potential (GWP) scale can measure these differences. This scale can be used for many time-period ranges, but the 100-year timescale is the most popular and is also used by the IPCC (IPCC, 2014). Figure 2.13 presents the GWP_{100} value of the major greenhouse gases. GWP_{100} measures the warming effect of a one-unit mass or one molecule of a greenhouse gas relative to carbon dioxide on the 100-year timescale (IPCC, 2014). For instance, the warming impact of a ton of methane gas is 28 times of the impact of carbon dioxide over the period of 100 years. The values of GWP_{100} are used to provide uniform emissions metric for all greenhouse gases, which are known as the carbon dioxide emissions counterparts (CO_2e). It is calculated by the multiplication of the releases of a particular greenhouse gas with the corresponding GWP_{100} dynamic. The total of carbon dioxide emissions counterparts' form of entire gases reflects the total greenhouse gas emission (IPCC, 2014).

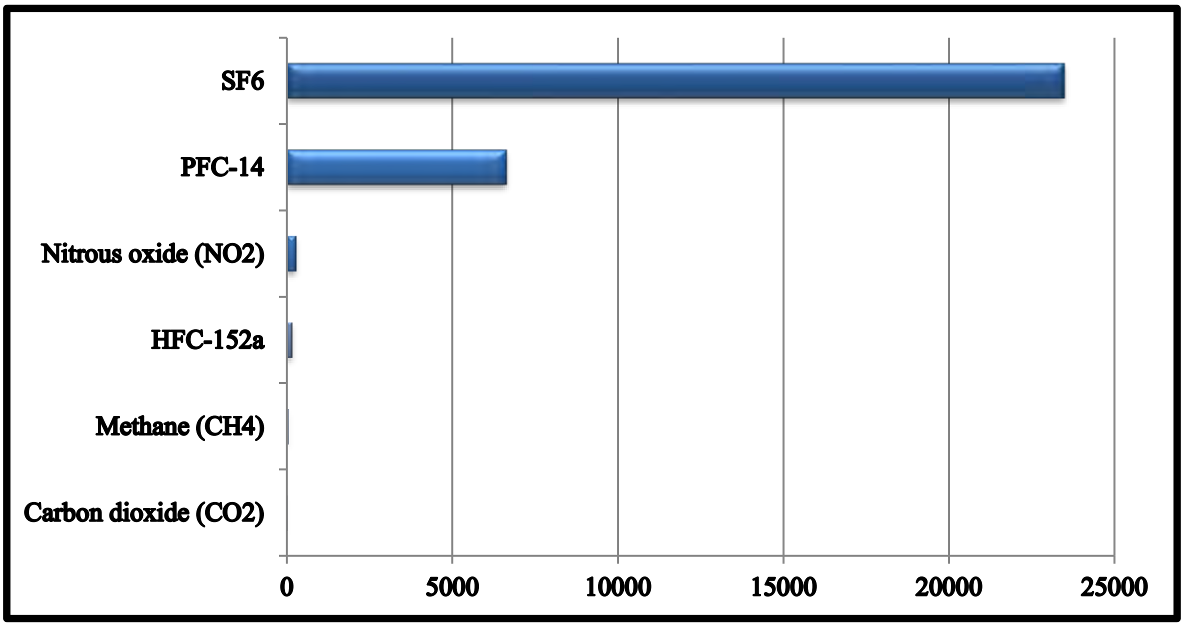


Figure 2.13: Global Warming Potential of Greenhouse Gases over a 100-Year Timescale

Source: Intergovernmental panel on climate change (2014)

2.7.1 Greenhouse Gas Emissions by Gas

Figure 2.14 reveals the contributions of various gases to the overall greenhouse emission measured because of their respective carbon dioxide equivalent values. It is evident from the chart that carbon dioxide emissions are answerable for about 75% of the entire greenhouse discharges, although, nitrous oxide and methane are also significant contributors summing up for 7% and 17% of discharges each. The 'F-gases' include SF_6, HFC and PFC gases. These gases have very high potential of global warming, but since very small quantities of these gases are emitted, their contribution to global warming remains small.

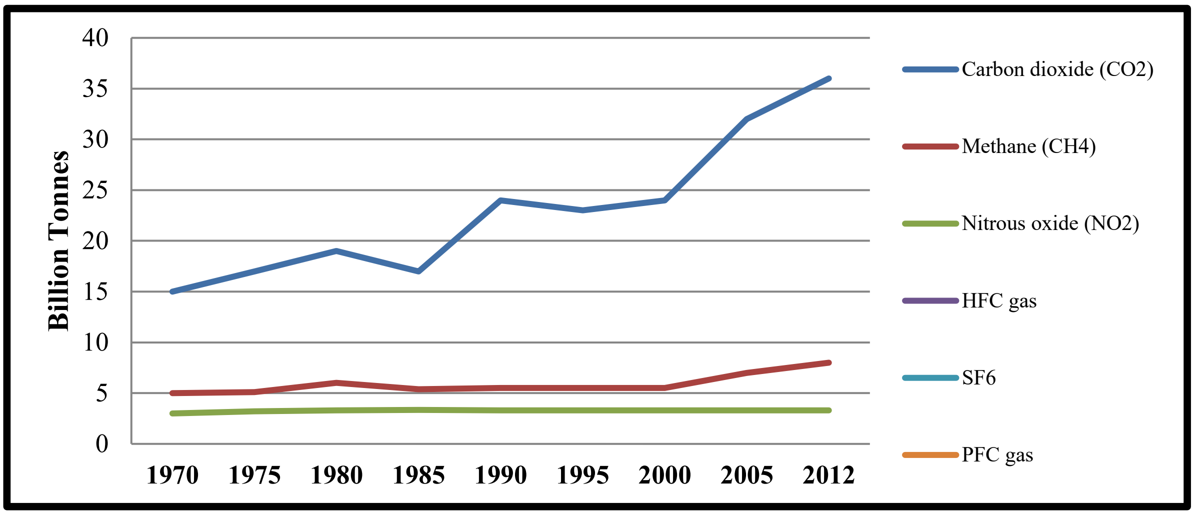


Figure 2.14: Greenhouse Gas Emissions by Gas, World

Source: World Development Indicators (2017)

2.8 Future Emission Scenarios

Another major concern is the future scenario of carbon dioxide emissions and the greenhouse gas emissions. Figure 2.15 below presents the potential future scenario of the global greenhouse gas emissions derived from the data sourced from climate action tracker. There can be five potential scenarios:

a. **No climate policies**: If there is no implementation of the climate policies, there would be an estimated rise to 4.1-4.8°C (relating to the pre-industrial temperature) in the global warming by the year 2100.

b. **Current climate policies**: The estimated emissions level based on the implementation of current climate policies indicates an estimated rise of 3.1-3.7°C.

c. **National pledges**: Even if all the countries adhere to their pledges/ targets decided as per the Paris climate agreement, still the average warming by 2100 is estimated to be approximately 2.6-3.2°C which is far higher than the targeted levels of Paris climate agreement for keeping the global warming under 2°C.

d. **2°C consistent**: There are several emissions pathways, which, can help in limiting the average global, warming to 2°C by 2100, however for this, the current pledges of the Paris climate agreement are required to be significantly increased.

e. **1.5°C consistent**: There are several emissions pathways, which can help in limiting the average global warming to 2°C by 2100, however for this, very urgent action is required and there must be rapid and urgent reduction in global greenhouse gas emissions to achieve this target.

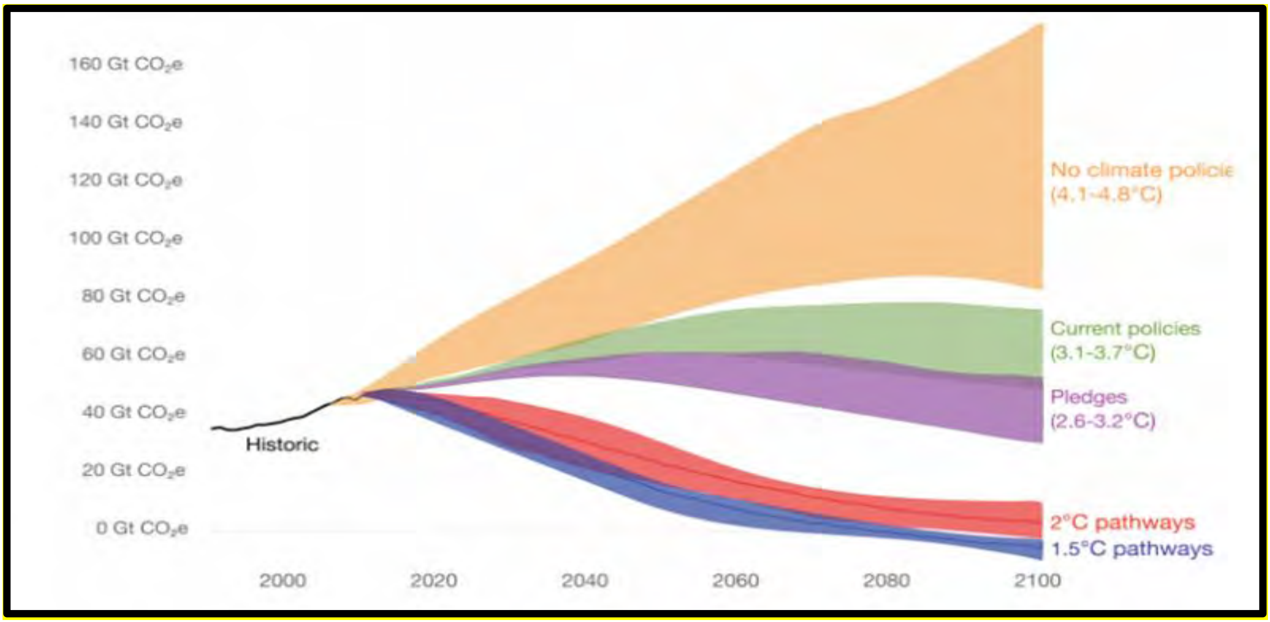


Figure 2.15: Global Greenhouse Gas Emission Scenarios.

2.8.1 Carbon Dioxide Intensity of Economies

It is interesting to note that while the growing carbon dioxide emissions have been historically linked with the economic growth, the countries having similar levels of per capita output have varied per capita carbon dioxide emission levels. This variation has been measured by the variation of the carbon dioxide intensity of the countries where the carbon dioxide intensity is the measure of the quantity of carbon dioxide emission per output unit (kg carbon dioxide per int-$). Two major factors influence the carbon dioxide intensity of a country, which are mentioned as below:

Energy Efficiency: It refers to the energy required per output unit. It is generally related to efficiency of technology and productivity, but it can also be associated with the kind of economic activity supporting the output. For instance, if there is transition in the economy of a country from manufacturing to service industry, then in such case there is less energy requirement for the production process and thus there is less consumption of energy per output unit.

Carbon Efficiency: It refers to the quantity of carbon dioxide emission per unit of energy (grams of carbon dioxide emitted per kilowatt-hour). It is mainly linked to the energy mix of the country. The economy dependent on coal- fired energy would have higher carbon dioxide emissions per unit of energy as compared to the economy using higher share of the renewable energy. With the increment in the use of renewable sources for energy generation in an economy, there is marked improvement in the efficiency and there is decline in the quantity of carbon dioxide emission per unit of energy (Du, et al. 2017).

Figure 2.16 shows that global carbon dioxide intensity is continuously declining since 1990. This might be due to technological efficiency and improved energy, which increases the renewables capacity (Du, et al. 2017). In the last few decades, the carbon intensity of most of the economies has reduced and the highest intensities are witnessed in South Africa, Eastern Europe, and Asia. This is the result of the compounded impact of heavily industrialized economies with energy systems, which are coal-dominated. The figure shows a gradual and steady decline in carbon emissions in the last few years, however there can be short term dramatic fluctuations in the carbon emission intensity due to major political upheaval or change in economic policies. A good example of such dramatic instance was witnessed in China during the period of 1950-1960 with the 'Great Leap Forward' campaign.

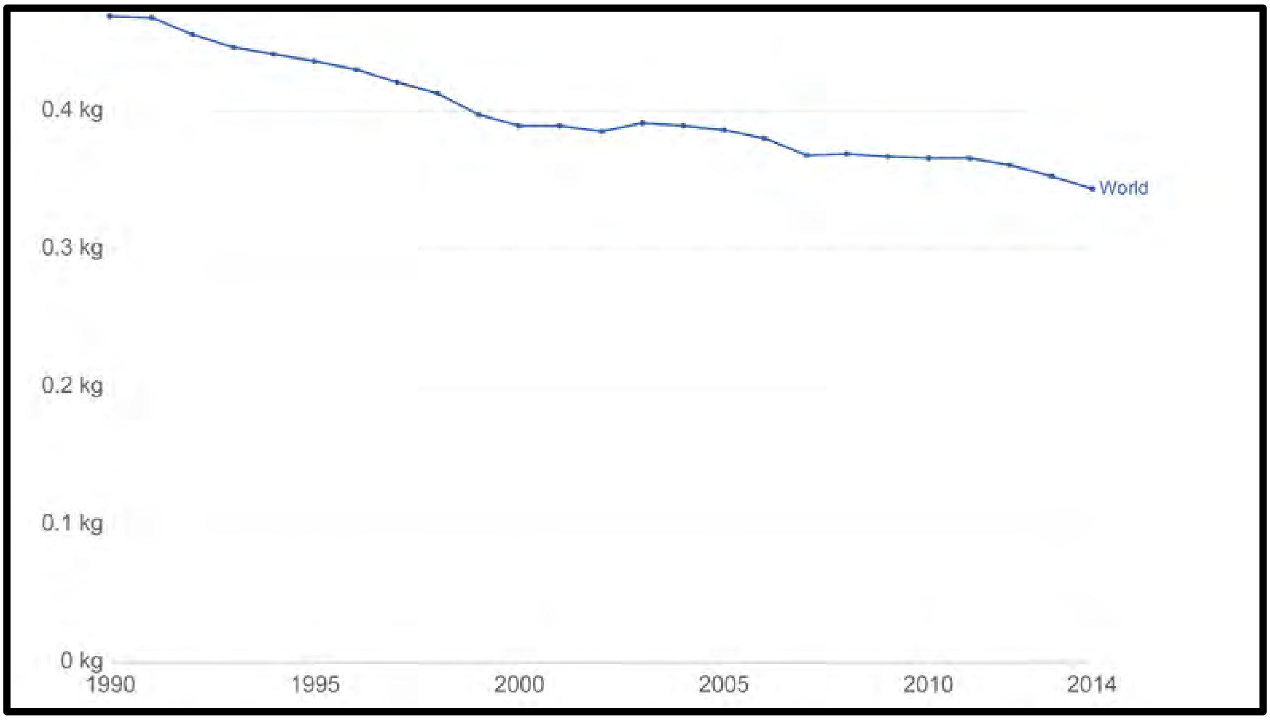


Figure 2.16: Carbon Emission Intensity of Economies

Source: The World Bank (2015)

2.8.2 Cost of Global Carbon Dioxide Emissions Mitigation

By analysing the interrelationship of global temperatures and knowing the emissions trend, a concern arises about ways of mitigating carbon emissions and the cost of global carbon dioxide emissions mitigation. Effectiveness of the measures of carbon dioxide emissions mitigation is majorly dependent on the potential cost benefit of climate change on the global and regional level. In recent times, the measurement of global carbon dioxide emissions concentration is done direct from the atmosphere through the instrumentation sensor technology. Mauna Loa Observatory (MLO) of Hawaii has presented the most extensive data of direct carbon dioxide emissions measurement. Since 1950, Mauna Loa Observatory has been recording the atmospheric composition and it presents the most precise data regarding carbon dioxide emissions concentration in the 20th and 21st century. For reconstructing the carbon dioxide concentration of long term, it is critical to refer to several chemical and geological analogues that record the atmospheric composition changes through the course of time.

To reconstruct long-term carbon dioxide emissions concentrations, we must rely on a variety of geological and chemical analogues that record changes in atmospheric composition across time. The ice-coring process provides the longest historical records of carbon dioxide emissions extending back to 800,000 years. The Vostok Ice Core of Antarctica is the most renowned ice core, and it is used for the historical reconstructions. It covers 4 interglacial- glacial periods and it extends back 420,000 years. A preserved record of atmospheric composition is imbibed in the ice cores with each layer of the ice core representing a past era. The ice cores can be 3 kms deep and it preserves tiny air bubbles what provide a glimpse of a certain period's atmospheric composition. The researchers try to relate periods with the ice core depths by isotopic dating which is a chemical dating technique. Therefore, by analysing the atmospheric concentration across several depth ranges, there can be reconstruction of the changes in atmospheric concentration through time.

2.9 Estimation techniques

For estimation techniques in this chapter, please refer to pages 73 and 79 in chapter three for descriptive statistics, Unit root test and pages 100, 105 and 106 in chapter four, for VAR specifications, VDF, and IRF explanations.

Model of Multi-Variate Analysis on Energy Consumption, Industrial Performance and Carbon Dioxide Emissions

To examine the dynamic link and forecast variance among energy use, industrial performance and carbon dioxide discharge in Nigeria, Ghana and South Africa, the study used a modified model by Ohlan, 2015 which is presented in the following equations:

CO_2 = f (ENG, IND), (2.1)

where carbon dioxide (CO2) is the emission discharge, energy consumption (ENG) represent fossil fuel energy consumption and industrial value means industrial performance (IND). The inclusion of fossil fuel energy consumption as the measurement of energy use in these countries is due the fact of availability of data as the data on biomass energy is not scientifically reliable. The data on biomass energy use is not available in these countries.

Equation 2.1 is further transformed into an econometric specification in equation 2.2, shown as follows:

$$CO2_t = \propto + \beta_1 ENG_t + \beta_2 IND_t + \varepsilon_t \quad (2.2)$$

where carbon dioxide emissions is (CO_2), fossil fuel energy consumption is (ENG), industrial performance represents (IND), Subscript t stands for the period (t = 1980Q1 to 2017Q1), α and β signify the parameters and ε denote the stochastic error, the rest as defined in the previous equation. The apriori expectation ($\beta_{1,}$ $\beta 2$ > 0), therefore energy consumption, and industrial performance are positively related to carbon dioxide discharge.

2.9.1 Nigeria: Impulse Response Function (IRF)

Figure 2.17 presents the impulse response function of the model for Nigeria ascertain the response of a variable because of one standard deviation innovation shock of other variables. Initially, the IRF was considered through the generalize impulse response analysis of multiple graphs and analytical asymptotic for the standard error. In addition, the default of ten quarter-period split is maintained to predict the impact of the shock on the concerned variable at each of the periods. An innovation shock of one standard deviation of the endogenous variables (left to right diagonal boxes) to themselves causes negative adjustment in the short run quarter period that shows decrease at constant rate from period of quarter five up to the long run quarter period in Nigeria. The response of carbon dioxide emissions to fossil fuel energy consumption shows that fossil fuel consumption had immediate positive shocks on carbon dioxide emissions in the first quarter five and from quarter six it continued to decrease at decreasing rate to the 10 quarter of the simulation periods. However, the response shows a decline at decreasing rate for each of the variables to itself. It implies that one shock in carbon dioxide emissions results to a change in energy use from the first quarter, which continually fell to the last quarter, in line with statistical prescriptions over the time horizon. The results of the fossil fuel energy consumption, industrial performance and carbon dioxide emissions support the outcome of earlier studies that energy resources influence carbon dioxide explosion positively (Zafar, et al. 2019). Hence, it is necessary for policymakers to continue enhancing the practical measures for mitigating the carbon dioxide discharge for environmental and economic sustainability.

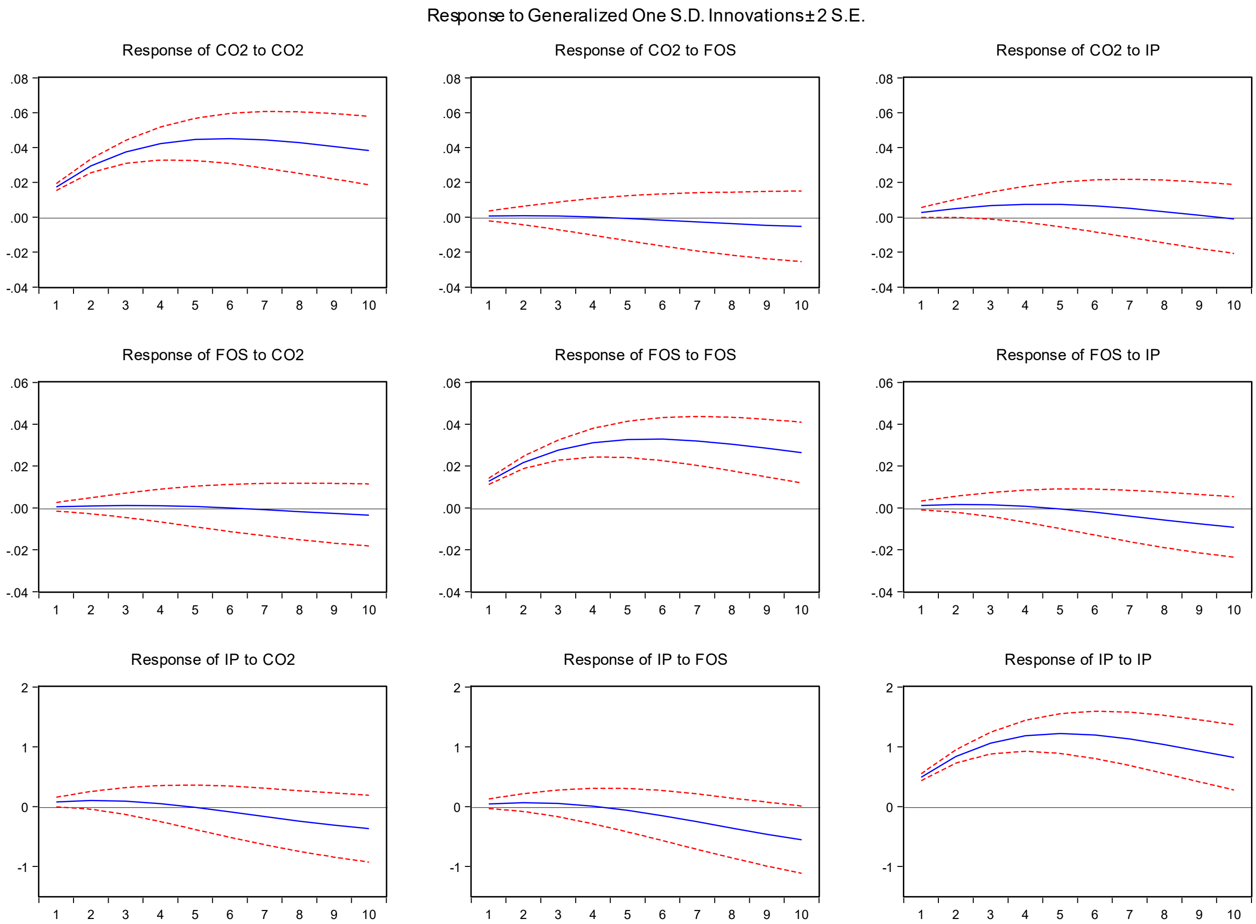


Figure 2.17: Generalized Impulse Response Function (Nigeria)
Source: Author, computed from data

2.9.2 Nigeria: Forecast Error Variance Decomposition (FEVD)

To investigate the relative importance of fossil fuel energy consumption shocks and industrial performance on carbon dioxide emissions, the forecast error variance decomposition is computed. The variance decomposition apportions the total fluctuations in a particular indicator to the constituent's shocks or innovations in the VAR system. The result is presented in table 2.1. The outcome reveals across the rows indicate the percentage forecast error variance by variables (fossil foil energy consumption and industrial performance). Each of the figures in the row table shows the percent of the forecast error variance in carbon dioxide emissions. Also, same with fossil fuel energy consumption and industrial performance. A ten (10) year forecast periods is chosen, and the periods are split into short run and long run from year one (1) to year four (4) is the short run while year five (5) to year ten (10) is the long run periods.

The variance decomposition of carbon dioxide emissions shows that in the short run year 1 to year 4 100% of forecast error variance decomposition in carbon dioxide emission is explained by the variable itself. Meaning that other variables in the model i.e., fossil fuel energy consumption and industrial performance do not have real strong influence on carbon dioxide emissions, they have strong exogenous impact, exogenous in the sense that they do not have influence on carbon dioxide at all in the short run, they exhibit weak influence in predicting carbon dioxide emissions. The result of carbon dioxide emissions in the long run 95% of forecast error variance decomposition of the variable is explained by carbon dioxide itself. So, carbon dioxide emission is showing strong influence right from the short run periods into the future as well. Similarly, the results show that fossil fuel energy consumption influence rising gradually over the years at 3.5%, but overall, it is still very weak. Furthermore, the results shows that the influence pattern of industrial performance is very insignificant.

From fossil fuel energy consumption variance decomposition, the outcome shows that the variable predict itself from year 1 into the future year 10 of the simulation periods. The influence from other variables in the model are not significant. Suggesting that fossil fuel energy consumption is strong influencer of itself into the future. Finally, on industrial performance the outcome shows that right from the short run periods into the future industrial performance in Nigeria does not strongly predict itself, even though the result shows that carbon dioxide emissions and fossil fuel energy consumption are predictors of industrial performance accounting 5.2% and 4.3% forecast error variance decomposition in the long run of the simulation periods. Overall, therefore, as shown from the outcome industrial performance dwindles by 90% in the long run.

The finding indicates significant link among energy consumption, industrial performance, and carbon dioxide discharge in Nigeria. This result is consistent with the finding of the study by Suleman and Baka, 2015.

Table 2. 1: Variance Decomposition of Carbon Dioxide Emission (Nigeria)

Variance Decomposition of CO2: Period	S.E.	CO2	FOS	IP
1	0.017449	100.0000	0.000000	0.000000
2	0.036172	99.93223	0.025027	0.042742
3	0.054331	99.86836	0.081445	0.050199
4	0.070705	99.75824	0.192209	0.049550
5	0.085038	99.55003	0.390778	0.059193
6	0.097473	99.19176	0.711280	0.096958
7	0.108313	98.62890	1.180177	0.190919
8	0.117899	97.81650	1.808765	0.374736
9	0.126549	96.73477	2.588808	0.676418
10	0.134530	95.39850	3.492966	1.108532
Variance Decomposition of FOS: Period	S.E.	CO2	FOS	IP
1	0.012756	0.066390	99.93361	0.000000
2	0.026334	0.023303	99.92942	0.047275
3	0.039468	0.010413	99.89347	0.096117
4	0.051298	0.009223	99.83577	0.155005
5	0.061662	0.021337	99.73443	0.244236
6	0.070673	0.054988	99.56004	0.384973
7	0.078536	0.119139	99.28372	0.597137
8	0.085470	0.219230	98.88510	0.895669
9	0.091669	0.355003	98.35819	1.286812
10	0.097300	0.520581	97.71318	1.766241
Variance Decomposition of IP: Period	S.E.	CO2	FOS	IP
1	0.490857	2.147041	0.853758	96.99920
2	0.992671	1.740101	0.527391	97.73251
3	1.477027	1.183967	0.326254	98.48978
4	1.911949	0.738548	0.196529	99.06492
5	2.287904	0.565971	0.185605	99.24842
6	2.607366	0.761876	0.379296	98.85883
7	2.878843	1.366285	0.863603	97.77011

8	3.112957	2.365330	1.694614	95.94006
9	3.319876	3.695730	2.879622	93.42465
10	3.507855	5.258382	4.374068	90.36755

Source: Author, computed from data

2.9.3 Ghana: Impulse Response Function

Similarly, the graphical representation of the impulse response function for Ghana in 2.18. The impulse response of carbon dioxide emissions to fossil fuel energy consumption shows a positive response on average throughout the simulation periods. Initially, the IRF was considered through the generalize impulse response analysis of multiple graphs and analytical asymptotic for the standard error. In addition, the default of ten quarter-period split is maintained to predict the impact of the shock on the concerned variable at each of the periods. An innovation shock of one standard deviation of the endogenous variables (left to right diagonal boxes) to themselves causes negative adjustment in the short run quarter period that shows decrease at constant rate from period of quarter five up to the long run quarter period in Nigeria. Evidently, carbon dioxide emissions had a steep and negative response to shocks in fossil fuel energy consumption throughout the last quarter periods. Therefore, shocks in fossil fuel energy consumption increase the discharge of carbon dioxide emissions from quarter one to the long run horizon. This means that shocks in carbon dioxide emissions increase the level of energy consumption from quarter two to long run horizon. Similarly, shocks in energy use increase the capacity of carbon dioxide emission from quarter one to long run. The result is similar with the report of previous studies of (Jabeur and Sghaier, 2018; Salahuddin and Gow, 2015). However, carbon dioxide emissions and energy consumption response their self positively from the first quarter to long run horizon. Overall, energy consumption shock exerted positive impact on carbon dioxide emission throughout the simulation periods.

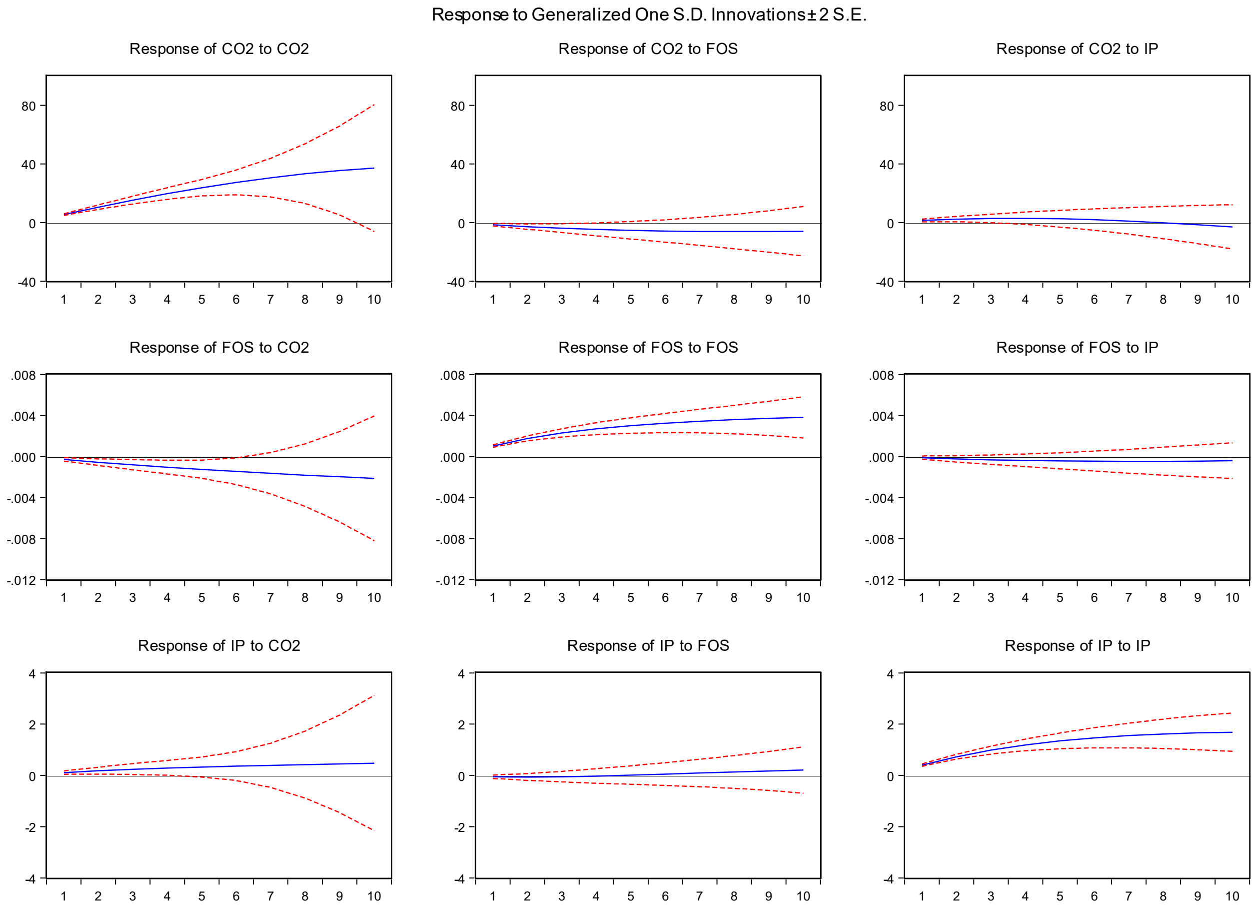


Figure 2.18: Generalized Impulse Responses (Ghana)

Source: Author, computed from data

2.9.4 Ghana: Forecast Error Variance Decomposition (FEVD)

The forecast error variance decomposition carbon dioxide emission was further used to examine the relative importance of fossil fuel energy consumption and industrial performance shocks in Ghana, as shown in table 2.2. As previously stated, variance decomposition assigns the entire fluctuations in each indicator in the VAR system's constituent shocks or innovations. The forecast error variance decomposition of carbon dioxide emissions in Ghana reveals across the rows in the table indicate the forecast error variance decomposition by fossil fuel energy consumption and industrial performance variables. The figures in the row table shows the percentage of forecast error variance decomposition in carbon dioxide emissions.

Ten (10) years forecast error variance decomposition is split into short run and long run periods, from year 1 to year 4 is the short run while year 5 to year 10 is the long run periods. As with other macroeconomic time series data, in the short run periods carbon dioxide emissions explains around 99.3% of its own variation, while fossil fuel energy consumption and industrial performance explains 1.9% and 2.0% respectively. Most empirical research has found that the biggest percentage error variance breakdown of macroeconomic variables often comes from past shocks, but that this is predicted to decrease overtime. As the prediction period lengthens, the falling characteristics shows that policy shocks are better transmitted to other variables in the system. Over a 1o period horizon, fossil fuel energy consumption and industrial performance shocks accounted for 1.9% and 2.0% of the variation in carbon dioxide emissions. This emphasises the relative importance of fossil fuel energy consumption and industrial performance shocks in understanding carbon dioxide emissions changes in Ghana. This implies that in the long run, the forecast analysis reveals that there will be higher influence of carbon dioxide emissions increase significantly due to effect of energy consumption and industrial value addition in Ghana. This result is consistent with studies by Khobai and Roux (2017).

Table 2. 2: Forecast Error Variance Decomposition of Carbon Dioxide Emission (Ghana)

Variance Decomposition of CO2: Period	S.E.	CO2	FOS	IP
1	0.054516	100.0000	0.000000	0.000000
2	0.119111	99.97101	0.016472	0.012516
3	0.196174	99.75766	0.133238	0.109100
4	0.283023	99.35020	0.354293	0.295509
5	0.377407	98.82104	0.632165	0.546796
6	0.477096	98.23763	0.926024	0.836342
7	0.579769	97.64438	1.213665	1.141953
8	0.683017	97.06636	1.487080	1.446562
9	0.784392	96.51608	1.746382	1.737535
10	0.881477	95.99872	1.995604	2.005677
Variance Decomposition of FOS: Period	S.E.	CO2	FOS	IP
1	0.001004	8.035280	91.96472	0.000000
2	0.002111	8.031865	91.93525	0.032882
3	0.003218	8.600976	91.33022	0.068809
4	0.004265	9.605619	90.29202	0.102357
5	0.005244	11.04420	88.81482	0.140979
6	0.006166	12.94857	86.85824	0.193185
7	0.007048	15.35066	84.38171	0.267633
8	0.007910	18.26151	81.36566	0.372835
9	0.008771	21.65660	77.82721	0.516193
10	0.009648	25.46872	73.82860	0.702676

Variance Decomposition of IP: Period	S.E.	CO2	FOS	IP
1	0.004006	7.821996	0.178592	91.99941
2	0.008433	7.763920	0.083653	92.15243
3	0.013117	7.910130	0.103570	91.98630
4	0.017854	8.364882	0.508415	91.12670
5	0.022554	9.218819	1.243229	89.53795
6	0.027179	10.55226	2.167426	87.28031
7	0.031724	12.43771	3.158237	84.40405
8	0.036214	14.93098	4.130865	80.93816
9	0.040692	18.05567	5.031815	76.91251
10	0.045217	21.78792	5.829155	72.38292

Source: Author, computed from data

2.9.5: Impulse Response Function for South Africa

The impulse response function for South Africa is presented in figure 2.19, which reveals the results. Initially, the IRF was considered through the generalize impulse response analysis of multiple graphs and analytical asymptotic for the standard error. In addition, the default of ten quarter-period split is maintained to predict the impact of the shock on the concerned variable at each of the periods. An innovation shock of one standard deviation of the endogenous variables (left to right diagonal boxes) to themselves causes negative adjustment in the short run quarter period that shows decrease at constant rate from period of quarter five up to the long run quarter period in Nigeria. The figure gives the description of carbon dioxide emissions reaction to shocks in fossil fuel energy consumption and industrial performance in the multivariate model, being estimated. The outcome shows the response of carbon dioxide emissions to positive shocks in fossil fuel energy consumption is immediate from first quarter periods to quarter five when it positively responds throughout to long run simulation periods. Similarly, the response of carbon dioxide emissions to industrial performance shows an immediate positive shock on carbon dioxide emissions in the first quarter to 10 quarter horizon periods at an increasing rate. This means that shocks in carbon dioxide emission increase due to shocks in fossil fuel energy consumption and industrial value addition from quarter one to last quarter of the simulation period. The result is similar with the findings of Salahuddin and Gow, 2015 in their previous studies.

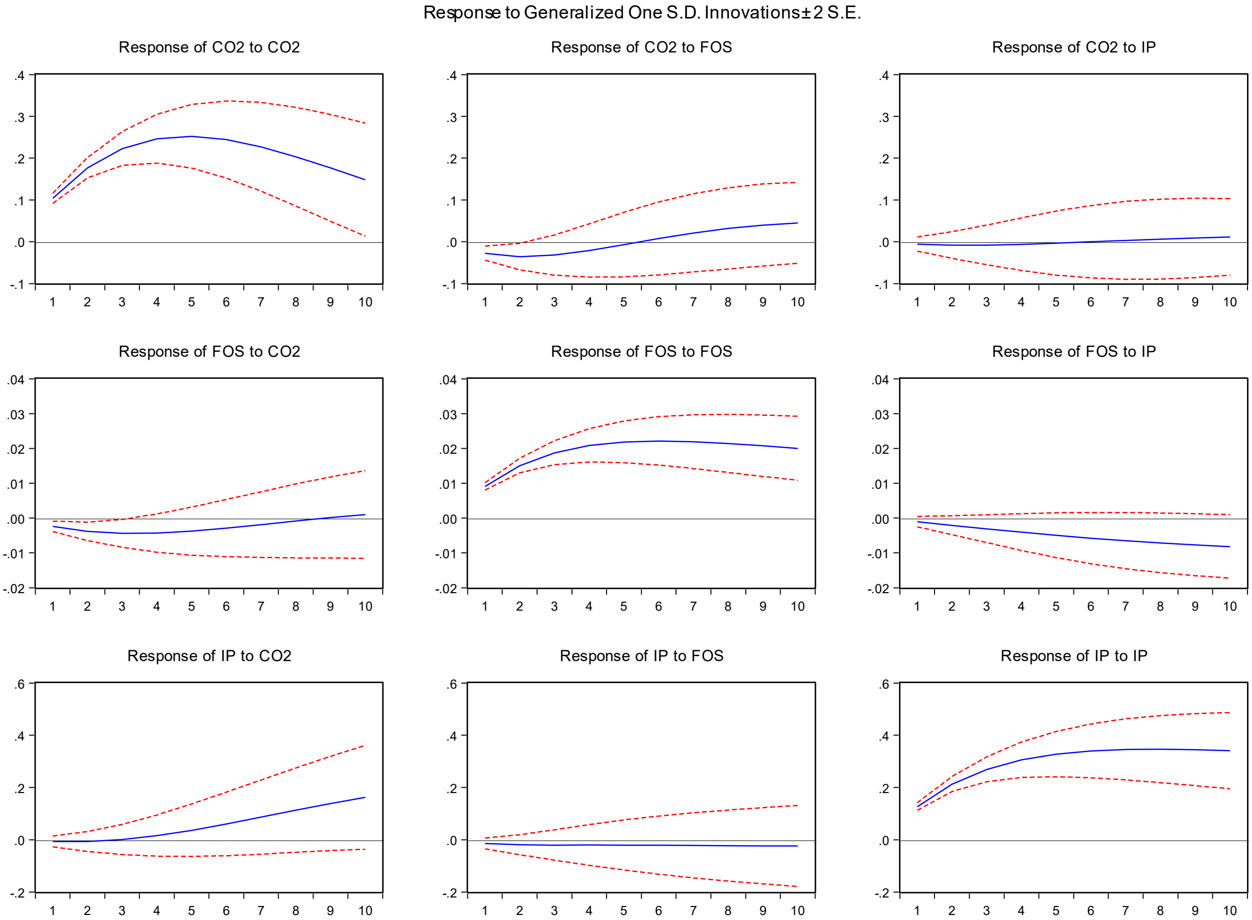


Figure 2.19: Generalized Impulse Responses (South Africa)
Source: Author, computed from data

2.9.6 South Africa: Forecast Error Variance Decomposition (FEVD)

Table 2.3 shows the forecast error variance decomposition of carbon dioxide emissions. From the table, the variance decomposition of carbon dioxide emissions for South Africa shows across the rows indicate the percentage error variance by the variables. Each of the figures in the table shows the percent forecast error variance in carbon dioxide emissions. Similarly same with fossil fuel energy consumption and industrial performance. A ten year forecast periods is chosen, and the periods are splitted into short run and long simulation horizon. So, in the short run year 1 to year 4, as expected of most macroeconomic time series data, 100% of forecast error variance decomposition in carbon dioxide emission is explained by the variable itself. Meaning that fossil fuel energy consumption and industrial performance do not have real strong influence on carbon dioxide emissions. Specifically, they have strong exogenous impact in the sense that they do not influence carbon dioxide emission in the short run. They exhibit weak influence in predicting carbon dioxide emissions. In the long run the outcome shows that 85.6% of forecast error variance decomposition of the variable is explained by carbon dioxide emissions itself. So, carbon dioxide emission is showing strong influence right from the short run periods to the future. However, the results show that fossil fuel energy consumption influence rising gradually over the years but overall, it is still very weak. Additionally, industrial performance shows that the influence is very insignificant.

Furthermore, from fossil fuel energy consumption variance decomposition the outcome shows that the variable strongly predict itself from year 1 into the future year 10 of the simulation periods. The influence from the other variables in the model are not significant at all. Suggesting that fossil fuel energy consumption is a strong influencer into the future. Finally, on industrial performance the outcome shows that right from the short run period into the future industrial performance in South Africa do not strongly predict itself, even though the result shows that carbon dioxide emissions is a predictor of industrial performance accounting for 11% forecast error variance decomposition in the long run of the simulation periods. Likewise, as shown from the outcome the industrial performance dwindles by 88% in the long run simulation periods. The result is similar with the findings of the studies by Ahad, et al. (2018). Hence, policymakers should focus in designing effective and efficient measure in mitigating the level of carbon dioxide discharge. This should be emphasised through encouraging citizens on the use of other alternative energy sources, which can emit low emission such as wind, solar and thermal energy for better and clean environment.

Table 2. 3: Forecast Error Variance Decomposition of Carbon Dioxide Emission (South Africa)

Variance Decomposition of CO2: Period	S.E.	CO2	FOS	IP
1	0.103863	100.0000	0.000000	0.000000
2	0.213179	99.89959	0.077376	0.023031
3	0.317342	99.25642	0.656739	0.086840
4	0.410187	97.88030	1.932634	0.187067
5	0.490735	95.94226	3.750476	0.307263
6	0.559633	93.73046	5.838210	0.431329
7	0.618012	91.48676	7.962421	0.550814
8	0.667163	89.36099	9.974661	0.664353
9	0.708407	87.42377	11.80182	0.774412
10	0.743017	85.69378	13.42160	0.884617

Varian
ce

Decomposition of FOS: Period	S.E.	CO2	FOS	IP
1	0.009090	6.108490	93.89151	0.000000
2	0.018694	4.920279	95.07923	0.000493
3	0.027675	4.059549	95.89744	0.043008
4	0.035557	3.344700	96.47058	0.184717
5	0.042406	2.735845	96.84430	0.419858
6	0.048429	2.232020	97.06057	0.707406
7	0.053830	1.835312	97.15946	1.005229
8	0.058771	1.540044	97.17505	1.284905
9	0.063372	1.333091	97.13431	1.532599
10	0.067715	1.197646	97.05758	1.744772
Variance Decomposition of IP: Period	S.E.	CO2	FOS	IP
1	0.126021	0.347208	1.706592	97.94620
2	0.258516	0.201516	1.755326	98.04316
3	0.384979	0.091792	1.425470	98.48274
4	0.498797	0.165726	1.057379	98.77689
5	0.600197	0.625061	0.770343	98.60460
6	0.691721	1.642364	0.580303	97.77733
7	0.776353	3.301626	0.473559	96.22481
8	0.856701	5.577734	0.434707	93.98756
9	0.934694	8.354051	0.452406	91.19354
10	1.011549	11.46290	0.518255	88.01885

Source: Author, computed from data

2.9.7 Post Estimation Checks

For establishing the validity of the estimated models, various diagnostic tests are performed such as serial correlation, normality of the residuals and Heteroskedasticity tests. Table 2.4 shows that the estimated model for Nigeria, Ghana and South Africa has no problems of serial correlation, Heteroskedasticity and the residual are normally distributed.

Table 2. 4: Post estimation tests

Test	Statistics	Prob.
Nigeria		
VEC Residual serial correlation	6.4034	0.142
VEC Residual Heteroskedasticity	42.074	0.364
VEC Residual Normality (Jarque-Bera)	0.3030	0.710
Ghana		
VEC Residual serial correlation	5.8802	0.208
VEC Residual Heteroskedasticity	37.965	0.150
VEC Residual Normality (Jarque-Bera)	1.1403	0.565

South Africa		
VEC Residual serial correlation	5.2841	0.442
VEC Residual Heteroskedasticity	31.730	0.387
VEC Residual Normality (Jarque-Bera)	3.1855	0.703

2.10 Conclusion

Although the UK was the earliest industrial scale emitting country, China is the current highest carbon dioxide emitting country across the globe, with the United States and India being the second and third carbon dioxide emitting countries, respectively. There are varying levels of carbon dioxide emissions based on the development trend of countries. In addition, the earning capability of countries plays a key role in ascertaining their carbon dioxide emission levels. In this regard, Qatar's earning prowess makes it the highest carbon dioxide emitting country with annual per capita emissions of 50 tonnes, while Chad is the lowest emitter. Electricity and heat production are major factors responsible for about 50% of global emissions, while the manufacturing and transport industries contributed 20% emissions, amongst other factors. The atmospheric carbon dioxide concentrations must be stabilised or reduced to achieve any form of reduction in carbon dioxide emissions across the globe. Finally, the chapter is linked with the trends of carbon dioxide emissions, energy use, industrial performance, and carbon dioxide emissions in the three largest economies in sub Saharan African countries through a Bi-variate analysis, which confirms the relative effect of energy use and industrial performance on carbon dioxide emissions.

CHAPTER THREE

EMPIRICAL EVIDENCE OF THE IMPACT OF MACRO-ECONOMIC VARIABLES ON CARBON DIOXIDE EMISSIONS IN THREE LARGEST ECONOMIES OF SSA

3.1 Introduction

Industrialization has resulted in an increase in energy-related carbon dioxide emissions around the world, and Africa, being in that stage of development, is no exception (Samu, et al. 2019). While carbon dioxide emission in Africa during 2017 was only 4% of the total global fossil fuel emission, but if the growth rate of 2010-2017 persists, then the emission will increase by almost 30%. Similar trends have been witnessed in sub-Saharan African countries due to high population, economic growth, and related factors (Hamilton and Kelly, 2017).

Preserving the environment and economic development are two main challenges that most of the economies are struggling to contend with. Environmental concern has been on the rise in both developed and developing economies due to the deteriorating quality of the environment, climate change, and global warming based on emissions by greenhouse gases (Salahuddin, et al. 2017; Kasman and Duman, 2015). The most important decisions that we must take regarding resources for our future generation is not only financial resource, but also environmental and ecology-related resources (Clayton, et al. 2016).

Industrial development and economic development are key drivers of economic growth of a country, but they lead to environmental degradation (Zou, 2018). Environmental degradation can be defined as the deterioration of the environment due to the destruction of the ecosystem; the depletion of resources like water, air, and soil; pollution; the extinction of wildlife; and habitat destruction (Conservation Energy Future [CEF], 2016). It can also be defined as the disturbance or change to the environment that is undesirable and harmful to it (Johnson *et al.* 1997). The environmental impact can be better understood with the help of the equation I = PAT. This equation depicts that environmental degradation or impact (I) is the combined result of persistent increase in economic growth or per capita affluence (A), increasing an already very large human population (P), and the application of polluting and resources draining technology (T) (Huesemann and Huesemann, 2011; Chertow, 2001).

There are different factors on which economic development and growth of an economy are dependent on. However, economic development and growth may bring a negative impact on the environment and natural resources (Phimphanthavong, 2013). The negative ramifications of rapid industrialisation, urbanisation, population growth, and fossil fuel use must be considered by countries while taking major economic decisions. Many such issues negatively influence our environment, causing, for instance, the deterioration of air quality, extinction of species, soil erosion, emissions of greenhouse gases, and global warming. However, the major concern that is being faced by all economies is the rise in greenhouse gases leading to global warming and the depletion of the ozone layer. The most abundantly released greenhouse gas is carbon dioxide, which is recognised as the major pollutant (Edoja, et al. 2016) because it contributes to $3/4^{th}$ of emissions by greenhouse gases (Abbasi and Riaz, 2016). The main sources of emissions from carbon dioxide in the atmosphere are industrial processes, the burning of fossil fuels, cement production, and alcohol factories. Thus, the proportion of environmental damage is said to be directly proportional to the number of economic activities (Aye, 2017).

Zaman and Moemen (2017) posit that economic development leading to environmental degradation is a cogent issue that requires global attention. Those countries where economic growth is happening rapidly and where industrialisation is growing have high levels of carbon emissions that is harming people's health (Ssali, et al. 2019). Nazeer *et al*. (2016) emphasized in their study that in developing countries, where the rules and policies are usually not that strict, urbanization, mechanisation, industrialisation, pesticides, fertilizers, and poor waste management have a severe impact on the environment. Huisingh, et al. (2015) confirmed in their study that the major reason for the change in climate and global warming all over the globe is the accumulative carbon emissions bestowed by the ignition of fossil fuels and deforestation. Asumadu-Sarkodie and Owusu (2016) confirmed in their study the contribution of energy use, population, economic growth, and foreign direct investment to environmental pollution.

Accordingly, the environmental degradation caused by human activities has put the whole world in a dilemma and has increased the global concern for climate change (Goldstone, 2018; Wang, et al. 2017; Meyer, 2017; Bonan 2015). In the last few years, the impact of carbon emissions, energy use, foreign direct investment, and economic growth have been a major topic of international debate (Achour and Belloumi 2016). As mentioned earlier, Africa is a developing region whose economies have been growing slowly. To accelerate this process, it needs to boost its energy sector by adopting institutional and technical measures to achieve a greater foreign direct investment inflow (Ssali, et al. 2019). According to a report by the World Bank (2014), foreign direct investment is the best capital source for developing economies. In the sub-Saharan African regions, foreign direct investment reached US$35 billion in 2012 from US$6.3 billion in 2000 (Ssali, et al. 2019). The development happening in sub-Saharan Africa has led to increased demand for energy, that in turn increased the inflow of foreign direct investment, and the economic development raised the alarm of environment pollution and carbon emissions (Bekhet, et al. 2017).

3.2 Literature Review

In the following sections, previous work regarding the impact of energy consumption, foreign direct investment, financial development, gross domestic product growth, and industrial performance on carbon dioxide emissions will be discussed.

3.2.1 Literature on Energy Consumption and Carbon Dioxide Emissions

Energy consumption and economic activities are perceived in the literature to be the major source of greenhouse gas emissions (Zhu, et al. 2016). Economic activities and energy consumption have grown tremendously due to rapid growth in population, increase in agricultural activities, increase in economic growth, and increase in energy demand (Shahbaz, et al. 2017; Asumadu-Sarkodie and Owusu 2017; McAusland 2010; Kofi Adom, et al. 2012). It has been shown by previous research that carbon emissions are the deadliest and highest polluting gases in developing countries (Khan *et al*. 2011). Carbon emissions constitute the main cause of various cardiovascular and respiratory diseases, and as per the report of the World Health Organisation (WHO), 7,000,000 lives annually are afflicted by air pollution (WHO 2018).

Alshehry and Belloumi (2015) in their study inspected the causal relationship between energy utilisation, energy cost, and economic exercise in Saudi Arabia. They find a unidirectional long-run causality amongst energy consumption and carbon dioxide emissions. It was also concluded in the study that there existed bidirectional causality amid carbon dioxide emissions and economic development. A uni-directional short run causality from carbon dioxide outflows to energy consumption and a unidirectional long-run unidirectional causality from the cost of energy to economic growth and carbon dioxide emissions were also reported in the study.

Ben Jebli and Belloumi (2017) applied Granger causality tests and used autoregressive distributed lag (ARDL) methodology to examine energy consumption patterns in Tunisia. The outcome shows that a short- run bidirectional causality among transport via sea and carbon-dioxide transmissions, and a short run unidirectional causality running from real output, combustible renewables and disposal of waste, railroad transport to carbon dioxide emissions existed. It was also revealed that there was a short - run unidirectional causality run from the gross domestic product, combustible fuels, and waste management, transport via rail to carbon dioxide emissions. Estimates in the long- run in the study also proved that real gross domestic product had a contribution to the drop in carbon-dioxide emissions, whereas railroad and sea transport, as well as fossil fuel burning had a positive contribution to carbon dioxide emissions.

Mirza and Kanwal (2017) also discovered a bi-directional causality in both the long and the short runs between economic growth, energy use and carbon emissions. Odugbesan and Rjoub (2020) examined the synergy among economic growth, carbon dioxide (CO_2) emissions, urbanisation, and energy consumption in MINT (Mexico, Indonesia, Nigeria, and Turkey) countries, using annual data from 1993 to 2017. The study employed the ARDL bounds test approach and found that the energy–growth hypothesis that assumed unidirectional causality from energy consumption was true for Nigeria and Indonesia, whereas Mexico and Turkey followed the feedback hypothesis, which indicates a bidirectional relationship. Meanwhile, all the MINT countries show a long-run relationship from economic growth, energy consumption, and CO_2 emissions to urbanisation. The study suggested that the policymakers in MINT countries should develop an energy conservation policy that will enhance the potential growth of their economy, promote green industries as well as ensure sustainable urbanization in MINT countries through the reduction in the urbanisation level but without compromising economic growth by the formulation of policies that will ensure the decrease in CO_2 emissions.

To evaluate the impact of energy resources in Nigeria, Yahaya, et al. (2020) employ an autoregressive distributive lag technique. They discovered a relationship between energy consumption and carbon dioxide emissions. In addition, Boutabba (2014) uses the autoregressive distributive lag technique to determine the impact of financial openness on carbon dioxide emissions in India. The findings show that increasing financial progress increases carbon dioxide emissions. According to Sehrawat, Giri, and Mohapatra (2015), India's financial resources increase the capacity for carbon dioxide emissions. The rise of Pakistan's financial sector, according to Javid and Sharif (2016), accelerates the rate of carbon dioxide emissions. With previous research findings (Charfeddine Kahia, 2019; Ganda, 2019;

Yahaya, et al. (2020). Furthermore, Soheila and Bahram (2017) provided an empirical analysis of the relationship between CO_2 emissions and economic growth, renewable energy consumption, and energy consumption over the period 1975–2014 in Germany. Using autoregressive distributed lag (ARDL) approach. The cointegration tests show that there is a long-run relationship between CO_2 emissions and the other variables in the analysis, though the relationship between real GDP and CO_2 emissions did not support the environmental kuznets curve. To estimate the shocks of renewable energy consumptions, the study applied the dynamic test of the impulse response function (IRF) under the VAR method. The increasing portion of renewable energy consumption in electricity generation would have no impacts on the environment.
In another dimension, Shahbaz, Mutascu, and Azim (2014) use an autoregressive distributive lag technique to investigate the impact of output performance on carbon dioxide emissions in Romania. Because of the increased output performance, carbon dioxide emissions have increased. According to Cetin and Ecevit (2017), Turkey's gross domestic product increases carbon dioxide release capacity. Similarly, Sulaiman and Abdul-Rahim (2017) find the same result in Malaysia and conclude that energy use increases carbon dioxide emissions.

Heidari, et al. (2015) employ the panel smooth transition technique to examine the connection between energy consumption, economic growth, and carbon-dioxide emissions in five ASEAN countries. It was concluded in the study that energy consumption leads to a rise in carbon dioxide in the atmosphere. Mirza and Kanwal (2017) investigated the presence of causality between economic growth, energy consumption, and environmental pollution in Pakistan. They utilised the autoregressive distributed lag (ARDL) method to investigate the strength of the long-term relation and presence of Grangers' casualty by using vector error correction model (VECM). They find that a bidirectional casualty exists among energy consumption, economic growth, and carbon emissions. It was suggested by them that more renewable sources should be used to combat growing pollution.

In addition, Isik, et al. (2018) in their study in China found an equilibrium long-run association between urbanisation, energy consumption, gross domestic product, and carbon emanations. It was also found in the study that energy consumption and the gross domestic product had a substantial influence on carbon releases. In a related study, Ahmad, et al. (2018) probed the influence of economic growth, population, and energy consumption on carbon emission for the period from 1971 to 2013 by using the autoregressive distributive lag model. They confirmed the connection of economic development and carbon emissions, while the presence of long-run association was also confirmed. Their study finds that economic development and energy use have a direct relationship with the growth in carbon emissions. It was also stressed in the study that the policymakers should focus on sustainable renewable energy sources for sustainable livelihood and economic development. Balcilar, et al. (2018), on the other hand, studied the association between economic growth, carbon dioxide emissions, and energy consumption in G-7 countries. They utilised the historical decomposition method and gave evidence of the need for the USA, Japan, Italy, and Canada to ban non-renewable energy sources to reduce carbon dioxide emissions.

Topcu and Payne (2018) utilised a panel structure-taking note of cross-sectional dependence and heterogeneity to examine carbon emissions and energy consumption in Organisation for economic co-operation and development (OECD) countries. They found a U-shaped pattern for the impact of trade on energy, which suggested that the influence of energy consumption on carbon emissions is greater than economic growth. Similarly, Behera and Dash (2017) investigated the association between carbon emissions and energy consumption of 17 South and Southeast Asian countries over the period of 1980 to 2012. Pedroni co-integration was utilised, and it was concluded that both fossil fuel energy and primary energy consumption contribute to a substantial upsurge in carbon emissions in the SSEA region (Behera and Dash, 2017).

Begum, et al. (2015), employed autoregressive distributive lag bounds test method to examine the influence of energy consumption, economic growth, and population growth on carbon-dioxide emissions in Malaysia over the period from 1970 to 1980. They find that both economic growth and energy consumption have a long-run influence on carbon emissions. Their suggestion was to use green energy for sustainable growth and reduction in carbon emissions.

Kasman and Duman (2015) did a study for a panel of European Union (EU) countries to examine the interrelationship between urbanisation, energy consumption, trade openness, economic growth, and carbon emissions over the period of 1992 to 2010. They used panel co-integration methodologies, panel unit root tests, and panel causality tests. Cai, et al. (2018) examined the interrelationship among economic growth, energy consumption and carbon emissions in G7 countries. They used structural breaks and autoregressive distributive lag bounds to test causality and co-integration and find that real output per capita is produced for economies like the United State of America, Canada, and Germany using renewable energy. It was recommended in the study that it was essential to intensify the use of clean energy to decrease carbon dioxide emissions. It was also observed that green energy could fill the void of environmental management and economic growth in G7 countries and other countries as well.

3.2.2 The Literature on Foreign Direct Investments and Carbon Dioxide Emissions

Foreign direct investment is one important factor that has been studied rigorously (Salahuddin, et al. 2018; Zhang and Zhou, 2016; Shahbaz, et al. 2015; Copeland and Taylor, 1994 to examine its impact on carbon dioxide emissions. Two main theories, which have been used extensively by researchers to study the influence of foreign direct investment on environmental quality: the Pollution Haven Hypothesis and the Pollution Halo Hypothesis.

The Pollution Haven Hypothesis: Most studies on foreign direct investment and emissions have been based on verifying the relevance of the Pollution Haven Hypothesis (PHH). As per Copeland and Taylor (1994), most overseas' firms engaged in so-called 'dirty sectors' are expected to reposition pollution-related activities from developed to developing countries. This is with an intention to cut down the domestic environmental control costs, which is associated with destabilising the environmental benefits associated with the 'recipient' country (Copeland and Taylor, 1994). This hypothesis posits that foreign direct investment will be more interested in the countries where environmental regulations are relatively less rigid. The multinational companies (MNCs) tend to move the high pollution level industries from industrialised economies with strict ecological guidelines to the newly industrialised economies with lower ecological protocols (Acharya, 2009).

Acharya (2009), posit that, the pollution haven hypothesis specifies that the foreign direct investment inflow will increase gas emissions/pollution levels in developing countries by increasing the activities of industries with high pollution level (Acharya, 2009) Wilson, et al. (2002) applied cross-country studies and cross-sectional data for testing the pollution haven hypothesis. They assessed the influence of ecological protocols over pollution-intensive industries in terms of export competition. While constructing the environmental regulations indictor, they considered factors including the estimated amount of money spent in the country for controlling water and air pollution and the level of efforts for reducing pollution (Wilson, et al. 2002). Their findings indicate that stricter environmental standards led to lesser export of dirty industries. Furthermore, implementing higher standards are largely impacted by reducing the net exports of developing countries in comparison to the developed countries, thus implying that developing countries have a higher level of pollution-intensive output (Wilson *et al.* 2002). Levinson and Taylor (2008) observe a negative correlation between the growth of economic activities and the standard of stringency. They explained that strict environmental regulations would result in higher input costs and thus cause the shifting of industries to countries with lower regulatory standards.

Multinational companies are flocking in economies that have lower environmental taxes and a lower degree of environmental regulation (Seker, et al. 2015). This means that, with a view to save on greater environmental expenses levied in industrialised countries, MNCs are moving the industries with high pollution levels to the developing economies. Due to this, developing economies are becoming pollution havens with a significant rise in their pollution level (Zhang and Zhou, 2016). This may harm the environment of the host countries if they do not take these issues seriously. To assess the effect of foreign direct investment on carbon dioxide discharge in Turkey, autoregressive distributive lag model and error correction model (ECM) was adopted in the project conducted by Seker, et al. (2015). The authors establishes that the effect of emission on foreign direct investment is positive in any case if assessed either for shorter or longer-term (Seker, et al. 2015). The presence of PHH in Ghana and China was assessed using a similar method, with the results indicating a significant connection between foreign direct investment and carbon dioxide emissions in both countries (Solarin, et al. 2017).

Salahuddin, et al. (2018) in Kuwait further analysed the approach of Tang and Tan (2015) by engaging the autoregressive distributive lag bounds examination method and adding vital aspects such as monetary evolution, fiscal progress, electricity consumption, and carbon emanation. The outcomes of the paper confirmed the association of foreign direct investment and emission both on short term and long term (Salahuddin, et al. 2018). Some scholars have preferred the pollution haven hypothesis; Shahbaz, et al. (2015), for instance, employed the fully modified ordinary least square (FMOLS) technique in various countries with varied income-levels to evaluate the nonlinear association between foreign direct investment and carbon dioxide emissions. The results established the inflow of foreign direct investment results in a proportionate rise in the levels of carbon dioxide discharges (Shahbaz, et al. 2015). Applying this concept at a broader level, tests were conducted by Tang and Tan (2015) in Vietnam to assess the correlation between foreign direct investment, carbon productions, energy ingestion, and returns. To achieve this, cointegration test and Granger causality were adopted, and the outcome depicted bidirectional causal connection between foreign direct investment and emissions (Tang and Tan, 2015).

The Pollution Halo Hypothesis: Few studies have affirmed that foreign direct investment inflows help in improving the efficiency of energy and delimiting pollution emission, as foreign direct investment has a positive effect on management procedures, technology acquisition, and employment growth. This is better termed the pollution halo hypothesis, according to which, the foreign direct investment will cause positive environmental spill-over in the host economy as the multinational corporations enjoy greater developed tools compared to their local counterparts, and therefore they will spread cleaner technology which is less tasking on the environment (Jalil and Feridun, 2011). The high-level investments made by foreign direct investment in research and development will provide for environment-friendly technologies and the multinational corporations with superior environmental management systems would have a positive impact on the host countries. This ultimately raises environmental consciousness and increases environmental standards (Hoffmann, et al. 2005). Owing to these reasons, the pollution halo hypothesis posits that the foreign direct investment movement will reduce emissions and improve the environmental quality in host economies (Shahbaz, et al. 2015).

The pollution haven hypothesis adequately explains the real intentions of the multinational corporations, which are moving the industries with high pollution levels to developing countries turning them into pollution havens and significantly increasing their pollution levels. It asserts that a certain flexible directive in the newly industrialised countries would give them a relative lead in the creation of pollution-centered merchandise over the industrialised countries. Various evidence has been provided to support this hypothesis. Zhou, Zhang, and Li (2013) to evaluate the outcome of the effect on the environment of industrial structural transformation; with the results affirming that a huge amount of foreign direct investment inflow would reduce emission, thereby substantiating the impact of pollution halo in China, used dynamic panel data. The association between foreign direct investment and energy usage was investigated by Mert and Bölük (2016) using ADR approach in almost 31 Kyoto protocol countries, and the results substantiated that foreign direct investment impedes carbon dioxide emissions (Mert and Bölük, 2016).

Lucas Paradox Lucas Paradox suggests that both theories could not be true, as foreign direct investment moves from developing countries to developed countries (Lucas, 1990). He (2006) debates the idea that the environmental regulation costs playing a vital role in determining the location of foreign direct investment, as proposed by the halo hypothesis and pollution haven hypothesis, are questionable. The example of China was considered by He (2006) to explain that due to initially cheap labour in China, there was a huge inflow of foreign direct investment in the country but now the situation is different as the inflow of foreign direct investment is now due to the ever-growing Chinese economy. The Chinese economic upturn has spurred the foreign companies to desire a strategic position in the Chinese market. This study suggested that the inflow of foreign direct investment in China is not due to the comparative advantage of environmental regulations.

Alfaro, et al. (2008) in their research confirmed the Lucas paradox. They demonstrated that for the period from 1970 to 2000, there was less inflow of capital per capita in developing countries than in developed countries. It was debated that this could be asymmetric information and human capital has an important role in deliberating the flow of capital (Alfaro, et al. 2008). This suggests that the haven hypothesis is invalid as per the Lucas paradox. This is more so as the inflow of capital is not dependent on environmental regulations stringency but is dependent on other factors.

In conclusion, it is sufficient to say that foreign direct investment has a detrimental influence on carbon dioxide emissions in countries at higher quintiles; with this negative effect increasing substantially with emissions. Evidently, based on research conducted by Huang, et al. (2019), it could be stated that the inverted U-shaped environmental kuznet curve is only applicable in areas with very low pollution levels. Nonetheless, "the positive indirect effects of foreign direct investment and foreign trade on carbon dioxide emissions are greater than the negative direct effects; thus, the total effects are positive" (Huang, et al. 2019).

3.2.3 Literature on Financial Development, Industrial Performance and Carbon Dioxide Emissions

Proper execution of services and goods over a period improves the financial development of the country. Similarly, the industrial performance of a country directly influences its financial development. Hence, industrial growth and financial development occur side by side. Without good industrial performance, there could be no financial development in a country. However, because financial development and industrial growth come at the price of environmental pollution due to carbon emission in some countries, it is important to understand the interrelationship between financial development, industrial performance, and carbon dioxide emissions. As per Han, et al. (2018), it is vital to get a complete understanding of the interrelationship between economic development and carbon emissions to regulate economic activities and protect the environment to cut down greenhouse emissions.

Rahman and Kashem (2017) examine the long and short run dynamics and causal relationships between carbon emissions, energy consumption and industrial growth in Bangladesh over the period 1972–2011. The ARDL bounds test methodology and Granger causality test in an augmented VAR framework were applied and the results confirmed long-run cointegration between carbon emissions, energy consumption and industrial production in Bangladesh; industrial production and energy consumption have significant positive impact on carbon emissions both in the short and long-runs. The results also indicated unidirectional causation from both industrial production and energy consumption to carbon emissions, implying that industrial development or economic development in Bangladesh is taking place at the cost of environmental quality.

Lin, Omoju and Okonkwo (2015) investigated the impact of industrial value-added on carbon dioxide emissions in Nigeria using the Kaya Identity framework and Augmented Dickey Fuller (ADF), Johansen′s cointegration technique and vector error correction model. The data spans 1980 to 2011. The result of the analysis shows that industrial value-added has an inverse and significant relationship with carbon dioxide emissions, which suggests that there is no evidence that industrialisation increases carbon emissions in Nigeria. Gross domestic product per capita and population has positive and significant impacts on carbon dioxide emission. Energy intensity and carbon intensity has positive but very weak significant impact (at 10% level) on carbon dioxide emission. The paper recommends that policy makers in Nigeria should pursue pragmatic industrialisation policies coupled with modest decarbonisation and energy-efficiency measures to ensure long-term industrial, economic, and sustainable development.

Few studies have analysed the influence of financial development on carbon-dioxide discharge. Shahbaz, et al. (2013) used South African data to assess the influence of fiscal progress on pollution in South Africa and discovered enhancements in air quality owing to financial development. It was also argued that financial development augments air purity by rising earnings and capitalisation, manipulating fresh equipment, as well as applying protocols about the ecosystem. Likewise, a study by Salahuddin, *et al.* (2015) applied (FMOLS) method to observe the effect of financial development on carbon dioxide discharges in GCC countries within the period from 1980 to 2012. The findings revealed that financial development reduces the amount of carbon dioxide discharges. Similarly, Al-mulali, et al. (2015) in their study of 129 countries maintained that financial development lessens carbon dioxide emissions. Dogan and Seker (2016) in a related study revealed a negative relation between financial development and carbon dioxide emissions in both industrialized and developing countries. Abid, (2016) employed the cross-country data of 25 SSA countries to examine the influence of fiscal progress on carbon dioxide emissions, utilising the Generalised Method of Moment (GMM) method from 1996 to 2010. The results suggest a negative association between financial development and carbon dioxide emissions. Relatedly, Isik, et al. (2018) employed the heterogeneous panel analysis technique to scrutinise the connection amongst urbanisation, economic growth, and environmental pollution in China. They utilised heterogeneous panel estimation and fully modified ordinary least square. The authors found out that a long-run equilibrium correlation exists between output, urbanisation, energy consumption, and carbon emissions. They also confirmed that output and financial development had substantial influence in all provincial panels. Furthermore, Cetin concluded that financial development increases carbon dioxide emissions in Turkey.

Ganda (2019) inspected the effect of economic development on ecological dilapidation in OECD countries between the interval of 2001 and 2012, utilising static and generalised method of moment's approaches. The result reveals a significant positive relationship amongst economic progress and ecological dilapidation. Javid and Sharif (2016) examined the effect of fiscal progress, output development, and energy use on carbon dioxide emissions in Pakistan. The findings show that financial development, output growth, and energy promotes carbon dioxide discharges. Meng, et al. (2018) revealed similar results in their study, confirming that financial development is constructively associated with carbon dioxide releases in Turkey and Saudi Arabia. In a related study, Charfeddine and Kahia (2019) suggested that growth in money supply resulted in remarkable surges in the level of carbon dioxide discharges in Middle East and North Africa (MENA) region. Gokmenoglu and Sadeghieh (2019) assessed the consequence of fiscal growth, energy, and output growth on ecological dilapidation in Turkey from 1960 to 2011. The results of the study pointed to a significant constructive link between fiscal growth and ecological dilapidation. This verdict supports the outcome obtained by

Zakaria and Bibi (2019), according to which financial development increases the level of environmental pollution in South Africa.

3.2.4 Empirical Literature: Energy Performance and Carbon Dioxide Emission

A few studies have analysed the links between energy performance, economic growth, financial development, and carbon dioxide discharge using VAR and VECM techniques across many countries. For instance, Wei, et al. (2021) carried out an empirical study of carbon emission impact factors. They utilise the VAR model. The results showed that the economic growth effect, energy intensity effect and embodied carbon in foreign trade were the key factors affecting carbon emissions, among which the economic growth effect contributed the most. In a similar study, Ewing, et al. (2017) investigated energy consumption, carbon emission and economic growth nexus in the United States for the period 1972-2006, using the Johansen Bivariate cointegration method, VAR, and the dynamic causal analysis. The result showed that carbon dioxide emissions granger causes economic growth in the short and long run. Results also indicated that unidirectional causality exists from energy consumption to economic growth both in the short and long run, while in the short run bidirectional relationship exists between energy consumption and economic growth. The study concluded that carbon emissions influenced economic growth.

In the same vein, Soytas and Sari (2017) examined the relationship between energy consumption, economic growth, and carbon emissions in Turkey. The investigation employed the granger causality perspective in a multivariate VAR framework. They discovered that carbon emissions seem to granger cause energy consumption, but the reverse is not true. The study concluded that there is a lack of a long-run causal link between income and emissions, which implied that to reduce carbon emissions; Turkey does not have to forgo economic growth. Furthermore, Chontanawat, et al. (2016) studied the dynamic modelling of a causal relationship between energy consumption, C02 emission and economic growth in India with the data covering 1971 to 2006. The methodology used was the VAR granger causality. The study confirmed the existence of bidirectional granger causality between energy consumption and carbon dioxide emissions in the long run, but neither carbon dioxide emissions nor energy consumption and income in any direction in the long run. The study concluded that India could pursue energy conservation and emission reduction with efficiency improvement policies without impeding economic growth. Similar study by Saibu and Jaiyesola (2013), examined the implication for energy policy and climate protection on the nexus between energy consumption, carbon emission and economic growth in Nigeria. The study employed a VAR granger causality and dynamic regression model and found that there was a causal relationship between oil production, carbon emission from gas flaring and economic growth in Nigeria, with a conclusion that carbon emission constituted an impediment to sustainable economic growth in Nigeria.

Sun, et al. (2011) empirically studied the relationship between economic growth and carbon emission in China. The study employed time series data from 1999-2009, applying a VAR model with the use of impulse response functions and variance decomposition. It was concluded that in resource-dependent cities, per capita GDP changes granger cause changes in carbon emissions; however, carbon emissions do not exhibit the inverted U-shaped relationship in the dynamic sense. Per capita GDP contribute significantly to the behaviour of variance decomposition of carbon emissions. Bowden and Payne (2009) worked on the causality between energy consumption and economic growth in Greece, using VAR model, and Toda and Yamamoto (1995) granger causality test. The investigation revealed that in aggregate there was a unidirectional causal relationship running from total energy consumption to real GDP, the study, therefore, concluded that energy consumption affects economic growth.

Yu, et al. (2008) in a causal relationship between energy consumption and economic growth analysis in Liberia engaged a parametric and non-parametric granger causality approach and found evidence of distinct bidirectional granger causality between energy consumption and economic growth. The study, therefore, concluded that energy consumption influences economic growth. Similarly, Apergis and Payne (2014) examine the influence of renewable energy, output and fossil fuel prices on carbon dioxide emissions in the United States of America, using VECM approach with data from 1980 to 2010. Their results show that energy use, fossil fuel prices, and output positively influences carbon dioxide discharge. Similarly, using VECM and impulse response analysis, Albiman, et al. (2015) investigate the relationship among energy resources, economic performance, and carbon dioxide discharge in Tanzania between 1975 and 2013, and their outcomes reveal that energy resources and economic performance positively influence the capacity of carbon dioxide. The variance decomposition analysis shows a very high percentage of variation due to shocks of energy use and economic performance.

Boyle (2015) used vector error correction technique to forecast the effect of industrial production on carbon dioxide pollution in Bangladesh. The outcome illustrates the hypothesis of a positive link between industrial production and carbon dioxide discharge in the 54 years under review. Alshehry and Belloumi (2015) investigate the influence of energy use, energy price and economic progress on carbon dioxide emissions in Saudi Arabia, using vector error correction model and variance decomposition analysis, and confirm a positive link among energy use, energy price, and the output of carbon dioxide emissions.

Similarly, Wang, et al. (2016) studied the influence of energy performance and output on carbon dioxide discharge in China from 1990 to 2012 by the vector error correction model technique and also confirmed the positive effect on carbon dioxide output of energy performance and economic progress. Chen, et al. (2016), examination of the link between energy performance, output, and carbon dioxide emissions in 188 countries between 1993 to 2010, using vector error correction model technique also indicates that energy performance has a positive link to carbon dioxide explosion. Findings by Khobai and Roux (2017) reaffirmed the same in their analysis using vector error correction model of the effect of energy performance, output, trade, and urbanization on carbon dioxide explosion in South Africa between 1971 and 2013.

Aminu's (2018) examination of the influence of energy price shock on economic performance in United Kingdom using vector error correction model and impulse response analysis reveals that a temporary decline in economic performance occurs due to energy price shocks. Aminu, et al. (2018) analysis of the effect of energy price shock on output performance by vector error correction model indicates that energy prices shocks reduce the level of output performance. Wang, et al. (2018) also employ vector error correction approach to examine the link between energy use, output, and urbanisation with carbon dioxide in 170 countries from 1980 to 2011. The outcome from vector error correction model analysis indicates a positive link between energy, gross domestic product growth, and urbanisation and carbon dioxide emissions.

Ahad (2018) employed vector error correction model, variance decomposition and impulse response techniques to investigate the influence of aggregate and disaggregate energy use, industrial growth, and carbon dioxide emissions in China from 1984 to 2015. Their outcome illustrates that aggregate, disaggregate energy use and industrial growth accelerates the level of carbon dioxide discharge. Waheed, et al. (2018) examine the effect of energy use and agricultural production on carbon dioxide emissions in Pakistan using vector error correction model approach from 1990 to 2014. The outcome shows that an increase in energy use accelerates the level of carbon dioxide discharge. The findings in Tunisia also shows that energy use and gross domestic product increase the level of carbon dioxide discharge as revealed in Benali and Feki's (2018) analysis of the effect of energy use and economic performance on carbon dioxide carbon dioxide emissions in the country from 1982 to 2016.

Jian, et al. (2019) investigates the influence of energy resources, gross domestic product, and the performance of the financial sector on the Chinese carbon dioxide explosion between 1982 and 2017. The result again reveals a positive influence. The outcome of Nugraha and Osman's (2019) investigation of the same in Indonesia between 1975 and 2014 using vector error correction model technique reveals that energy consumption has a positive influence on carbon dioxide discharge. Peng and Wu (2019) examine the association of energy use, economic progress, and the carbon dioxide explosion in China from 2004 to 2016 using vector error correction model and fully modified ordinary least square methods to show that energy use increases the capacity of carbon dioxide explosion.

Zhang (2020) also used vector error correction model technique to examine the link between energy use, economic performance, and carbon dioxide discharge from 2000 to 2017 in Chinese provinces. The outcome of the estimate reveals that energy use accelerates the level of carbon dioxide discharge. Similarly, Destek and Aslan (2020) used vector error correction model and variance decomposition analysis to investigate the effect of the aggregates and disaggregates of renewable energy use, economic performance, and carbon dioxide output in G-7 countries from 1991 to 2014. The outcome indicates a positive influence of the disaggregate form of renewable energy on carbon dioxide discharge. Chandio (2020) analyses the performance of energy consumption, foreign direct investment, and gross domestic product in relation to carbon dioxide emissions in Pakistan from 1997 to 2017 by applying vector error correction method, showing a positive association between energy performance and carbon dioxide explosion.

In another development, Salazar-Núñez, et al. (2020) examine the influence of energy performance and economic progress on carbon dioxide output in 79 countries, using fully modified ordinary least square method. The outcome shows that energy performance accelerates the capacity of carbon dioxide discharge. Ibrahiem and Hanafy (2020) also used fully modified ordinary least square technique to study the effect of energy use, output, and population growth on carbon dioxide emissions from 1971 to 2014 in Egypt. The estimates reveal that increased energy use increases the levels of carbon dioxide emissions. However, a study on this outcome is similar to the findings of earlier studies Baimani, et al. 2021; Clifton, et al. (2020).

3.2.5 Literature Review on the Nexus between Energy Consumption and Carbon Dioxide Emissions

In recent times, the increase in carbon dioxide emissions has been linked with the increase in energy consumption by limited research that has been carried out on the topic. Sassana and Putri (2018) analysed the impact of fossil fuel consumption, the consumption of renewable energy, and population growth on carbon-dioxide emissions in Indonesia. They used the OLS approach along with multiple linear regression analysis on time series data for the period of 1990 to 2004. They concluded that population growth and fossil fuel energy consumption have a positive impact on the carbon-dioxide releases in the region.

Thao and Chon (2016) found a positive impact of energy consumption on the environment. They went further in stressing that carbon dioxide emissions are not only due to fossil fuel consumption but also due to the extraction process of fossil fuels. It was also found in the same study that a negative association exists between energy consumption and carbon-dioxide emissions. Li, et al. (2010) in their study of 28 provinces in China used panel data to find that economic growth and energy consumption in the long run influence carbon-dioxide emanation, however, long-term economic growth and carbon-dioxide emission have an impact on energy consumption. Moreover, Ito (2017) find   negative influence of fossil energy consumption on economic growth of developing countries, and it was further concluded that economic growth was positively impacted by energy consumption. The burning of fossil fuels is harmful to the environment; they cause excessive amounts of pollution. Renewable energy sources on the other hand do not damage the environment and thus can be termed as environment friendly (Ito, 2017).

Shafei and Ruhul (2013) in their study of OECD countries tested the concept of Kuznets curve hypothesis about the relationship between carbon-dioxide emissions and urbanisation and found that fossil fuel energy has a positive association with carbon-dioxide emissions, suggesting that an increase in fossil fuel consumption leads to increase in carbon-dioxide emissions. It was also concluded in the study that a negative association exists between renewable energy consumption and carbon-dioxide emissions, which indicates that there will be a reduction in carbon-dioxide emissions with increased consumption of renewable energy.

Fathinah and Djoni (2016) concluded that for ASEAN countries a significant and negative association exists between the quantity of renewable energy consumption and carbon dioxide emissions. Bilgili, et al. (2016) reported similar results in their study where it was found that the consumption of renewable energy has a significant and negative influence on the carbon dioxide released into the environment. The results of the study suggested that renewable energy consumption could be instrumental in reducing the level of carbon dioxide emissions. It was concluded in the study that by increasing renewable energy consumption, the reliance on fossil fuel energy could be minimized and thus, carbon-dioxide releases can be reduced. Paramati, et al. (2017) discovered in their study of G20 countries that renewable energy consumption cuts carbon-dioxide releases, which increases the economic output of the countries.

In a related study, Zoundi (2017), note that the consumption of renewable energy has a significant and negative impact on carbon-dioxide emissions, and it was established that renewable energy is more environment friendly than fossil fuels. It is expected that in the long-run fossil energy will be replaced by renewable energy due to environmental concerns (Zoundi, 2017). Liu, et al. (2017) in their study of four ASEAN countries (namely Thailand, Philippines, Indonesia, and Malaysia) found similar results that consumption of renewable energy has a negative influence on carbon-dioxide emissions. The estimation results pointed out that carbon dioxide emissions could be reduced by increasing the consumption of renewable energy. The study suggested the efficient utilisation of renewable energy towards attaining a healthier and cleaner environment.

Bulut (2017), in his study found a positive effect of fossil fuel energy sources on carbon-dioxide emission in Turkey for the period 1970 to 2013. Shafiei and Ruhul (2013), relatedly pronounced the similar results in their study of OECD countries, for the period 1980 to 2011, where consumption of fossil energy resulted in an increase in carbon-dioxide emissions. Similarly, Dogan and Fahri (2016) in their study of european countries also found a direct relationship between fossil fuel energy consumption and an increase in carbon-dioxide emissions. They concluded that there exists a causal indirect relationship between carbon-dioxide emissions and non-renewable energy consumption. In a study of Pakistan by Danish, et al. (2017), it was found that fossil fuel energy consumption has a positive effect on carbon-dioxide releases. It was further concluded that the main cause of carbon-dioxide emissions in Pakistan was the consumption of fossil energy and people's health and environment face danger due to the release of carbon dioxide during the combustion of fossil fuels. Zheng-Xin and De-Jun (2017) provided evidence for a direct relationship between fossil energy and carbon dioxide emissions. In another study (Chibueze, et al. 2013) in Nigeria for the period of 1971 to 2009, it was concluded that in the long term and short term, the consumption of fossil fuels has a significant and positive impact on the carbon dioxide released in the environment.

Based on the reviewed literature, it is possible to suggest that some studies have analysed the influence of energy demand macroeconomic activities and carbon dioxide discharge, using techniques of estimation such as, autoregressive distributive lag, generalize method of moment, and panel autoregressive distributive lag. However, the number of analyses of these relationships using vector autoregressive/vector error correction models, variance decomposition, and impulse response techniques specifically for South Africa, Ghana, and Nigeria is very limited. No previous studies investigated, furthermore, the interaction effect of energy use and the development of the financial sector, using the well-established econometric tools like vector autoregression (VAR), Toda Yamamoto in VAR framework, Impulse response function, variance decomposition, granger causality and autoregressive distributive lag (ARDL) techniques for the three largest economies of sub-Saharan African countries, which is precisely the focus of this study which is the examination of the influence of energy consumption industrial performance and some other macro-economic variables on carbon dioxide emissions in three largest economies of sub Saharan African countries.

The framework depicting the inter-connectedness between the dependent variable (carbon dioxide) and independent variables (foreign direct investment, industrial performance, gross domestic product growth, energy consumption and financial development) is shown in figure 3.1.

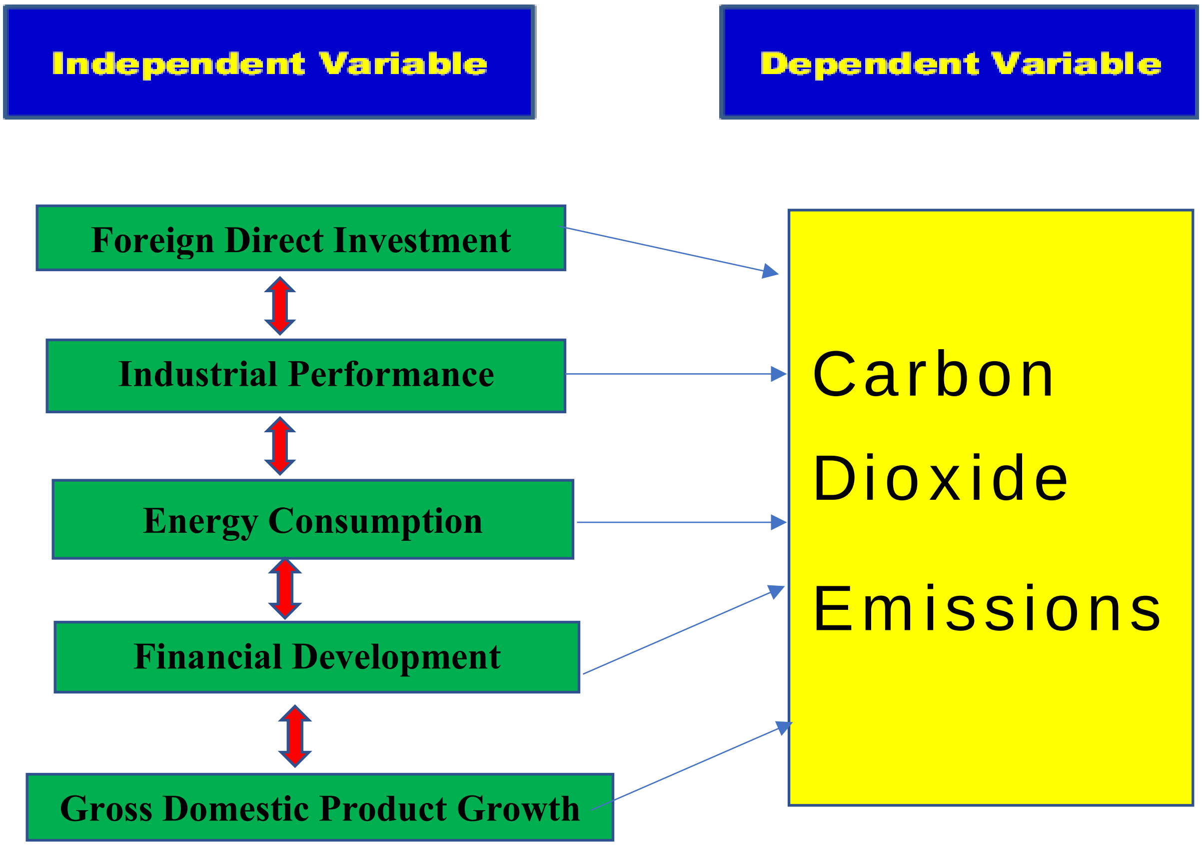


Figure 3. 1: Research Framework

Source: Author's Conceptualisation

3.3 Research Methodology

3.3.1 Empirical Modelling of the Impact of Energy Use and other Macroeconomic Variables on Carbon Dioxide Emissions in Three Largest Economies in Sub Saharan Africa.

This study adopted a modified version of the pollutant emissions model that was developed by Ang in 2007 to investigate the effects of fossil fuel usage, foreign direct investment, financial development, industrial performance and economic output growth on environmental quality, proxy by carbon dioxide (CO_2) emission, using quarterly data from 1980Q1 to 2017Q1.

The functional form of the relationship is represented in equation 3.1

$CO_2 = f\,(ENG, FDI, FD, IND, GDP_g)$ ……………………………………………........(3.1)

where carbon dioxide emission/discharge is (CO2), fossil fuel energy consumption (ENG), foreign direct investment (FDI), financial development (FD), industrial performance is (IND), and output growth measured by growth rate of gross domestic product is (GDPg).
The econometric specification of equation 3.1 is expressed in equation 3.2, as follows:

$$CO2_t = \propto + \beta_1 ENG_t + \beta_2 FDI_t + \beta_3 FD_t + \beta_4 IND_t + \beta_5 GDPg + \varepsilon_t \dots\dots\dots\dots\dots \quad (3.2)$$

where: Subscript t stand for the period (t = $1980Q_1$ to $2017Q_1$), α and β signify the parameters coefficients and ε denotes the stochastic error term, the rest as defined in the previous equation. The apriori expectation ($\beta_1\beta_2\beta_3\beta_4\beta_5 > 0$), therefore ENG, FDI, FD, IND and GDPg are positively related to carbon dioxide discharge.

3.3.2: Economic Rationale for Explanatory Variables inclusion in Estimated Model

Carbon Dioxide (CO2) Emissions

Carbon dioxide emissions, largely by – product of energy production and use, account for the largest share of greenhouse gases, which are associated with global warming. Anthropogenic carbon dioxide emissions result primarily from fossil fuel combustion and cement manufacturing. In combustion different amounts of carbon dioxide for the same level of energy use: Oil releases about 50% more carbon dioxide than natural gas, and coal releases about twice as much. Burning of carbon-based fuels since the industrial revolution has rapidly increased concentrations of atmospheric carbon dioxide.

Industrial Performance (IP)

Industry, value added (% of GDP) - Value added is the value of gross output of producers less the value of intermediate goods and services consumed in production before accounting for consumption of fixed capital in production. An economy's growth is measured by the change in the volume of its output or in the real incomes of its residents. The volume of GDP is the sum of value added, measured at constant prices, by households, governments, and industries operating in the economy. GDP accounts for all domestic production, regardless of whether the income accrues to domestic or foreign institutions.

Fossil fuel Usage (ENG)

Fossil fuel consumption (% of Total) - fossil fuels are non – renewable resources because they take millions of years to form, and reserves are being depleted much faster than new ones are being made. In developing economies growth in energy use is closely related to growth in the modern sectors – industry, motarised transport, and urban areas but energy use also reflects climatic, geographic, and economic factors (such as the relative price of energy). Energy use has been growing rapidly in low – and – middle -income economies, but high – income economies still use almost five times as much energy on a per capita basis.

Financial Development (FD)

Domestic credit provided by the financial sector includes all credits to various sectors on a gross basis, except for credit to the central government, which is net. The financial sector includes monetary authorities and deposit money banks, as well as other financial corporations such as finance and leasing companies, money lenders, insurance corporations, pension funds, and foreign exchange companies. Credit is an important link in money transmission, it finances production, consumption, and capital formation, which in turn affect economic activity. Domestic credit provided by the financial sector as a share of GDP measures banking sector depth and financial sector development in terms of size.

Tapping private sector initiative and investment for socially useful purposes are critical for poverty reduction. In parallel with public sector efforts, private investment, especially in competitive markets, has tremendous potential to contribute to growth. Private markets are the engine of productivity growth, creating productive jobs and higher incomes. More so, with government playing a complementary role of regulation, funding, and service provision, private initiative and investment can help provide the basic services and conditions that empower poor people by improving health, education, and infrastructure. Both banking and financial systems enhance growth, the main factor in poverty reduction. At low levels of economic development commercial banks tend to dominate the financial system, while at higher levels domestic stock markets tend to become more active and efficient. It is evident that the size and mobility of international capital flows make it increasingly important to monitor the strength of financial systems. Robust financial systems can increase economic activity and welfare, but instability can disrupt financial activity and impose widespread costs on the economy.

Gross Domestic Product Growth (GDPg)

The volume of GDP (constant USD) is the sum of value added, measured at constant prices, by households, governments, and industries operating in the economy. GDP accounts for all domestic production, regardless of whether the income accrues to domestic or foreign institutions.

3.3.3 Sources of Data, Variables Measurement and Definitions

Table 3.1: Description of the Study Variables

Variables	Description	Definition	Sources
CO_2	DV	Environmental quality measured by Carbon dioxide (CO_2) emissions per capita (metric tons)	WDI
FDI	IV	Foreign Direct Investment, net inflows (% of GDP)	WDI
IND	IV	Industry (including construction), value added (% of GDP)	WDI
FD	IV	Financial development is proxy by domestic credit by financial sector (% of GDP)	WDI
ENG	IV	Fossil energy consumption measured by Petroleum and other liquid consumption (% of total energy)	EIA
GDPg	IV	Economic growth measured by Gross domestic product growth rate	WDI

Note: *DV refers to dependent variable and *IV refers to independent variable

This study employs quarterly time series data for Ghana, Nigeria, and South Africa from 1980Q1 to 2017Q1, with data carbon dioxide emissions, energy consumption, industrial performance, economic output growth, foreign direct investment, and financial development from the World Bank's World Development Indicators (WDI) and Energy Information Administration (EIA). One of the reasons to choose WDI and EIA is that they are one of the premier compositions of data that do not only provide details of a country but also support cross-country analysis. The indicators help in measuring the development experienced by each country individually as well as in comparison to its counterparts. The information obtained from these databases is appropriate, and accurate along with being of higher quality.

Carbon dioxide emissions are measured in per capita (Metric tons) while foreign direct investment percentage of output measures foreign direct investment. Energy consumption is measured by fossil fuel consumption that consists of petroleum, natural gas, and coal and oil production. The industrial performance will be measured in terms of value-added, gross domestic product growth rate is a measure market size, and financial development is a proxy domestic credit as a percentage of gross domestic product.

A. *Carbon Dioxide Emissions in per capita (metric tons)*

Carbon dioxide emissions mainly comprise of emissions that arise due to burning or combustion of fossil fuels. These are also known as greenhouse gases (GHG) which pollute and remain harmful to the quality of the environment. These gasses are harmful mainly because they tend to captivate as well as release infrared radiations, which are hazardous to the entire universe. They keep the heat trapped and do not allow it to be released in space. The outcome is the rising temperatures of the earth making it a difficult place to live. The calculations for carbon dioxide emission are done by calculating the total number of people living and the overall quantum of carbon dioxide emitted per person (Saboori Sulaiman 2013), which results an average to identify per capita emissions. For simplicity, and ensuring a holistic analysis is executed in the present study, carbon dioxide emissions are measured based on per capita (metric tons) and is the dependent variable employed in the study.

B. Foreign Direct Investment

Foreign direct investment is investments made by individuals and companies into a foreign country to generate mutual companies (Bhasin, 2012). Foreign direct investments are executed with the primary intention to pursue business in a foreign land. A country welcomes foreign direct investment as it supports industrial development which in turn promotes overall national development. Through foreign direct investment, a country can get additional sources of funds and thus add to resources required for capital building. Foreign direct investment also helps countries to develop powerful and positive international relationships. Foreign direct investment is not only about the channelisation of funds into foreign lands. It also consists of a transfer of knowledge, competencies, skills, and technologies (Sahoo, Nataraj, and Dash 2013). With the help of foreign direct investments, it is possible for individuals or firms to use their idle capital and thus support economic progress by encouraging the movement of funds and other resources from the haves to the have-nots. The inclusion of foreign direct investment as a determinant of emissions aims to ascertain the extent to which the pollution hypothesis (PHH) or pollution halo hypothesis hold true in sub-Saharan Africa, as foreign energy firms may locate their factories/companies to poorly regulated developing economies to avoid paying environmental control costs obtainable in developed countries. This practice may invariably enhance emissions/pollutants that would directly degrade the environment, as documented in Shahbaz, et al. (2015); Tang and Tan (2015); Sun, et al. (2017); Solarin, et al. (2017); and Salahuddin, et al. (2018).

C. Industry (Including Construction), Value Added (Percentage of Gross Domestic Product)

This variable captures the level of industrial performance in producing output. In simple terms, it refers to the overall value addition done by an industry in the process of economic growth and development of a country (Bureau of Economic Analysis, 2006). Thus, industrial value-added is the overall contribution of the industry to the gross domestic product (output) of a country or region (Bureau of Economic Analysis, 2008). This industry can be private or owned by the government. In addition, companies within a particular industry can be either private or public in nature. Value addition by industry is done through employee compensation, taxes paid on manufacturing, deduction of subsidies on imports, and gross operational excess. Value addition by industry is the discrepancy amidst the total output by industry and the costs of all the transitional inputs used by the industry.

The gross output comprises the sales and other sources of operational income, changes in inventory, and commodity taxes. Transitional inputs on the other hand consist of energy, work-in-progress, semi-finished or unfinished goods and services, and raw materials procured from diverse sources (Bureau of Economic Analysis, 2008). This variable enters the carbon dioxide emissions model because firms use energy, whether fossil fuels or renewable power supply, in the process of generating desired output. To this end, the nature of energy use adopted by players in the industrial sector would significantly affect the level of environmental quality through carbon emissions.

D. Financial Development (Credit to the Private Sector as a Percentage of Gross Domestic Product)

Financial development can be defined as the progress in the production of information about likely investment opportunities and capital allotment (Hermes and Lensink, 2013). It also implies simplification of the overall process of imports and exports. In circumstances when exposure to risks is minimised, it can be stated that financial development has taken place. Other aspects of financial development comprise increased trading, increased savings, effective utilisation of savings, and enhancements in diversification.

Credit to the private sector (percentage of gross domestic product) is considered in extant studies as the most appropriate measures of financial development, unlike interest rate spread and ratio of broad money to gross domestic product (M2/ gross domestic product), because it captures the core intermediating role of the financial sector, as channel between the surplus economic units (savers) and the deficit economic units (investors). Thus, private sector credit as a percentage of gross domestic product is considered a good indicator for ascertaining financial sector depth in any economy, as seen in De Gregorio and Guidotti, (1995); Beck, Levine, and Loayza, (2000); Tressel and Detragiache, (2008). From extant studies, like Ozturk and Acaravci, (2013), it is believed that an increase in credit to firms for investment in less innovative energy-using technology will enhance the level of emission and reduce level of environmental quality, and the converse holds.

E. ***Fossil fuel Consumption (Energy consumption) (Percentage of total energy)***

Energy consumption/ energy use implies the basic use of energy prior to its transmission into other forms of fuels mainly those termed as end-use ones (Santamouris, 2018). This usage is the same as the in-house creation of energy and that procured through imports and changes in stock. However, in this energy use, the deduction is made of fuels that are exported or provided to ships and aircraft in global transportation. Kg of oil equivalent (kgoe) is the standardised unit of measurement of energy. This is an equivalent value as kgoe is the energy that is extracted from 1 kilogram of crude oil. Extant literature on similar study shows energy usage have positive and statistically significant effects on CO2 emissions, and these studies include Zhang and Cheng (2009); Apergis and Payne, (2010); Kohler, M. (2013); Farhani, et al. (2014), Kasman, and Duman, (2015); Sun, et al. (2020).

F. Gross Domestic Product Growth Rate (Percentage)

Gross domestic product refers to the total monetary/market value of all finished commodities and services produced within a country's borders at a point in time. It captures the overall domestic economic activities and production, and thus, effectively measures the economic scorecard of a given country. In economic literature, the gross domestic product is often employed as a measure of market size and often a lure for market-seeking investments to a particular economy and is computed annually as well as quarterly.

In the meantime, and due to the paucity of data on actual employment level, as well as issues around the reliability and methodology of computing employment metrics in the sampled countries, this study employed gross domestic product growth rate as proxy for level of economic activities, as indicated in extant literature, like Kapsos (2005); Khan (2007); Seyfried (2011); ILO (2013). This is sequel to the axiom that, high employment translates to greater amount of goods produced, especially for labour intensive global countries, since creating jobs helps the economy by increasing gross domestic product (Okun 1970), although the link might change over time due to rate of technical progress (Dokpe 2001). The sampled countries being particularly labour intensive in their production process, labour input would, therefore, closely mirror goods produced, measured by gross domestic product growth rate, and in line, ILO (2015) posited that, economic growth remains a prerequisite for increasing productive employment, as it sets the absolute maximum within which employment and labour productivity growth can take place.

Simon Kuznets' works, which culminated into the Environmental Kuznets Curve Hypothesis, holds that, carbon dioxide emissions will continue to increase with economic growth rate, reaches a turning point, before which carbon dioxide emissions level will begin to decline, on the back of increased demand for improved environmental quality. This is effectively displayed in the Kuznets' inverted U-shaped relationship between carbon dioxide emissions and economic development, and the intuition is that carbon dioxide growth does not preclude having, in the long run, cleaner environmental quality, as documented in Ang (2007); Zhang and Cheng (2009); Adedoyin and Zakari, 2020; Sun, et al. (2020). Higher level of output would support greater economic activities and production, which would expectedly enhance level of carbon dioxide emissions, but pollution, could decline with increasing gross domestic product growth, if there is greater demand for improved environmental quality. Thus, gross domestic product growth can either enhance or reduce level of carbon emissions, in line with the inverted U-shaped curve of the EKC hypothesis.

The identification and choice of all these variables are based on the research objectives as well as the review of the literature. The variables are present within the macro environment and beyond the control of the researcher. The changes within these variables are bound to influence the overall region and the industry therein. All the chosen variables are primarily situational variables as they are present within the environment. These variables are thus extraneous variables that bear an impact on the functioning of an industry thereby influencing economic development of a country (Peck and Devore, 2011).

3.3.4 Estimation Techniques and Stability Test

This section presents some estimation techniques employed for analysis in this study. Discussions covers the ARDL-bound cointegration test approach augmented dickey – fuller (ADF) unit root test, and CUSUM stability test.

3.3.5 Autoregressive Distributive Lag-Bound Cointegration Test Approach

The autoregressive distributive lag -bound testing approach will be used to investigate long-run cointegration among the variables in this study. The autoregressive distributive lag technique is superior to other techniques because it has certain econometric advantages, such as: (1) the method can be used regardless of whether the variables are integrated of order zero I(0), order one I(1), or a combination of both, as opposed to other techniques such as Johansen, which require the variables to be integrated of the same order; (2) this method accommodates a small sample size, as argued by Narayan (2005). Because of these characteristics, the autoregressive distributive lag test has lately become a popular method.

The autoregressive distributive lag model to be used in this study is given by equation (3.3):

$$\Delta \ln CO_{2t} = \vartheta_0 + \sum_{k=1}^{p} \vartheta_{1k} \Delta \ln CO_{2_{t-k}} + \sum_{k=1}^{q} \vartheta_{2k} \Delta \ln FDI_{t-k} + \sum_{k=1}^{q} \vartheta_{3k} \Delta \ln ENG_{t-k} + \sum_{k=1}^{q} \vartheta_{4k} \Delta \ln FD_{t-k} +$$
$$\sum_{k=1}^{q} \vartheta_{5k} \Delta \ln IND_{t-k} + \sum_{k=1}^{q} \vartheta_{6k} \Delta \ln GDP_{t-k} + \delta_{11} \ln CO_{2_{t-1}} + \delta_{12} \ln FDI_{t-1} + \delta_{13} \ln ENG_{t-1} + \delta_{14} \ln FD_{t-1}$$
$$+ \delta_{15} \ln IND_{t-1} + \varepsilon_{1t} \qquad (3.3)$$

where: ε_{1t} are the residual, which is assumed to be normally distributed, Δ represents the first difference operator and ϑ is the dynamics of error correction as δ represents long-run relationships. Using F-test, cointegration relationship is examined among the variables where the null hypothesis that $H_0 : \delta_{11} = \delta_{12} = \delta_{13} = \delta_{14} = \delta_{15} = \delta_{16} = 0$ is tested against $H_0 : \delta_{11} \neq \delta_{12} \neq \delta_{13} \neq \delta_{14} \neq \delta_{15} \neq \delta_{16} \neq 0$. In deciding the cointegration among the variables, H_0 is rejected if the F-statistic is greater than the upper bound. On the contrary, if F-statistic is less than the lower bound, H_0 cannot be rejected, while the result becomes inconclusive if the F-statistic is between the upper and the lower bounds. In this circumstance, we then consider adding or dropping some variables in the study.

3.4 Stationarity Test

Most macroeconomic time series data have trends and are in some cases non-stationary. A standard practice in econometric analysis using time series is ensuring stationarity in their mean/average value. The data to be used in empirical analysis must be stationarity to detrend before the analysis. Thus, to estimate the relationship of carbon dioxide emissions with its determinants, including energy consumption, industrial performance, output growth, foreign direct investments, and financial development, the first task is testing for unit root presence. This aim is to ensure that analysis is only conducted using stationary time series data to avoid estimating spurious results, which remain not suitable for policy formulation and forecasting in panel data, even in country-specific analysis. In this regard, there are procedures for detrending, and these include differencing and conducting time-trend regressions, which are commonly used to make the data stationary.

To avoid spurious regressions, it becomes necessary to carry out a pre-testing for unit root before conducting co-integration analysis. The investigation of the presence of long-term relation between energy consumption, foreign direct investment, financial development, industrial performance, gross domestic product growth and carbon dioxide emissions in sub-Saharan African countries, starts with the test for the existence of unit root test for time series of the variables. There are various standard tests in the literature, one of which is: Augmented Dickey – Fuller (ADF). It is critical to define the order of integration of the variables before modeling time series data. There are various unit root tests available for testing the time series properties of the variables. This research proposes the use of the ADF unit root test.

3.4.1 Augmented Dickey – Fuller (ADF) Unit Root Test

ADF as introduced (1979) is computed as explained in the next lines. It is based on the t-statistic calculated from the OLS equation in equations 3.4 to 3.6. The test does not have an asymptotic standard normal distribution, according to Lutkepohl (2004). Simulation yields critical values, which differ when a constant or linear factor is included. According to Lutkepohl (2004), the test does not reflect an asymptotic standard normal distribution, the critical values are calculated by simulation, and they are different when a linear term or constant is included. As a result, if y = 0, the first difference data series is adjudicated to have a unit root or stationery, and if the coefficient of a difference adds to one, y = 0 and the series has a unit root. The test assumes that the mistakes are independent and that their variance is constant. In the tests, the errors are assumed to be independent and have a constant variance. If the null hypothesis is rejected in this scenario, it indicates that the time series under consideration is non-stationary.

This study uses the ADF (1979) tests to check the stationary property of the variables. For this purpose, all the data series of carbon dioxide emissions, foreign direct investment, industrial performance, financial development, and energy consumption will be examined using the ADF unit root test.

The ADF consists of estimating the following:

$$\Delta Y_t = \beta_1 + \beta_2 t + \delta Y_{t-1} + \sum\nolimits^{v}_{t-I} \alpha_t \Delta Y_{t-1} + \varepsilon_t \tag{3.4}$$

$$\Delta Y_t = \beta_1 + \delta Y_{t-1} + \sum\nolimits^{v}_{t-I} \alpha_t \Delta Y_{t-1} + \varepsilon_t \tag{3.5}$$

$$\Delta Y_t = \delta Y_{t-1} + \sum\nolimits^{v}_{t-I} \alpha_t \Delta Y_{t-1} + \varepsilon_t \tag{3.6}$$

where β_1 represents the intercept, ε_t is the error term, and Δ is the first difference operator.

3.4.2 Determination of Lags

Lagged values of the dependent variable and independent variables are included when applying regressions on time series data. The number of stars in lagged denotes the number of lags that should be utilised in the experiment. Aside from that, determining the lag length of vector autoregressive (VAR) models is an important part of the model design process (Ozcicek McMilin 1999). Furthermore, according to Ozcicek and McMilin (1999), lag length determination is critical because if the vector autoregressive used lag length in the estimation differs from a true lag length, the result with impulse functions and variance decompositions from the vector autoregressive is inconsistent. The Sequential Modified LR test statistic (LR), Final Prediction Error (FPE), Akaike Information Criterion (AIC), Schwarz Information Criterion (SIC), and Hannan-Quinn (HQ) information criterion were utilized in this study to estimate the lag length for analysis. The Akaike Information Criterion (AIC) and Schwarz's Bayesian Information Criterion (SBIC) are the most utilized criteria (SBIC). Below are explanations of AIC and SIC (Gujirati, 2003):

$$\mathrm{AIC} = e^{2k/n}\,\Sigma\frac{\hat{u}2i}{n} = e^{\frac{2k}{n}}RSS/n \tag{3.7}$$

$$\mathrm{SIC} = n^{2k/n}\,\Sigma\frac{\hat{u}2i}{n} = n^{\frac{k}{n}}RSS/n \tag{3.8}$$

The number of regressors in this model is k, and the number of observations in this model is n. In AIC, 2k/n is a punishment factor, but in SIC, [k/n ln n] is a penalty factor. These two criteria, however, cannot be employed at the same time. The (AIC) rule states that the lower the AIC value, the better the model, which Gujarati also states (2003). After determining the number of lagged variables, a cointegration test can be used to determine their cointegration.

3.5 Descriptive Statistics

Table 3.2 presents descriptive statistics of each variable series employed for Nigeria, Ghana, and South Africa, within the period 1980Q1 to 2017Q1. The average industrial performance, value-added as a percentage of GDP during the period under review was 31.99%, 30.00% and 21.32% for South Africa, Nigeria, and Ghana, respectively. Average energy consumption effectively mirrored the industrial performance patterns of the studied countries, with South Africa using 0.96% of total fossil fuel energy consumption, followed by Nigeria, which consumed 0.55% of the total fossil fuels, while Ghana consumed the least 0.07% among the three (3) countries studied. In addition, average carbon dioxide (CO_2) emissions were the highest in South Africa 8.92 per capita metric tons, followed by Nigeria 7.24 per capita metric tons and Ghana 0.61 per capita metric tons, and thus, effectively indicating a direct proportional relationship of carbon dioxide emissions with energy use and industrial performance in these countries.

The average economic growth rate stood at 11.2% in South Africa, marking the highest among the three countries, followed by Nigeria with a gross domestic product growth rate of 9.21%, and Ghana, had the lowest economic growth rate of 9.15%, which maybe reflective of extant economic advancement levels and existing capacity for growth among the three countries. Meanwhile, Ghana attracted the highest average foreign direct investment of US$2.91 billion among the three countries during the period under review, with Nigeria and South Africa recording an average of US$1.52 billion and US$2.22 billion as foreign direct investment during the reviewed period.

Table 3.2: Descriptive Statistics

NIGERIA						
	Carbon-dioxide Emissions per capita (Metric tons)	**Financial Development (% of GDP)**	**Foreign direct investment, net inflows (% GDP US$ Billion)**	**Fossil fuel energy consumption (% of total energy)**	**Gross Domestic Product Growth (%)**	**Industrial performance, value added (% of GDP)**
Mean	0.61	9.21	1.52	0.55	3.51	30.00
Median	0.61	8.14	1.26	0.53	4.10	29.85
Maximum	0.92	19.62	5.79	0.90	15.87	39.24
Minimum	0.32	4.95	-1.15	0.34	-11.55	18.17
Std. Dev.	0.17	3.48	1.33	0.13	5.81	5.29

GHANA						
Mean	7.24	9.15	2.91	0.07	4.48	21.32
Median	0.31	10.22	1.70	0.05	4.69	23.72
Maximum	268	15.88	9.51	0.17	13.44	34.85
Minimum	-4.47	1.54	0.04	0.02	-7.14	6.24
Std. Dev.	43.56	5.30	2.34	0.04	3.69	6.77
SOUTH AFRICA						
Mean	8.92	112.39	2.22	0.96	2.33	31.92
Median	8.82	115.93	0.51	0.92	2.65	29.62
Maximum	9.97	160.12	5.98	1.35	6.53	45.27
Minimum	7.36	53.96	-0.766	0.64	-2.61	26.02
Std. Dev.	0.68	33.60	1.26	0.22	2.28	5.51

Source: World Development Indicators &International Energy Agency

Nigeria

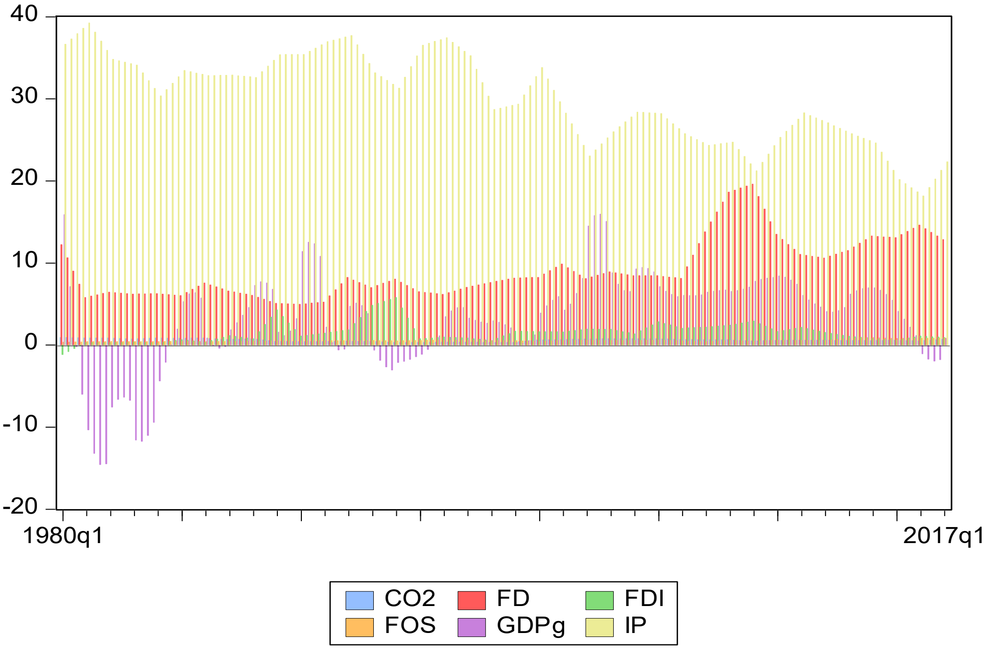


Figure 3. 2: Descriptive Statistic Chart for Nigeria

Ghana

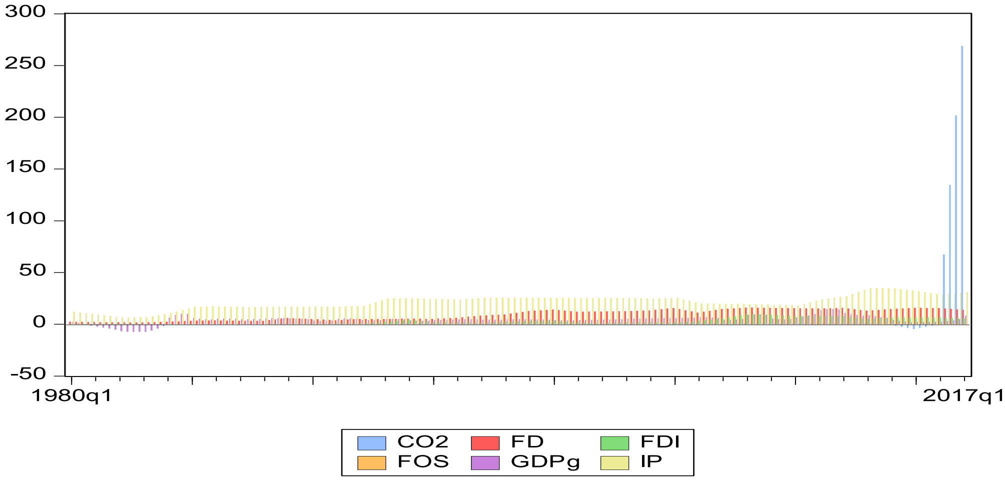


Figure 3. 3: Descriptive Statistic Chart for Ghana

South Africa

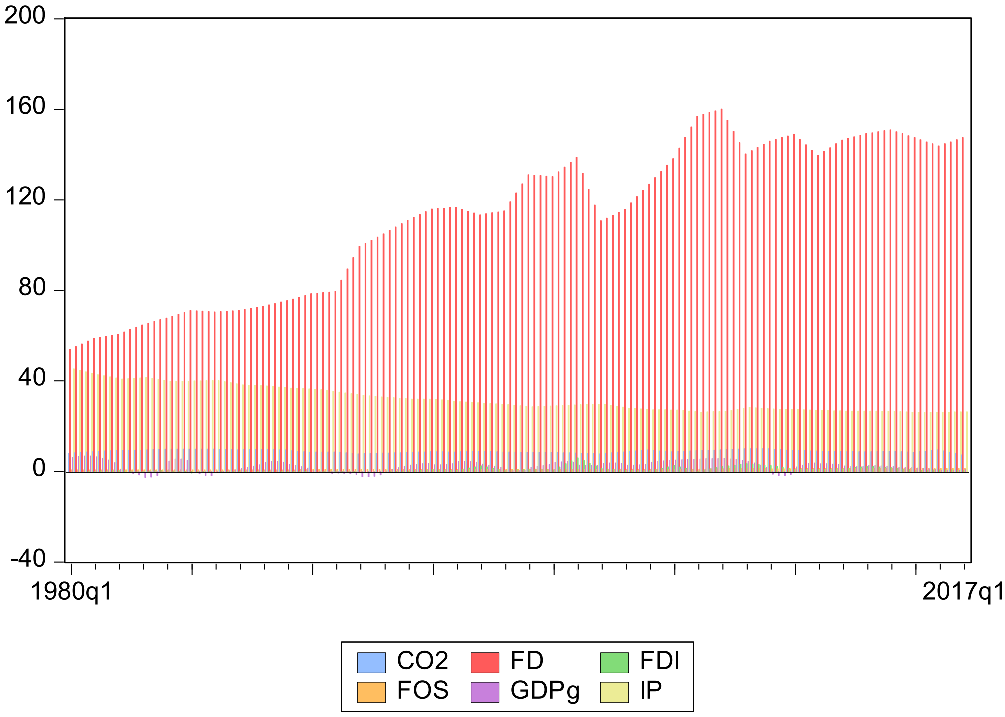


Figure 3. 4: Descriptive Statistic Chart for South Africa

3.5.1 Trend Analysis of Data Employed

This section presents the trend analysis of data used in the study to identify changes overtime, as well as allow for useful comparison on the performance of each data among countries studied by way of ascertaining any systemic connections in pattern of relationships.

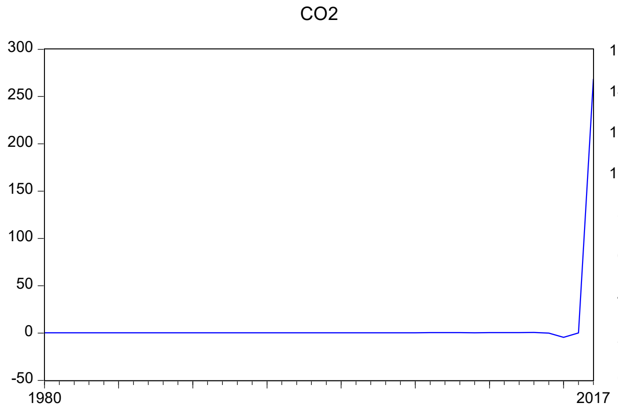
From figures 3.5, 3.6 and 3.7, Nigeria, South Africa, and Ghana, witnessed a rising carbon dioxide emission level (a measure of environmental quality) in the period under review from 1980 to 2017, though the former recorded higher level of emission. The carbon dioxide emission in Nigeria were also clearly rising between 1980Q1 to 2017Q1, though exhibited marked cyclical/ seasonal trend. The trend of fossil fuel energy Consumption (% of total), a proxy for energy usage, exhibited a rising tendency over time in the three (3) countries studied, namely Ghana, Nigeria, and South Africa. This may closely explain the direct impact of fossil fuel consumption, as a highly significant contributor of carbon dioxide emissions/pollution in these countries. This could further explain the structure of economies of these countries, which tilts mainly towards the extractive industries, often with weak linkage effect to the rest of the economy.

From figure 3.5, 3.6 and 3.7 only Ghana recorded growth, on average, in its industrial performance, measured by industrial performance (% of gross domestic product), for the period from 1980 to 2017, with both Nigeria and South Africa, witnessing noticeable decline throughout the same period. This could support government of Ghana strategy to leverage on developing the industrial sector to enhance inclusive growth and development. The growth trajectory in gross domestic product (%) for South Africa showed evidently volatile path in the studied period (1980 to 2017), and growth was broadly sideways, averaging 2.33% for the period. Ghana's gross domestic product growth was relatively more stable overtime among the studied countries, averaging 4.43% over the period, while Nigeria gross domestic product growth also portrayed evidence of seasonality, though experienced average growth of 3.28% over the period from 1980 to 2017.

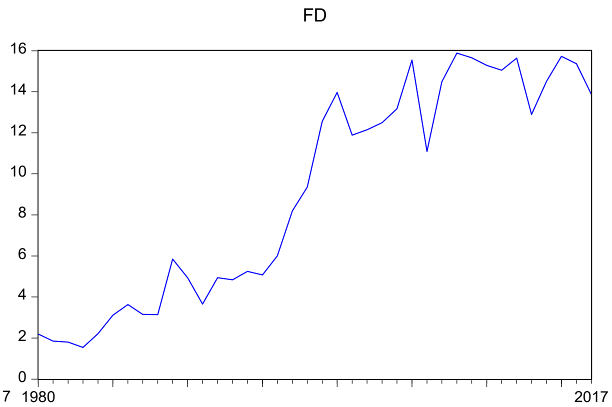
The performance of foreign direct investment (net inflows) in the studied countries was noticeably low in the 1980s, up until the late 1990s. Foreign direct investment inflows picked up gradually in Nigeria from year 2000, growing steeply between 2004 to 2011, and declined markedly between 2011 and 2017. The trajectory of foreign direct investment inflow in Ghana only witnessed sharp growth in 2005 and has remained relatively high for the rest of the periods. Domestic credit provided by the financial sector (% of gross domestic product) rose both in Ghana and South Africa throughout the 1980 to 2017 periods, though South Africa data shows higher credit intermediated by the financial sector. Credit advanced by financial sector in Nigeria averaged 7.33% from 1980 to 2006, before rising steeply to about 19% and declining to 12.85% in 2017.

Ghana

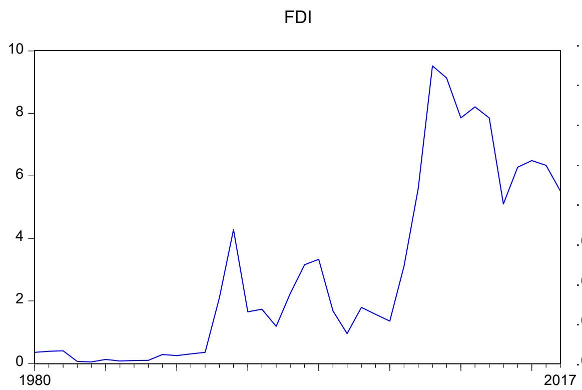
Carbon dioxide emissions (per-capita)



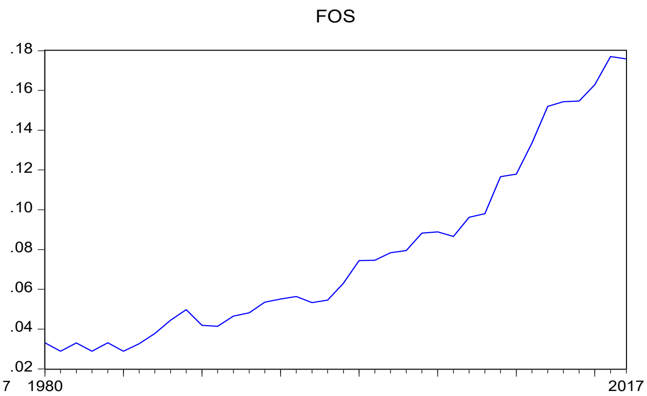
Domestic credit (% of GDP)



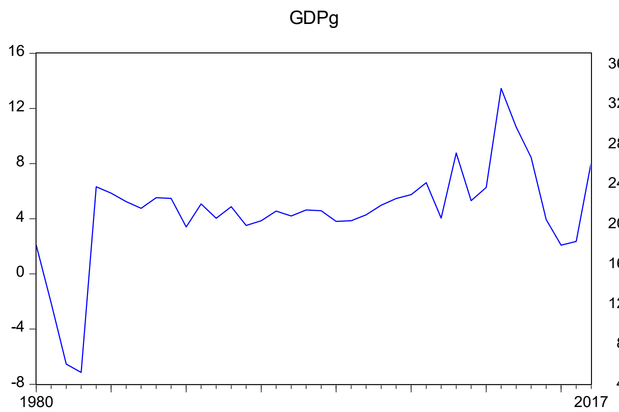
Foreign direct investment (% of GDP)



Fossil fuel energy use (% of total)



Gross domestic product (per-capita)



Industrial value (% of GDP)

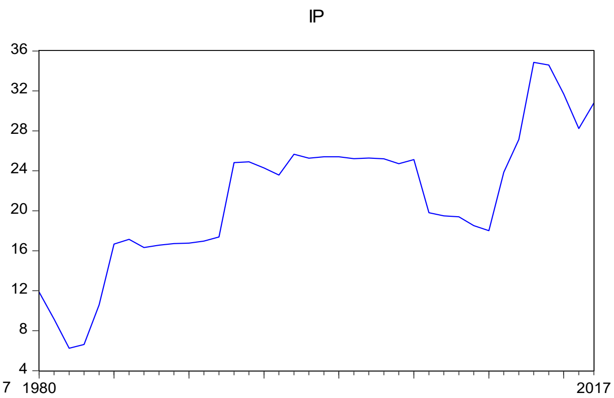
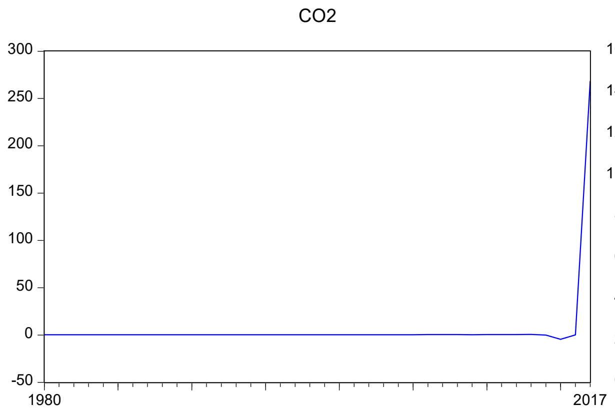


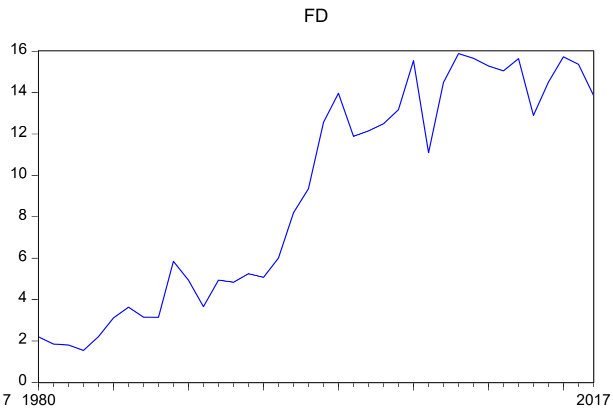
Figure 3. 5: Ghana trend analysis

Nigeria

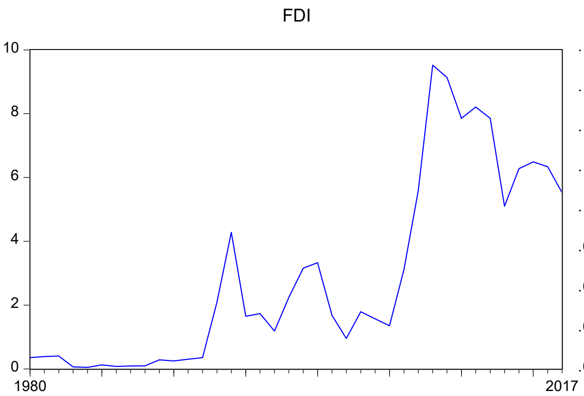
Carbon dioxide emissions (per-capita)



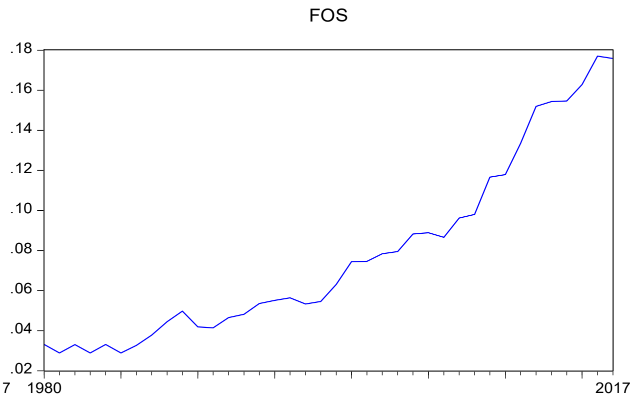
Domestic credit (% of GDP)



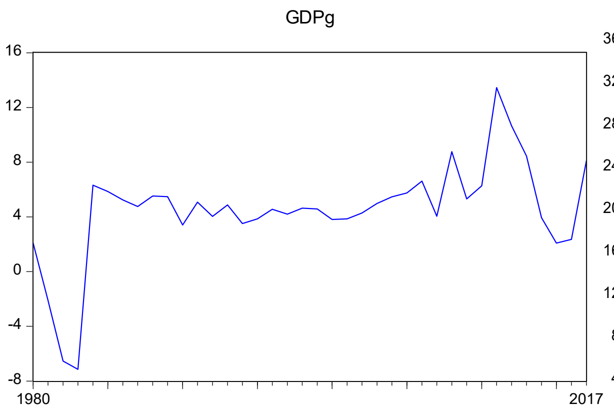
Foreign direct investment (% of GDP)



Fossil fuel energy use (% of total)



Gross domestic product (per-capita)



Industrial value (% of GDP)

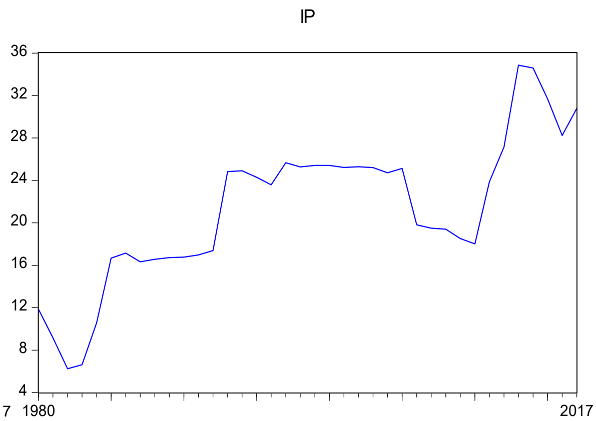
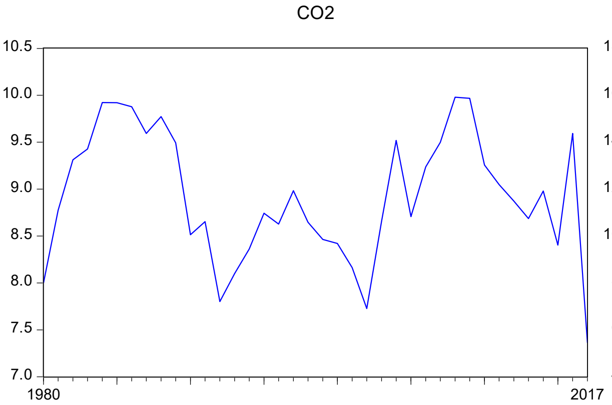


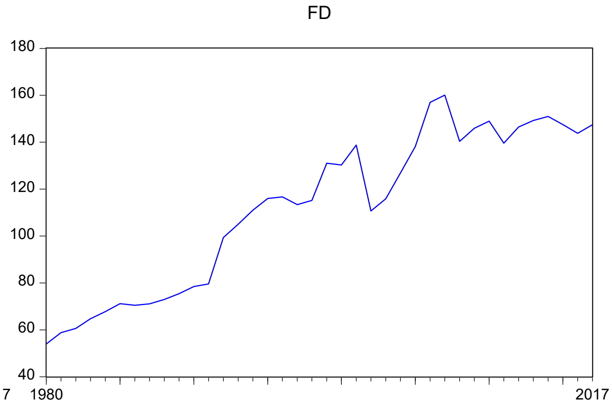
Figure 3. 6: Nigeria trend analysis

South Africa

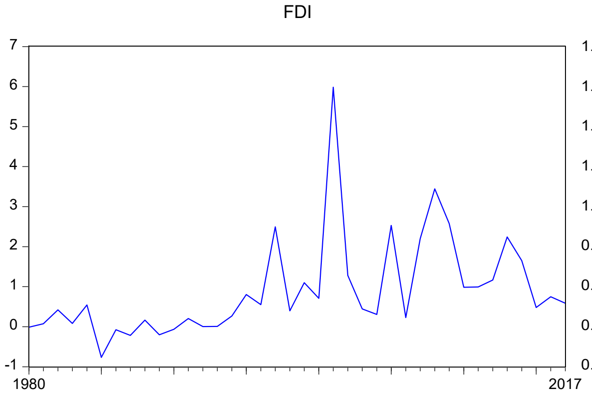
Carbon dioxide emissions (per-capita)



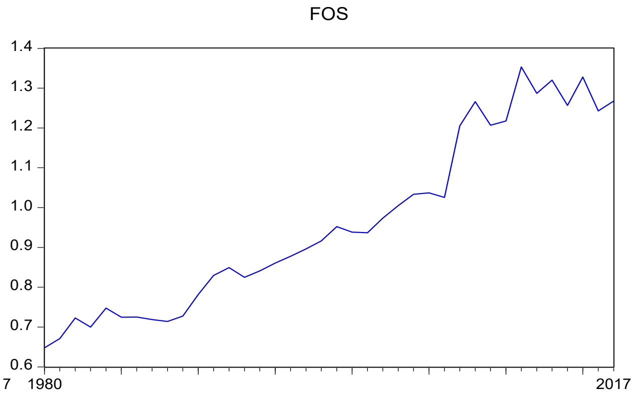
Domestic credit (% of GDP)



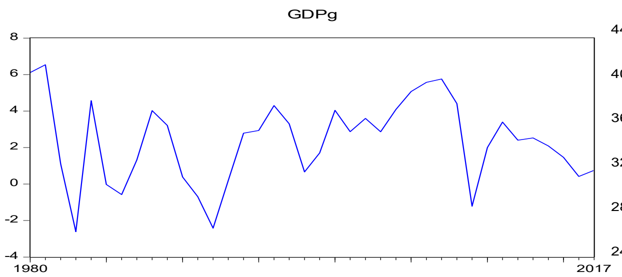
Foreign direct investment (% of GDP)



Fossil fuel energy use (% of total)



Gross domestic product (per-capita)



Industrial value (% of GDP)

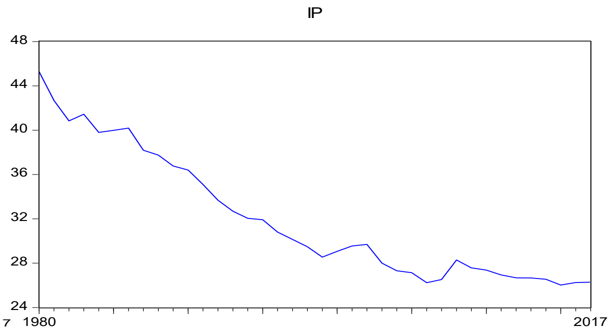


Figure 3. 7: South Africa trend analysis

3.5.2 Unit Root Test

The (ADF) unit root test results for the variables employed in this study for the three (3) countries, namely Nigeria, Ghana, and South Africa, are shown in Table 3.3. For Nigeria, Ghana, and South Africa, all the variables are stationary after first difference, that is, the variables are integrated of order 1. In this regard, the null hypothesis of the presence of unit root for first differences of the series is rejected, that is, they are integrated of order 1.

Table 3. 3: Unit Root Test (Augmented Dickey-Fuller)

	Without Intercept and Trend		**Intercept and Trend**		
	Level	**First Difference**	**Level**	**First Difference**	**Remark**
NIGERIA					
Carbon-dioxide Emissions	-0.71	-3.15**	-2.17	-3.27**	I(1)
Credit provided by Financial Sector	-0.61	-4.50***	-4.09**	-4.38***	I(1)
Foreign Direct Investment	-1.65	-4.45***	-3.52**	-4.46***	I(1)
Petroleum & other Liquid Consumption	0.67	-2.80**	-2.56	-2.97	I(1)
Gross Domestic Product Growth	-2.36**	-4.24***	-3.40*	-4.61***	I(0)
Industry Value Added	-1.11	-3.20**	-2.61	-3.46**	I(1)
GHANA					
Carbon-dioxide Emissions	-1.30	-3.02***	-3.02	-3.43**	I(1)
Credit provided by Financial Sector	0.72	-3.01***	-1.56	-3.52**	I(1)
Foreign Direct Investment	-1.11	-4.11***	-3.41*	-4.10***	I(1)
Petroleum & other Liquid Consumption	2.82	-2.31**	-1.09	-4.01***	I(1)
Gross Domestic Product Growth	-0.47	-5.62***	-4.71***	-6.04***	I(0)
Industry Value Added	0.27	-3.79***	-3.29*	-3.89**	I(1)
SOUTH AFRICA					
Carbon-dioxide Emissions	-0.63	-3.52**	-2.26	-3.51*	I(1)
Credit provided by Financial Sector	0.98	-3.60***	-3.97*	-2.28**	I(1)
Foreign Direct Investment	-1.18	-3.32***	-2.28	-3.35***	I(1)
Petroleum & other Liquid Consumption	0.78	-1.63*	-2.84	-1.84	I(1)
Gross Domestic Product Growth	-1.23	-3.97***	-2.47	-3.98**	I(1)
Industry Value Added	-2.54*	-1.92*	-0.78	-4.52***	I(1)

Notes: ***, ** and * signify significance at 1%, 5% and 10% level respectively.

3.5.3 Autoregressive Distributive Lag (ARDL) Bounds Test for Cointegration

Following the nature of unit root test results of the variables; this study employed the autoregressive distributive lag modeling framework to examine the cointegration relationships among the variables. The autoregressive distributive lag technique is particularly suited to investigate cointegration among variables, especially if they are either I(0), I(1) or mixture or both. The autoregressive distributive lag bounds test for cointegration is shown in Table 3.4. The null hypothesis of no cointegration is rejected for Nigeria, Ghana, and South Africa since the F-statistic is higher than I0 bound and I1 bound at 5%, thus depicting the presence of cointegration among the variables employed in these countries.

Table 3. 4: ARDL Bounds Test

Test Statistic	Nigeria	Ghana	South Africa
F-statistic	4.00	8.96	4.83

Critical Value Bounds

Significance	I 0 Bound	I 1 Bound
10%	2.26	3.35
5%	2.62	3.79
1%	3.41	4.68

3.6 Results and Discussion

This section contains empirical analysis and discussion of results obtained from the autoregressive distributive lag (ARDL) modelling approach adopted in this study to estimate both the short-run dynamics and long-run relationship between a battery of macroeconomic energy- demand factors and carbon dioxide emission. There was evidence of a long run relationship in the three (3) largest economies of (SSA) countries, namely Ghana, Nigeria, and South Africa, among fossil fuel energy consumption/usage (FOS), foreign direct investment (FDI), financial development (FD), industrial performance (IND) and gross domestic product growth (GDPg) on environmental quality, measure by level of pollution (carbon dioxide (CO_2) emissions). The model to ascertain the determinants of carbon dioxide emissions uses quarterly time series data from 1980Q1 to 2017Q1.

Tables 3.5 and 3.6 present the short-run and long run ARDL estimated model and analysis for Nigeria. In the short run estimate, the coefficient of the error correction term (ECT), which reveals the speed of convergence to long-run equilibrium in the case of shock to any of the variables in the system, carried the appropriate negative sign and was statistically significant at the 5% level. This suggests that any short run disequilibrium adjust by about 60% annually to their long run equilibrium values each year. This indicates a relatively quick pace of adjustments toward its long-run equilibrium in case of any short run misalignment in the Nigerian economy.

Fossil fuel usage/consumption, proxy by petroleum and other liquid fuels, exerted a negative and significant impact on carbon dioxide emissions at the 10% significance level. The finding shows that, a percentage increase in fossil fuel usage will result in 0.01 per capita metric tons reduction in carbon emissions in the country. The result aptly draws attention to the need for sustainable energy consumption, with attendant effects on improved environmental quality.

The coefficient representing foreign direct investment was also found to be negative and significant at the 5% level of significance. The finding shows that, a percentage rise in foreign direct investment inflows leads to 0.02 per capita metric tons decline in carbon emissions in the short run. Thus, indicating increases in influx of foreign direct investment leads to fall in carbon dioxide emissions in Nigeria during the period under review, giving credence to the Pollution Halo Hypothesis, affirming that foreign direct investment inflows reduce emissions and improve the environmental quality in host economies. This finding supports conclusion found in studies like Shahbaz, et al. 2015, Jalil and Feridun, 2011, Hoffmann, et al. 2005.

Additionally, the coefficient of financial development, proxy by credit provided by banks to the private sector, was found to have a negative and significant impact on carbon-dioxide emissions at the 10% level. The result indicates that, a percentage increase in private sector credit leads to 0.01 per capita metric tons decrease in carbon emissions in the short run. Thus, suggesting a rising adherence to the principles of sustainable financing in financial sector's lending decisions by focusing on environment, social and governance issues towards achieving improved environmental sustainability.

The coefficient of industrial production was found to have a significantly positive short-run impact on carbon-dioxide emission in Nigeria. The finding shows that, a percentage increase in industrial production results in 0.04 per capita metric tons rise in carbon emissions in the short run, suggesting that higher level of industrial production tends to negatively degrade the environment through resultant higher levels of carbon dioxide emissions.

However, the coefficient of economic growth was not statistically significant at conventional tests levels in determining environmental damage, though negatively signed in the short-run and long run ARDL model. This finding is in line with conclusions in studies conducted by Odugbesan and Rjoub (2020), Yahaya, et al. (2020), Ahmad, et al. 2018, Soheila and Bahram (2017), Begum, et al. 2015.

Meanwhile, the findings in the short-run ARDL Model was effectively robust to its long run ARDL estimates, in terms of sign of the parameter estimates, with the exception of the coefficient of industry performance value add, which was negative and significant in the long run ARDL model. Only the coefficient of Gross Domestic Product Growth remained not statistically significant at conventional test levels in both the estimated short run and long run ARDL models, with both negatively signed.

Table 3. 5: Short Run Coefficients.

Dependent Variable:ΔlC0 $_2$Emissions. ARDL (5, 0, 2, 0, 5)

Nigeria

Variables	Coefficient	Standard Error	t-statistic	Prob.
ΔCredit provided by Financial Sector	-0.01**	0.07	-1.88	0.06
ΔForeign Direct Investment	-0.02***	0.05	-4.12	0.01
ΔPetroleum & other Liquid Consumption	-0.02*	0.01	-1.68	0.09
ΔGross Domestic Product Growth	-0.03	0.02	-1.37	0.17
ΔIndustry Value Added	0.04**	0.02	1.96	0.05
ECT_{t-1}	-0.06***	0.01	-3.92	0.01

Note: Δ is the first difference operator; ***, ** and * signify significance at 1%, 5% and 10% level, respectively.

Table 3. 6: Long run coefficients Dependent Variable: ΔlC0 $_2$Emissions. ARDL (5, 0, 2, 5, 0)

Nigeria

Variables	Coefficient	Standard Error	t-statistic	Prob.
Credit provided by Financial Sector	-0.03***	0.01	-2.03	0.04
Foreign Direct Investment	-0.10***	0.03	-3.14	0.02
Petroleum & other Liquid Consumption	-0.06***	0.29	-2.04	0.04
Gross Domestic Product Growth	-0.06	0.06	-1.37	0.17
Industry Value Added	-0.04***	0.01	-3.68	0.03
C	2.92***	0.59	4.91	0.00

Note: ***, ** and * signify significance at 1%, 5% and 10% level, respectively.

To ensure the efficiency of the models it is important to apply the post estimation checking. Table 3.7 shows the diagnostic test of the ARDL model.

Table 3.7: Diagnostic Checking

Country	*Nigeria*	
	F-stat	**Prob.**
Autocorrelation	5.89	0.20
Heteroskedasticity	1.09	0.36
Normality	1.72	0.10

Table 3.8 and 3.9 present the short-run and long run ARDL estimated model and analysis for Ghana. The ECM term, which indicates the adjustment time before long-run relationship can be achieved between the dependent and explanatory variables, carried the appropriate negative sign and was statistically significant at the 1% level. Precisely, the ECM coefficient shows that 67% of the disequilibrium errors in the short run are corrected annually, suggesting a relatively quick pace of adjustment to the long run equilibrium.

All the coefficients in the short-run ARDL model were positive and significant, namely credit provided by the financial sector, foreign direct investment, fossil fuel consumption/usage, and economic output, except the coefficient representing growth in Industry Value Added, which was negative and statistically significant.

The coefficient representing financial development, measured by credit provided by financial sector to the private sector, was found to have a positive and significant at the 5% significance level, suggesting that, a percentage increase in credit advanced to the private sector results in 0.27 per capita metric tons rise in carbon emissions in the short run. Meanwhile in the long-run ARDL model, the coefficient was negative and significant, suggesting that in the long run, increases in credit channeled to the private sector (deficit economic units) of the economy, reduces the level of carbon dioxide emission/pollution in Ghana.

The coefficients representing foreign direct investment was positive, but not significant in the short-run ARDL model, suggesting that, a percentage increase in foreign direct investment leads to 0.02 per capita metric tons increase in carbon-dioxide emissions. FDI coefficient was, however, negative, and significant at the 5% level in the long run ARDL model, suggesting that, a percentage increase in FDI results in 0.10 per capita metric tons decrease in spate of environmental damage in the long run.

Fossil fuel usage/consumption coefficient, proxy by petroleum and other liquid fuels, was positive and statistically significant at the 5% level in the short run ARDL estimation, suggesting that, a percentage rise in fossil energy usage will result in 7.16 per capita metric tons increase in carbon emissions in the country, confirming its harmful effects on the environment. In the long run, the fossil energy usage coefficient was negative and significant at the 5% level, perhaps, showing increasing efforts at creating innovative ways of using fossil fuel in a sustainable way that preserves the environment.

The coefficient of industrial production was found to have a significantly negative impact on carbon-dioxide emission in both the short-run and long run. The finding suggests that a percentage increase in industrial production results in 0.56 per capita metric tons and 0.04 per capita metric tons decrease in carbon emissions in the short run and long run, respectively. This suggests that higher level of industrial production tends to negatively degrade the environment through resultant lower levels of carbon dioxide emissions. Findings confirmed conclusion in studies by Chibueze, et al. 2013, and Shafei and Rahul (2013). This situation is associated with the recent sustainable development policies initiatives in Ghana. Therefore, policymakers should continue emphasizing on environmental quality measures to pursue sustainable development. The outcome is similar with the result of findings reported by Ahmad, et al. (2018), Riti, et al. (2017), Chibueze, et al. 2013, and Shafei and Rahul (2013).

Table 3. 8: Short Run Coefficients. Dependent Variable: $\Delta lC0_2$Emissions. ARDL (10, 4, 0, 2, 4, 1)

Ghana

Variables	Coefficient	Standard Error	t-statistic	Prob.
ΔCredit provided by Financial Sector	0.27	0.11	1.88	0.01
ΔForeign Direct Investment	0.02	0.02	1.23	0.21
ΔPetroleum & other Liquid Consumption	7.16**	3.42	2.09	0.03
ΔGross Domestic Product Growth	0.16**	0.05	3.03	0.03
ΔIndustry Value Added	-0.56*	0.04	-3.22	0.01
ECT_{t-1}	-0.67*	1.27	-5.32	0.00

Note: Δ is the first difference operator; ***, ** and * signify significance at 1%, 5% and 10% level, respectively.

Table 3. 9: Long Run Coefficient. Dependent Variable: $\Delta lC0_2$Emissions. ARDL (10, 4, 0, 2, 4, 1)

Ghana

Variables	Coefficient	Standard Error	t-statistic	Prob.
Credit provided by Financial Sector	-0.03***	0.01	-2.03	0.04
Foreign Direct Investment	-0.10***	0.03	-3.14	0.02
Petroleum & other Liquid Consumption	-0.06***	0.29	-2.04	0.04
Gross Domestic Product Growth	-0.06	0.06	-1.37	0.17
Industry Value Added	-0.04***	0.01	-3.68	0.03
C	2.92***	0.59	4.91	0.00

Note: ***, ** and * signify significance at 1%, 5% and 10% level, respectively.

To ensure the efficiency of the models it is important to apply the post estimation checking. Table 3.10 shows the diagnostic test of the ARDL model.

Table 3. 10: Diagnostic Checking

Country	*Ghana*	
	F-stat	**Prob.**
Autocorrelation	0.91	0.40
Heteroskedasticity	1.66	0.33
Normality	1.33	0.10

Table 3.11 and 3.12 present the short-run and long run ARDL estimated model for South Africa. The error correction term (ECT) coefficient is negative, as prescribed in economic theory, and was also statistically significant at the 5% level of significance. Precisely, the ECM coefficient shows that 70% of the disequilibrium errors in the short run are corrected annually, suggesting a relatively fast adjustment dynamics to its long run path.

The coefficient of credit provided by financial sector to the private sector of the economy, a measure of financial development, was positive and significant at the 10% level in explaining dynamics in carbon dioxide emissions in South Africa. The result suggests that in the short run, a percentage rise in private sector credit will lead to a marginal 0.01 per capita metric tons decrease in the level of carbon emission. Meanwhile, the coefficient of private sector credit was positive and significant at 5% level, suggesting that, a percentage rise in private sector credit by banks will increase carbon emission by 0.06 per capita metric tons in the long run ARDL model.

The coefficient of foreign direct investment was found to have a significantly positive impact on carbon dioxide emissions, suggesting that, a percentage rise in foreign direct investment will result in 0.01 per capita metric tons and 0.40 per capita metric tons increase in carbon emissions, respectively, in the short run and long run in South Africa.

The coefficient of energy consumption/usage variable was negative, and highly significant at the 1% level in the short-run ARDL model but was observed in the long run to have no statistically significant effects on carbon dioxide emissions at conventional significance test levels in South Africa. This could show increasing efforts at creating innovative ways of using fossil fuels in a sustainable way that preserves the environment.

The coefficient of gross domestic product growth is positive and significant in both the short-run ARDL and long run ARDL equations, though was not significant in the short run model. The result suggests that a percentage increase in GDP growth will lead to 0.29 per capita metric tons rise in carbon emission. The positive relationship between gross domestic product growth and carbon dioxide emissions aptly depicts the tenets of the Environmental Kuznets Curve Hypothesis that pollution increases at the early stages of a country's development.

The coefficient of industrial production showed mixed results, while it was negative and significant at the 5% level in the short run ARDL model, it was positive and highly significant at the 1% level in the long run ARDL model. The results suggest that, a percentage increase in industry value added production will lead to 0.11 per capita metric tons decrease in environmental degradation in the short run, and a 0.48 per capita metric tons increase in carbon emissions in the long run, suggesting industrial production is associated with environmental degradation and its crucial role in propagating and ameliorating environmental damage in a globalised world.

Therefore, policymakers should promote all possible measures on these factors to mitigate carbon dioxide emissions for better environmental quality. The results of this findings are similar with the findings of Ahmad, et al. 2018, Salahudin, et al. 2018, and Shabaz, et al. 2015.

Table 3.11: ARDL Short-Run Model Estimates (South Africa) Short Run Coefficients. Dependent Variable: **$\Delta lC0_2$**Emissions. ARDL (6, 2, 9, 2, 4, 1) South Africa

South Africa

Variables	**Coefficient**	**Standard Error**	**t-statistic**	**Prob.**
ΔCredit provided by Financial Sector	-0.01**	0.06	-1.82	0.07
ΔForeign Direct Investment	0.01**	0.06	2.04	0.04
ΔPetroleum & other Liquid Consumption	-4.08*	0.94	-4.33	0.00
ΔGross Domestic Product Growth	0.03	0.09	0.39	0.69
ΔIndustry Value Added	-0.11**	0.05	-2.17	0.03
ECT_{t-1}	-0.07*	0.01	-4.08	0.01

Note: Δ is the first difference operator; ***, ** and * signify significance at 1%, 5% and 10% level, respectively

Table 3.12: Long Run Coefficient. Dependent Variable: $\Delta lC0_2$Emissions. ARDL (6, 2, 9, 2, 4, 1)

South Africa

Variables	**Coefficient**	**Standard Error**	**t-statistic**	**Prob.**
Credit provided by Financial Sector	0.06***	0.02	2.39	0.04

Foreign Direct Investment	0.40***	0.20	2.00	0.04
Petroleum & other Liquid Consumption	0.07	1.39	0.05	0.95
Gross Domestic Product Growth	0.29*	0.07	3.72	0.00
Industry Value Added	0.48*	0.10	4.72	0.00
C	-1.45**	5.04	-2.88	0.04

Note: ***, ** and * signify significance at 1%, 5% and 10% level, respectively.

Table 3.13: Diagnostic Checking

To ensure the efficiency of the models it is important to apply the post estimation checking. **Table 3.13** shows the diagnostic test of the ARDL model.

Country	***South Africa***	
	F-stat	**Prob.**
Autocorrelation	1.51	0.16
Heteroskedasticity	2.42	0.39
Normality	9.29	0.21

3.6.1 Stability Analysis of Regression Relationships: CUSUM

The study examined the stability of the parameters using the plots of the cumulative sum of the residuals (CUSUM), following procedure developed by Brown, Durbin, and Evans, (1975). Essentially, the presence of instability in regression relationships is established if the CUSUM of residuals go outside the bands represented by the two critical (dotted) lines at the 5 per cent level, as evident in figures 3.8 to 3.9, and 3.10. The CUSUM test is appropriate and suitable for detecting systematic changes in the regression coefficients, and according to the plots, the CUSUM remained inside the 5% critical lines throughout the study period. This implied that the model is stable, and consequently, the conclusion is reasonably reliable for policy making and formulation.

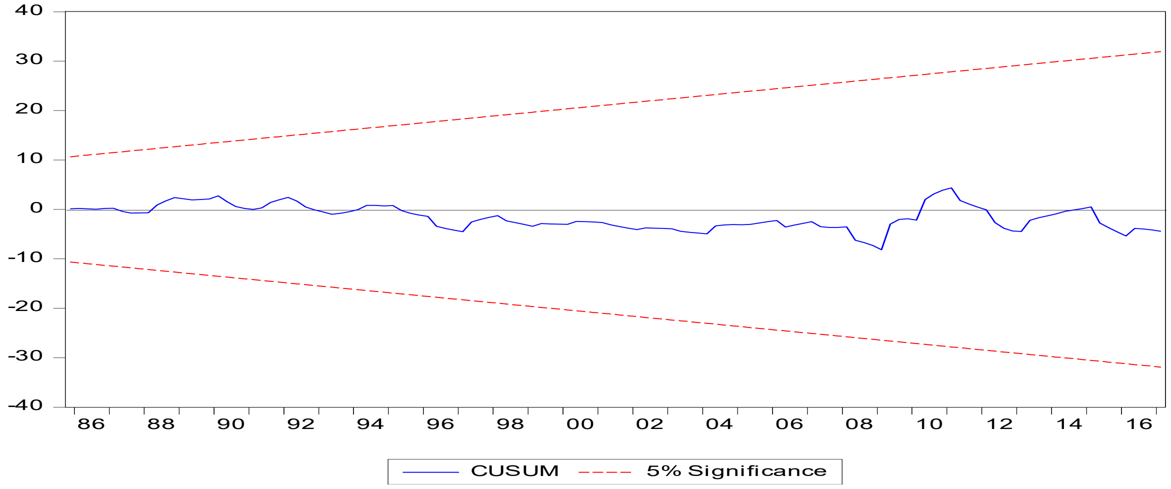


Figure 3. 8: Stability Test Using Cumulative Sum of Residuals (CUSUM): Nigeria

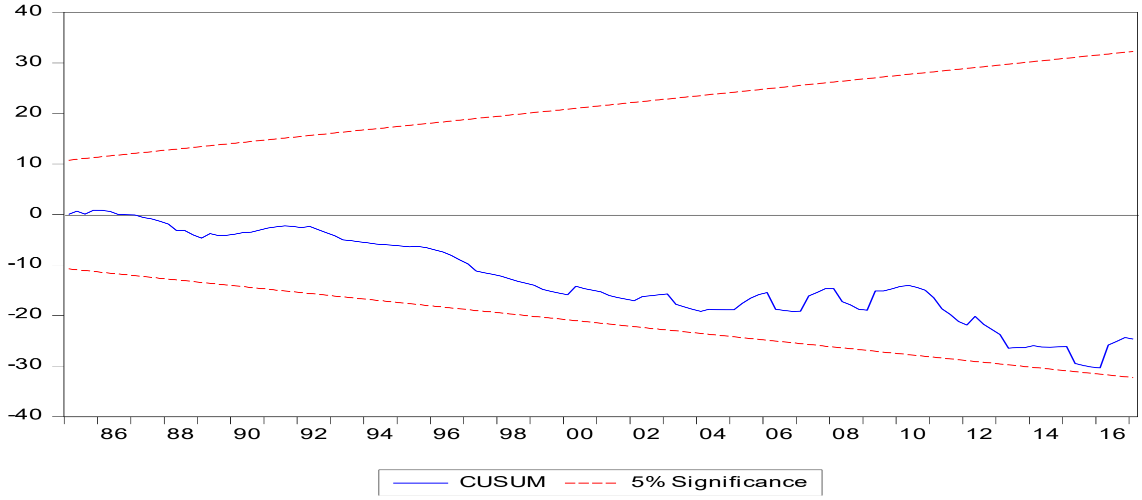


Figure 3. 9: Stability Test Using Cumulative Sum of the Residuals (CUSUM): Ghana

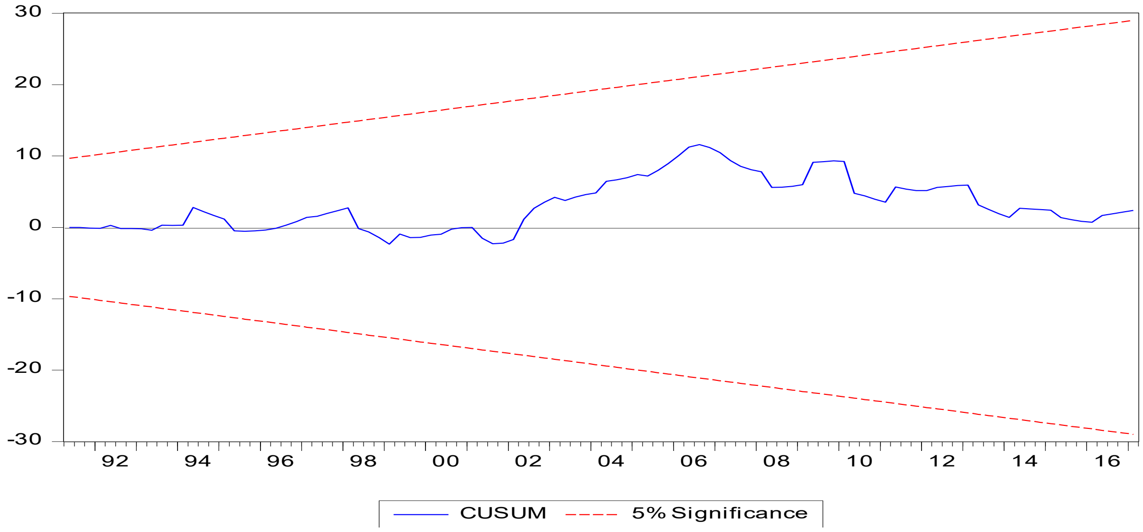


Figure 3. 10: Stability Test Using Cumulative Sum of Residuals (CUSUM): South Africa

3.7 Conclusion

This chapter explored the empirical evidence on the impact of fossil fuel energy consumption/usage (FOS), foreign direct investment (FDI), financial development (FD), industrial performance (IND) and gross domestic product growth (GDPg) on environmental quality, measure by level of pollution (carbon dioxide (C02) emissions). The model to ascertain the determinants of carbon dioxide emissions uses quarterly time series data from 1980Q1 to 2017Q1 for the three (3) largest economies of (SSA) countries, namely Ghana, Nigeria, and South Africa. The ADF unit root test was employed to conduct the stationarity status of the variables employed in this study. The results show presence of both I(1) variables for Nigeria, Ghana, and South Africa as all the variables were stationary only after first difference, that is, were I(1).

Autoregressive distributed lag (ARDL) test for cointegration was adopted, being well-suited especially if included variables are either I(0), I(1) or mixture or both, to examine the cointegrating relationships among the variables. For Nigeria, Ghana, and South Africa the test results show existence of a long-run relationship among the variables, suggesting the need to estimate an ECM to ascertain the speed level of adjustments between the short-run dynamic changes with the long-run steady state equilibrium.

CHAPTER FOUR
NEXUS BETWEEN ENERGY USE AND CARBON DIOXIDE EMISSIONS

4.1 Introduction

Climate change is the greatest concern being deliberated by the United Nations, and, relatedly, is global warming that is being caused by the accumulation of greenhouse gas emissions and mainly carbon dioxide (Boontome, et al. 2017). Global emissions are at all-time highs, with no signs of slowing down. The five hottest years on record occurred between 2015 and 2019, Arctic winter temperatures have risen by 3 degrees Celsius since 1990, with sea levels rising, coral reefs dying, and we are beginning to see the life-threatening effects of climate change on health, including air pollution, heat waves, and food security threats (Guterres, 2019). Both developed and developing countries contribute to carbon-dioxide emissions in the atmosphere. Developed countries emit carbon dioxide in the form of industrial pollution, vehicular emissions, and energy usage. Developing countries also contribute to emissions by consuming energy, which is very essential for better living standards and sustainable economic development (Yildirim and Aslan, 2012).

Liberty, et al. (2013) that to sustain life, it is very essential to use natural resources, highlighted it. Humans to sustain and support the economic and developmental activities of humans are exploiting natural resources, both renewable and non-renewable. Energy is being utilised by people to carry out their daily activities and economic activities as well. Energy plays a pivotal role in the modern economy. All the goods and services that we enjoy today are the result of energy use. Energy therefore plays a major role in raising the living standards of people. It is not possible to run or build cities or factories that offer jobs, goods, and homes, and neither is it possible to enjoy modern amenities and technology without power, heat, and light. Therefore, energy is considered as oxygen for any economy (Kulionis, 2013). The Sun is the main energy source to support life on Earth. Animals and plants store this energy, and it remains stored in them even after they have died. The energy stored in dead animals and plants over many years is converted to fossil fuels. One of the main side effects of burning fossil fuels as an energy source is that burning releases greenhouse gases, carbon dioxide being one of these (Sasana and Putri, 2018).

The quality of the environment has been deteriorating due to the increased human consumption of energy (Sasana and Putri, 2018). Increasing pollutants or emissions caused by energy exploration are used to measure the deteriorated quality of air. Pollutants and carbon dioxide emissions have an adverse effect on the environment in the long run. Although there are several challenges associated with energy sources, in this research project, the focus is on the main challenge of the use of fossil fuels and relatedly, the emission of carbon dioxide that will impacts the environment and has been a significant hurdle to sustainable development. It has been a topic of scientific discussion for a long time, whether fossil fuels have a major role in climate change or not. As is widely known nowadays, the main contributor to climate change is the increase of environmental greenhouse gases, of which carbon dioxide is considered the greatest contributor. Carbon dioxide is also the main gas released during fossil fuel combustion (Kulionis, 2013).

The level of carbon dioxide in the environment is also used as an indicator of air pollution. As per the US Energy Information Administration (2017), carbon dioxide, which is the one of the main greenhouse gases, has been increasing in the atmosphere due to the human lifestyle. Ruijven, et al. (2016) believe that the air's carbon-dioxide content has become the indicator of pollution because of its emission in most of the processes in chemical industries, mining industries, and other industries. For instance, almost 0.5 kg of carbon dioxide is released in the environment for producing a kg of cement in the cement industry. This is the major reason for carbon dioxide being considered the major indicator in all sectors for measuring air quality (Sasana and Putri, 2018).

Thus, it can be assumed that energy consumption and pollution are interlinked. Few studies have been done by researchers on the topic of the relationship between energy consumption, economic growth, environmental pollution, and carbon-dioxide emissions. It has been found that the need for energy security, depleting sources of fossil fuel energy resources, greenhouse gas accumulations, and related environmental issues have led to the need to look for alternate sources of energy that can replace traditional energy sources (Boontome, et al. 2017). It has been stated by many researchers that to combat climatic changes drastic measures need to be taken before it is too late (Apergis, et al. 2010). Consequently, initialised countries must endure a major part of the task of minimizing GHG releases because of their past responsibilities for climate change. However, even massive reductions in the emissions levels of these industrialised countries would not be adequate to meet these targets. Therefore, the emission levels in the sub – Saharan African region may have a nominal rise in the short term to boost growth, but in the long term, it needs to go below the current levels (Richards Tyldesley, 2011; King, 2012). This atmospheric limitation conflicts with the growth trend witnessing the rapid growth of GHG emissions in the region owing to increased fossil fuel extraction and use, population growth, deforestation, and rise in cattle production (International Energy Agency, 2014; Food and Agriculture Organisation, 2015).

Since industrialisation in the sub-Saharan African region is still limited, most of the emissions are not because of fossil fuels but are rather due to land-use changes and agriculture. However, the estimated growth of population and economy suggests that GHG emissions in the sub–Saharan African region will rise rapidly owing to increased extraction and consumption of fossil fuel, deforestation, and cattle production expansion (Energy information Agency, 2014; Food and Agriculture Organization, 2015). This issue of energy consumption and rise in carbon-dioxide emissions has become a policy issue especially for developing countries such as those in the sub-Saharan African region.

Therefore, this chapter analyses the dynamics and transmission nexus between energy consumption factors and environmental quality metrics, measured by carbon dioxide emissions in three (3) largest economies of sub-Saharan African countries, namely Ghana, Nigeria, and South Africa. This chapter evaluates the fossil fuel energy use and carbon dioxide emissions nexus, focusing on variance decomposition and impulse response analysis. Accordingly, section 4.1 provides a brief introduction on the focus of the chapter; section 4.2 provides a brief literature review on the topic under study; and 4.3 highlights the research methodology, which dwells on the variance decomposition method and the impulse response method. In addition, section 4.4 highlights the results and discussions of analysis; and section 4.5 provides the concluding remarks of the chapter.

4.2 Literature Review

This section provides a brief literature review on the topic under study in this chapter. To achieve this, this section is divided into two main parts:

4.2.1 Literature Review on the Nexus between Energy Consumption and Carbon Dioxide Emissions

In recent times, the increase in carbon dioxide emissions has been linked with the increase in energy consumption by the significant amount of research that has been carried out on the topic. Sasana and Putri (2018) analysed the impact of fossil fuel energy consumption, the consumption of renewable energy, and population growth on carbon-dioxide emissions in

Indonesia. They used the Ordinary Least Square approach along with multiple linear regression analysis on time series data for the period of 1990 to 2004. It was concluded in the study that population growth and fossil fuel energy consumption have a positive impact on the carbon-dioxide releases in the region.

Thao and Chon (2016) also find a positive impact of energy consumption on the environment. They went further in stressing that carbon dioxide emissions are not only due to fossil fuel consumption but also due to the extraction process of fossil fuels. It was also found in the same study that a negative association exists between energy consumption and carbon-dioxide emissions. Li, et al. (2010) in their study of 28 provinces in China used panel data to find that economic growth and energy consumption in the long run influence carbon-dioxide emanation, however, long-term economic growth and carbon-dioxide emissions have an impact on energy consumption. Moreover, Ito (2017) find a negative influence of fossil energy consumption on economic growth of developing countries, and it was concluded that economic growth was positively impacted by energy consumption. The burning of fossil fuels is harmful to the environment; they cause excessive amounts of pollution. Renewable energy sources on the other hand do not damage the environment and thus can be termed as environment friendly (Ito, 2017).

Shafei and Ruhul (2013) in their study of Organisation for Economic Co-operation and Development (OECD) countries test the concept of Kuznets curve hypothesis about the relationship between carbon-dioxide emissions and urbanisation and find that fossil fuel energy has a positive association with carbon-dioxide emissions, suggesting that an increase in fossil fuel consumption leads to increase in carbon-dioxide emission. It was also concluded in the study that negative association exists between renewable energy consumption and carbon-dioxide emissions, which indicates that there will be a reduction in carbon-dioxide emissions with increased consumption of renewable energy.

Fathinah and Djoni (2016) assert that for ASEAN countries significant and negative association exists between the quantity of renewable energy consumption and carbon-dioxide emission. Bilgili, et al. (2016) reported similar results in their study where it was found that the consumption of renewable energy has a significant and negative influence on the carbon dioxide released into the environment. The results of the study suggested that renewable energy consumption could be instrumental in reducing the level of carbon dioxide emissions. It was concluded in the study that by increasing renewable energy consumption, the reliance on fossil fuel energy could be minimized and thus, carbon-dioxide releases can be reduced.

Paramati, et al. (2017) discovered in their study of G20 countries that renewable energy consumption cuts carbon-dioxide releases, which increases the economic output of the countries. In a related study by Zoundi (2017), it was averred that the consumption of renewable energy has a significant and negative impact on carbon-dioxide emissions, and it was established that renewable energy is more environment friendly than fossil fuels. It is expected that in the long-run fossil energy will be replaced by renewable energy due to environmental concerns (Zoundi, 2017). Liu, et al. (2017) in their study of four ASEAN countries (namely Thailand, Philippines, Indonesia, and Malaysia) found similar results that consumption of renewable energy has a negative influence on carbon-dioxide emissions. The estimation results pointed out that carbon dioxide emissions could be reduced by increasing the consumption of renewable energy. The study suggested the efficient utilisation of renewable energy towards attaining a healthier and cleaner environment.

Bulut (2017) finds a positive effect of fossil fuel energy sources on carbon-dioxide emission in Turkey for the period 1970 to 2013. Shafiei and Ruhul (2013) pronounced the same results in their study of OECD countries, for the period 1980 to 2011, where that consumption of fossil energy resulted in an escalation in carbon-dioxide emission. Dogan and Fahri (2016) in their study of European countries also find a direct relationship between fossil fuel energy consumption and an increase in carbon-dioxide emissions. They concluded that there exists a causal indirect relationship between carbon-dioxide emissions and non-renewable energy consumption.

Danish, et al. (2017), reveal that fossil fuel energy consumption has a positive effect on carbon-dioxide releases. It was further concluded in the study that the main cause of carbon-dioxide emission in Pakistan was the consumption of fossil energy and people's health and environment face danger due to the release of carbon dioxide during the combustion of fossil fuels. Zheng-Xin and De-Jun (2017) provided evidence for a direct relationship between fossil energy and carbon dioxide emissions. In another study (Chibueze, et al. 2013) in Nigeria for the period of 1971 to 2009, it was concluded that in the long term and short term, the consumption of fossil fuels has a significant and positive impact on the carbon dioxide released in the environment.

4.2.2 Energy Consumption in the Sub-Saharan African Region

Energy usage is the major cause of harmful discharges in the sub-Saharan African region. Therefore, numerous opportunities for reducing emissions arising from energy include actions in other sectors either for adopting more energy-efficient practices and technologies or for switching to fuel sources with lower emissions.

4.2.3 Biomass Energy

The burning of solid biomass is the prominent source of energy in sub Saharan Africa, generating almost 80% of the energy consumed in this region, with the main consumption being household cooking. Almost 80% of households in the sub-Saharan African region do not have modern cooking facilities and are dependent upon charcoal or wood fuel for cooking (Energy Information Agency, 2014). While in rural areas, the use of fuel wood is more prevalent as it is available free, the urban areas use charcoal for cooking as its energy content per kilogram is higher and it is more suitable for transportation from the rural areas. Furthermore, biomass is the biggest energy source for industries that use it to produce process heat (Energy Information Agency, 2014). Relatedly, charcoal and fuel wood industries are generating significant employment opportunities for charcoal and wood producers, vendors, and transporters. For example, In Rwanda, the charcoal markets and fuel wood transaction values were $122 million in 2007, which was 5 per cent of the output, and approximately 50% of these revenues remained in the rural region (Energy Information Agency, 2014).

The sale of forest products including charcoal in Zambia contributes 30-32% to household income in rural regions (Gumbo, et al. 2013). The marketplace worth of the charcoal market of the Sub-Saharan African region in 2012 was $11 billion (Energy Information Agency, 2014). However, even after being such a significant source of employment and income generation, a major part of charcoal production and consumption is carried out in the informal economy. According to data from the World Bank (2009), over 80% of the manufacture and sale of charcoal in Tanzania is in the informal economy.

As per the report from "United Nations Environment Programme (UNEP) and International Criminal Police Organisation" (INTERPOL) (2014), the lack of regulation in the charcoal industry has made it into a profitable foundation of generating revenue for the local paramilitaries and is an unexploited prospect for the regime to earn profits. It is projected that African governments lose approximately US$1.9 billion of potential revenue yearly due to a lack of regulation in the charcoal industry. In addition, the use of charcoal and fuel wood in traditional cooking practices poses a major health hazard, more so in deprived houses.

According to The World Health Organisation (2014), there are around 600 thousand premature deaths in Africa every year due to indoor air pollution. Interior air contamination was ranked the second largest hazard cause in the East, West, and Central Africa causing the disease burden (calculated in disability-adjusted life years) among children just after the risk of low body weight due to malnutrition (Lim, et al. 2012). Generally, African women are more prone to this indoor air pollution than men are as they spend more time near the stoves.

4.2.4 Biomass Energy and Carbon Dioxide Emissions

As per data from the International Energy Agency (2014), the total fuel wood consumption in sub-Saharan Africa, including fuel wood used for charcoal consumption and direct consumption by households was 658 million tons in 2012, which was 0.5% of the overall accessible biomass store of 130 gigatons. However, the estimation of the overall carbon dioxide emission level produced due to biomass burning is very difficult. Since biomass is a renewable energy form, if it is consumed and harvested in a sustainable manner, it will create a nil or even negative impact on GHG emissions. Nevertheless, due to the unsustainable rate of harvesting and consumption of biomass, it can lead to climate change because of deforestation. The present rate of consumption is already causing the depletion of biomass stores in several regions. Further, even deforestation causes limited conservational effects such as reduced watershed maintenance and soil erosion (Chidumayo and Gumbo, 2013).

As per the Food and Agriculture Organisation (FAO) (2010), the collection of fuel woods is responsible for over 75% of woodcutting from the African forest region. Nonetheless, the degree of deforestation caused due to fuel wood collection is a highly debated subject matter. In general, the fuel wood collected and consumed by rural people for their household consumption is mostly from dead trees while the wood, which is converted into charcoal to be used for industrial and urban household consumption, is from floored plants (Practical Action, 2014). Hence, although the unsustainable assortment of fuel wood contributes to forestry dilapidation, charcoal business causes both deforestation and jungle depletion. When there is charcoal production from the felled trees, subsequent deforestation often happens there for timber production or for agriculture.

For instance, Chidumayo, et al. (2001) investigated charcoal production in Zambia and discovered that most of the forest harvested for charcoal production was thereafter converted into agricultural land and settlement. Even though it is difficult to determine the major forces responsible for deforestation, it is estimated that charcoal production has resulted in 14% of the overall deforestation in the sub-Saharan African region in 2009 (Chidumayo and Gumbo, 2013). However, this phenomenon had a huge variation in sub-Saharan African countries wherein Zimbabwe it was merely 0.33% and Tanzania where charcoal production caused 33.16% of the total deforestation. The countries with the highest level of forest loss due to charcoal production include Tanzania, Nigeria, Zambia, and DR Congo. During the production of charcoal, the earth-mound kilns create an oxygen-poor environment, which causes the partial combustion of fuelwood and leads to the generation of methane. Consequently, charcoal production causes emissions that have a greater potential of global warming as compared to emissions created from the burning of fuelwood or charcoal (Kammen Lew, 2005).

In 2009, the sub-Saharan African region produced 67.23 Mt carbon dioxide emissions from the charcoal production process, and out of this, about 30% was caused by methane (Chidumayo Gumbo, 2013). While some of the carbon dioxide emitted during the manufacturing process of charcoal can be mitigated with forest regeneration, methane emissions cannot be undone (Chidumayo and Gumbo, 2013). As per the Energy Information Agency's new policies scenario projection, the overall consumption of biomass is expected to reach 1031 million tons by 2040. In addition, by 2040, the urban population of the sub-Saharan African region is projected to rise to 560 million people that will lead to the demand for charcoal surpassing the demand for fuel wood. This creates concerns regarding the likelihood of future biomass to cause further deforestation.

The graphical depiction of trade across diverse areas in Africa in the new policies scenario based on coal, oil, gas, and bioenergy between 2012 and 2040, as well as total installed capacity and key indicators for sub Saharan Africa power pools can be perused at figure 4.1 and table 4.1, respectively.

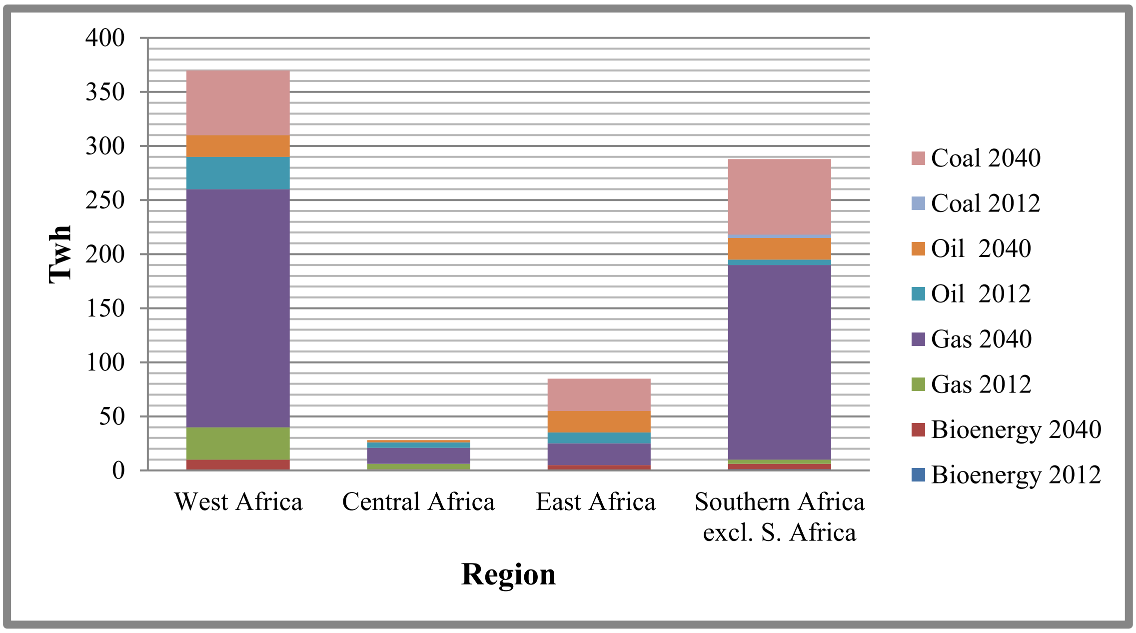


Figure 4. 1: Trade across Diverse Areas in Africa in the New Policies Scenario based on Coal, Oil, Gas and Bioenergy between 2012 and 2040

Source: Data from the International Energy Agency, 2014, pp. 197-222.

Table 4. 1: Total Installed Capacity and Key Indicators for SSA Power Pools

Power Pool	**CAPP**	**EAPP**	**WAPP**	**SAPP**
	2009	2008	2010	2010
Installed capacity (GW)	6.07	28.37	14.09	49.88
Hydropower share	86%	24%	30%	17%
Fossil fuel share	14%	73%	70%	83%
kW/1000 habitants	49	74	54	311

Source: EIA (2014)

4.3. Research Methodology

This section covers second objective of this study. Objective 2 aims to analyse the dynamics and transmission channels of the energy consumption – carbon dioxide emission nexus in select largest economies of sub-Saharan African countries. Variance decomposition method and impulse response analysis are used for this purpose and the details of model specification for this objective and the estimation techniques used are discussed in the following section.

4.3.1 Vector Autoregressive Model (VAR)

The vector Auto regression (VAR) model is one of the most successful, flexible, and easy to use models for the analysis of multivariate time series. It is a natural extension of the univariate autoregressive model to dynamic multivariate time series. The VAR model has proven to be especially useful for describing the dynamic behavior of economic, environmental, and financial time series and for forecasting. It often provides superior forecasts to those from univariate time series models and elaborate theory-based simultaneous equations models. Forecasts from VAR models are quite flexible because they can be made conditional on the potential future paths of specified variables in the model. In addition to data description and forecasting, the VAR model is also used for structural inference and policy analysis. In structural analysis, certain assumptions about the causal structure of the data under investigation are imposed, and the resulting causal impacts of unexpected shocks or innovations to specified variables on the variables in the model are summarised. These causal impacts are usually summarised with impulse response functions and forecast error variance decompositions. This focuses on the analysis of covariance stationary multivariate time series using VAR models. The other segment describes the analysis of nonstationary multivariate time series using VAR models that incorporate cointegration relationships.

4.3.2: Specification of Vector Autoregression (VAR) Model

Let $Y_t = (y_{1t} - y_{2t} - - - y_{\pi t})$ 0 denote an (n×1) vector of time series variables. The basic p-lag vector autoregressive (VAR (p)) model has the form $Y_t = c + \pi 1_{yt} - 1 + \pi 2_{yt} - 2 + \cdots . + \pi_p y_t - p + e_t = 1 \ldots . T$ -1

Where π_i are (n× n) coefficient matrices and εt is an (n × 1) unobservable zero mean white noise vector process (serially uncorrelated or independent) with time invariant covariance matrix Σ. Hence, the VAR (p) model is just a seemingly unrelated regression (SUR) model with lagged variables and deterministic terms as common regressors.

The basic VAR (p) model may be too restrictive to represent sufficiently the main characteristics of the data. Other deterministic terms such as a linear time trend or seasonal dummy variables may be required to represent the data properly. Additionally, stochastic exogenous variables may be required as well. The general form of the VAR (p) model with deterministic terms and exogenous variables is given by $Y_t = \pi_1 Y_t - 1 + \pi_2 Y_t - 2 + \cdots . + \pi_p Y_t - p + \emptyset D_t + G X_t + e_t$ (4.1) where Dt represents an (l × 1) matrix of deterministic components, Xt represents an (m × 1) matrix of exogenous variables, and Φ and G are parameter matrices.

4.3.3 Vector Error Correction Model (VECM)

In econometrics, a relational model can be developed between economic variables in a non-structural way by making use of Vector Error Correction model and the Vector Autoregressive model. The statistical properties of data are the basis for the vector autoregressive model. Each endogenous variable in the vector autoregressive model is taken as the lagged value of all the endogenous variables in the overall model, hence the univariate autoregressive model is generalized by consisting multivariate time series variables to the "vector" autoregressive model (Zou, 2018). Christopher Sims (1980) introduced the vector autoregressive model into the economic field that encouraged its extensive usage in dynamic analysis of economic systems.

Engle and Granger created the trace error correction model by combining co-integration and error correction models. The error correction model can be developed from the autoregressive distributed lag model thanks to a co-integration relationship between variables. The vector autoregressive model has all the equations of an autoregressive distributed lag model; hence the vector error correction (VEC) model can be a vector autoregressive (VAR) model with co-integration restrictions. Vector error correction expressions can confine the long-term behavior of endogenous variables and be convergent to their co-integration relationship when there is a vast range of short-term dynamic fluctuations, as there is in the vector error correction model. Only the vector error correction model (VECM) may be computed if the variables are co-integrated. The co-integrated series' short- and long-run dynamics are investigated using the vector error correction model. The long-run behavior of endogenous variables is constrained by this model to converge to their co-integrating term. The term "co-integrating" is sometimes known as "error correction term." A lag is lost when vector autoregressive is differenced to obtain a vector error correction model.

Assuming t=1,2,….,T and y_t ` I(1) , $y_t=(y_{1t},y_{2t},\ldots\ldots,y_{kt})$` as k-dimensional stochastic time series, each y_{it}~I(1), i=1,2,……,k is influenced by the exogenous time series of d-dimension $x_t=(x_{1t},x_{2t},\ldots..,x_{dt})$`; then the vector autoregressive (VAR) model can be established as follows:

$$y_t = A_1y_{t-1}+A_2y_{t-2}+\ldots.+ A_p y_{t-p} + B x_t +\mu_t, \quad t=1,2,\ldots,T \tag{4.2}$$

If y_t is not affected by the exogenous time series of d-dimension $x_t = (x_{1t}, x_{2t}, \ldots, x_{dt})'$, then the VAR model of formula (4.2) can be written as follows:

$$y_t = A_1 y_{t-1} + A_2 y_{t-2} + \ldots + A_p y_{t-p} + \mu_t, \quad t=1,2,\ldots,T \tag{4.3}$$

with the co-integration transformation of formula (4.4), we can get that

$$\Delta y_t = \prod y_{t-1} + \sum_{i=1}^{p-1} \Gamma_i \Delta y_{t-i} + \mu_t \tag{4.4}$$

Where:

$$\prod = \sum_{i=1}^{p} A_i - I$$

$$\Gamma_i = -\sum_{j=i+1}^{p} A_j$$

If y_t has a co-integration relationship, then $\prod y_{t-1} \approx I(0)$ and formula (4.4) can be written as follows:

$$\Delta y_t = \alpha\beta' y_{t-1} + \sum_{i=1}^{p-1} \Gamma_i \Delta y_{t-i} + \mu_t \tag{4.5}$$

where $\beta' y_{t-1} = ecm_{t-1}$ is the error correction term, which reflects long-term equilibrium relationships between variables and the above formula can be written as follows:

$$\Delta y_t = \alpha ecm_{t-1} + \sum_{i=1}^{p-1} \Gamma_i \Delta y_{t-i} + \mu_t \tag{4.6}$$

Formula (4.7) is the VECM, in which each equation is an error correction model.
Using the assumption that each equation contains k lag values of carbon dioxide, the following regression estimations were developed from (Gujirati and Porter 2009):

$$CO2_{t1} = \alpha + \sum_{j=1}^{k} \alpha_i \, CO2_{t-j} + \sum_{j=1}^{n} Y_j \, X_{t-j} + \mu_{1t} \tag{4.7}$$

$$IND_{t1} = \alpha + \sum_{j=1}^{k} \gamma_i \, CO2_{t-j} + \sum_{j=1}^{n} \delta j \, IND_{t-j} + \mu_{2t} \tag{4.8}$$

$$ENG_{t1} = \alpha + \sum_{j=1}^{k} \gamma_i \, CO2_{t-j} + \sum_{j=1}^{n} \delta j \, ENG_{t-j} + \mu_{2t} \tag{4.9}$$

$$FDI_{t1} = \alpha + \sum_{j=1}^{k} \gamma_i \, CO2_{t-j} + \sum_{j=1}^{n} \delta j \, FDI_{t-j} + \mu_{2t} \tag{4.10}$$

$$FD_{t1} = \alpha + \sum_{j=1}^{k} \gamma_i \, CO2_{t-j} + \sum_{j=1}^{n} \delta j \, FD_{t-j} + \mu_{2t} \tag{4.11}$$

$$GDP_{gt1} = \alpha + \sum_{j=1}^{k} \gamma_i \, CO2_{t-j} + \sum_{j=1}^{n} \delta j \, GDP_{t-j} + \mu_{2t} \tag{4.12}$$

In the equation above, disturbances of μ_{1t} and μ_{2t} are uncorrelated. The above equation also indicates that the dependent and the independent will influence each other.

where: carbon dioxide =Environmental quality (proxy by carbon emissions); IND=Industrial performance (proxy by industry value added); ENG=Energy use (proxy by petroleum and other liquid fuel consumption); FDI=foreign direct investment; FD=financial development (proxy by credit to the private sector as a % of GDP); and GDPg=Output growth (proxy by growth rate of GDP).

4.4: Model Specifications: Empirical Model of the Dynamics and Forecast Error Variance Decomposition Analysis between Energy Use and Carbon Dioxide Discharge

To analyse the dynamics and the forecast variance among energy use and carbon dioxide discharge, consistent with empirical literature, the study used a modified model by (Ohlan, 2015) which is presented in the following model specified in equations:

CO_2 = f (ENG), (4.13)

where carbon dioxide emission is (C02), and fossil fuel energy consumption represents (ENG). The inclusion of fossil fuel energy consumption as the measurement of energy use in these countries is due the fact of availability of data as the data on biomass energy is not scientifically reliable. The data on biomass energy usage is not available in these countries.

Equation 4.13 is further transformed into an econometric specification in equation 4.14, shown as follows:

$$CO2_t = \propto + \beta_1 ENG_t + \varepsilon_t \quad (4.14)$$

where carbon dioxide emission is (C02), and fossil fuel energy consumption represents (ENG), Subscript t stands for the period (t = 1980Q1 to 2017Q1), α and β signify the parameters and ε denote the stochastic error, the rest as defined in the previous equation. The apriori expectation (β_1> 0), therefore energy consumption, is positively related to carbon dioxide discharge.

4.4.1: Definitions of Variables:

Fossil fuel energy consumption (percentage of total energy)

Energy consumption/ energy use implies the basic use of energy prior to its transmission into other forms of fuels mainly those termed as end-use ones (Santamouris, 2018). This usage is the same as the in-house creation of energy and that procured through imports and changes in stock. However, in this energy use, the deduction is made of fuels that are exported or provided to ships and aircraft in global transportation. Kg of oil equivalent (kgoe) is the standardized unit of measurement of energy. This is an equivalent value as kgoe is the energy that is extracted from 1 kilogram of crude oil. Extant literature on similar study shows energy usage have positive and statistically significant effects on carbon dioxide (CO_2) emissions, and these studies include Zhang and Cheng (2009); Apergis and Payne, (2010); Kohler, M. (2013); Farhani, et al. (2014). Kasman, and Duman, (2015); Sun, et al. (2020).

Carbon Dioxide Emissions Per Capita (Metric Tons)

Carbon dioxide emissions mainly comprise of emissions that arise due to burning or combustion of fossil fuels. These are also known as greenhouse gases (GHG) which pollute and remain harmful to the quality of the environment. These gasses are harmful mainly because they tend to captivate as well as release infrared radiations, which are hazardous to the entire universe. They keep the heat trapped and do not allow it to be released in space. The outcome is the rising temperatures of the Earth making it a difficult place to live. The calculations for carbon dioxide emission are done by calculating the total number of people living and the overall quantum of carbon dioxide emitted per person (Saboori Sulaiman 2013), which results an average to identify per capita emissions. For simplicity, and ensuring a holistic analysis is executed in the present study, carbon dioxide emissions are measured based on per capita (metric tons) and is the dependent variable employed in the study.

4.5: Estimation Techniques

Impulse response and forecast error variance decomposition analysis will be employed for the select largest economies in sub-Saharan African countries. Prior to conducting the variance decomposition and impulse response analysis, the time series data was checked for the presence of unit roots by means of a stationarity test. For carrying out the stationarity test, ADF unit root test procedure was adopted. An essential element in the specification of vector auto regression

(VAR) models is the determination of the lag length of VAR (Ozcicek and McMilin 1999).AIC and SBIC are used in the study to determine the lag of the VAR model for the study. VAR model is the base for generating variance decomposition for the variables as well as for impulse response analysis.

4.5.1 Forecast Error Variance Decomposition Analysis

This study also generated both the variance decomposition and impulse response functions from the empirical models due to their intrinsic benefits in empirical research to capture the nature and weight of dynamic interactions among included variables within a modelled framework. The analysis of variance decomposition improves understanding of relationship among variables within a VAR framework and effectively provides answers to explaining how relevant and useful sets variables are in helping to forecast changes in other variables in a defined system. Thus, variance decomposition analysis as an econometric technique indicates the proportion of variations in one variable that is effectively explained by shocks (innovations) of another variable over a defined period.

Meanwhile, most macroeconomic data is often explained by its own trend shocks within the forecast error variance in the short run, which should decline over the horizon, effectively indicating that the percentage share accounted for by other variables will increase, as the number of lags increase over the time periods. While impulse response estimates look at the amount and direction of a variable's response to a one-time innovation in another, variance decomposition looks at the proportion contribution of each form of shock to the variable's prediction error variance (Kilian, 2009). It provides a relative explanation for each shock based on the system's other endogenous factors. Variance decomposition can reveal which factors are related to dependent variables in the short and long run. The fraction of unexpected variation in each variable caused by shocks from other variables is calculated using the variance decomposition of the forecast error. The percentage of variations in a time series of variables can also be described using variance decomposition. Furthermore, the chosen independent variables can be used to explain variations in the dependent variable. The link between Y and X is used to explain variation. The variance of Y (dependent variable) will expect two conditions as follows:

$E(Var[Y|X])$ = explained variation directly because of changes in X.

$Var(E[Y|X])$ = unexplained variation that comes from other than X.

Variance decomposition is based on complete variance decomposition of the uncertainty of y. It is expressed as follows:

$$V\ (CO2) = \sum_{j=1}^{nx} Vj + \sum_{j=1}^{nx} \sum_{k=j+1}^{nx} VjK + \cdots V_{12,nx}(\qquad (4.15)$$

where Vj = Contribution of xj to V (carbon dioxide)

Vjk = Contribution of the interaction of xj and xk to V (carbon dioxide).

$V_{12......n}$x = Contribution of the interaction X1, X2, X_n to V (carbon dioxide).

4.5.2 Impulse Response Function

The evolution of the variable of interest over a given time horizon after a shock at each moment is described by the impulse response function. It has also used to illustrate "pass-through," or how changes in one variable are passed on to other variables at different stages, either directly or indirectly. One standard deviation shock to one of the innovations is traced using an impulse response graph on present and future values of the endogenous variable. It is useful for determining the long- and short-term effects of a single system variable. The impulse response function, in essence, depicts how one variable reacts to shocks in other variables within the system while keeping other variables constant. It shows how one standard deviation shock in a variable affects the variables' current and future values.

The central difference between the variance decomposition and impulse response function rests on the fact that, while the later traces effect of a shock to an endogenous variable and to other variables within the framework, variance decomposition isolates the respective forecast variances for each variable into separate components attributable to each endogenous variable within the system (Enders, 1995).

4.6. Results and Discussions of Analysis

4.6.1 Unit Root Test

The Augmented Dickey-Fuller test of stationarity of the two variables, carbon-dioxide emission, and energy consumption is presented in table 4.2. The two series are stationary after first difference that is I(1) across the three countries, Nigeria, Ghana, and South Africa.

Table 4. 2: ADF Unit Root Test

	Without Intercept and Trend		Intercept and Trend		
	Level	First Difference	Level	First Difference	Remark
NIGERIA					
Carbon-dioxide Emissions	-0.17	-3.15**	-2.17	-3.27**	I(1)
Petroleum & Other Liquid Consumption	0.67	-2.80***	-2.56	-2.97	I(1)
GHANA					
Carbon-dioxide Emissions	-1.30	-3.02**	-3.02	-3.43*	I(1)
Petroleum & Other Liquid Consumption	2.82	-2.31**	-1.09	-4.02**	I(1)
SOUTH AFRICA					
Carbon-dioxide Emissions	-0.63	-3.52**	-2.26	-3.51*	I(1)
Petroleum & Other Liquid	0.78	-1.63*	-2.84	-1.85**	I(1)

***, ** and * signify significance at 1%, 5% and 10% level respectively.

4.7: Bivariate Model (Carbon-dioxide Emission and Energy Consumption)

4.7.1: Nigeria: Impulse Response Function

As noted earlier, the applicable method to analyse the dynamic nexus and transmission channels of fossil fuel energy consumption to carbon dioxide emissions for the countries under study is the vector autoregressive (VAR) -in-difference modelling framework. The impulse response function for the bivariate model is shown in figure 4.2. The impulse responses explain how shocks transmit in the entire system of the bivariate model for Nigeria and determines the response of a variable because of one standard deviation innovation shock of another variable. Initially, the IRF was considered through the generalize impulse response analysis of multiple graphs and analytical asymptotic for the standard error. Similarly, the default of ten quarter-period split is maintained to predict the impact of the shock on the concerned variable at each of the periods. An innovation shock of one standard deviation of the endogenous variables (left to right diagonal boxes). Figure 4.2 is divided into four panels i.e., panel A to panel D, where panel A shows the response of carbon dioxide emissions to itself, panel B shows response of carbon dioxide emissions to fossil fuel energy consumption, panel C represents response of fossil fuel energy consumption to carbon dioxide emissions and panel D shows response of fossil fuel energy consumption to itself. Panel B fossil fuel energy consumption (FOS) had immediate positive shocks on carbon dioxide emissions in the first quarter of the 10 year horizon periods at an increasing rate. Panel C response of fossil fuel energy consumption to carbon dioxide emissions also shows an increase at increasing rate through the first quarter to ten quarter. However, panels A and D, are responses which reveals a decreasing at decreasing rate for each variable to itself. It implies that one shock in carbon dioxide emissions results to a change in energy use from the first quarter to positive increase over last quarter period. The results of the fossil fuel energy consumption and carbon dioxide discharge support the outcome of earlier studies that energy resources influence explosion positively (Zafar, et al. 2019). Therefore, it is imperatively important for policymakers to enhance the practical measures for mitigating the carbon dioxide discharge for environmental and economic sustainability.

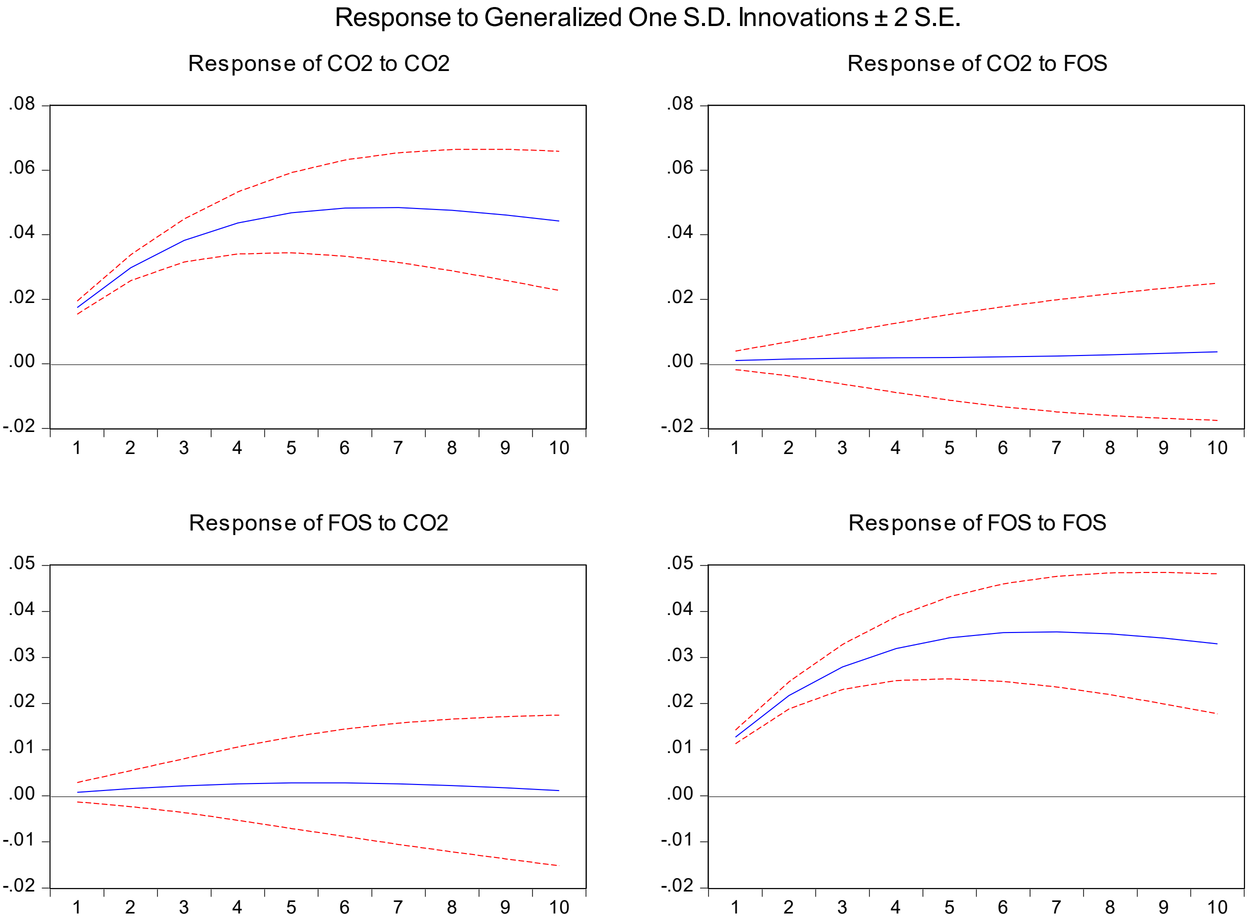


Figure 4.2: Impulse Response (Nigeria)

Source: Author, computed from data

4.7.2 Nigeria: Forecast Error Variance Decomposition

To further investigate the relative importance of energy consumption shocks on carbon dioxide emissions, the forecast error variance decomposition of carbon dioxide emissions is computed. The variance decomposition apportions the total fluctuations in a particular indicator to the constituent shocks or innovations in the VAR system. The result is presented in table 4.3 for the short run horizon of ten quarters. The estimation shows carbon dioxide emission's shocks dominates the contribution of standard errors with over 99% across all the quarters, which reveals the higher influence in the short term for Nigeria. Comparatively, energy consumption contributes a minimum of 0.5% and a maximum of 1.24% during the period. Energy consumption made a linear contribution over 10 quarter simulation period between 0% and 0.6% carbon dioxide emission. However, it dominated the contribution of energy consumption with over 98% over the period. Nonetheless, the finding of the study confirmed the crucial importance of energy consumption as a major determinant of variation in carbon dioxide emissions in Nigeria. This result is consistent with the results of the studies by Khobai and Roux 2017, and Albiman, et al. 2015, that energy use positively determines carbon dioxide emissions (CO_2). Hence, carbon dioxide emission (CO_2) mitigation measures must be put in place for better environmental quality.

Table 4. 3: Variance Decomposition of Carbon Dioxide Emission (Nigeria)

Variance Decomposition of CO2: Period	S.E.	CO2	Energy consumption
1	0.014305	100.0000	0.000000
2	0.030171	99.99044	0.009556
3	0.047723	99.97218	0.027823
4	0.066088	99.95109	0.048911
5	0.078893	99.90063	0.099372
6	0.088472	99.81775	0.182249
7	0.095775	99.70251	0.297486
8	0.101337	99.55857	0.441428
9	0.107574	99.44580	0.554204
10	0.114312	99.38919	0.610813
Variance Decomposition of FOS: Period	S.E.	CO2	Energy consumption
1	0.011914	0.551429	99.44857
2	0.024652	0.548941	99.45106
3	0.038386	0.548882	99.45112

4	0.052475	0.551030	99.44897
5	0.063223	0.625433	99.37457
6	0.071643	0.734287	99.26571
7	0.078263	0.870672	99.12933
8	0.083453	1.033404	98.96660
9	0.088330	1.157589	98.84241
10	0.093120	1.243369	98.75663

Source: Author, computed from data.

4.7.3: Impulse Response Function (Ghana)

The graphical representation of the impulse response scenarios for the Ghanian bivariate model is presented in figure 4.3. Dividing the plots into four (4) panel A to D. The central focus is on panel B, which shows the impulse response of carbon dioxide emissions to fossil fuel energy consumption (FOS). From the graph, the responses remained positive on average throughout the 10 periods horizon. Specifically, carbon dioxide emissions had a very steep positive response to shock in fossil fuel energy consumption till the fourth quarter before a little moderation. Overall, fossil fuel energy consumption shocks exerted positive impact on carbon dioxide emissions through the simulation periods. The result is similar with the report of previous studies (Beneli and Feki 2018; Jabeur and Sghaier 2018; Salahuddin and Gow 2015).

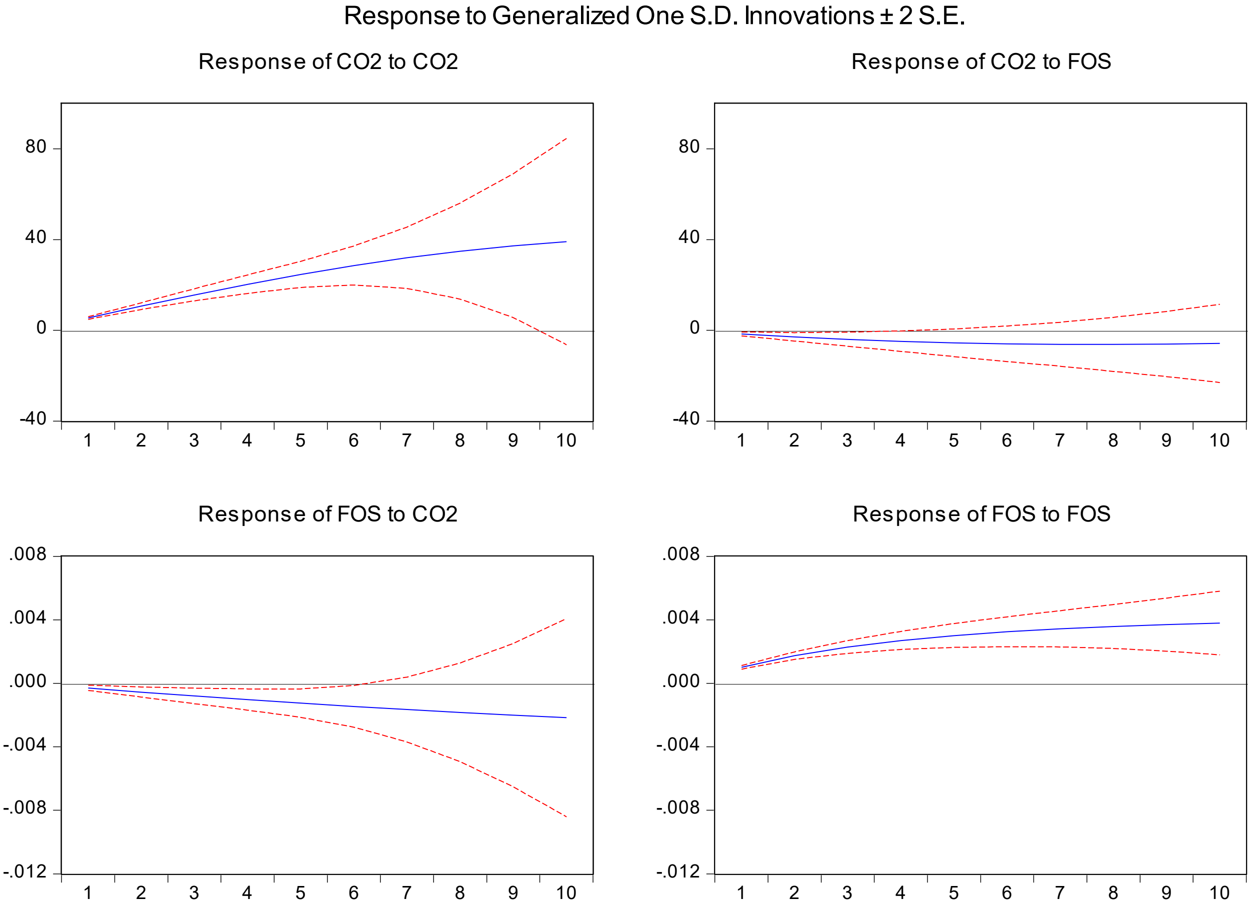


Figure 4. 3: **Impulse Responses (Ghana)**

Source: Author, computed from data

4.8: Forecast Error Variance Decomposition (Ghana)

The forecast error variance decomposition of carbon dioxide emissions was used to further examine the relative relevance of energy consumption shocks on carbon dioxide emissions in Ghana. Table 4.4 shows the variance decomposition of carbon dioxide emissions in Ghana and reveals that, as with other macroeconomic time series data, the first quarter explains the short run horizon of ten quarters. The estimation shows that carbon dioxide emission shocks dominate the contribution of the standard errors with over 99% throughout the simulation period, signifying higher influence in the short term for Ghana. Similarly, energy consumption contributes a minimum of 5.41% and maximum of 5.71%. Most empirical research have found that the biggest percentage error variance breakdown of macroeconomic variables often comes from the past shocks, but this is predicted to decrease over time. This implies that in the long run the forecast analysis reveals that explosion of carbon dioxide discharge may raise by 5.71% because of the shocks in energy utilisation in Ghana. The result is consistent with the findings of studies by Khobai and Roux 2017, and Albiman, et al. 2015.

Table 4. 4: Forecast Error Variance Decomposition of Carbon Dioxide Emission (Ghana)

Variance Decomposition of CO2: Period	S.E.	CO2	FOS
1	0.013529	100.0000	0.000000
2	0.016258	99.98531	0.014686
3	0.016368	99.86042	0.139576
4	0.016425	99.27582	0.724184
5	0.151237	99.99101	0.008992
6	0.151318	99.93746	0.062538
7	0.160186	99.74444	0.255555
8	0.163013	98.69654	1.303456
9	1.213642	99.96736	0.032644
10	2.01623	99.96657	0.033434

Variance Decomposition of FOS: Period	S.E.	CO2	FOS
1	0.000860	0.520652	99.47935
2	0.001860	0.146651	99.85335
3	0.003021	0.055749	99.94425
4	0.004262	0.028197	99.97180
5	0.006090	25.34721	74.65279
6	0.007254	29.31038	70.68962
7	0.007877	25.54990	74.45010
8	0.008566	21.67486	78.32514
9	0.035417	94.58279	5.417207
10	0.036152	94.28450	5.715500

Cholesky Ordering: CO2 FOS

Source: Author, Computed from Data

4.8.1: Impulse Response Function (South Africa)

The impulse responses of the variables employed in the bivariate model for South Africa is shown in figure 4.5. Breaking down the figure into four (4) panels A to D. From panel B of the figure, which is response of carbon dioxide emissions to fossil fuel energy consumption shocks. Fossil fuel energy consumption had immediate positive shocks on carbon dioxide emissions in the first quarter of the 10 horizon periods, with a steeper tangent between 1st quarter through to 8th quarter. However, the positive shocks reduced considerably until 9th quarter and remained positive before the response became negative until the final period of the 10 periods horizon. The result is similar with the report of previous studies (Jabeur and Sghaier 2018; Khobai and Roux 2017; Salahuddin and Gow 2015).Carbon dioxide emissions and fossil fuel energy consumption response to their self positively in the first quarter and decline in the last quarter.

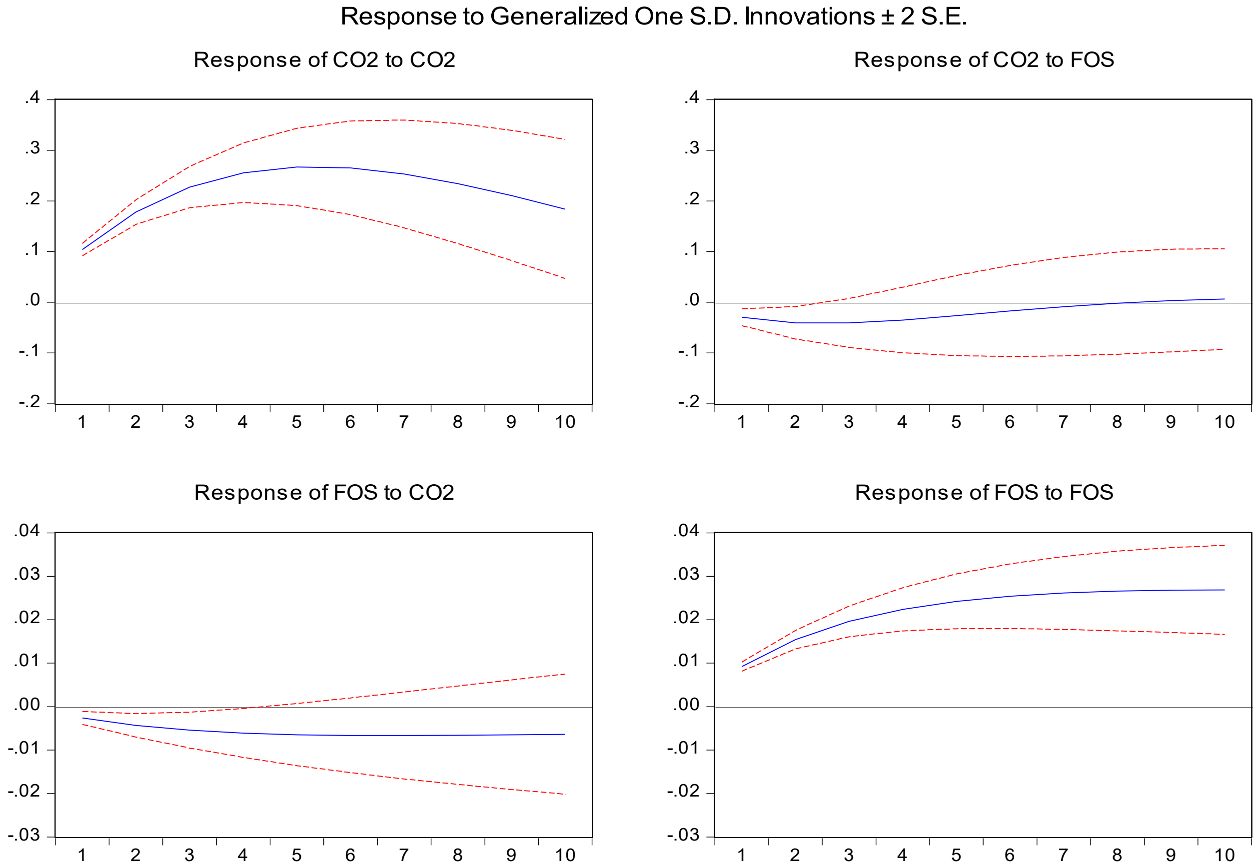


Figure 4.5: Impulse Responses (South Africa)

Source: Author, computed from data

4.8.2: Forecast Error Variance Decomposition (South Africa)

The forecast error variance decomposition was used to further examine the relative importance of fossil fuel energy consumption shocks on carbon dioxide emissions in South Africa as shown in table 4.5. As previously stated, the variance decomposition assigns the entire fluctuations in each indicator to the VAR systems constituents shocks or innovations. A ten year short run and long run simulation periods is chosen from year one to year 4 short run while from year five to year ten is the long run periods. The variance decomposition of carbon dioxide emissions in South Africa reveals that, as with other macroeconomic time series data the short run explains 100% of its own variation, meaning that carbon dioxide emissions is strongly endogenous, it has strong influence from its own variable. Suggesting that fossil fuel energy consumption do not have real strong influence on carbon dioxide emissions, fossil fuel energy consumption has strong exogenous impact in the sense that it does not influence carbon dioxide emissions in the short run, it exhibits weak influence in predicting carbon dioxide emissions. Furthermore, the result of carbon dioxide emissions in the long run 99.9% of forecast error variation decomposition of the variable is explained by carbon dioxide emissions itself. So, carbon dioxide emissions show strong influence from short run to long run simulation periods. However, fossil fuel energy consumption explains a minimum of 5.41% and maximum of 5.71% in the long run simulation periods. The result is similar with the findings of the studies by Ahad, et al. 2018, and Kobai and Roux 2017. Thus, policymakers should focus in designing effective and efficient measures in mitigating the level of carbon dioxide discharge. This should be emphasised through encouraging citizens on the other energy sources which can emit low emission such as wind, solar and thermal energy for better and clean environment.

Table 4.5: Forecast Error Variance Decomposition of Carbon Dioxide Emission (South Africa)

Variance Decomposition of CO2: Period	S.E.	CO2,	FOS
1	0.077349	100.0000	0.000000
2	0.161703	99.99566	0.004345
3	0.253355	99.98756	0.012439
4	0.347281	99.97857	0.021429
5	0.407711	99.30160	0.698396
6	0.450877	97.78269	2.217313
7	0.483247	95.51066	4.489337
8	0.508335	92.62107	7.378932
9	0.533495	91.75322	8.246779
10	0.558910	91.97430	8.025697
Variance Decomposition of FOS: Period	S.E.	CO2	FOS
1	0.007851	1.43E-06	100.0000
2	0.016327	0.005973	99.99403
3	0.025542	0.020288	99.97971
4	0.035073	0.041245	99.95875
5	0.041997	0.169323	99.83068
6	0.047268	0.295383	99.70462
7	0.051314	0.367575	99.63242
8	0.054410	0.381396	99.61860
9	0.057663	0.343044	99.65696
10	0.061124	0.353728	99.64627
Cholesky Ordering: CO2 FOS			

Source: Author, computed from data

4.8.3 Post estimation checks

For establishing the validity of the estimated models, various diagnostic tests are performed such as serial correlation, normality of the residuals and Heteroskedasticity tests. Table 4.6 shows that the estimated model for Nigeria, Ghana and South Africa has no problems of serial correlation, Heteroskedasticity and the residual are normally distributed.

Table 4.6: Post Estimation Tests

Test	Statistics	Prob.
Nigeria		
VEC Residual serial correlation	4.4684	0.346
VEC Residual Heteroskedasticity	32.074	0.364
VEC Residual Normality (Jarque-Bera)	0.3030	0.915
Ghana		
VEC Residual serial correlation	5.8802	0.208
VEC Residual Heteroskedasticity	37.965	0.150
VEC Residual Normality (Jarque-Bera)	1.1403	0.565
South Africa		
VEC Residual serial correlation	3.0841	0.543
VEC Residual Heteroskedasticity	31.730	0.380
VEC Residual Normality (Jarque-Bera)	3.1855	0.203

4.9: Conclusion

This objective of the study investigated the transmission path of the energy consumption and carbon dioxide emissions nexus in three largest economies sub-Saharan African countries, namely Ghana, Nigeria, and South Africa, within a bivariate modelling framework, using quarterly time series data from 1980Q1 to 2017Q1. Variance decomposition method and impulse response analysis were employed for estimation of the variables. Variance decomposition, on the other hand, provides and identifies the percentage of unexpected variations in each variable(s) caused by shocks from other variables, whereas impulse response estimates examine the magnitude and direction of a variable's response to a one-time innovation in another. Both strategies are useful for tracking the long- and short-term impacts of a single variable in a system. Most empirical investigations have found that the biggest percentage error variance decomposition of macroeconomic variables generally stems from past shocks, but that this is projected to decrease throughout projection periods.

ADF unit root test procedure was adopted to test for stationarity of included parameters in the studied countries in which all the variables significant at first difference in Nigeria, Ghana, and

South Africa. Lastly, post estimation checks were adopted to validate the models for efficient policy recommendations.

CHAPTER FIVE

MARKET - INDUCED VARIABLES AND DYNAMISM IN CARBON DIOXIDE EMISSIONS IN THREE LARGEST ECONOMIES OF SUB-SAHARAN AFRICA

5.1 Introduction

The greenhouse gas carbon dioxide emission is one of the major reasons for global warming. Its main source of origination is human activities due to which it is present in the atmosphere in abundance, thereby causing ecological issues and climatic transformations (IPCC, 2014). Climate change is a worldwide problem that poses a serious threat. Temperature fluctuations have been seen to cause an imbalance in the region's environment, posing a threat to human health (UN Environment, 2019). Climate change is having a major impact on people's lives, affecting national economies, and costing us a lot of money today and tomorrow. However, there is a growing realisation that now is the time to implement affordable, scalable solutions that will allow all countries to make the transition to cleaner, more resilient economies (Guterres, 2019). Climate and environmental change are occurring at a faster rate than expected, putting enormous pressure on governments to act quickly to undo the damage to our planet Earth (IPCC, 2014). The World Health Organisation estimates that almost seven million people die each year because of poor air quality, with nearly three million of those deaths occurring prematurely.

Major sources of air pollution, as we have seen, are the consumption of fossil fuels, industrial activities, and inefficient transport systems. Total anthropogenic carbon-dioxide emissions in the atmosphere were 2040 ± 310 $GTCO_2$ for the years = from 1750 to 2011. Almost 40 per cent of these emissions are still in the environment (880 ± 35 $GTCO_2$) (IPCC, 2014); while the remaining 60 per cent have been absorbed by land (in soil and plants) as well as in the water bodies and oceans. Due to these environmental threats and climatic changes, the life expectancy of humans is in danger because of the lack of access to pure water, land, and food. Hence, it is imperative to minimise carbon dioxide emissions in the environment (IPCC, 2014).

In normal conditions, the carbon dioxide emissions from humans, animals, volcanoes, and other sources are almost balanced by the equal amount being absorbed by photosynthesis by plants and oceans. Nevertheless, this equilibrium is being disturbed by human activities involving the consumption of fossil fuels, industry, mining, transportation, and domestic use, all of which significantly increase carbon emissions in the environment (Rahman and Hasan, 2017). This imbalance in the environment is also referred to as the greenhouse effect, which leads to global warming, ice sheets melting at poles, the consequent rise in sea level, submergence of coastal areas, as well as damage to agriculture, plant life, animal life, and human life. The greenhouse gases worldwide have been showing an increasing trend due to human activities with an increase in carbon dioxide emissions level in the atmosphere (EPA, 2014). Carbon dioxide is the most abundant greenhouse gas; it accounts for 77 per cent of the overall global greenhouse gas emissions whereas methane, N_20, and other gases account for only 14 per cent, 8 per cent, and 1 per cent respectively (IPCC, 2007). The intergovernmental panel has also reported it on climate change in 2007 that within the next 100 years, there will be approximately 1.1℃ and 6.4℃ increase in average global temperature (IPCC, 2007).

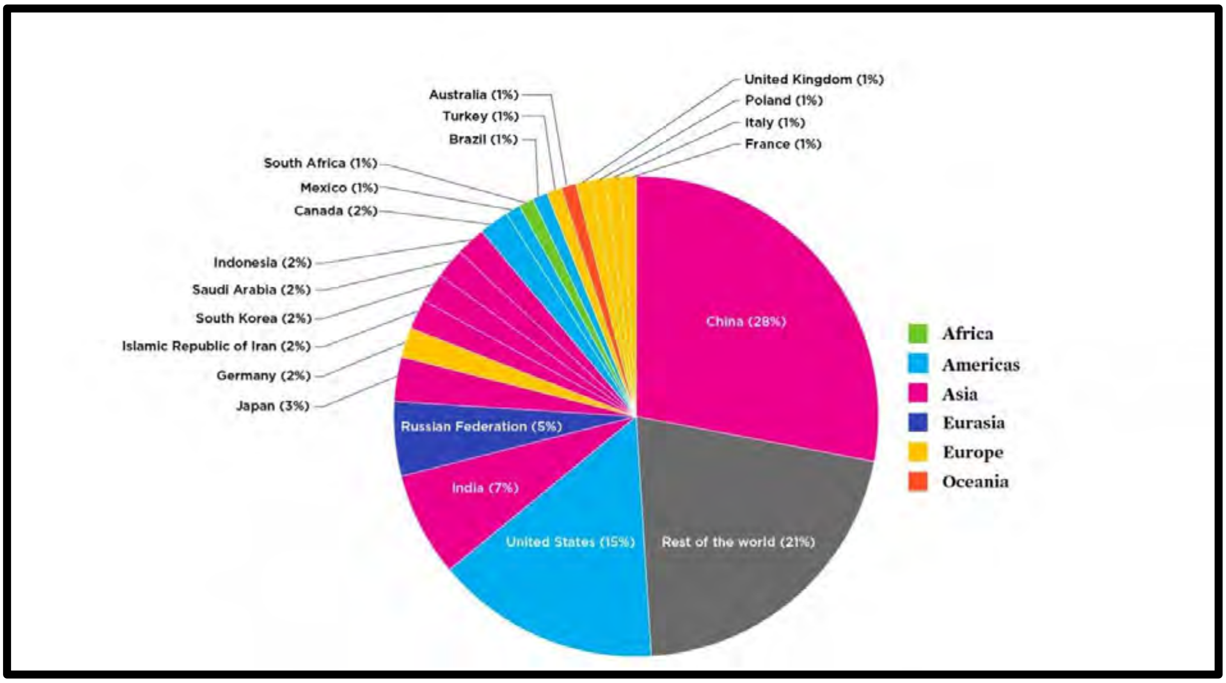


Figure: 5.1 Top Carbon Dioxide Emitting Countries in 2020

Source: ATLAS, 2020

As seen in figure 5.1, South Africa from the sub-Saharan African region is on the thirteenth rank in carbon dioxide emissions. It means sub-Saharan Africa contributes to carbon dioxide emissions significantly. The fifth chapter of this thesis examines the extent to which energy consumption financial development, foreign direct investment, industrial performance, and gross domestic product growth explains systematic dynamism in carbon dioxide emissions in three largest economies of sub-Saharan African countries. To accomplish this goal, Section 5.1

covers the introduction, while section 5.2 provides a brief literature review on the subject under study. Section 5.3 covers the model specification; and section 5.4 highlights the presentation and discussion of results focusing on unit root test, estimation of multivariate models for the countries. Lastly, section 5.5 presents the conclusion of the chapter.

5.2 Literature Review

In line with the report of the third Assessment by IPCC (2007), fundamental changes in the environment have occurred due to global warming. According to a report of IPCC (2001), there will be an expected loss of 20.7 per cent in landmass due to a one-meter sea level rise and a loss of 10.9 per cent in landmass due to a 45cm increase in sea level. It has been scientifically proven that the major reason for global warming is the increase in the levels of carbon dioxide in the atmosphere, which is due to various human activities (Querol, et al. 2018; UN Environment, 2019; Fogarty, 2019).

Sarkar, et al. (2015) posits that there is an increase of 6.7 per cent per annum in carbon dioxide emissions in Bangladesh, which is much higher than its energy consumption, and growth of output (Sarkar, et al. 2015). In another study conducted in the Cox's Bazar and the Sylhet region of Bangladesh, it was found that there is a significant increase in temperature by 0.021 degree Celsius per year (Rahman and Hasan, 2017). It has been concluded in some studies that the production and use of energy affects the climate and air quality (Ciupageanu, et al. 2017, 2019; Capellán-Péreza, et al. 2019; Herrerias, 2012; Wang, 2013). Between 2014 and 2016, stagnation was observed in fossil fuel emissions with an increase in the global gross domestic product (output). However, the trend discontinued in 2017 when global emissions jumped by 1.6 per cent. It has been projected by the Global Carbon Project that the carbon dioxide emissions will rise by approximately 2.7 per cent up to 37.1 gigatons at the end of the year 3000 (Fogarty, 2019).

Climate change and global warming have been issues of scientific discussion for decades, few of studies have examine that with the doubling of carbon dioxide emissions, the global mean temperature is going to increase from 3℃ to 4℃ (Reddy, et al. 1995). The relationship between financial development and environmental quality is very significant for policymakers to comprehend the interaction between financial development and the environment (Mitic, et al. 2017). It is very critical to understand the influence of financial development on carbon dioxide emissions, being that the main purpose of any economy is to maximise financial development

(Živanovi´c, et al. 2016; Narayan and Narayan, 2010). Significant environmental degradation is occurring which has raised alarms in both the scientific community and political circles. The main factors for this environmental degradation have been identified to be population growth, transportation, industrialisation, exploitation of natural resources, and the liberal use of fossil fuels (Borhan, et al. 2012).

The global trend of carbon dioxide discharge is becoming a threat to all countries' ecosystem and development (Sehrawat, et al. 2015). It is argued that in recent years, the portion of carbon dioxide explosion from the countries in industrialised and emerging economies increases the level of deteriorating environmental quality due to atmospheric heat and climate alteration (Meratizaman, et al. 2015; Nejat, et al. 2015). Nowadays, countries like China, India, sub-Saharan African countries, North Africa, Asia, and Latin America account for almost 63 per cent of the total carbon dioxide discharge in the globe (Hansen Sato, 2016; IPCC, 2014). Hence, developing countries become increasingly vulnerable to all effects of carbon dioxide explosion. The increased incidences of disease outbreak, changes in the ecosystem and water ways alterations, floods, drought, low yields of agricultural productivity, extreme poverty all adversely affect human welfare and development Danlami, et al. (2018). These have translated into rising crises especially in the African countries with reference to issues of farmers-herdsmen and Boko Haram conflicts that have seriously affected economic and human development (Edward, 2014).

In sub-Saharan Africa, the level of carbon dioxide discharge has taken an increasing dimension with the upsurge of economic progress, financial resources, population growth, urbanization and fossil fuel use for domestic and industrial utilization (Asongu, 2018; Yahaya, Mohd-jali, Raji, 2020). The manufacturing industry, non-renewable sources of energy and fossil fuels are mostly used for the generation of electricity (Mitic, et al. 2017). Carbon dioxide emissions and other greenhouse gases are emitted on the combustion of such fuels, which damage the environment. Financial development is directly related to an increase in production, which suggests that an increase in financial development and fossil fuel consumption leads to an increase in carbon dioxide emissions in the environment.

Financial development has been associated with environment quality by a considerable number of studies (Charfeddine and Kahia, 2019; Jiang and Ma, 2019; Khan, et al. 2019; Shahbaz, et al. 2013; Boutabba, 2014; Zhang, 2012; Tamazian, et al. 2009). The financial development of the region assists firms to put more funds in research and development, which has a positive impact on the environment. However, some authors have focussed more on investigating the relationship between pollution and financial development, with no common theory established. On one hand, it has been argued that financial development can lead to an increase in pollution due to increased activities. On the other hand, it has been argued that financial development can lead to a reduction in emissions due to more funding in the cleaner energy sector (Bui, 2020). Accordingly, the environmental Kuznets curve hypothesis has been the subject of most investigations on the relationship between economic growth and carbon dioxide emissions. Under this hypothesis, environmental degradation increases during the early stages of economic expansion until some threshold level or turning point in relation to income is achieved, after which environmental degradation begins to drop. (Heidari, et al. 2015). (p. 785). This hypothesis proposes an inverted U-shaped curve for the relationship between economic growth and environmental pollution.

Some research studies have examined the environmental kuznets curve hypothesis and yet no consensus was found on the topic (Mitic, et al. 2017). The association among energy use, financial development, growth performance and foreign direct investment is given considerable concern in the literature. Bolük and Mert (2014), for example, estimate the performance of energy on carbon dioxide emissions in 16 EU countries from 1990 to 2008 using the fixed effect technique. They discovered that the use of energy hastens the carbon dioxide explosion. From 1989 to 2011, Mahdi (2015) used the PVAR method to assess the impact of energy use on carbon dioxide emissions in European and Asian countries. He discovered that increasing energy utilization increases carbon dioxide explosion capacity. According to Begum, et al. (2015), the utilisation of energy resources in Malaysia increases carbon dioxide emissions.

Mirzaei and Bekri (2017) provide evidence for their work by calculating the impact of energy use on carbon dioxide emissions in Iran. The findings show that using a lot of energy causes more carbon dioxide emissions. Danish, et al. (2018) assesses the impact of energy resources on Pakistan's carbon dioxide emissions. They reveal that energy accelerates carbon dioxide emissions. The influence of fossil fuel on Nigeria was investigated by Yahaya, et al. (2019). They established that increasing the amount of energy usage increases the capacity to discharge carbon dioxide. Nguyen and Kakinaka (2019), on the other hand, revealed that energy use in 170 countries reduces carbon dioxide emissions. In contrast, Acheampong (2018) finds that industrial growth performance slows the rate of carbon dioxide emissions in 116 emerging economies using PVAR analysis. Ren, et al. (2014), for example, used the generalised method of moments technique to assess the impact of foreign direct investment on carbon dioxide emissions in China from 2000 to 2010, concluding that foreign direct investment raises carbon dioxide emissions. Foreign direct investment and energy resources in Turkey, according to Gökmenolu and Taspinar (2016), increase the amount of carbon dioxide explosion. This conclusion is backed by earlier findings (Shao 2018). Therefore, it is important to know the level of emissions by the region at present as well as in the future. As greenhouse gases are aggravating, environmental issues so the prediction of carbon-dioxide emissions has become a major concern worldwide (Nyoni and Bonga, 2019). It has also become important to forecast carbon dioxide emissions so that public awareness could be created with the hope that this will help resolve environmental issues (Abdullah and Pauzi, 2015). To make a reliable prediction about future environmental scenarios, it is vital to forecast carbon dioxide emissions, and this research has set out to model and forecast carbon-dioxide emissions in selected largest economies of sub-Saharan Africa countries (i.e., Ghana, Nigeria, and South Africa).

5.3 Model Specification

This study employed a modified model developed by Ohlan (2015) to investigate the extent to which fossil fuel energy use, foreign direct investment, financial development, industrial performance and gross domestic product growth explains dynamics in carbon dioxide emissions using forecast error variance decomposition and impulse response analysis.
The functional form of the model is presented in equation 5.1:

$$CO_2 = f\,(ENG, FDI, FD, IND, GDPg), \tag{5.1}$$

where carbon dioxide emissions is (CO2), fossil fuel energy consumption represents (ENG), foreign direct investments indicates (FDI), financial development is (FD), industrial performance is (IND), while gross domestic product growth is (GDPg).
The econometric specification of the functional form equation 5.1 is represented as follows in equation 5.2:

$$CO2_t = \propto + \beta_1 ENG_t + \beta_2 FDI_t + \beta_3 FD_t + \beta_4 IND_t + \beta_5 GDPg_t + \varepsilon_t \tag{5.2}$$

where Subscript t stands for the quarterly period from 1980-2017,α and β signify the parameters and ε denotes the stochastic error, the rest as defined in the previous equation. The apriori expectation is $\beta_1 > 0; \beta_2 > 0; \beta_3 > 0; \beta_4 > 0; \beta_5 </> 0$, therefore ENG, FDI, FD, IND, and GDPg are positively related to carbon dioxide discharge while theory provides that gross domestic product growth could either increase or decrease carbon dioxide emission depending on the stage of economic development.

5.4: Estimation of Multivariate Models for the Countries

Following the determination of the stationary properties of the variables and the investigation of the long run relationship among the variables for the three (3) countries under study, the next step is to estimate the multivariate models for the respective countries. In this view, Toda-Yamamoto model (T-Y model) in the VAR framework, proposed by Toda and Yamamoto (1995) is the appropriate estimation method for Nigeria, Ghana, and South Africa since they are I(1) variables in their respective models which can be accommodated in T-Y estimation model.

5.5: VAR Lag Order Selection Criteria (Nigeria, Ghana, and South Africa)

Tables 5.1, 5.2 and 5.3 present the VAR lag order selection criteria for both Nigeria Ghana and South Africa. As indicated in the table, the VAR lag order selection criteria show the optimal lag preference for Nigeria (6), Ghana (8) and South Africa (6) as identified by all available information criterion at the 5% significance level, namely Sequential Modified LR test statistic (LR), Final Prediction Error (FPE), Akaike Information Criterion (AIC), Schwarz Information Criterion (SIC) and Hannan-Quinn (HQ) information criterion. Thus, optimal lag employed in the Toda-Yamamoto multivariate models is justified.

Table 5. 1: VAR Lag Order Selection Criteria (Nigeria)

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-1133.978	NA	0.424280	16.16990	16.29538	16.22089
1	135.7614	2413.405	1.07e-08	-1.329949	-0.451595	-0.973016
2	457.2701	583.7321	1.86e-10	-5.379718	-3.748489*	-4.716843*
3	466.4034	15.80513	2.75e-10	-4.998629	-2.614526	-4.029812
4	481.3896	24.65822	3.75e-10	-4.700562	-1.563583	-3.425802
5	568.8007	136.3861	1.85e-10	-5.429797	-1.539944	-3.849095
6	669.2496	148.1799*	7.63e-11*	-6.343966*	-1.701238	-4.457322
7	680.9144	16.21485	1.13e-10	-5.998785	-0.603182	-3.806199
8	698.6001	23.07928	1.55e-10	-5.739009	0.409469	-3.240480

- indicates lag order selected by the criterion

Table 5. 2: VAR Lag Order Selection Criteria (Ghana)

Lag	LogL	LR	FPE	AIC	SC	HQ

0	-1781.389	NA	4128.914	25.35303	25.47851	25.40402
1	-127.8468	3142.902	4.48e-07	2.409174	3.287528	2.766107
2	150.7392	505.8014	1.44e-08	-1.031762	0.599467*	-0.368887
3	161.0871	17.90710	2.09e-08	-0.667903	1.716201	0.300915
4	186.8762	42.43299	2.44e-08	-0.523066	2.613913	0.751694
5	397.8432	329.1684	2.09e-09	-3.004868	0.884986	-1.424166
6	498.8033	148.9340	8.57e-10	-3.926288	0.716441	-2.039643
7	528.9848	41.95448	9.73e-10	-3.843756	1.551847	-1.651170
8	654.7118	164.0692*	2.90e-10*	-5.116479*	1.031999	-2.617950*

* indicates lag order selected by the criterion

Table 5. 3: VAR Lag Order Selection Criteria (South Africa)

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-1332.880	NA	7.127366	18.99120	19.11668	19.04219
1	74.78371	2675.559	2.53e-08	-0.465017	0.413337	-0.108084
2	350.6753	500.9096	8.45e-10	-3.867735	-2.236506*	-3.204860
3	367.8095	29.65064	1.11e-09	-3.600135	-1.216031	-2.631318
4	392.2911	40.28184	1.33e-09	-3.436754	-0.299775	-2.161994
5	500.4479	168.7552	4.87e-10	-4.460254	-0.570400	-2.879552
6	646.4951	215.4456*	1.05e-10*	-6.021208*	-1.378479	-4.134564*
7	656.8960	14.45791	1.59e-10	-5.658099	-0.262496	-3.465513
8	670.1417	17.28518	2.33e-10	-5.335343	0.813135	-2.836814

* Indicates lag order selected by the criterion

5.5.1 Granger Causality Test Results (Nigeria, Ghana, and South Africa)

The Toda-Yamamoto estimation model for Nigeria, Ghana and South Africa are presented and discussed, respectively**.** The granger causality test results for Nigeria, Ghana and South Africa are presented in table 5.4. Among all variables, foreign direct investment granger causes carbon dioxide emissions in Nigeria, and credit provided by financial sector granger causes carbon dioxide emissions. In this regard, energy consumption granger causes carbon dioxide emissions in Nigeria, directly pointing to the country's reliance on the hydrocarbon industry for fiscal sustenance. Similarly, carbon dioxide emissions granger causes industrial performance on one hand, as well as carbon dioxide emissions and output growth, measured by the growth rate of gross domestic product, on the other. However, there was no causality between credit to the private sector and carbon dioxide emission in Nigeria. This is in line with findings of Chontanawat, et al. (2016), Wei, et al. (2021).

For Ghana, there is presence of unidirectional causality between gross domestic credit and carbon dioxide emissions, but the causation running from gross domestic product growth to carbon dioxide emissions was found to have stronger significance and more potent. Similar to the findings of Saibu and Jaiyesola. (2013), Sun, et al. (2011), Bowden and Payne (2009), Yu, et al. (2008). In addition, there was a unidirectional causality between energy consumption and carbon dioxide emission in Ghana. For the other variables, there was no observed causality among carbon dioxide emissions, foreign direct investment, industrial performance, and financial development.

In the case of South Africa, none of the exogenous variable's granger causes carbon dioxide emission. Similarly, carbon dioxide emissions do not granger cause any of the exogenous variables. This result further reinforces the omnipotent role of the country's financial sector development and ensuing financing structure/arrangements in determining economic interactions and activities, with profound effects on the environmental quality in South Africa. This result is remarkably instructive and aptly confirms position of South Africa's financial sector as some of the most dominant in the African continent.

Table 5. 4: Granger Causality Test

	Null Hypothesis	Chi-square	P-Value	Remark
NIGERIA	CO_2 Emission does not granger cause FD	2.37	0.88	No causality
	FD does not granger cause CO_2 Emission	17.6	0.00	Causality
	CO_2 Emission does not granger cause IP	18.7	0.00	Causality
	IP does not granger cause CO_2 Emission	29.4	0.00	Causality
	CO_2 Emission does not granger cause GDPg	11.6	0.00	Causality
	GDPg does not granger cause CO_2 Emission	20.6	0.00	Causality
	CO_2 Emission does not granger cause FOS	1.88	0.92	No causality
	FOS does not granger cause CO_2 Emission	12.5	0.05	Causality
	CO_2 Emission does not granger cause FDI	40.3	0.00	Causality
	FDI does not granger cause CO_2 Emission	2.85	0.82	No causality
GHANA	CO_2 Emission does not granger cause FD	5.62	0.68	No causality
	FD does not granger cause CO_2 Emission	3.62	0.69	
	CO_2 Emission does not granger cause IP	14.9	0.05	Causality
	IP does not granger cause CO_2 Emission	4.44	0.81	No Causality
	CO_2 Emission does not granger cause GDPg	10.6	0.22	No causality
	GDPg does not granger cause CO_2 Emission	17.4	0.02	Causality
	CO_2 Emission does not granger cause FOS	7.34	0.49	No causality
	FOS does not granger cause CO_2 Emission	78.5	0.00	Causality
	CO_2 Emission does not granger cause FDI	5.52	0.70	No causality
	FDI does not granger cause CO_2 Emission	3.62	0.88	
SOUTH	CO_2 Emission does not granger cause FD	1.20	0.97	No causality
	FD does not granger cause CO_2 Emission	3.83	0.69	
	CO_2 Emission does not granger cause IP	2.22	0.87	No causality
	IP does not granger cause CO_2 Emission	0.91	0.98	
	CO_2 Emission does not granger cause GDPg	4.51	0.60	No causality

AFRICA	GDPg does not granger cause CO2 Emission	0.43	0.99	
	CO2 Emission does not granger cause FOS	6.26	0.48	No causality
	FOS does not granger cause CO2 Emission	4.22	0.64	
	CO2 Emission does not granger cause FDI	5.52	0.48	No causality
	FDI does not granger cause CO2 Emission	6.22	0.29	

Note: FDI=Foreign Direct Investment; FD=Financial Development; IP=Industrial Performance; CO2= CO2 Emissions; GDPg=GDP Growth Rate; FOS=Fossil Energy Consumption

5.5.2 Impulse Responses of Carbon Dioxide Emissions to other Variables (Nigeria)

Figure 5.2 shows the impulse response function of the models for Nigeria that determine the response of a variable because of one standard deviation shock of other variables. The impulse response function (IRF) was considered through the generalized impulse response analysis of multiple graphs, and analytical asymptotic for the standard error. Similarly, the default of ten-period split is maintained to predict the impact of the shock on the concerned variable at each of the quarter periods. A shock of one standard deviation of almost all variables to themselves apart from carbon dioxide emissions and fossil fuel energy use leads negative adjustment in the short run up to the long run quarter period in Nigeria.

The response reveals that one shock in carbon dioxide discharge results to a negative change in fossil fuel energy use, foreign direct investments, domestic credit, and industrial performance over a certain period. The result further illustrates that fossil fuel energy use response negatively to carbon dioxide discharge from the short run to long run horizons. Similarly, foreign direct investments, financial progress, and industrial performance have decreased the capacity of carbon dioxide emissions from period of short to the long run. However, economic growth has increasing response on carbon dioxide explosion in Nigeria. These results are similar with the outcome of earlier studies (Sulaiman and Abdul-Rahim 2017; Qureshi, et al. 2016). Their findings confirm the negative effect of these variables on carbon dioxide discharge. Thus, it is essential for government and policymakers to continue with enhance measures for mitigating the carbon dioxide discharge for environmental and economic sustainability.

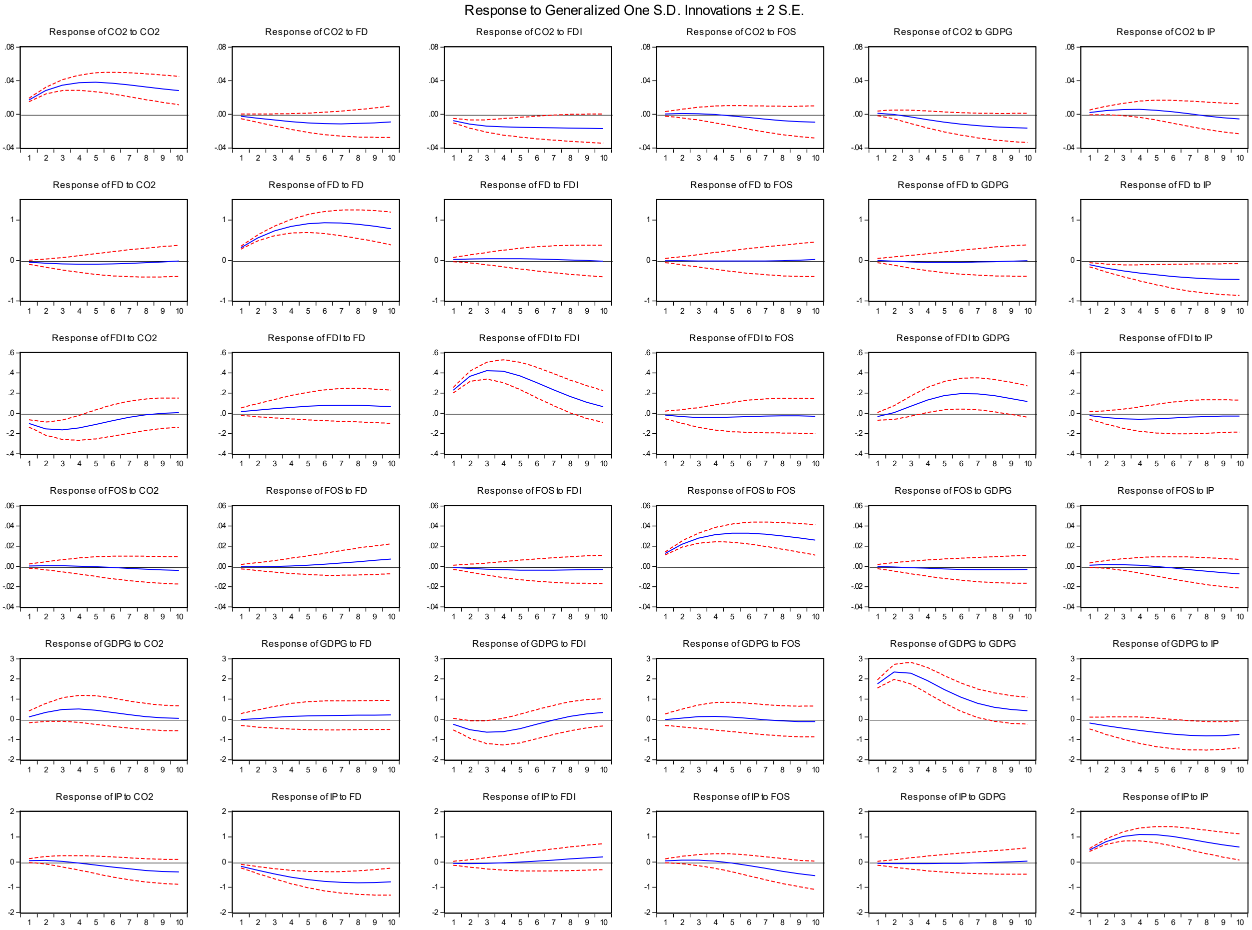


Figure 5.2: **Impulse Responses of Carbon Dioxide Emissions to other Variables (Nigeria)**

5.5.3 Forecast Error Variance Decomposition of Carbon Dioxide Emissions (Nigeria)

The relative importance of the shocks of each variable on variance of carbon dioxide emissions is presented as forecast error variance decomposition for Nigeria in table 5.5. Economic growth has the relative importance among the variables as its shocks explained 1.09% and 6.45% in the short run and long run of the ten quarter simulation periods. This followed by foreign direct investment whose shocks also explained about 4.32% of the variation in carbon dioxide emissions at quarter 10 of the simulation periods. Similarly, the result of forecast error variance decomposition of industrial performance shows 0.40% and 3.55% in the short run and long run horizon. Suggesting the importance of both gross domestic product growth, foreign direct investments, and industrial value addition as key determinants in explaining the variations in environmental quality (measured by carbon dioxide emissions) in Nigeria. True to expectation, the variance in carbon dioxide emissions like most macroeconomic variables, declined from its own past shocks, as expected over the forecast horizon. From the results, gross domestic product growth (6.45%), foreign direct investments (4.32%), industrial performance (3.55%), financial development (2.7%), and energy consumption (1.89%) explained marginal shocks in carbon dioxide emissions in the 10th quarter of the forecast horizon, are important in explaining variations in carbon dioxide emissions in Nigeria. Therefore, the hierarchical order for policymakers in mitigating carbon dioxide emission could begin with economic growth and foreign direct investments with greater emphasis followed by domestic credit. It is argued that increase in economic growth and foreign direct investments and energy utilisation accelerates the capacity of environmental pollution. This is consistent with studies conducted by Ohlan, 2015

Table 5.5: Forecast Error Variance Decomposition of Carbon dioxide (CO2) Emissions (Nigeria)

Period	S.E.	Financial Development	Foreign Direct investment	Industrial Performance	GDP Growth	Energy Consumption	CO2 Emission
1	0.017293	0.000000	0.000000	0.000000	0.000000	0.000000	2.305781
2	0.035600	0.026661	0.209376	0.274901	0.462561	0.014419	2.558611
3	0.053449	0.130021	0.502493	0.400334	1.094373	0.017800	2.478252
4	0.069670	0.337874	0.884249	0.518895	1.880686	0.036687	2.326168
5	0.084102	0.656631	1.355049	0.707105	2.778199	0.100539	2.187723
6	0.096992	1.067563	1.906275	1.019524	3.723213	0.250181	2.084458
7	0.108701	1.530064	2.514403	1.486074	4.631010	0.516958	2.014832
8	0.119555	1.993569	3.144559	2.099516	5.419859	0.903539	1.970642
9	0.129783	2.412494	3.758030	2.813104	6.034067	1.379404	1.942964
10	0.139515	2.757018	4.320677	3.555495	6.454869	1.891985	1.924195

Source: Author’s Computations

5.5.4 Impulse Responses of Carbon Dioxide Emissions to other Variables (Ghana)

The impulse responses of carbon dioxide emissions to the shocks of other variables in the multivariate model of Ghana are shown in figure 5.3. The shocks response of financial development, which is proxy by the credit provided by the financial sector, exerted a negative response on carbon dioxide emissions throughout the simulation periods. Similarly, foreign direct investment shocks exerted an immediate positive response in the 1st four quarters of the simulation periods before maintaining an almost steady response on carbon dioxide emissions for the rest of the simulation periods. The response of carbon dioxide emissions to industrial performance is moderately/slightly positive over the horizon. However, a positive shock in gross domestic product growth induced a slow and even response from carbon dioxide emissions. There was a sharp positive response of carbon dioxide emissions to fossil fuel energy consumption proxy by petroleum and other liquid energy consumption, up to the fourth quarter, before the response became sideways throughout the rest of the periods. The response of carbon dioxide emissions to itself was first positive, before declining asymptotically for the rest of the periods.Hence, the finding is confirmed by the outcome of the study by Ahad, 2018; Rasli and Zaman 2016 , that elavorates the nagetive linkage among the variables.

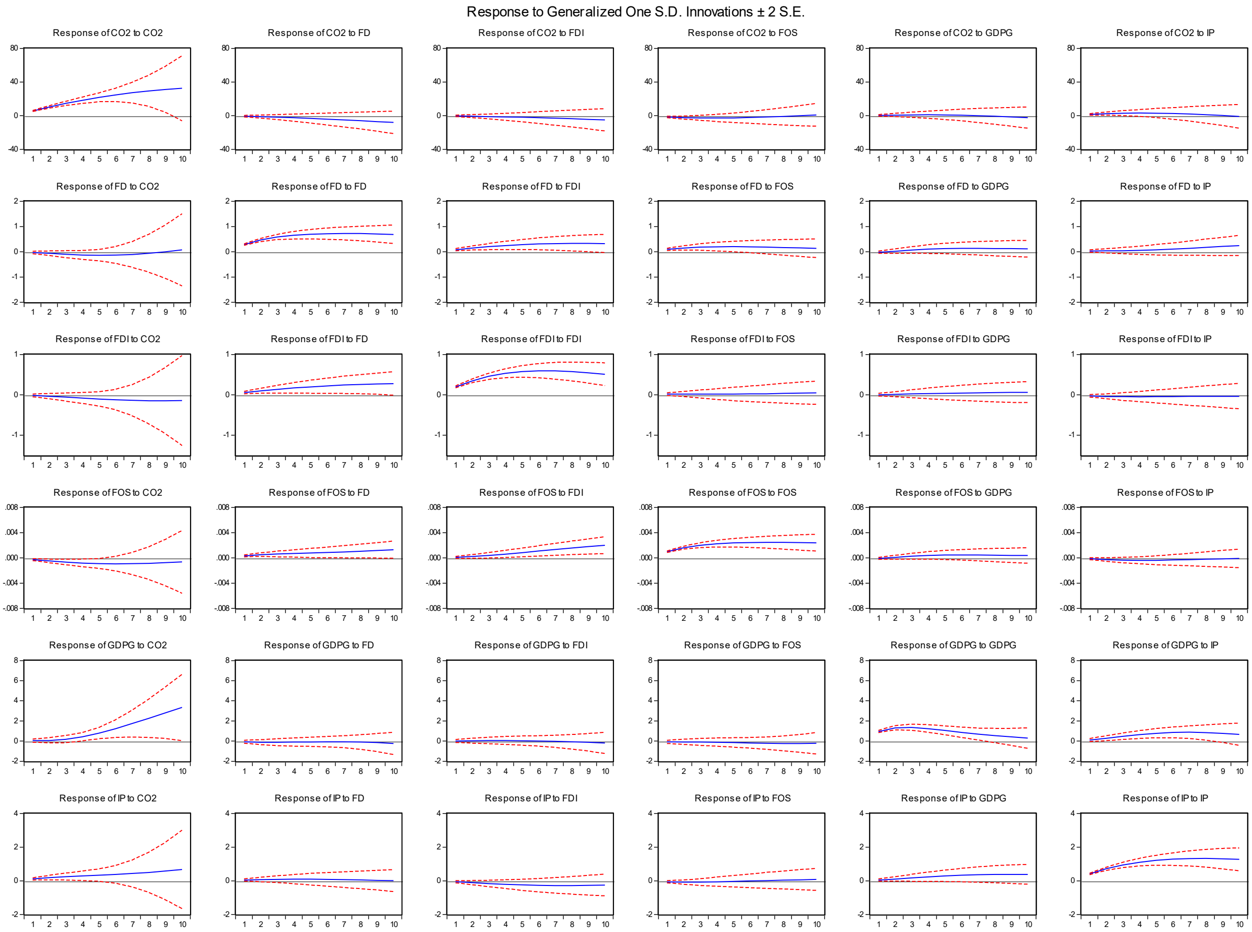


Figure 5. 3: Impulse Responses of Carbon Dioxide Emission to other Variables (Ghana)

Source: Author's Computations

5.5.5 Forecast Error Variance Decomposition of Carbon Dioxide Emissions (Ghana)

Table 5.6 indicates that in Ghana more than 10% forecast variance against carbon dioxide emissions for both short and long run quarter period among the determinants in the vector. Similarly, shocks in fossil fuel energy consumption is strongly endogenous to carbon dioxide and has the relative importance among the other variables in explaining the variation in carbon dioxide emissions in Ghana. The shocks in fossil fuel energy consumption accounted for 0.34% and 5.4% in the short run and long run in the simulation periods. Industrial performance, which explained 0.20% variation in carbon dioxide emissions in the short run account for 2.33% in the forecast errors of carbon dioxide emissions in the 10 quarter periods. The other variables, financial development (0.16%), gross domestic product growth (0.12%), and foreign direct investment (0.018%), explained relatively marginal variance in carbon dioxide emissions in the final quarter. From the result, fossil fuel energy consumption, industrial performance, and perhaps financial development, gross domestic product growth, and foreign direct investments are real determinants of carbon dioxide emissions. The finding is similar with the result reported by Sulaiman and Abdul-Rahim (2017); Eso and Keho 2016. Therefore, the hierarchical order for policymakers in mitigating carbon dioxide emissions could start with foreign direct investments and industrial performance with greater emphasis followed by financial development.

Table 5.6: Forecast Error Variance Decomposition of Carbon Dioxide (CO_2) Emissions (Ghana)

Period	S.E.	Financial Development	Foreign Direct investment	Industrial Performance	GDP Growth	Energy Consumption	CO2 Emission
1	0.055749	0.000000	0.000000	0.000000	0.000000	0.000000	1.066038
2	0.122041	0.003290	0.006795	0.045731	0.001062	0.041609	1.306589
3	0.200804	0.021054	0.005020	0.203138	0.000393	0.349270	1.585789
4	0.291229	0.050133	0.002540	0.446454	0.000224	0.944152	2.060043
5	0.393579	0.082872	0.001392	0.738479	0.001564	1.720597	2.709554
6	0.508732	0.113001	0.000958	1.053364	0.007995	2.567164	3.463935
7	0.637887	0.137033	0.001704	1.376179	0.022910	3.399720	4.225180
8	0.782388	0.153987	0.004610	1.699097	0.047630	4.166574	4.907766
9	0.943624	0.164506	0.010275	2.018118	0.081261	4.843448	5.462394

10	1.122978	0.169972	0.018679	2.330980	0.121520	5.425201	5.878238

Source: Author's Computations

5.6: Impulse Response Function (South Africa)

The impulse response function of South Africa is presented in figure 5.4 which illustrates the results. The figure gives the description of carbon dioxide emissions reactions to the shocks or innovation in other variables in the South Africa multivariate model, being estimated. The response of carbon dioxide emissions to a positive shock in fossil fuel energy consumption is sluggish and negatively retarding. This response is also like the reaction of carbon dioxide emissions to shocks in financial development, foreign direct investment, and industrial performance. However, among all the variables, only shock in gross domestic product growth induced a positive response from carbon dioxide emissions, while response from carbon dioxide emissions to itself rose throughout the simulation periods. The result is consistent with the outcome of previous studies (Abbasi and Riaz, 2016; Salahuddin and Gow, 2016). Thus, since credit provided by the financial sector and economic activities positively influence carbon dioxide explosion in South Africa policies should be focus on carbon dioxide emissions mitigation to enhance environmental quality.

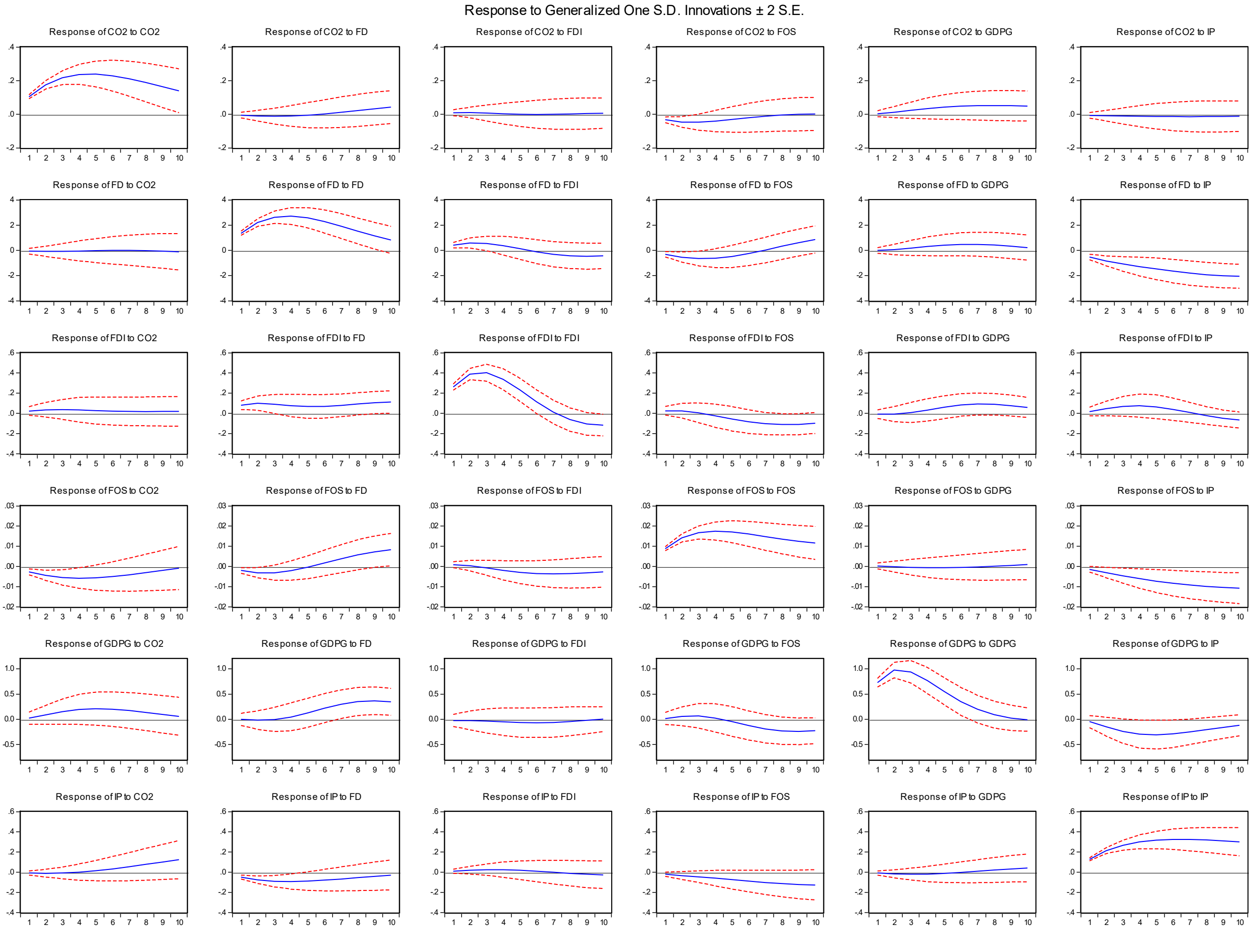


Figure 5.4: Impulse Responses of Carbon Dioxide Emission to other Variables (South Africa)

Source: Author's Computation

5.6.1: Forecast Error Variance Decomposition of Carbon Dioxide Emissions (South Africa)

Table 5.7 illustrates that in South Africa more than 50% forecast error variance against carbon dioxide emissions for both short and long run quarter period among the determinants in the vector. The highest percentage error emanates from its own shocks throughout the simulation periods. Apart from its own shocks, energy consumption shocks accounted for 0.47% and 9.82% of the total variations in carbon dioxide emissions in the first quarter of the simulation periods. Shocks in energy consumption has the highest relative importance in explaining the variance in carbon dioxide emissions. In the final period, the variables that provided explanations for variations in carbon dioxide emissions include energy consumption (9.82%), gross domestic product growth (1.8%), foreign direct investments (1.76%), financial development and industrial performance explained negligible variances in carbon dioxide emissions over the forecast horizon at only 0.77% and 0.18% respectively, in the 10th quarter. The overall outcome shows fossil fuel energy consumption and economic growth have the highest influence compared to other variables within the vector. The result is accordance with the findings of Salahuddin and Gow (2016). Hence, the hierarchical order for policymakers in mitigating carbon dioxide emission could consider energy consumption and growth performance with greater emphasis followed by industrial performance and financial development.

Table 5.7: Forecast Error Variance Decomposition of Carbon Dioxide Emission (South Africa)

Period	S.E.	Financial Development	Foreign Direct investment	Industrial Performance	GDP Growth	Energy Consumption	CO2 Emission
1	0.107127	0.000000	0.000000	0.000000	0.000000	0.000000	0.688463
2	0.222840	0.011167	0.006041	2.44E-08	0.139022	0.046957	0.861407
3	0.334856	0.054167	0.075193	0.000278	0.337156	0.470853	0.946721
4	0.438328	0.143495	0.228004	0.000193	0.592513	1.479545	0.974004
5	0.533910	0.267021	0.446831	0.001269	0.873247	2.941035	0.985112
6	0.623094	0.400762	0.705153	0.009158	1.149434	4.590920	1.000206
7	0.706912	0.524741	0.979714	0.030256	1.392667	6.201703	1.023889
8	0.785922	0.628753	1.253653	0.067875	1.585971	7.638882	1.053432
9	0.860421	0.710323	1.516308	0.120934	1.724933	8.848481	1.084235
10	0.930618	0.771301	1.761510	0.185017	1.814913	9.827688	1.112521

Source: Author's Computation

5.6.2: Post Estimation Checks

The post estimation diagnostic tests such as the serial correlation, normality of the residuals and Heteroskedasticity tests have been conducted to ensure the model is free from such econometric problems for the reliability of the estimated model. Table 5.8 indicates that the estimated model for Nigeria, Ghana and South Africa has no problems of serial correlation; Heteroskedasticity and the residual are normally distributed.

Table 5.8: Post Estimation Tests

Test	Statistics	Prob.
Nigeria		
VEC Residual serial correlation	13.479	0.970
VEC Residual Heteroskedasticity	295.35	0.915
VEC Residual Normality (Jarque-Bera)	11.869	0.293

Ghana		
VEC Residual serial correlation	20.153	0.738
VEC Residual Heteroskedasticity	167.24	0.516
VEC Residual Normality (Jarque-Bera)	0.4795	0.786
South Africa		
VEC Residual serial correlation	25.974	0.408
VEC Residual Heteroskedasticity	199.61	0.150
VEC Residual Normality (Jarque-Bera)	6.1196	0.805

5.6.3: Conclusion

The study examines the transmission channel of the fossil fuel energy consumption and carbon dioxide emissions nexus in three largest economies in sub-Saharan African countries, including other key control variables, namely foreign direct investment, financial development (proxy by financial sector credit to the private sector as a % of gross domestic product), industrial performance (measured by industry value added as a % of gross domestic product) and output growth. The analysis was conducted for Ghana, Nigeria, and South Africa, within a multivariate modelling framework, using quarterly time series data from 1980Q1 to 2017Q1.

The Augmented Dickey-Fuller (ADF) unit root test was employed to conduct the stationarity status of the variables used in this study. The results showed the existence of both I I(1) variables for Nigeria, Ghana, and South Africa. Based on the nature and order of variable integration/ stationarity, as well as existence of cointegrating long run relationships, the Toda-Yamamoto model within a VAR framework is considered the appropriate estimation method for Nigeria, Ghana, and South Africa.

CHAPTER SIX

SUMMARY OF FINDINGS, CONCLUSION, POLICY RECOMMENDATIONS, LIMITATIONS OF THE STUDY, AND AGENDA FOR FURTHER STUDIES

6.1 Introduction

The sixth chapter of this research establishes the policy recommendations for reducing carbon dioxide emissions. Section 6.1 provides an introductory statement into the focus of the chapter, while 6.2 Summary of the study's findings and section 6.3 identify key policy implications and recommendations.

The impact of carbon dioxide emission is gravely affecting both the ecosystem, humanity and causes several environmental hazards. Rapid industrialisation and urbanisation have led to an increase in energy-related carbon dioxide emissions and environmental degradation. The one of the major sources of energy in developing countries is fossil fuels, which lead to the issue of lowering the efficiency of energy consumption and increasing carbon dioxide emissions. There has been an upsurge in energy-related carbon dioxide emissions around the world and Africa due to its stage of development, which will most likely contribute to global warming and greenhouse gases emissions in the coming years.

The future energy use of Africa is expected to increase due to its growing economy, the pace of economic development, and a rapidly increasing population (USEIA, 2018). Hence this empirically examine the impact of energy consumption, financial development, foreign direct investment, gross domestic product growth, and industrial performance on carbon dioxide emissions in the three largest economies of sub - Saharan African countries namely: Nigeria, Ghana, and South Africa by applying autoregressive distributive lag model (ARDL), vector autoregressive and Toda-Yamamoto causality techniques from first quarter 1980 to first quarter 2017. The study firstly, starts with descriptive statistics analysis of all the variables for all the three the countries in which the variables response well on carbon dioxide emissions.

6.2 Summary of the study's Findings

The major findings from the first objective of the study reveal an existence of cointegration among the variables in the estimated models of the three largest economies of sub-Saharan African countries. The results confirm the African continent's pollution–haven hypothesis. Similarly, the finding from the estimated model for Nigeria illustrates a negative and significant relationship between fossil fuel energy consumption, financial development, foreign direct investments, gross domestic product growth and industrial performance and carbon dioxide emissions. The result from the model of Ghana also reveals a negative link among fossil fuel energy consumption, domestic credit provided, foreign direct investments, industrial value addition, gross domestic product growth, and carbon dioxide emissions. Signifying energy use also intensifies carbon dioxide emissions, thus confirming the reliance and dependence on fossil fuels for fiscal sustainability in the region, with attendant effects on environmental quality.

The results show a high gross domestic product growth level enhances the range of environmental degradation because of increased in carbon dioxide emissions. It effectively supports the applicability of the environmental Kuznets "inverted U-shaped" curve hypothesis. However, the outcome from South African model shows that domestic credit provided by the financial sector, foreign direct investments, economic growth, and industrial value addition increase the level of carbon dioxide emissions. This finding confirmed fossil fuel energy consumption as a key determinant of carbon dioxide emissions in the studied countries, and in the overall African continent. These results are in line with findings from the outcome of the studies by Salahuddin, et al. (2015)

In another development, the findings form the second objective reveals the estimated outcome of impulse response and variance forecasting models on fossil fuel energy use and carbon dioxide emissions nexus of the three largest economies in sub-Saharan Africa. The result from the impulse response model of Nigeria shows a positive shock among fossil fuel energy consumption and carbon dioxide emissions from the short run to long quarter periods. Similarly, the finding from the impulse response model for Ghana and South Africa also illustrates that shock in energy use accelerates the capacity of carbon dioxide emission in these countries. Moreover, the estimate from the variance decomposition in Nigeria, Ghana and South Africa reveals a positive and significant shock of fossil fuel energy consumption on carbon dioxide emission. This means fossil fuel use increase the level of carbon dioxide emissions in these countries. Moreover, the finding from the third objective show estimated model of impulse response and variance decomposition on market-induced variables and carbon dioxide emissions in Nigeria, Ghana, and South Africa.

The result of impulse response for Nigeria, Ghana and South Africa indicates negative shocks of fossil fuel energy consumption, foreign direct investments, credit provided by the financial sector and industrial performance towards carbon dioxide emissions. This finding illustrates that the overall situation from the first quarter period to last quarter these variables reduce the capacity of carbon dioxide emissions. However, domestic credit and economic growth positively influence carbon dioxide in South Africa. Nonetheless, the result from variance decomposition for Nigeria, Ghana and South Africa reveals that fossil fuel use, economic growth, foreign direct investments, and industrial performance forecast positively on the trend of carbon dioxide emissions in long-run quarter in these countries. The outcome is justified by the work of Zafar, et al. (2019).

Lastly, the outcome from the Toda-Yamamoto causality model in Nigeria shows the existence of causality between economic growth, industrial value, credit, fossil fuel energy consumption and carbon dioxide emissions. In the case of Ghana and South Africa, the result reveals no causality among the variables. However, fossil fuel energy use has no influence on carbon dioxide discharge in South Africa. Previous studies on energy, financial development, industrial performance, and carbon dioxide exists in the literature among them are Salahuddin, et al. (2015), Paramati, et al. (2017) Meng, et al. (2018) and Zafar, et al. (2019). However, none of these studies examines the influence of energy use, financial development, foreign direct investments, and industrial performance on carbon dioxide discharge for quarterly data basis in Nigeria, Ghana, and South Africa. This study examined the influence of energy use, financial development, foreign direct investments, and industrial performance on carbon dioxide discharge for quarterly data.

6.3 Conclusion

The present study empirically examines the effect of energy consumption, financial progress, foreign direct investments, and industrial performance on carbon dioxide discharge in Nigeria, Ghana, and South Africa by applying ARDL, VAR, IRF, VDF, and Toda-Yamamoto techniques from first quarter of 1980 to first quarter of 2017. The result shows the existence of cointegration among the variables. The outcome for Nigeria reveals that energy use, financial progress, foreign direct investments, and industrial performance decelerate carbon dioxide discharge. Financial development and industrial performance reduce the capacity of carbon dioxide explosion in Ghana. The estimated result from the model of South Africa illustrates that industrial performance and financial development increase carbon dioxide, while foreign direct investments negatively influence carbon dioxide discharge. However, the outcome from the causality estimate reveals causality between economic growth, industrial value, fossil fuel energy consumption, and carbon dioxide emissions in Nigeria. However, Ghana and South African estimate reveals no causality among the variables.

The findings provide broader information concerning the contribution of fossil fuel energy consumption and industrial performance on carbon dioxide in Nigeria, Ghana, and South Africa. Hence, the research is significant to Nigerian, Ghanaian and South African policymakers on the policies aimed at mitigating carbon dioxide emissions. Various studies in the literature have analyse the effect of energy consumption and industrial performance on carbon dioxide. However, the effect of quarterly data on these variables in Nigeria, Ghana and South Africa has been left uninvestigated. Therefore, the findings of this study contribute to the existing literature as none of the studies investigated these effects in Nigeria, Ghana, and South Africa.

6.4 Policy implications and Recommendations

This thesis provides its academic inputs by presenting pertinent information and evidence-based findings to relevant stakeholders in the policymaking sphere to assist them formulate suitable environmental and industrial policies towards effective maintenance of environmental quality in the sub-Saharan African region. Based on the empirical investigation of fossil fuel energy consumption, industrial performance and other market induced macro-economic variables in the three largest economies of sub-Saharan African countries namely: Nigeria, Ghana and South Africa, the following key policy implications and recommendations were offered for governments and policymakers to consider:

- It has become essential for sub-Saharan African countries to explore cleaner and greener energy sources due to the impact of fossil fuel consumption on carbon dioxide emissions. The concentration of clean and green energy should however not be strictly on industries but must also be available for household usage and transportation. In addition, low carbon household units are prerequisites for the attainment of low-carbon transition in economic development by vigorously endorsing the usage of wind power, biogas/biofuel, solar power, and other clean renewable energy. Thus, a shift towards a low-carbon economy holds potentials to evade carbon lock-in and path dependence along with the urban infrastructural development and high energy-consuming infrastructure in creating of utilities for households' consumption.

- The result of the study suggested that foreign direct investment inflow in the region have broadly enhance carbon dioxide emission across the three (3) countries, alluding to the prevalence of bulk of investments in the region that is mostly in the hydrocarbon sector, known for intense pollution and driver of environmental degradation. Therefore, this study recommends the need for governments of sub-Saharan African countries to leverage on foreign direct investment inflow to sectors where carbon emissions are low and or used to help transfer efficient green technologies from other countries. The study noted that developed countries possess notable multinational companies with state-of-the-art clean technologies, which could be transferred to developing countries. Thus, countries in sub-Saharan African region and other developing countries could consider the conduct of environmental impact assessments of foreign direct investment inflows to ensure that such investments remain green, emphasises environment-friendly economic growth, that curtail adverse effects on the environment from industrial production process. This verdict will guarantee that these developing countries attain economic growth and achieve noteworthy reduction in environmental emissions.

- The study established that financial development, proxy by credit to the private sector, enhances carbon-dioxide emissions in the three largest sub-Saharan African countries. This ultimately implies that financial development will in the long run inherently increase carbon-dioxide emissions in the environment. This situation is due to increase emissions in industries and players in the transportation sector due to investment in inefficient energy sources. The proposition to mitigate the impact of financial development on carbon dioxide emissions can be actualised through increased investment in research and development towards facilitating efficient and greener production processes, exploring green energy, and apt utilisation of solar energies. With efficient financial development, sub-Saharan African countries can afford to invest funds in research and development for green energy.

- Financial systems regulators of sub-Saharan African countries should develop regulatory incentives to encourage banking credit intermediation for businesses to adopt environmentally friendly energy sources in their production activities. This call for increased awareness of the benefits of enhancing environmental quality and heightened demand for innovative energy technologies that reduce environmental degradation.

- It is imperative for sub-Saharan African countries to design their economic development path and frameworks in such ways that do not cause a large-scale rise in greenhouse gas (GHG) emissions. The tenets of the environmental kuznets hypothesis, notwithstanding, that pollution increases with economic growth/activities, should be technically and strategically be decoupled through the adoption of innovative modern energy sources in the production process. This will effectively provide scope for tackling of several prevalent developmental challenges related to healthcare, lack of access to renewable energy-sources, amidst widespread poverty and environmentally induced socio-economic conflicts, and ultimate environmental degradation.

- Governments of sub-Saharan Africa should as a matter of urgency strengthen their environmental protection laws and regulations to avoid a situation where the region is increasingly being seen as haven for pollution by foreign companies due to lax control and monitoring. Consequently, authorities in the region should continue to pay attention to improving environmental quality through appropriate pricing, imposition of penalties/sanctions and setting of standards, as foreign energy firms, for example, often relocate their factories/companies to poorly regulated developing economies to avoid paying environmental control costs obtainable in developed countries. The practice of non-compliance of firms to extant laws will no doubt enhance emissions that directly degrade the environment.

6.5 Limitations of the Study

This study is not free from limitations despite the efforts made at obtaining robust reasonable findings. One probable inherent limitation to this study is unavailability of data on some sub-Saharan African countries. In addition, this shortage of data availability has prevented further disaggregation of some variables into different components and their inclusion in the models. This constraint is recognised while pursuing this research. However, attempt was made to overcome to a reasonable extent, and it is believed that this study can possibly provide useful information to understanding of the impact of energy consumption and industrial performance in determining carbon dioxide discharge in Nigeria, Ghana, and South Africa as well as a signal to future studies in the area.

The study-utilises variables like, fossil fuel energy consumption, foreign direct investments financial development, industrial performance, and gross domestic product growth that explain the dependents variable. Nevertheless, certain variables such as banks liquidity ratio, energy prices and other disaggregated energy variables that have been used in the earlier studies were not considered in this study. The study also considered the use of time series analysis due the fact that it provides efficient and unbiased estimation. Nonetheless, the analysis was limited to the period first quarter of 1980 to first quarter of 2017 due to the unavailability of data for long period especially those on the carbon dioxide emission variable. Furthermore, the study was limited to only Nigeria, Ghana, and South Africa due to the unavailability of data employed especially data on carbon dioxide and fossil fuel energy consumption. Moreover, the data employed, and the number sample limited the choice of using other estimations techniques such as the Generalized System of Moments (GMM), which requires a greater number of samples.

6.6 Suggestions for Further Research

Following the limitations of this study, the study suggests that further research should consider the following issues. Firstly, future studies should expand the coverage by extending the data set to cover the whole sub-Saharan African countries if data is available as the issue of carbon dioxide, fossil fuel energy consumption are not only limited to the sampled countries, but rather, the whole sub-Saharan African countries. Furthermore, this study only examines fossil fuel energy consumption as well as industrial performance and their relationship with carbon dioxide by including financial development and foreign direct investments as the determinants of carbon dioxide discharge.

However, there are other factors that determine carbon dioxide emissions, which were not included in this study. Therefore, future research should investigate these other factors such as energy prices and population density and integrate them into the relationship to see how they affect carbon dioxide discharge; also, further studies could consider panel study of sub-Saharan African countries. This will require a large data set that will include all the countries in sub–Saharan African countries. Finally, this study employed ARDL, VAR, IRF, VDF, causality, and Toda-Yamamoto techniques. Future studies may consider other approach in terms of panel analysis such as FMOLS, GMM and DOLS to study energy consumption, industrial performance, and carbon dioxide emissions in sub–Saharan African countries. Besides, future research should expand the scope of this study by making a comparison with other continents in the world to see the extent to which the result differs across different continents.

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APPENDIXES

APPENDIX 1: Impulse response and variance decomposition and Toda-Yamamoto causality

Nigeria

VAR Lag Order Selection Criteria
Endogenous variables: CO2 FD FDI FOS GDPG IP
Exogenous variables: C
Date: 09/04/22 Time: 10:03
Sample: 1980Q1 2017Q1
Included observations: 141

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-1133.978	NA	0.424280	16.16990	16.29538	16.22089
1	135.7614	2413.405	1.07e-08	-1.329949	-0.451595	-0.973016
2	457.2701	583.7321	1.86e-10	-5.379718	-3.748489*	-4.716843*
3	466.4034	15.80513	2.75e-10	-4.998629	-2.614526	-4.029812
4	481.3896	24.65822	3.75e-10	-4.700562	-1.563583	-3.425802
5	568.8007	136.3861	1.85e-10	-5.429797	-1.539944	-3.849095
6	669.2496	148.1799*	7.63e-11*	-6.343966*	-1.701238	-4.457322
7	680.9144	16.21485	1.13e-10	-5.998785	-0.603182	-3.806199
8	698.6001	23.07928	1.55e-10	-5.739009	0.409469	-3.240480

* indicates lag order selected by the criterion
LR: sequential modified LR test statistic (each test at 5% level)
FPE: Final prediction error
AIC: Akaike information criterion
SC: Schwarz information criterion
HQ: Hannan-Quinn information criterion

VAR Granger Causality/Block Exogeneity Wald Tests
Date: 09/04/22 Time: 10:01
Sample: 1980Q1 2017Q1
Included observations: 135

Dependent variable: CO2

Excluded	Chi-sq	df	Prob.
FD	17.66794	6	0.0071
FDI	2.853565	6	0.8270
FOS	12.53149	6	0.0511
GDPG	20.64562	6	0.0021
IP	29.47766	6	0.0000
All	66.07075	30	0.0002

Dependent variable: FD

Excluded	Chi-sq	df	Prob.

CO2	2.376754	6	0.8820
FDI	0.693422	6	0.9946
FOS	4.977721	6	0.5467
GDPG	1.904177	6	0.9283
IP	2.624549	6	0.8543
All	13.56539	30	0.9957

Dependent variable: FDI

Excluded	Chi-sq	df	Prob.
CO2	40.37014	6	0.0000
FD	4.374424	6	0.6261
FOS	3.099535	6	0.7963
GDPG	4.894590	6	0.5574
IP	7.117329	6	0.3101
All	56.69572	30	0.0023

Dependent variable: FOS

Excluded	Chi-sq	df	Prob.
CO2	1.888630	6	0.9297
FD	7.986798	6	0.2391
FDI	5.539876	6	0.4767
GDPG	6.950852	6	0.3254
IP	7.648394	6	0.2650
All	23.41312	30	0.7979

Dependent variable: GDPG

Excluded	Chi-sq	df	Prob.
CO2	11.63622	6	0.0706
FD	7.584822	6	0.2701
FDI	6.821386	6	0.3377
FOS	10.21623	6	0.1158
IP	12.14948	6	0.0587
All	43.11246	30	0.0573

Dependent variable: IP

Excluded	Chi-sq	df	Prob.
CO2	18.75145	6	0.0046
FD	32.59812	6	0.0000
FDI	2.309134	6	0.8892
FOS	13.86531	6	0.0312
GDPG	8.183881	6	0.2249
All	44.98924	30	0.0387

Date: 09/04/22 Time: 07:21
Sample (adjusted): 1981Q2 2017Q1
Included observations: 144 after adjustments
Trend assumption: Linear deterministic trend
Series: CO2 FD FDI FOS GDPG IP
Lags interval (in first differences): 1 to 4

Unrestricted Cointegration Rank Test (Trace)

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None *	0.338798	99.84054	95.75366	0.0254
At most 1	0.110335	40.26841	69.81889	0.9435
At most 2	0.091932	23.43326	47.85613	0.9536
At most 3	0.040266	9.546519	29.79707	0.9862
At most 4	0.024562	3.628230	15.49471	0.9312
At most 5	0.000327	0.047068	3.841466	0.8282

Trace test indicates 1 cointegrating eqn(s) at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

Unrestricted Cointegration Rank Test (Maximum Eigenvalue)

Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	0.05 Critical Value	Prob.**
None *	0.338798	59.57213	40.07757	0.0001
At most 1	0.110335	16.83516	33.87687	0.9279
At most 2	0.091932	13.88674	27.58434	0.8304
At most 3	0.040266	5.918289	21.13162	0.9845
At most 4	0.024562	3.581162	14.26460	0.9007
At most 5	0.000327	0.047068	3.841466	0.8282

Max-eigenvalue test indicates 1 cointegrating eqn(s) at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

Unrestricted Cointegrating Coefficients (normalized by b'*S11*b=I):

CO2	FD	FDI	FOS	GDPG	IP
7.693430	0.567019	0.212941	10.30344	0.145579	0.658661
2.131149	-0.320327	-0.040828	-5.141754	0.088715	-0.089442
4.002219	-0.006857	1.303330	0.657494	-0.030803	0.001419
0.704810	0.167282	0.099445	-3.413362	-0.186493	0.042929
-1.722921	0.199429	-0.420277	-9.557123	0.101756	-0.069834
5.671899	-0.002142	0.017685	5.589902	-0.050259	-0.042129

Unrestricted Adjustment Coefficients (alpha):

D(CO2)	-0.006305	-0.003157	-0.002031	-0.000193	-0.000264	3.63E-
D(FD)	-0.003891	0.057463	-0.015534	-0.030264	-0.020839	0.0023
D(FDI)	0.038915	0.032433	-0.032437	-0.004179	0.019665	-0.0006
D(FOS)	9.59E-05	-0.000559	0.000686	0.000674	0.000652	0.0001
D(GDPG)	-0.404463	0.184818	0.007491	0.180073	-0.017735	-0.0010
D(IP)	-0.159654	-0.016364	0.075284	-0.026736	0.037294	-0.0009

1 Cointegrating Equation(s): Log likelihood 536.1009

Normalized cointegrating coefficients (standard error in parentheses)

CO2	FD	FDI	FOS	GDPG	IP
1.000000	0.073702	0.027678	1.339252	0.018922	0.085613
	(0.01045)	(0.01995)	(0.20420)	(0.00457)	(0.00838)

Adjustment coefficients (standard error in parentheses)

D(CO2)	-0.048507
	(0.01052)
D(FD)	-0.029935
	(0.21152)
D(FDI)	0.299389
	(0.14381)
D(FOS)	0.000738
	(0.00836)
D(GDPG)	-3.111705
	(0.85315)
D(IP)	-1.228286
	(0.30937)

2 Cointegrating Equation(s): Log likelihood 544.5185

Normalized cointegrating coefficients (standard error in parentheses)

CO2	FD	FDI	FOS	GDPG	IP
1.000000	0.000000	0.012269	0.104825	0.026393	0.043637
		(0.04868)	(0.50112)	(0.01131)	(0.01233)
0.000000	1.000000	0.209081	16.74896	-0.101360	0.569541
		(0.64224)	(6.61155)	(0.14920)	(0.16264)

Adjustment coefficients (standard error in parentheses)

D(CO2)	-0.055234	-0.002564
	(0.01066)	(0.00087)
D(FD)	0.092528	-0.020613
	(0.21539)	(0.01757)
D(FDI)	0.368509	0.011676
	(0.14731)	(0.01202)
D(FOS)	-0.000454	0.000234
	(0.00866)	(0.00071)

D(GDPG)	-2.717829	-0.288540
	(0.87479)	(0.07136)
D(IP)	-1.263160	-0.085285
	(0.32080)	(0.02617)

3 Cointegrating Equation(s): Log likelihood 551.4619

Normalized cointegrating coefficients (standard error in parentheses)

CO2	FD	FDI	FOS	GDPG	IP
1.000000	0.000000	0.000000	0.101378	0.027733	0.045292
			(0.52222)	(0.01113)	(0.01280)
0.000000	1.000000	0.000000	16.69021	-0.078527	0.597734
			(6.32494)	(0.13479)	(0.15499)
0.000000	0.000000	1.000000	0.280980	-0.109207	-0.134847
			(3.20274)	(0.06825)	(0.07848)

Adjustment coefficients (standard error in parentheses)

D(CO2)	-0.063363	-0.002550	-0.003861
	(0.01181)	(0.00086)	(0.00175)
D(FD)	0.030358	-0.020507	-0.023420
	(0.24060)	(0.01755)	(0.03560)
D(FDI)	0.238690	0.011899	-0.035314
	(0.16261)	(0.01186)	(0.02406)
D(FOS)	0.002289	0.000229	0.000937
	(0.00967)	(0.00071)	(0.00143)
D(GDPG)	-2.687847	-0.288592	-0.083909
	(0.97855)	(0.07137)	(0.14478)
D(IP)	-0.961858	-0.085801	0.064791
	(0.35348)	(0.02578)	(0.05230)

4 Cointegrating Equation(s): Log likelihood 554.4210

Normalized cointegrating coefficients (standard error in parentheses)

CO2	FD	FDI	FOS	GDPG	IP
1.000000	0.000000	0.000000	0.000000	0.024805	0.044077
				(0.01148)	(0.01164)
0.000000	1.000000	0.000000	0.000000	-0.560441	0.397672
				(0.31431)	(0.31870)
0.000000	0.000000	1.000000	0.000000	-0.117320	-0.138215
				(0.06763)	(0.06857)
0.000000	0.000000	0.000000	1.000000	0.028874	0.011987
				(0.01833)	(0.01859)

Adjustment coefficients (standard error in parentheses)

D(CO2)	-0.063499	-0.002582	-0.003880	-0.049410
	(0.01185)	(0.00089)	(0.00175)	(0.01591)
D(FD)	0.009028	-0.025570	-0.026430	-0.242464
	(0.24005)	(0.01802)	(0.03551)	(0.32233)
D(FDI)	0.235744	0.011200	-0.035729	0.227129
	(0.16308)	(0.01224)	(0.02412)	(0.21897)
D(FOS)	0.002765	0.000342	0.001004	0.002014
	(0.00969)	(0.00073)	(0.00143)	(0.01301)
D(GDPG)	-2.560930	-0.258469	-0.066001	-5.727376
	(0.97030)	(0.07283)	(0.14352)	(1.30287)
D(IP)	-0.980702	-0.090273	0.062132	-1.420084
	(0.35389)	(0.02656)	(0.05234)	(0.47519)

5 Cointegrating Equation(s): Log likelihood 556.2116

Normalized cointegrating coefficients (standard error in parentheses)

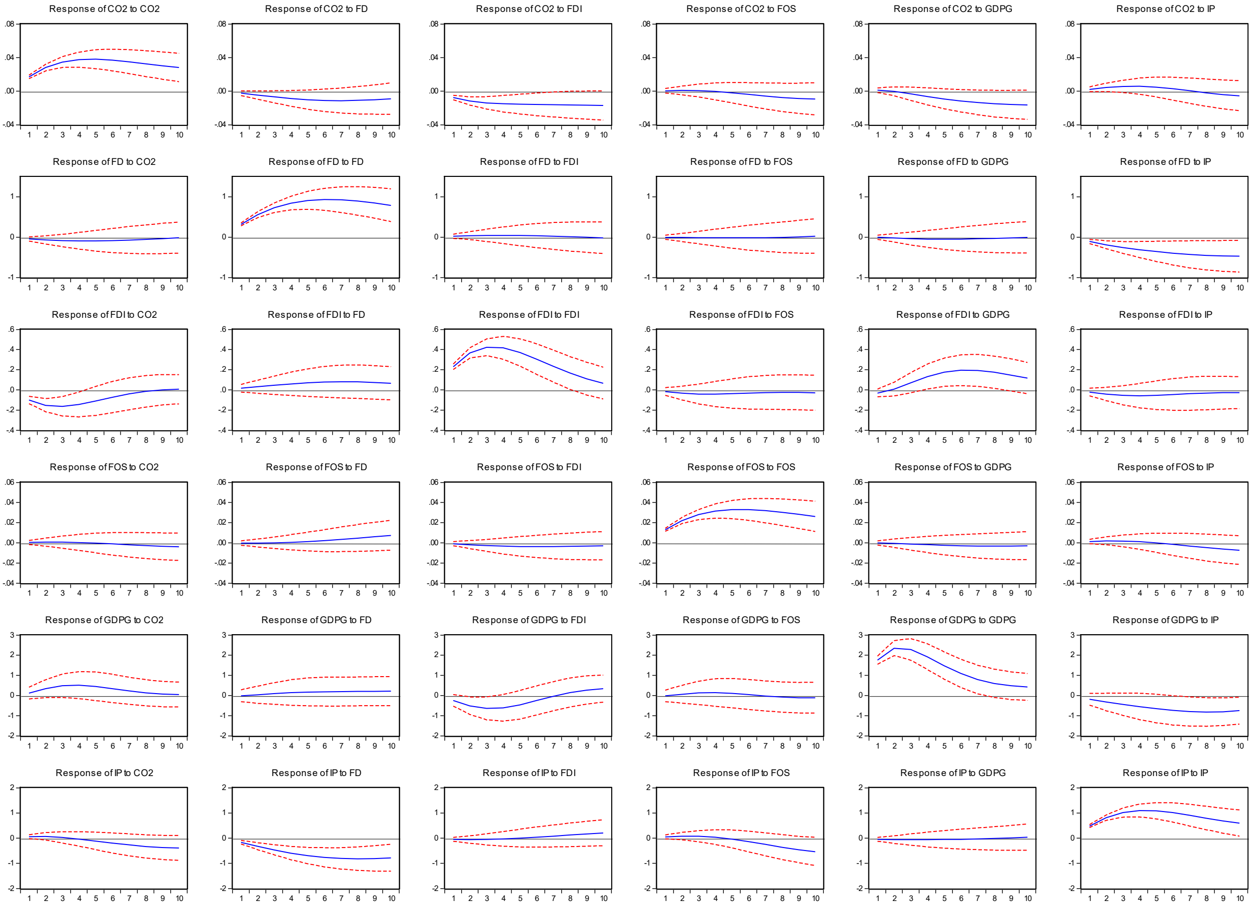
CO2	FD	FDI	FOS	GDPG	IP
1.000000	0.000000	0.000000	0.000000	0.000000	0.044936
					(0.01671)
0.000000	1.000000	0.000000	0.000000	0.000000	0.378256
					(0.17044)
0.000000	0.000000	1.000000	0.000000	0.000000	-0.142279
					(0.08327)
0.000000	0.000000	0.000000	1.000000	0.000000	0.012987
					(0.00885)
0.000000	0.000000	0.000000	0.000000	1.000000	-0.034644
					(0.48636)

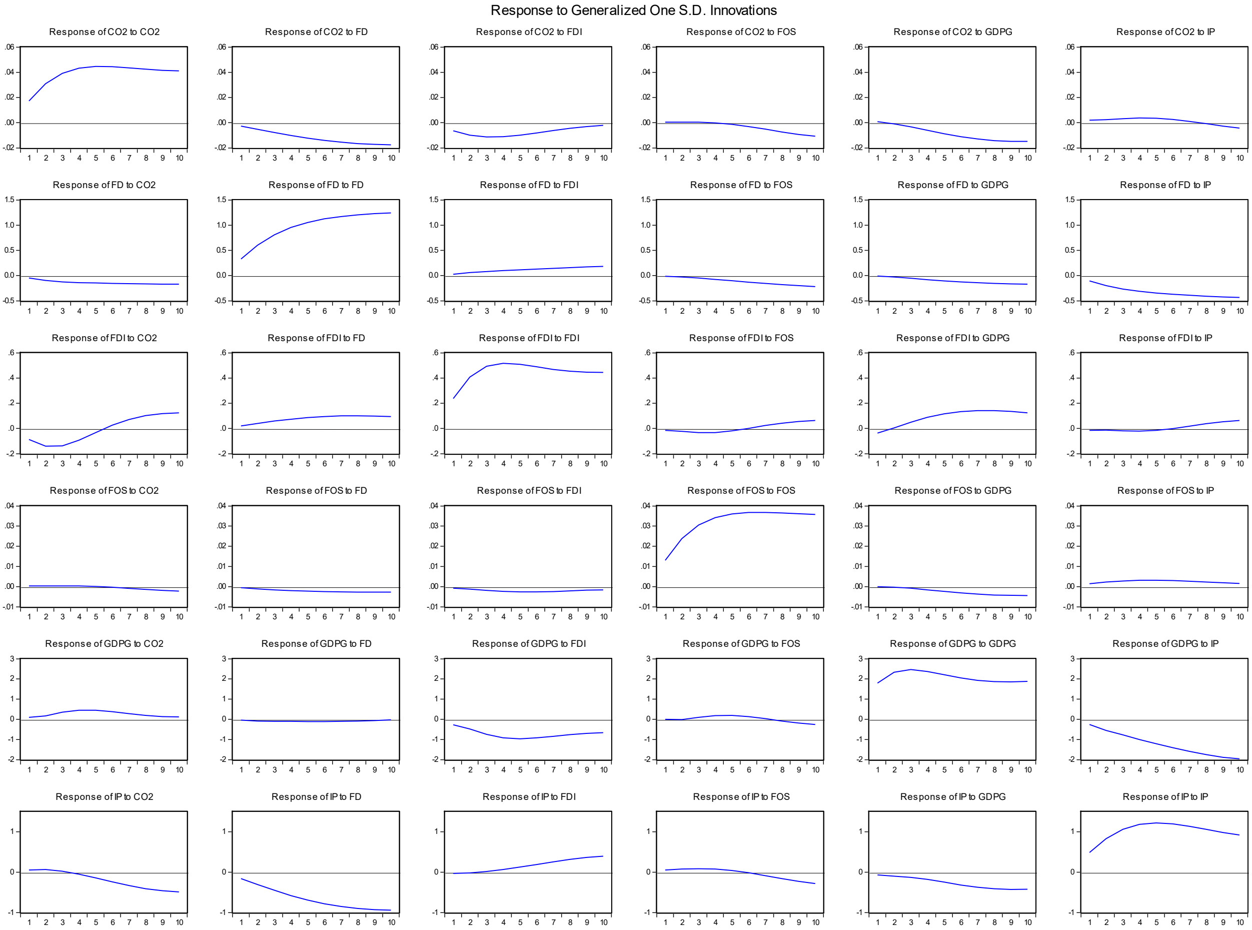
Adjustment coefficients (standard error in parentheses)

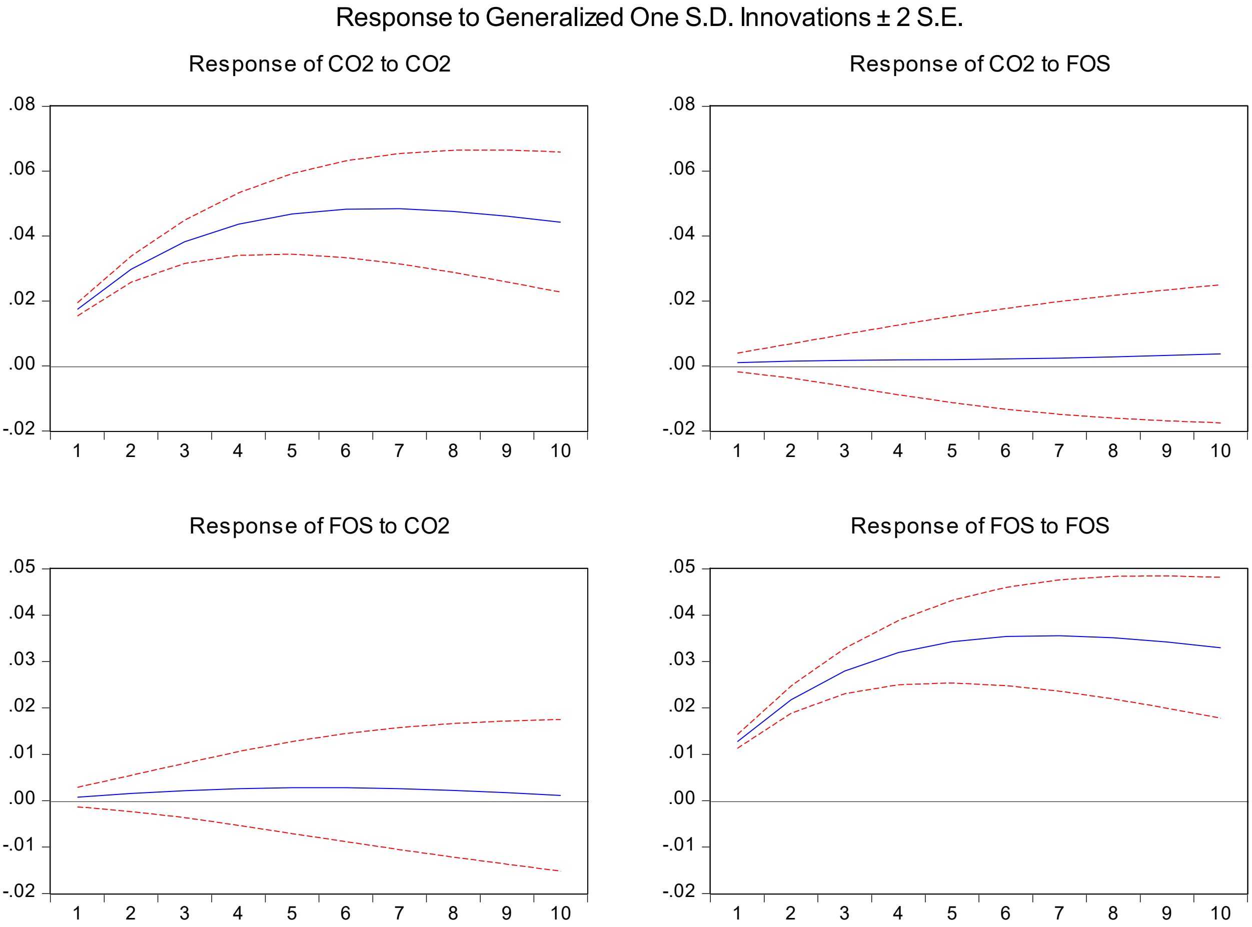
D(CO2)	-0.063044	-0.002635	-0.003769	-0.046886	-0.001126
	(0.01206)	(0.00093)	(0.00184)	(0.02032)	(0.00036)
D(FD)	0.044932	-0.029725	-0.017672	-0.043302	0.008533
	(0.24383)	(0.01875)	(0.03715)	(0.41064)	(0.00733)
D(FDI)	0.201862	0.015121	-0.043994	0.039184	0.012322
	(0.16524)	(0.01271)	(0.02518)	(0.27829)	(0.00497)
D(FOS)	0.001641	0.000472	0.000730	-0.004222	-0.000116
	(0.00985)	(0.00076)	(0.00150)	(0.01659)	(0.00030)
D(GDPG)	-2.530373	-0.262006	-0.058548	-5.557878	-0.078103
	(0.98797)	(0.07596)	(0.15055)	(1.66387)	(0.02969)
D(IP)	-1.044957	-0.082836	0.046458	-1.776512	-0.018232
	(0.35901)	(0.02760)	(0.05471)	(0.60463)	(0.01079)

Impulse response Nigeria

Response to Generalized One S.D. Innovations ± 2 S.E.




Response to Generalized One S.D. Innovations
Response of CO2 to CO2
Response of CO2 to FD
Response of CO2 to FDI
Response of CO2 to FOS
Response of CO2 to GDPG
Response of CO2 to IP
Response of FD to CO2
Response of FD to FD
Response of FD to FDI
Response of FD to FOS
Response of FD to GDPG
Response of FD to IP
Response of FDI to CO2
Response of FDI to FD
Response of FDI to FDI
Response of FDI to FOS
Response of FDI to GDPG
Response of FDI to IP
Response of FOS to CO2
Response of FOS to FD
Response of FOS to FDI
Response of FOS to FOS
Response of FOS to GDPG
Response of FOS to IP
Response of GDPG to CO2
Response of GDPG to FD
Response of GDPG to FDI
Response of GDPG to FOS
Response of GDPG to GDPG
Response of GDPG to IP
Response of IP to CO2
Response of IP to FD
Response of IP to FDI
Response of IP to FOS
Response of IP to GDPG
Response of IP to IP

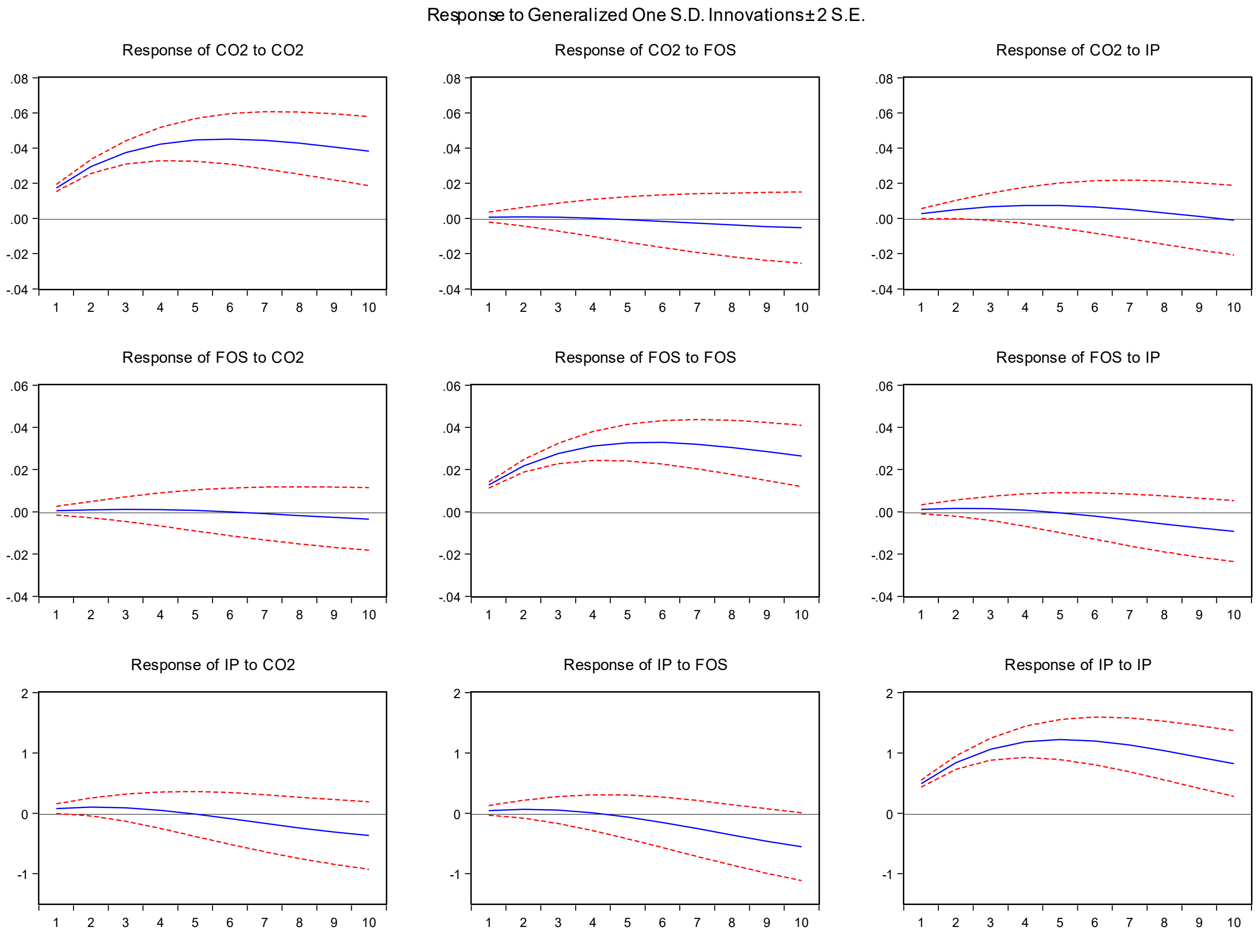


Variance decomposition Nigeria

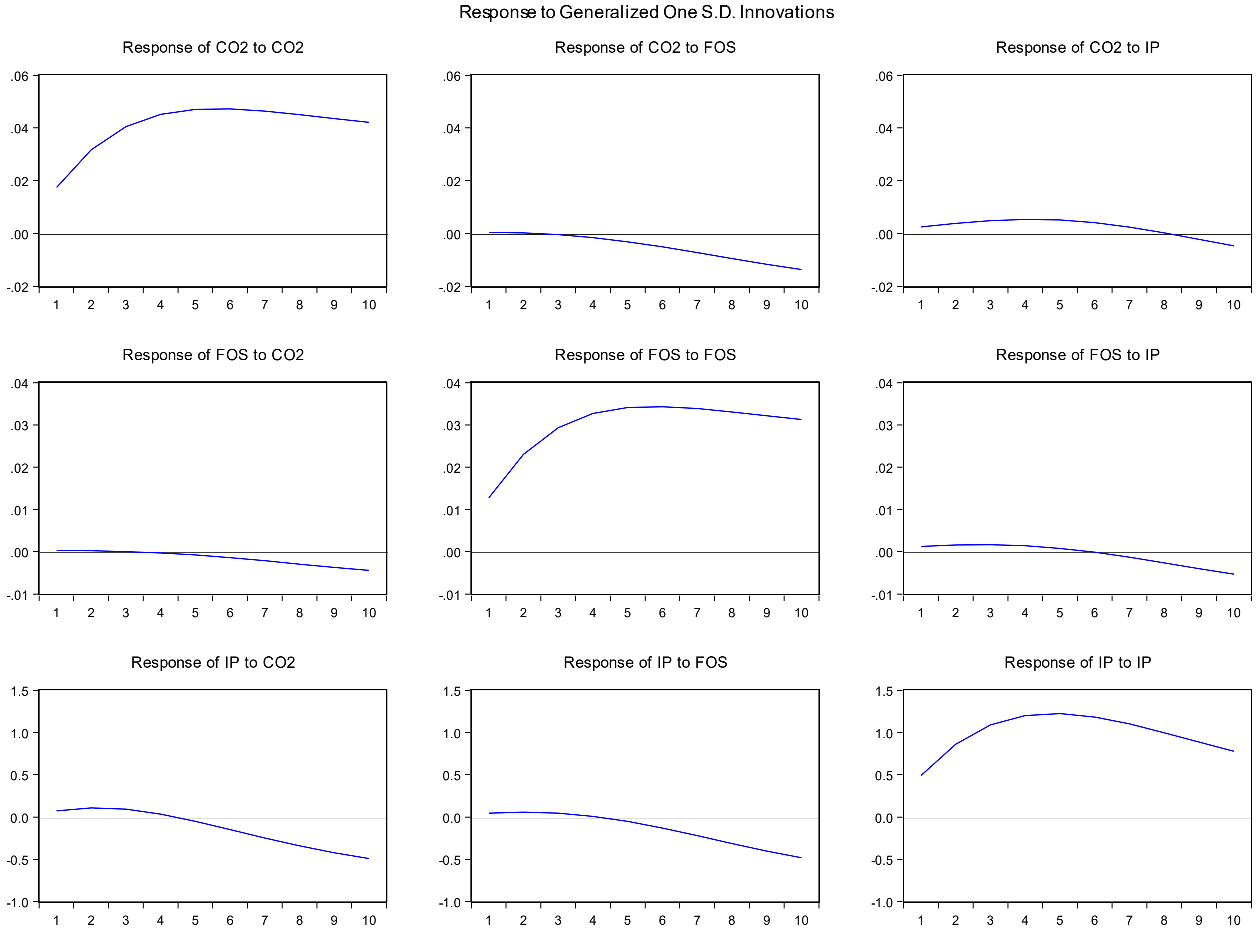
Variance Decomposition of CO2: Period	S.E.	CO2	FD	FDI	FOS	GDPG	IP
1	0.017293	100.0000	0.000000	0.000000	0.000000	0.000000	0.000000
2	0.035600	99.01208	0.026661	0.209376	0.014419	0.462561	0.274901
3	0.053449	97.85498	0.130021	0.502493	0.017800	1.094373	0.400334
4	0.069670	96.34161	0.337874	0.884249	0.036687	1.880686	0.518895
5	0.084102	94.40248	0.656631	1.355049	0.100539	2.778199	0.707105
6	0.096992	92.03324	1.067563	1.906275	0.250181	3.723213	1.019524
7	0.108701	89.32149	1.530064	2.514403	0.516958	4.631010	1.486074
8	0.119555	86.43896	1.993569	3.144559	0.903539	5.419859	2.099516
9	0.129783	83.60290	2.412494	3.758030	1.379404	6.034067	2.813104
10	0.139515	81.01996	2.757018	4.320677	1.891985	6.454869	3.555495

Variance Decomposition of FD:

NIGERIA



Response to Generalized One S.D. Innovations ± 2 S.E.
Response of CO2 to CO2
Response of CO2 to FOS
Response of CO2 to IP
Response of FOS to CO2
Response of FOS to FOS
Response of FOS to IP
Response of IP to CO2
Response of IP to FOS
Response of IP to IP



VARIANCE DECOM

Variance Decomposition of CO2: Period	S.E.	CO2	FOS	IP
1	0.017449	100.0000	0.000000	0.000000
2	0.036172	99.93223	0.025027	0.042742
3	0.054331	99.86836	0.081445	0.050199
4	0.070705	99.75824	0.192209	0.049550
5	0.085038	99.55003	0.390778	0.059193
6	0.097473	99.19176	0.711280	0.096958
7	0.108313	98.62890	1.180177	0.190919
8	0.117899	97.81650	1.808765	0.374736
9	0.126549	96.73477	2.588808	0.676418
10	0.134530	95.39850	3.492966	1.108532

Variance Decomposition of FOS: Period	S.E.	CO2	FOS	IP
1	0.012756	0.066390	99.93361	0.000000

2	0.026334	0.023303	99.92942	0.047275
3	0.039468	0.010413	99.89347	0.096117
4	0.051298	0.009223	99.83577	0.155005
5	0.061662	0.021337	99.73443	0.244236
6	0.070673	0.054988	99.56004	0.384973
7	0.078536	0.119139	99.28372	0.597137
8	0.085470	0.219230	98.88510	0.895669
9	0.091669	0.355003	98.35819	1.286812
10	0.097300	0.520581	97.71318	1.766241

Variance Decomposition of IP: Period	S.E.	CO2	FOS	IP
1	0.490857	2.147041	0.853758	96.99920
2	0.992671	1.740101	0.527391	97.73251
3	1.477027	1.183967	0.326254	98.48978
4	1.911949	0.738548	0.196529	99.06492
5	2.287904	0.565971	0.185605	99.24842
6	2.607366	0.761876	0.379296	98.85883
7	2.878843	1.366285	0.863603	97.77011
8	3.112957	2.365330	1.694614	95.94006
9	3.319876	3.695730	2.879622	93.42465
10	3.507855	5.258382	4.374068	90.36755

Cholesky Ordering: CO2 FOS IP

APPENDIX 2: Impulse response and variance decomposition and Toda-Yamamoto causality

Ghana

VAR Lag Order Selection Criteria
Endogenous variables: CO2 FD FDI FOS GDPG IP
Exogenous variables: C
Date: 09/04/22 Time: 10:06
Sample: 1980Q1 2017Q1
Included observations: 141

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-1781.389	NA	4128.914	25.35303	25.47851	25.40402
1	-127.8468	3142.902	4.48e-07	2.409174	3.287528	2.766107
2	150.7392	505.8014	1.44e-08	-1.031762	0.599467*	-0.368887
3	161.0871	17.90710	2.09e-08	-0.667903	1.716201	0.300915
4	186.8762	42.43299	2.44e-08	-0.523066	2.613913	0.751694
5	397.8432	329.1684	2.09e-09	-3.004868	0.884986	-1.424166
6	498.8033	148.9340	8.57e-10	-3.926288	0.716441	-2.039643
7	528.9848	41.95448	9.73e-10	-3.843756	1.551847	-1.651170
8	654.7118	164.0692*	2.90e-10*	-5.116479*	1.031999	-2.617950*

* indicates lag order selected by the criterion
LR: sequential modified LR test statistic (each test at 5% level)
FPE: Final prediction error
AIC: Akaike information criterion
SC: Schwarz information criterion
HQ: Hannan-Quinn information criterion

VAR Granger Causality/Block Exogeneity Wald Tests
Date: 09/04/22 Time: 10:08
Sample: 1980Q1 2017Q1
Included observations: 131

Dependent variable: CO2

Excluded	Chi-sq	df	Prob.
FD	5.568740	8	0.6954
FDI	3.623159	8	0.8894
FOS	78.59650	8	0.0000
GDPG	17.43800	8	0.0259
IP	4.445924	8	0.8148
All	129.3149	40	0.0000

Dependent variable: FD

Excluded	Chi-sq	df	Prob.
CO2	5.622040	8	0.6895
FDI	3.107491	8	0.9274
FOS	10.14145	8	0.2552
GDPG	8.211693	8	0.4131
IP	9.634200	8	0.2916

All	42.76392	40	0.3533

Dependent variable: FDI

Excluded	Chi-sq	df	Prob.
CO2	5.524988	8	0.7003
FD	5.828360	8	0.6665
FOS	10.88224	8	0.2085
GDPG	7.658577	8	0.4675
IP	20.45998	8	0.0087
All	73.21050	40	0.0010

Dependent variable: FOS

Excluded	Chi-sq	df	Prob.
CO2	7.346246	8	0.4998
FD	6.611623	8	0.5791
FDI	16.27358	8	0.0386
GDPG	12.06151	8	0.1485
IP	1.171874	8	0.9969
All	56.93926	40	0.0401

Dependent variable: GDPG

Excluded	Chi-sq	df	Prob.
CO2	10.62615	8	0.2238
FD	19.34467	8	0.0131
FDI	11.18685	8	0.1913
FOS	11.81412	8	0.1597
IP	18.49432	8	0.0178
All	54.09793	40	0.0675

Dependent variable: IP

Excluded	Chi-sq	df	Prob.
CO2	14.96455	8	0.0598
FD	9.645847	8	0.2908
FDI	9.766311	8	0.2818
FOS	11.69413	8	0.1654
GDPG	12.43362	8	0.1329
All	44.00591	40	0.3058

Date: 09/04/22 Time: 07:29
Sample (adjusted): 1981Q2 2017Q1
Included observations: 144 after adjustments
Trend assumption: Linear deterministic trend
Series: CO2 FD FDI FOS GDPG IP
Lags interval (in first differences): 1 to 4

Unrestricted Cointegration Rank Test (Trace)

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None *	0.849199	344.5724	95.75366	0.0000
At most 1 *	0.214705	72.15442	69.81889	0.0322
At most 2	0.125550	37.35025	47.85613	0.3312
At most 3	0.060970	18.03118	29.79707	0.5637
At most 4	0.060218	8.972471	15.49471	0.3679
At most 5	0.000202	0.029074	3.841466	0.8646

Trace test indicates 2 cointegrating eqn(s) at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

Unrestricted Cointegration Rank Test (Maximum Eigenvalue)

Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	0.05 Critical Value	Prob.**
None *	0.849199	272.4180	40.07757	0.0001
At most 1 *	0.214705	34.80418	33.87687	0.0387
At most 2	0.125550	19.31907	27.58434	0.3903
At most 3	0.060970	9.058706	21.13162	0.8277
At most 4	0.060218	8.943397	14.26460	0.2909
At most 5	0.000202	0.029074	3.841466	0.8646

Max-eigenvalue test indicates 2 cointegrating eqn(s) at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

Unrestricted Cointegrating Coefficients (normalized by b'*S11*b=I):

CO2	FD	FDI	FOS	GDPG	IP
-1.718250	-0.057473	-0.024701	11.49071	-0.039084	0.024341
-0.694776	0.321161	0.124341	-9.501048	0.129119	-0.134749
0.220741	-0.198542	0.383672	-18.66993	0.087444	0.240550
-0.554741	0.212495	0.564320	-65.36143	-0.340551	0.116832
-0.108171	0.339086	-0.590697	-9.893706	-0.113740	0.052391
-1.479430	0.146590	0.174666	-54.19535	0.318896	-0.041723

Unrestricted Adjustment Coefficients (alpha):

D(CO2)	4.069014	0.152754	-0.000216	0.013433	-0.008469	0.001991
D(FD)	-0.014937	-0.029669	0.050150	0.005980	0.007061	-0.002641
D(FDI)	-0.004940	0.031103	-0.015562	-0.018326	0.021467	-0.001665
D(FOS)	-0.000122	0.000277	0.000169	2.70E-05	-6.82E-05	-1.85E-06
D(GDPG)	0.011165	0.021213	-0.121510	0.148768	-0.003344	-0.002463
D(IP)	0.036647	-0.041899	-0.036492	-0.011823	-0.073031	-0.002058

1 Cointegrating Equation(s):		Log likelihood	372.0229		

Normalized cointegrating coefficients (standard error in parentheses)

CO2	FD	FDI	FOS	GDPG	IP
1.000000	0.033449	0.014376	-6.687451	0.022747	-0.014166
	(0.01192)	(0.02050)	(1.77787)	(0.01115)	(0.00689)

Adjustment coefficients (standard error in parentheses)

D(CO2)	-6.991581
	(0.27727)
D(FD)	0.025666
	(0.03879)
D(FDI)	0.008488
	(0.02888)
D(FOS)	0.000210
	(0.00013)
D(GDPG)	-0.019185
	(0.11329)
D(IP)	-0.062968
	(0.05722)

2 Cointegrating Equation(s):		Log likelihood	389.4250		

Normalized cointegrating coefficients (standard error in parentheses)

CO2	FD	FDI	FOS	GDPG	IP
1.000000	0.000000	0.001329	-5.313442	0.008671	-0.000123
		(0.02369)	(1.96783)	(0.01301)	(0.00792)
0.000000	1.000000	0.390037	-41.07821	0.420799	-0.419836
		(0.44820)	(37.2362)	(0.24610)	(0.14979)

Adjustment coefficients (standard error in parentheses)

D(CO2)	-7.097711	-0.184800
	(0.29794)	(0.05245)
D(FD)	0.046280	-0.008670
	(0.04154)	(0.00731)
D(FDI)	-0.013121	0.010273
	(0.03069)	(0.00540)
D(FOS)	1.74E-05	9.59E-05
	(0.00013)	(2.4E-05)
D(GDPG)	-0.033923	0.006171
	(0.12214)	(0.02150)
D(IP)	-0.033858	-0.015563
	(0.06130)	(0.01079)

3 Cointegrating Equation(s):		Log likelihood	399.0845		

Normalized cointegrating coefficients (standard error in parentheses)

CO2	FD	FDI	FOS	GDPG	IP
1.000000	0.000000	0.000000	-5.239438	0.008184	-0.000577
			(1.25808)	(0.01292)	(0.00748)
0.000000	1.000000	0.000000	-19.36561	0.277693	-0.552909
			(21.7117)	(0.22290)	(0.12916)
0.000000	0.000000	1.000000	-55.66801	0.366904	0.341182
			(26.4684)	(0.27173)	(0.15746)

Adjustment coefficients (standard error in parentheses)

D(CO2)	-7.097759	-0.184757	-0.081597
	(0.30005)	(0.06140)	(0.06496)
D(FD)	0.057350	-0.018627	0.015921
	(0.04093)	(0.00838)	(0.00886)

D(FDI)	-0.016556	0.013363	-0.001981
	(0.03079)	(0.00630)	(0.00667)
D(FOS)	5.47E-05	6.24E-05	0.000102
	(0.00013)	(2.7E-05)	(2.9E-05)
D(GDPG)	-0.060745	0.030296	-0.044258
	(0.12122)	(0.02480)	(0.02624)
D(IP)	-0.041913	-0.008317	-0.020116
	(0.06142)	(0.01257)	(0.01330)

4 Cointegrating Equation(s): Log likelihood 403.6139

Normalized cointegrating coefficients (standard error in parentheses)

CO2	FD	FDI	FOS	GDPG	IP
1.000000	0.000000	0.000000	0.000000	0.104539	-0.007213
				(0.03589)	(0.01669)
0.000000	1.000000	0.000000	0.000000	0.633834	-0.577438
				(0.28395)	(0.13203)
0.000000	0.000000	1.000000	0.000000	1.390662	0.270672
				(0.61226)	(0.28468)
0.000000	0.000000	0.000000	1.000000	0.018390	-0.001267
				(0.00718)	(0.00334)

Adjustment coefficients (standard error in parentheses)

D(CO2)	-7.105211	-0.181903	-0.074017	44.43056
	(0.31301)	(0.07026)	(0.11157)	(11.1868)
D(FD)	0.054033	-0.017356	0.019295	-1.216881
	(0.04269)	(0.00958)	(0.01522)	(1.52566)
D(FDI)	-0.006390	0.009469	-0.012323	1.136069
	(0.03196)	(0.00717)	(0.01139)	(1.14209)
D(FOS)	3.97E-05	6.82E-05	0.000117	-0.008946
	(0.00014)	(3.1E-05)	(4.9E-05)	(0.00491)
D(GDPG)	-0.143273	0.061908	0.039695	-7.528385
	(0.12362)	(0.02775)	(0.04406)	(4.41809)
D(IP)	-0.035354	-0.010830	-0.026788	2.273252
	(0.06404)	(0.01437)	(0.02283)	(2.28871)

5 Cointegrating Equation(s): Log likelihood 408.0856

Normalized cointegrating coefficients (standard error in parentheses)

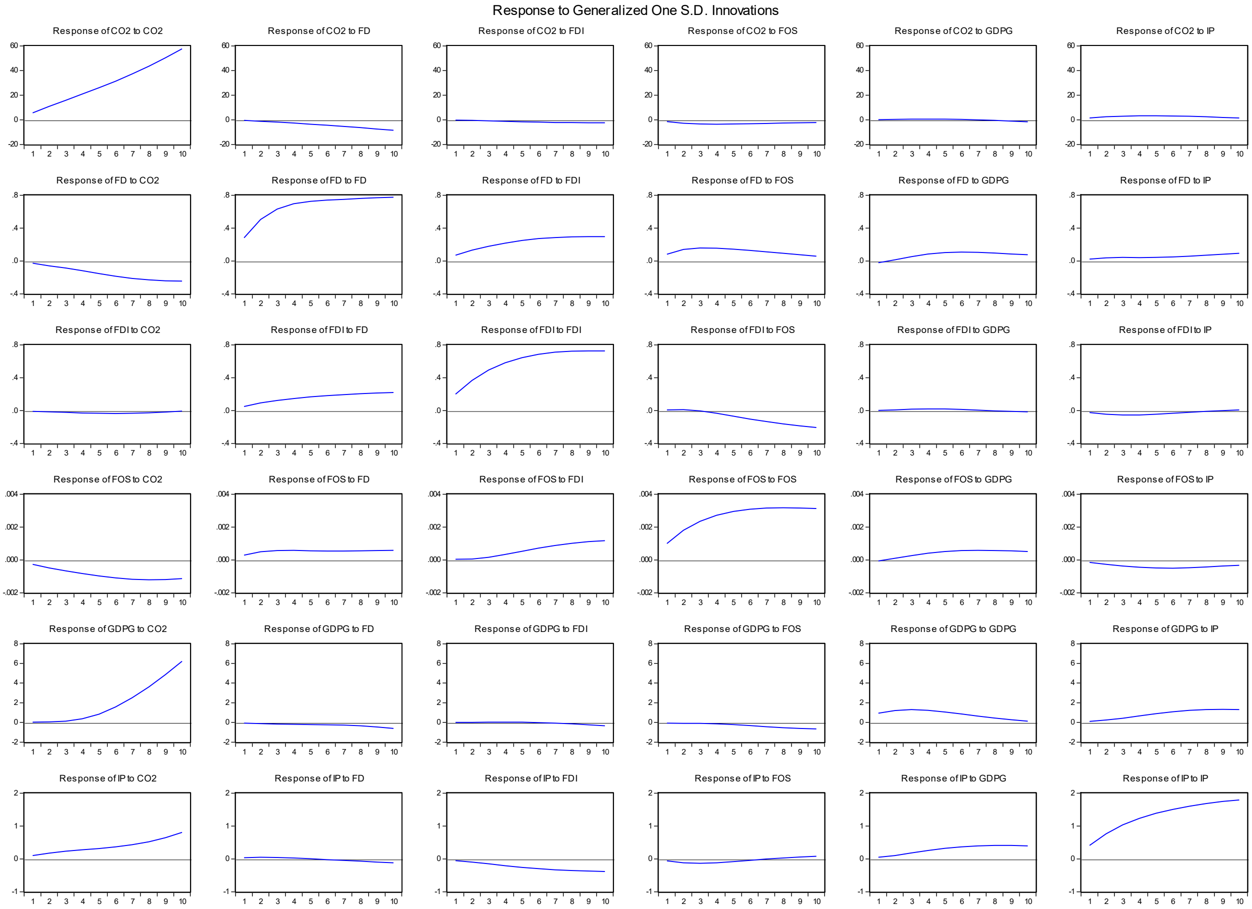
CO2	FD	FDI	FOS	GDPG	IP
1.000000	0.000000	0.000000	0.000000	0.000000	-0.067367
					(0.01611)
0.000000	1.000000	0.000000	0.000000	0.000000	-0.942155
					(0.15358)
0.000000	0.000000	1.000000	0.000000	0.000000	-0.529536
					(0.15944)
0.000000	0.000000	0.000000	1.000000	0.000000	-0.011849
					(0.00258)
0.000000	0.000000	0.000000	0.000000	1.000000	0.575415
					(0.23960)

Adjustment coefficients (standard error in parentheses)

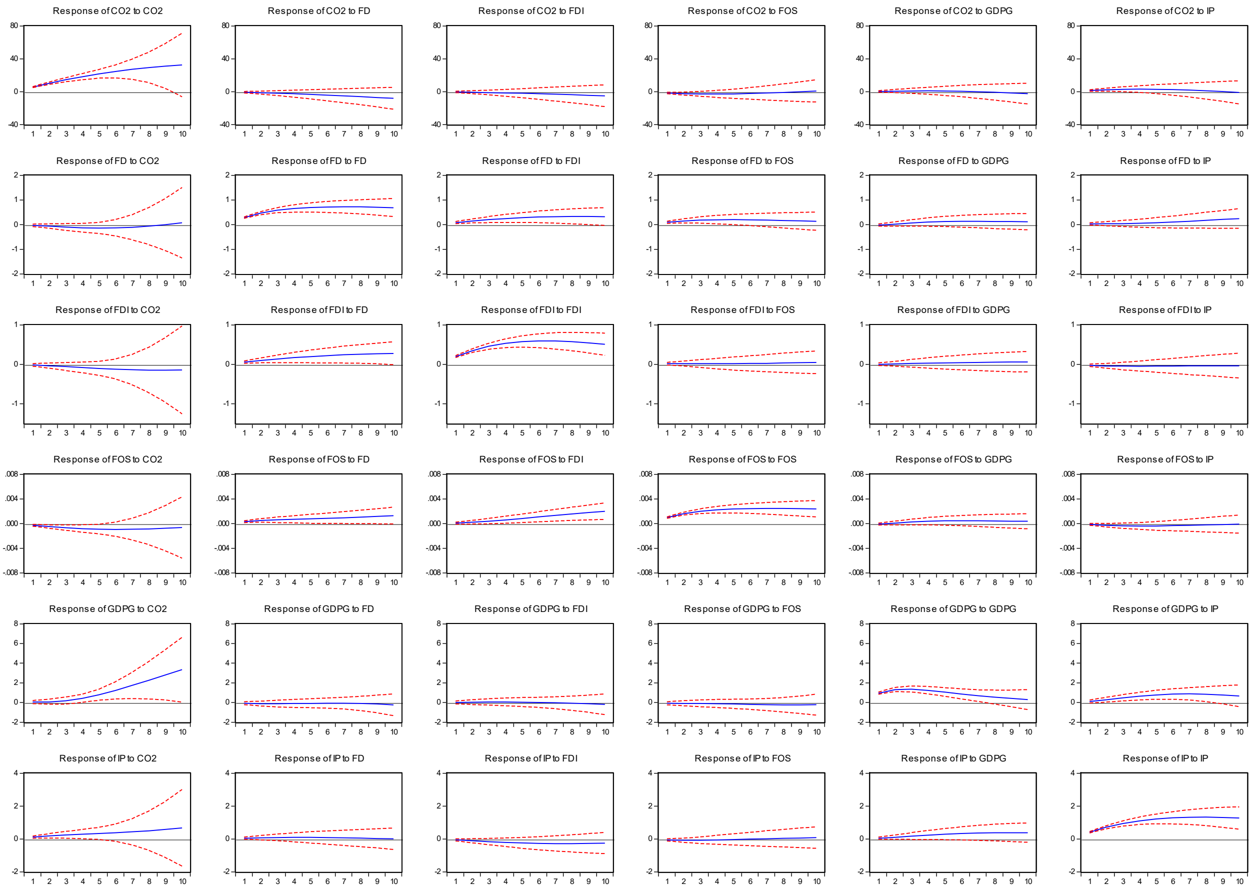
D(CO2)	-7.104295	-0.184775	-0.069014	44.51435	-0.142941
	(0.31349)	(0.08892)	(0.14651)	(11.2991)	(0.06324)
D(FD)	0.053269	-0.014962	0.015124	-1.286743	-0.001701
	(0.04274)	(0.01212)	(0.01997)	(1.54032)	(0.00862)
D(FDI)	-0.008712	0.016748	-0.025004	0.923679	0.006648
	(0.03177)	(0.00901)	(0.01485)	(1.14518)	(0.00641)
D(FOS)	4.71E-05	4.50E-05	0.000158	-0.008271	5.38E-05
	(0.00014)	(3.9E-05)	(6.4E-05)	(0.00494)	(2.8E-05)

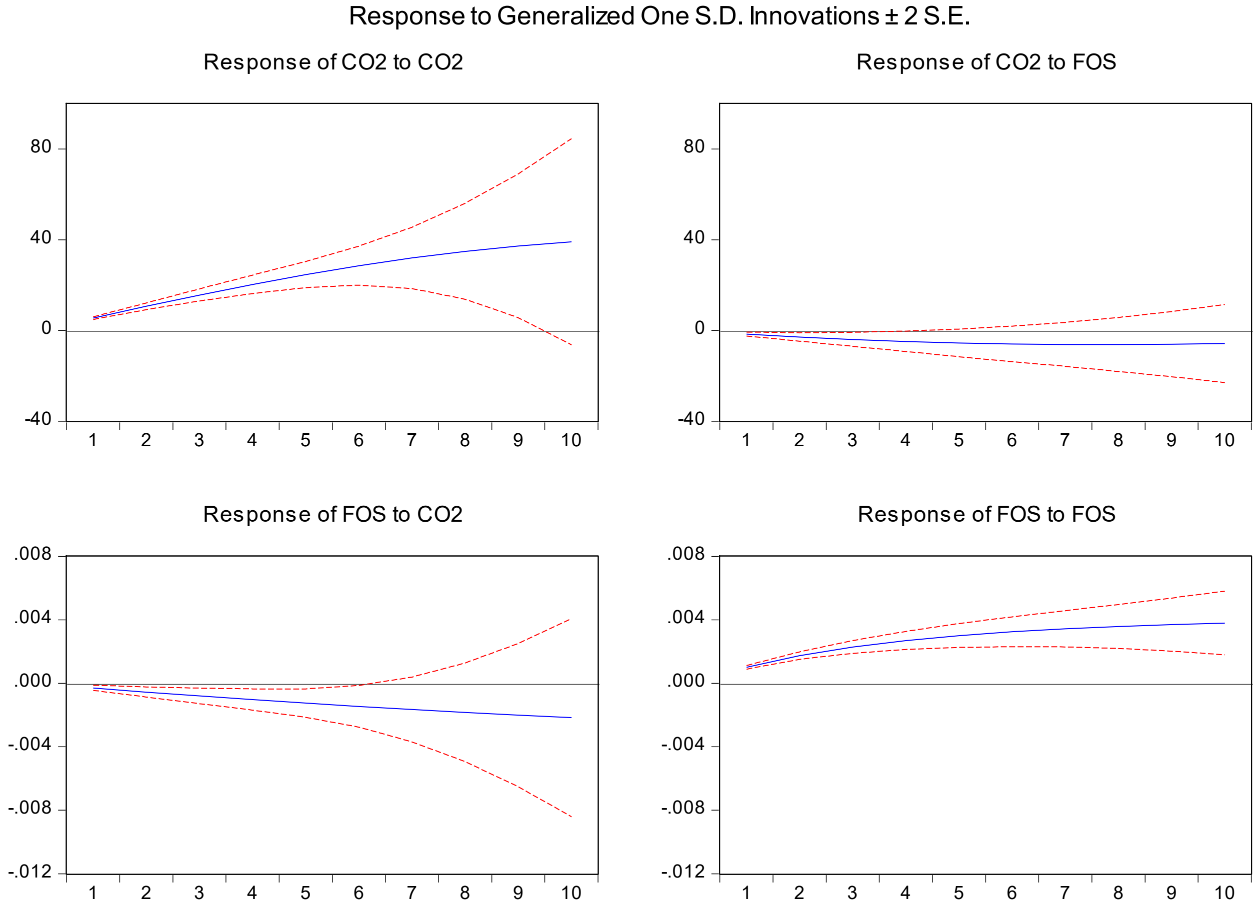
D(GDPG)	-0.142911	0.060775	0.041670	-7.495305	-0.058606
	(0.12381)	(0.03512)	(0.05786)	(4.46247)	(0.02497)
D(IP)	-0.027454	-0.035593	0.016351	2.995795	0.002300
	(0.06278)	(0.01781)	(0.02934)	(2.26290)	(0.01266)

Impulse response Ghana



Response to Generalized One S.D. Innovations ± 2 S.E.





Variance decompo Ghana

Variance Decomposition of CO2: Period	S.E.	CO2	FD	FDI	FOS	GDPG	IP
1	5.574958	100.0000	0.000000	0.000000	0.000000	0.000000	0.000000
2	12.20418	99.90151	0.003290	0.006795	0.041609	0.001062	0.045731
3	20.08047	99.42112	0.021054	0.005020	0.349270	0.000393	0.203138
4	29.12297	98.55650	0.050133	0.002540	0.944152	0.000224	0.446454
5	39.35791	97.45510	0.082872	0.001392	1.720597	0.001564	0.738479
6	50.87325	96.25752	0.113001	0.000958	2.567164	0.007995	1.053364
7	63.78872	95.06245	0.137033	0.001704	3.399720	0.022910	1.376179
8	78.23881	93.92810	0.153987	0.004610	4.166574	0.047630	1.699097
9	94.36248	92.88239	0.164506	0.010275	4.843448	0.081261	2.018118
10	112.2978	91.93365	0.169972	0.018679	5.425201	0.121520	2.330980

Variance Decomposition of FD: Period	S.E.	CO2	FD	FDI	FOS	GDPG	IP
1	0.280023	1.066038	98.93396	0.000000	0.000000	0.000000	0.000000
2	0.578970	1.306589	97.82175	0.003808	0.038404	0.817532	0.011919

3	0.864428	1.585789	96.44912	0.055332	0.182320	1.692514	0.034921
4	1.121070	2.060043	94.82111	0.188759	0.431287	2.453015	0.045784
5	1.350471	2.709554	93.10580	0.382451	0.772904	2.989072	0.040219
6	1.558633	3.463935	91.42512	0.592322	1.197179	3.291215	0.030225
7	1.751018	4.225180	89.87324	0.780437	1.691885	3.398907	0.030351
8	1.931386	4.907766	88.50771	0.925704	2.239008	3.372555	0.047259
9	2.101975	5.462394	87.35197	1.022608	2.815187	3.269220	0.078625
10	2.264032	5.878238	86.40168	1.075717	3.395063	3.131838	0.117460

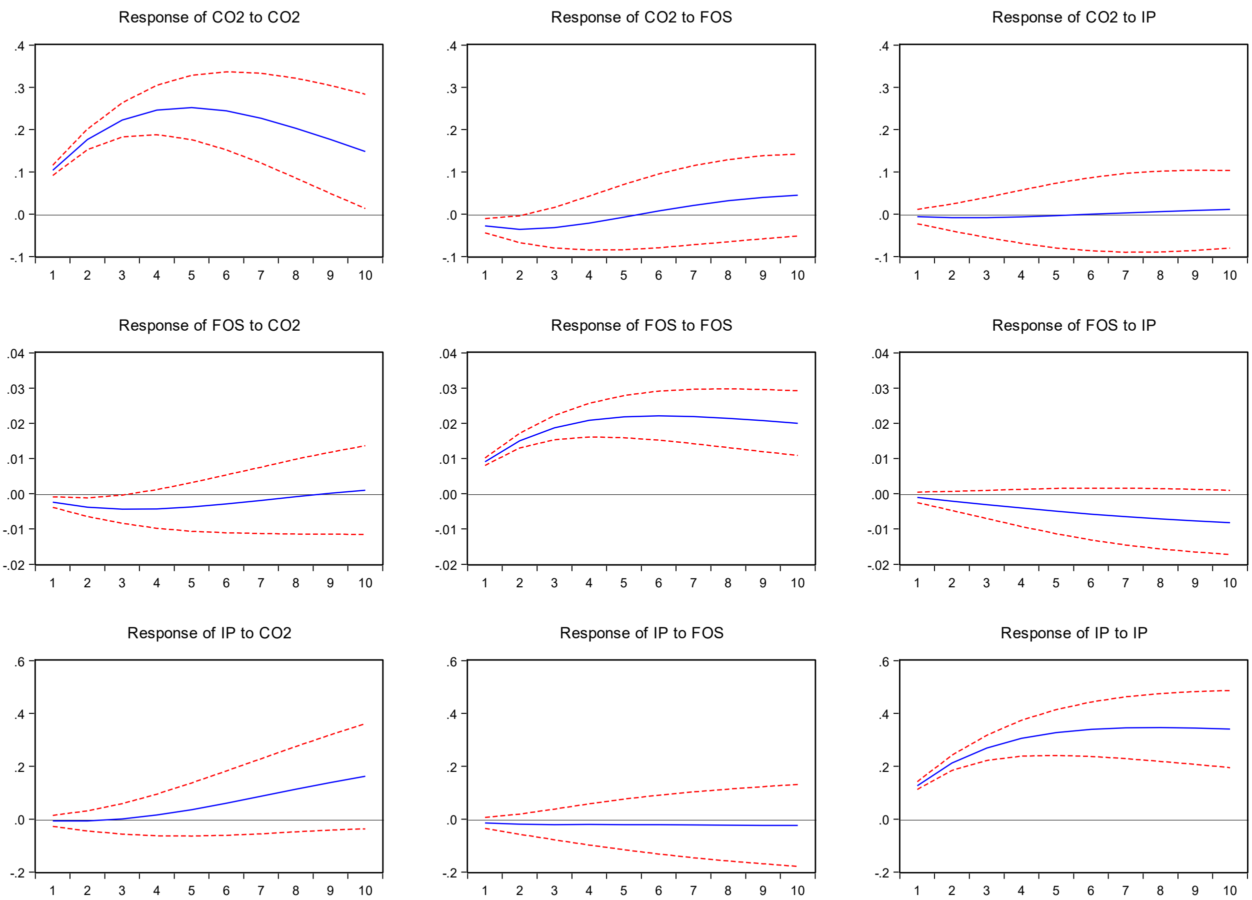
Variance Decomposition of FDI: Period	S.E.	CO2	FD	FDI	FOS	GDPG	IP
1	0.197967	0.281272	6.024381	93.69435	0.000000	0.000000	0.000000
2	0.417025	0.236358	6.066195	93.66117	0.000464	0.035810	5.88E-06
3	0.645267	0.230473	6.086767	93.48955	0.116586	0.071222	0.005405
4	0.870724	0.240897	6.104744	93.05404	0.493057	0.079860	0.027400
5	1.087607	0.252615	6.155371	92.33355	1.119213	0.069136	0.070114
6	1.293021	0.254901	6.253681	91.38191	1.927078	0.052401	0.130026
7	1.485756	0.243407	6.396706	90.28049	2.840762	0.039778	0.198854
8	1.665607	0.220101	6.572519	89.11188	3.792362	0.035929	0.267214
9	1.832965	0.191029	6.766677	87.94652	4.727220	0.041069	0.327480
10	1.988573	0.163288	6.965792	86.83743	5.605424	0.052934	0.375126

Variance Decomposition of FOS: Period	S.E.	CO2	FD	FDI	FOS	GDPG	IP
1	0.000989	7.820223	7.015768	0.252489	84.91152	0.000000	0.000000
2	0.002066	7.633382	6.148027	0.238782	84.84014	1.138273	0.001395
3	0.003156	7.750458	5.185466	0.102402	84.75183	2.207901	0.001943
4	0.004215	8.204856	4.278955	0.216749	84.18827	3.109707	0.001463
5	0.005224	8.821081	3.556738	0.641052	83.21357	3.755204	0.012354
6	0.006173	9.467826	3.031725	1.291341	81.99590	4.162783	0.050430
7	0.007054	10.03529	2.671960	2.061739	80.72651	4.379907	0.124594
8	0.007863	10.44593	2.438775	2.867334	79.55336	4.461661	0.232936
9	0.008602	10.65739	2.299390	3.650942	78.57179	4.455736	0.364748
10	0.009276	10.65949	2.228043	4.378617	77.83088	4.397929	0.505043

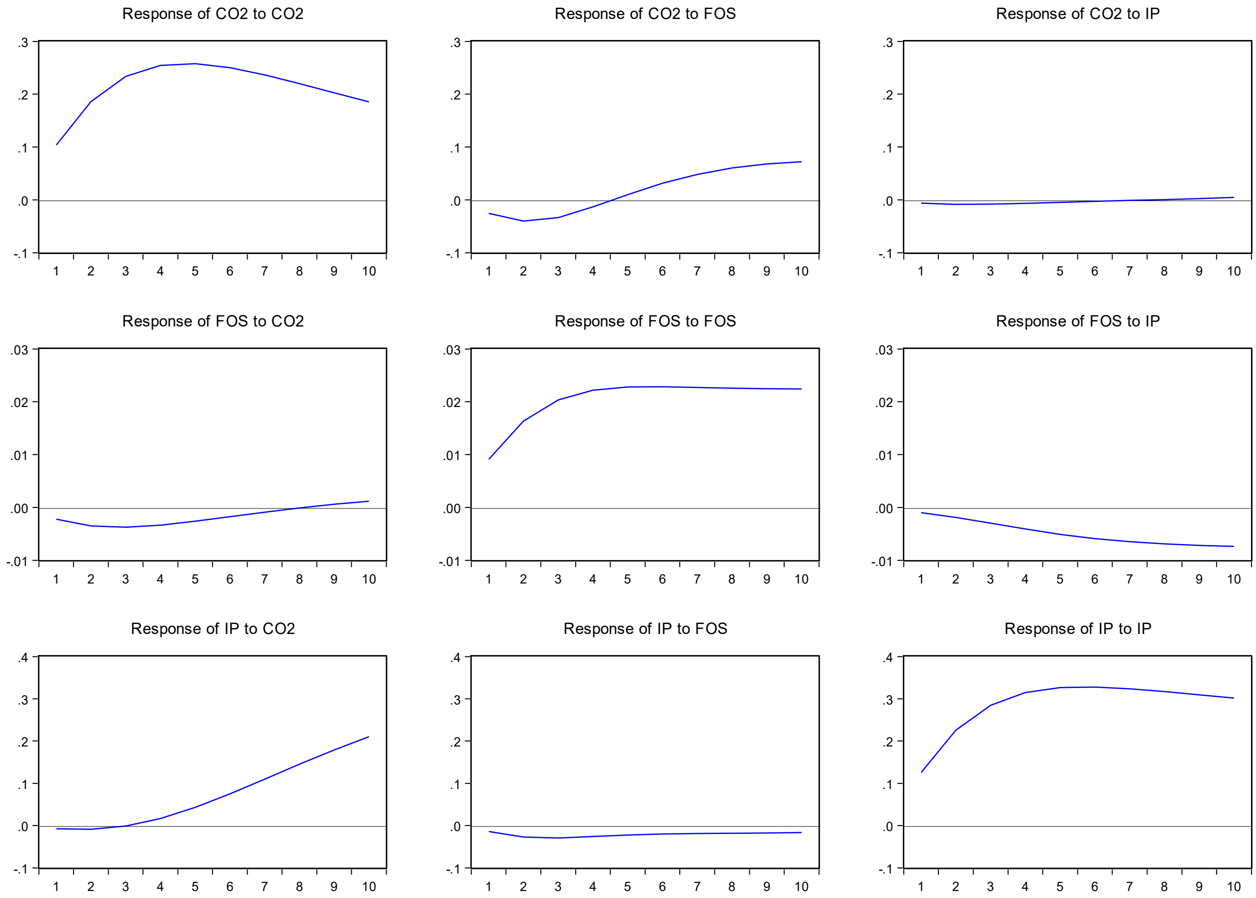
Variance Decomposition of GDPG: Period	S.E.	CO2	FD	FDI	FOS	GDPG	IP
1	0.924948	0.080113	0.565802	0.043243	0.210243	99.10060	0.000000
2	1.518296	0.200927	0.779061	0.104263	0.215586	98.15079	0.549369
3	2.033837	0.431665	1.000226	0.212316	0.144946	95.60346	2.607393
4	2.457800	2.458894	1.080455	0.309374	0.101029	90.07536	5.974892
5	2.877729	10.36519	0.968753	0.352970	0.131214	78.83432	9.347544
6	3.451863	27.71938	0.715141	0.312034	0.305890	60.42568	10.52187
7	4.359175	50.20284	0.450095	0.216576	0.671721	39.71633	8.742435
8	5.714028	69.08172	0.263361	0.129022	1.187881	23.54055	5.797470
9	7.548226	81.02761	0.153489	0.073942	1.782980	13.54584	3.416139
10	9.851476	87.48667	0.091012	0.043706	2.411000	7.952333	2.015281

Variance Decomposition of IP: Period	S.E.	CO2	FD	FDI	FOS	GDPG	IP
1	0.410572	6.132577	1.051057	2.173963	1.770373	1.122382	87.74965
2	0.868234	5.431394	0.824204	2.049998	1.791267	1.545898	88.35724
3	1.350457	5.157059	0.594901	2.244508	1.352884	2.337045	88.31360
4	1.835008	5.024858	0.413333	2.550050	0.899901	3.162557	87.94930
5	2.313336	5.000578	0.284098	2.849102	0.576568	3.880787	87.40887
6	2.781775	5.141875	0.199370	3.087356	0.418706	4.413684	86.73901
7	3.238901	5.531274	0.147199	3.248810	0.418394	4.742254	85.91207
8	3.684990	6.268536	0.116299	3.336879	0.553606	4.882451	84.84223
9	4.122261	7.470342	0.098174	3.361593	0.802943	4.865653	83.40130
10	4.555191	9.263161	0.087339	3.332766	1.151043	4.725524	81.44017
Cholesky Ordering: CO2 FD FDI FOS GDPG IP							

Response to Generalized One S.D. Innovations ± 2 S.E.



Response to Generalized One S.D. Innovations



VARIANCE DECOMPO

Variance Decomposition of CO2: Period	S.E.	CO2	FOS	IP
1	0.103863	100.0000	0.000000	0.000000
2	0.213179	99.89959	0.077376	0.023031
3	0.317342	99.25642	0.656739	0.086840
4	0.410187	97.88030	1.932634	0.187067
5	0.490735	95.94226	3.750476	0.307263
6	0.559633	93.73046	5.838210	0.431329
7	0.618012	91.48676	7.962421	0.550814
8	0.667163	89.36099	9.974661	0.664353
9	0.708407	87.42377	11.80182	0.774412
10	0.743017	85.69378	13.42160	0.884617

Variance Decomposition of FOS: Period	S.E.	CO2	FOS	IP
1	0.009090	6.108490	93.89151	0.000000

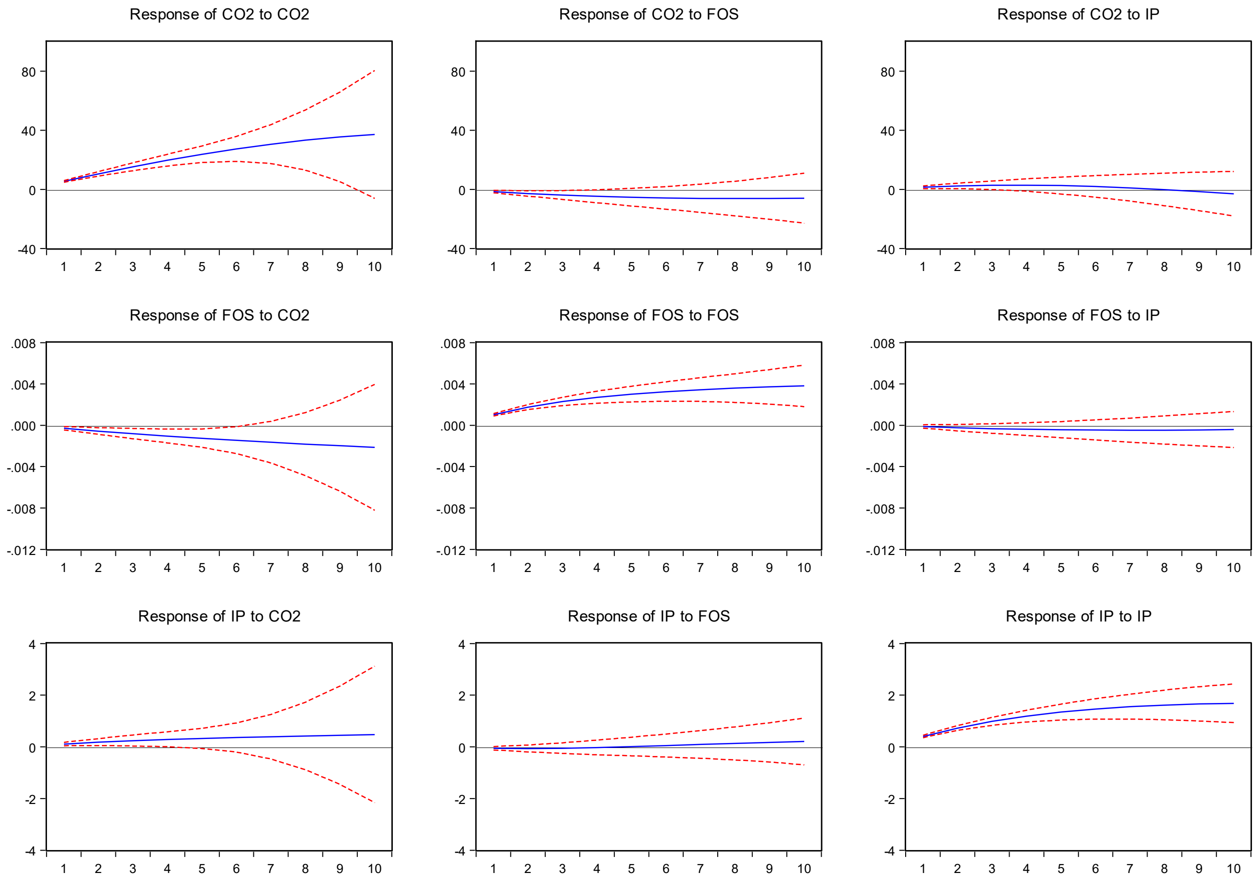
2	0.018694	4.920279	95.07923	0.000493
3	0.027675	4.059549	95.89744	0.043008
4	0.035557	3.344700	96.47058	0.184717
5	0.042406	2.735845	96.84430	0.419858
6	0.048429	2.232020	97.06057	0.707406
7	0.053830	1.835312	97.15946	1.005229
8	0.058771	1.540044	97.17505	1.284905
9	0.063372	1.333091	97.13431	1.532599
10	0.067715	1.197646	97.05758	1.744772

Variance Decomposition of IP: Period	S.E.	CO2	FOS	IP
1	0.126021	0.347208	1.706592	97.94620
2	0.258516	0.201516	1.755326	98.04316
3	0.384979	0.091792	1.425470	98.48274
4	0.498797	0.165726	1.057379	98.77689
5	0.600197	0.625061	0.770343	98.60460
6	0.691721	1.642364	0.580303	97.77733
7	0.776353	3.301626	0.473559	96.22481
8	0.856701	5.577734	0.434707	93.98756
9	0.934694	8.354051	0.452406	91.19354
10	1.011549	11.46290	0.518255	88.01885

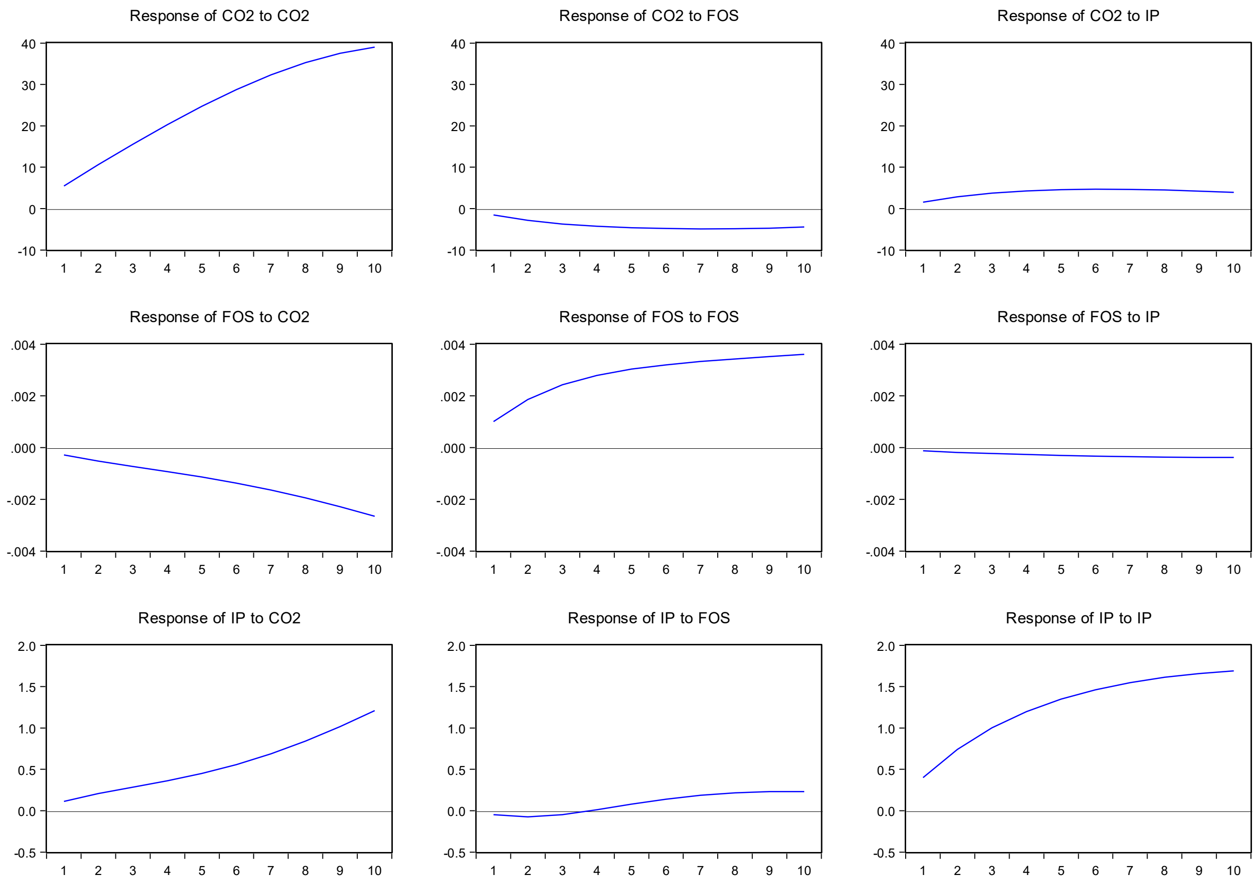
Cholesky Ordering: CO2 FOS IP

GHANA

Response to Generalized One S.D. Innovations±2 S.E.



Response to Generalized One S.D. Innovations



VARIANCE DECOMPO

Variance Decomposition of CO2: Period	S.E.	CO2	FOS	IP
1	5.451628	100.0000	0.000000	0.000000
2	11.91112	99.97101	0.016472	0.012516
3	19.61747	99.75766	0.133238	0.109100
4	28.30235	99.35020	0.354293	0.295509
5	37.74077	98.82104	0.632165	0.546796
6	47.70968	98.23763	0.926024	0.836342
7	57.97699	97.64438	1.213665	1.141953
8	68.30178	97.06636	1.487080	1.446562
9	78.43923	96.51608	1.746382	1.737535
10	88.14771	95.99872	1.995604	2.005677
Variance Decomposition of FOS: Period	S.E.	CO2	FOS	IP
1	0.001004	8.035280	91.96472	0.000000
2	0.002111	8.031865	91.93525	0.032882
3	0.003218	8.600976	91.33022	0.068809
4	0.004265	9.605619	90.29202	0.102357
5	0.005244	11.04420	88.81482	0.140979
6	0.006166	12.94857	86.85824	0.193185
7	0.007048	15.35066	84.38171	0.267633
8	0.007910	18.26151	81.36566	0.372835
9	0.008771	21.65660	77.82721	0.516193
10	0.009648	25.46872	73.82860	0.702676
Variance Decomposition of IP: Period	S.E.	CO2	FOS	IP
1	0.400639	7.821996	0.178592	91.99941
2	0.843320	7.763920	0.083653	92.15243
3	1.311738	7.910130	0.103570	91.98630
4	1.785434	8.364882	0.508415	91.12670
5	2.255451	9.218819	1.243229	89.53795
6	2.717940	10.55226	2.167426	87.28031
7	3.172494	12.43771	3.158237	84.40405
8	3.621464	14.93098	4.130865	80.93816
9	4.069294	18.05567	5.031815	76.91251
10	4.521721	21.78792	5.829155	72.38292

Cholesky Ordering: CO2 FOS IP

APPENDIX 3: Impulse response and variance decomposition and Toda-Yamamoto causality

South Africa

VAR Lag Order Selection Criteria
Endogenous variables: CO2 FD FDI FOS GDPG IP
Exogenous variables: C
Date: 09/04/22 Time: 10:11
Sample: 1980Q1 2017Q1
Included observations: 141

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-1332.880	NA	7.127366	18.99120	19.11668	19.04219
1	74.78371	2675.559	2.53e-08	-0.465017	0.413337	-0.108084
2	350.6753	500.9096	8.45e-10	-3.867735	-2.236506*	-3.204860
3	367.8095	29.65064	1.11e-09	-3.600135	-1.216031	-2.631318
4	392.2911	40.28184	1.33e-09	-3.436754	-0.299775	-2.161994
5	500.4479	168.7552	4.87e-10	-4.460254	-0.570400	-2.879552
6	646.4951	215.4456*	1.05e-10*	-6.021208*	-1.378479	-4.134564*
7	656.8960	14.45791	1.59e-10	-5.658099	-0.262496	-3.465513
8	670.1417	17.28518	2.33e-10	-5.335343	0.813135	-2.836814

* indicates lag order selected by the criterion
LR: sequential modified LR test statistic (each test at 5% level)
FPE: Final prediction error
AIC: Akaike information criterion
SC: Schwarz information criterion
HQ: Hannan-Quinn information criterion

VAR Granger Causality/Block Exogeneity Wald Tests
Date: 09/04/22 Time: 10:17
Sample: 1980Q1 2017Q1
Included observations: 135

Dependent variable: CO2

Excluded	Chi-sq	df	Prob.
FD	3.832659	6	0.6993
FDI	6.222138	6	0.3988
FOS	4.228128	6	0.6458
GDPG	0.438287	6	0.9985
IP	0.914594	6	0.9886
All	19.58750	30	0.9268

Dependent variable: FD

Excluded	Chi-sq	df	Prob.
CO2	1.267136	6	0.9734

FDI	8.616984	6	0.1963
FOS	12.10675	6	0.0596
GDPG	0.697373	6	0.9945
IP	9.951108	6	0.1267
All	49.61091	30	0.0136

Dependent variable: FDI

Excluded	Chi-sq	df	Prob.
CO2	5.510822	6	0.4801
FD	11.91834	6	0.0638
FOS	9.866574	6	0.1304
GDPG	6.220861	6	0.3989
IP	14.01919	6	0.0294
All	41.46276	30	0.0795

Dependent variable: FOS

Excluded	Chi-sq	df	Prob.
CO2	6.261657	6	0.3945
FD	28.49753	6	0.0001
FDI	32.97575	6	0.0000
GDPG	11.01770	6	0.0878
IP	7.563214	6	0.2719
All	58.98318	30	0.0012

Dependent variable: GDPG

Excluded	Chi-sq	df	Prob.
CO2	4.513092	6	0.6076
FD	28.03433	6	0.0001
FDI	10.70062	6	0.0981
FOS	6.861338	6	0.3339
IP	23.54132	6	0.0006
All	79.14093	30	0.0000

Dependent variable: IP

Excluded	Chi-sq	df	Prob.
CO2	2.445770	6	0.8745
FD	10.63951	6	0.1002
FDI	1.014277	6	0.9851
FOS	19.87404	6	0.0029
GDPG	17.77245	6	0.0068
All	54.87653	30	0.0037

Date: 09/04/22 Time: 07:35
Sample (adjusted): 1981Q2 2017Q1
Included observations: 144 after adjustments
Trend assumption: Linear deterministic trend
Series: CO2 FD FDI FOS GDPG IP
Lags interval (in first differences): 1 to 4

Unrestricted Cointegration Rank Test (Trace)

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None *	0.290542	124.4531	95.75366	0.0001
At most 1 *	0.214890	75.02453	69.81889	0.0181
At most 2	0.117508	40.18637	47.85613	0.2159
At most 3	0.089889	22.18564	29.79707	0.2883
At most 4	0.048245	8.622436	15.49471	0.4015
At most 5	0.010376	1.501913	3.841466	0.2204

Trace test indicates 2 cointegrating eqn(s) at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

Unrestricted Cointegration Rank Test (Maximum Eigenvalue)

Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	0.05 Critical Value	Prob.**
None *	0.290542	49.42854	40.07757	0.0034
At most 1 *	0.214890	34.83816	33.87687	0.0383
At most 2	0.117508	18.00073	27.58434	0.4951
At most 3	0.089889	13.56321	21.13162	0.4019
At most 4	0.048245	7.120523	14.26460	0.4750
At most 5	0.010376	1.501913	3.841466	0.2204

Max-eigenvalue test indicates 2 cointegrating eqn(s) at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

Unrestricted Cointegrating Coefficients (normalized by b'*S11*b=I):

CO2	FD	FDI	FOS	GDPG	IP
-0.982572	0.067824	0.267496	-0.602735	0.530995	0.547248
-0.934344	-0.028268	-1.072400	0.821306	0.129490	-0.038463
-0.462940	0.172012	-0.632115	-0.202712	-0.283603	0.914813
-0.640809	-0.132502	1.638285	10.46690	-0.152521	-0.081697
0.117145	0.107288	0.345917	-12.93340	-0.516403	0.154771
1.873781	0.028386	0.044092	-4.914379	-0.040756	0.021458

Unrestricted Adjustment Coefficients (alpha):

D(CO2)	0.030798	0.000977	0.006172	0.007034	0.005342	-0.005923
D(FD)	-0.181950	0.232896	-0.313463	-0.004042	-0.087946	-0.060332
D(FDI)	0.041360	0.057982	-0.001517	-0.051446	-0.009168	-0.001713
D(FOS)	0.001841	-0.000754	-0.000940	-0.000217	0.000482	0.000575
D(GDPG)	-0.144101	0.009490	-0.004300	-0.035560	0.093897	-0.015970

D(IP)	-0.002874	-0.035643	0.014089	-0.021441	-0.005084	-0.001424

1 Cointegrating Equation(s): Log likelihood 468.6387

Normalized cointegrating coefficients (standard error in parentheses)

CO2	FD	FDI	FOS	GDPG	IP
1.000000	-0.069027	-0.272241	0.613426	-0.540413	-0.556954
	(0.03724)	(0.30797)	(2.31877)	(0.11529)	(0.15060)

Adjustment coefficients (standard error in parentheses)

D(CO2)	-0.030261
	(0.00766)
D(FD)	0.178779
	(0.11727)
D(FDI)	-0.040639
	(0.02049)
D(FOS)	-0.001808
	(0.00067)
D(GDPG)	0.141590
	(0.04723)
D(IP)	0.002824
	(0.01050)

2 Cointegrating Equation(s): Log likelihood 486.0578

Normalized cointegrating coefficients (standard error in parentheses)

CO2	FD	FDI	FOS	GDPG	IP
1.000000	0.000000	0.715033	-0.424219	-0.261039	-0.141103
		(0.26020)	(1.50776)	(0.10549)	(0.07001)
0.000000	1.000000	14.30280	-15.03252	4.047333	6.024510
		(4.51941)	(26.1887)	(1.83229)	(1.21601)

Adjustment coefficients (standard error in parentheses)

D(CO2)	-0.031174	0.002061
	(0.01057)	(0.00057)
D(FD)	-0.038826	-0.018924
	(0.15919)	(0.00863)
D(FDI)	-0.094814	0.001166
	(0.02733)	(0.00148)
D(FOS)	-0.001104	0.000146
	(0.00093)	(5.0E-05)
D(GDPG)	0.132723	-0.010042
	(0.06517)	(0.00353)
D(IP)	0.036127	0.000813
	(0.01378)	(0.00075)

3 Cointegrating Equation(s): Log likelihood 495.0581

Normalized cointegrating coefficients (standard error in parentheses)

CO2	FD	FDI	FOS	GDPG	IP
1.000000	0.000000	0.000000	0.142006	-0.546043	-0.189472
			(1.59633)	(0.10685)	(0.06779)
0.000000	1.000000	0.000000	-3.706343	-1.653579	5.056979
			(15.3245)	(1.02577)	(0.65074)
0.000000	0.000000	1.000000	-0.791885	0.398587	0.067646
			(1.80433)	(0.12078)	(0.07662)

Adjustment coefficients (standard error in parentheses)

D(CO2)	-0.034031	0.003123	0.003289

	(0.01114)	(0.00145)	(0.00990)
D(FD)	0.106289	-0.072843	-0.100284
	(0.16305)	(0.02129)	(0.14490)
D(FDI)	-0.094112	0.000905	-0.050158
	(0.02888)	(0.00377)	(0.02567)
D(FOS)	-0.000669	-1.55E-05	0.001895
	(0.00097)	(0.00013)	(0.00086)
D(GDPG)	0.134713	-0.010781	-0.046005
	(0.06886)	(0.00899)	(0.06119)
D(IP)	0.029604	0.003236	0.028549
	(0.01445)	(0.00189)	(0.01284)

4 Cointegrating Equation(s): Log likelihood 501.8397

Normalized cointegrating coefficients (standard error in parentheses)

CO2	FD	FDI	FOS	GDPG	IP
1.000000	0.000000	0.000000	0.000000	-0.528866	-0.193922
				(0.10239)	(0.03457)
0.000000	1.000000	0.000000	0.000000	-2.101874	5.173126
				(1.08745)	(0.36712)
0.000000	0.000000	1.000000	0.000000	0.302806	0.092462
				(0.10229)	(0.03453)
0.000000	0.000000	0.000000	1.000000	-0.120953	0.031337
				(0.03305)	(0.01116)

Adjustment coefficients (standard error in parentheses)

D(CO2)	-0.038538	0.002191	0.014812	0.054607
	(0.01216)	(0.00178)	(0.01607)	(0.08147)
D(FD)	0.108879	-0.072308	-0.106905	0.322186
	(0.17862)	(0.02609)	(0.23613)	(1.19701)
D(FDI)	-0.061145	0.007722	-0.134440	-0.515476
	(0.03075)	(0.00449)	(0.04065)	(0.20609)
D(FOS)	-0.000530	1.32E-05	0.001540	-0.003806
	(0.00106)	(0.00016)	(0.00141)	(0.00712)
D(GDPG)	0.157501	-0.006070	-0.104262	-0.276681
	(0.07526)	(0.01099)	(0.09949)	(0.50435)
D(IP)	0.043344	0.006077	-0.006578	-0.254820
	(0.01552)	(0.00227)	(0.02052)	(0.10401)

5 Cointegrating Equation(s): Log likelihood 505.4000

Normalized cointegrating coefficients (standard error in parentheses)

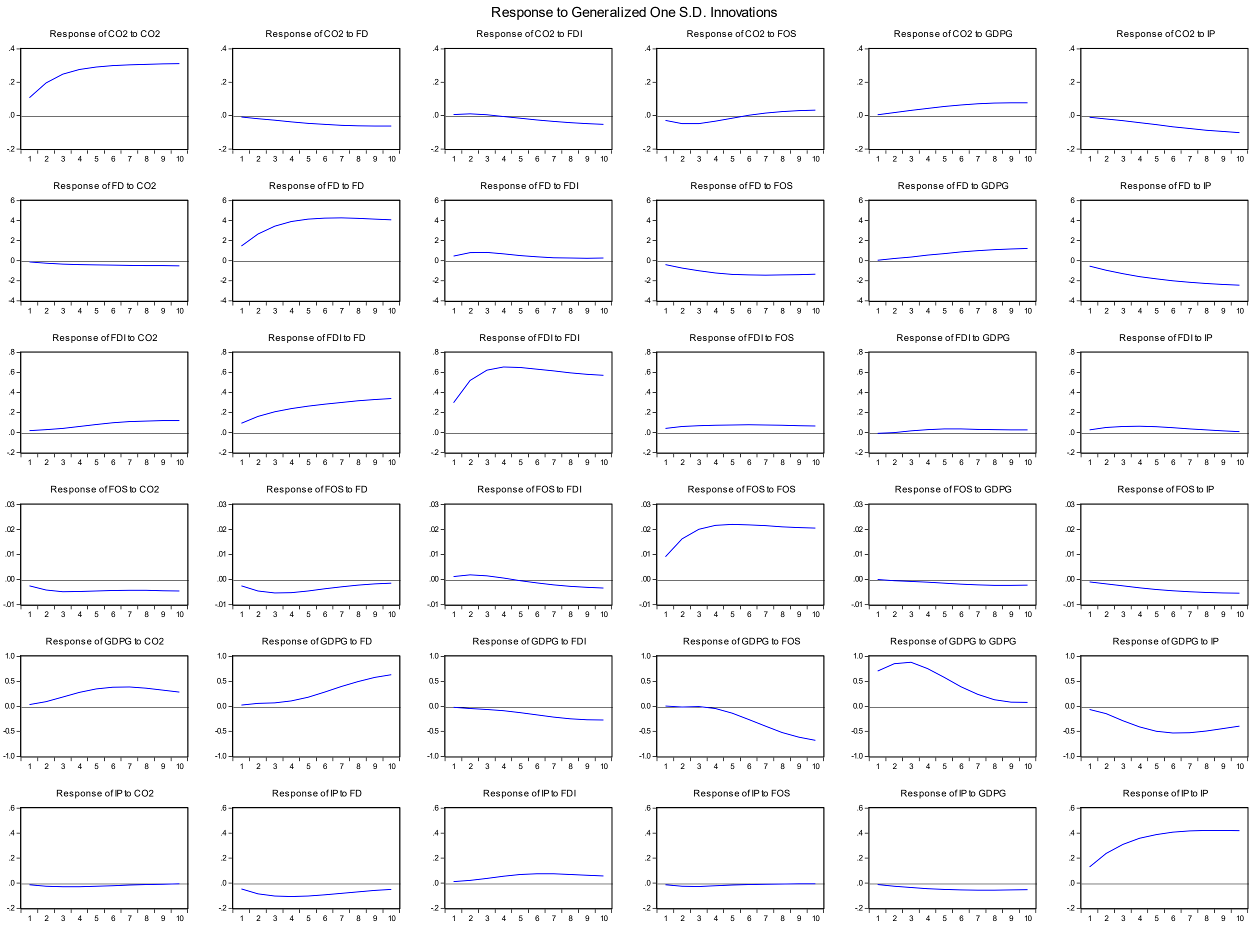
CO2	FD	FDI	FOS	GDPG	IP
1.000000	0.000000	0.000000	0.000000	0.000000	-0.192748
					(0.04229)
0.000000	1.000000	0.000000	0.000000	0.000000	5.177790
					(0.32887)
0.000000	0.000000	1.000000	0.000000	0.000000	0.091790
					(0.02913)
0.000000	0.000000	0.000000	1.000000	0.000000	0.031606
					(0.00709)
0.000000	0.000000	0.000000	0.000000	1.000000	0.002219
					(0.08049)

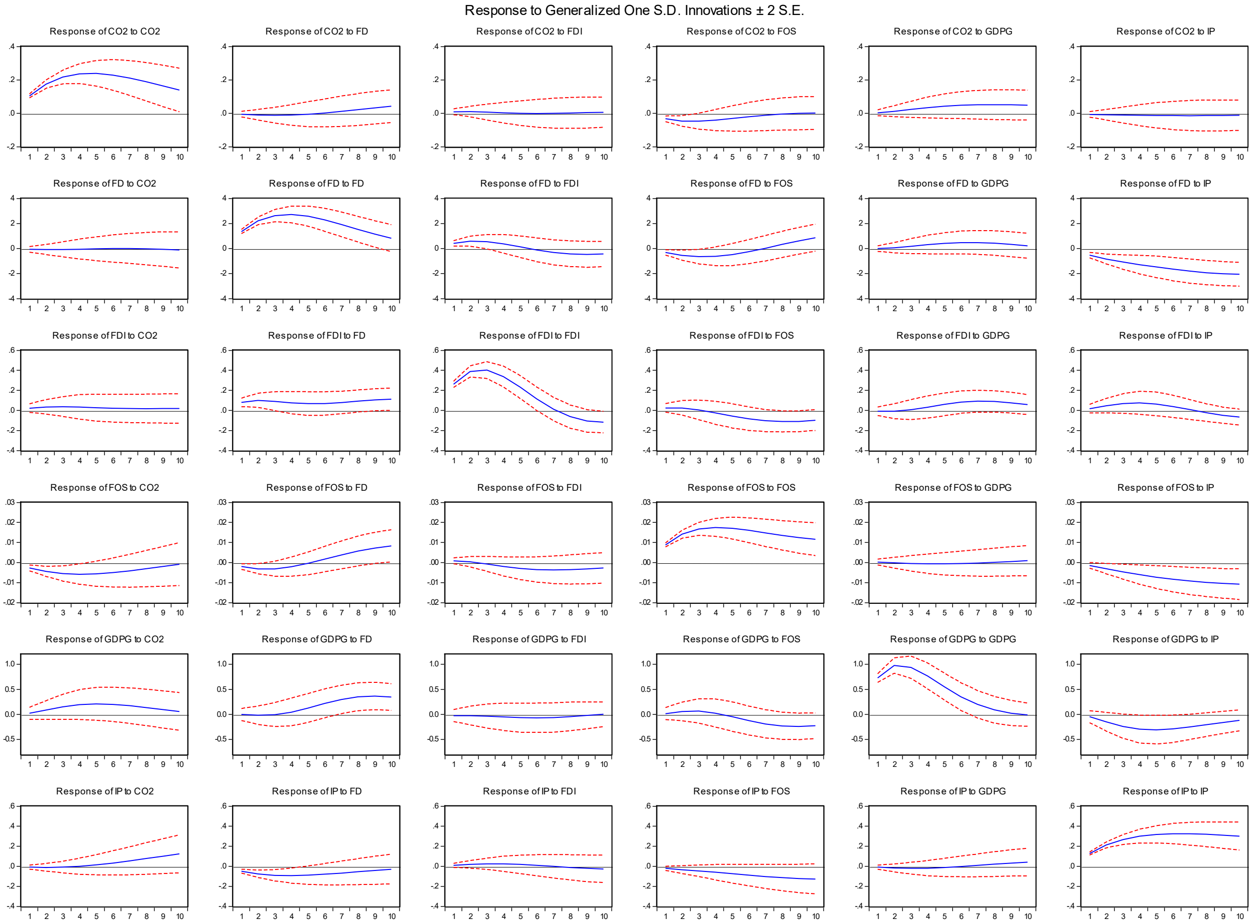
Adjustment coefficients (standard error in parentheses)

D(CO2)	-0.037913	0.002764	0.016660	-0.014481	0.010898
	(0.01217)	(0.00196)	(0.01626)	(0.12886)	(0.00632)
D(FD)	0.098576	-0.081743	-0.137327	1.459625	0.068474
	(0.17866)	(0.02873)	(0.23878)	(1.89235)	(0.09285)
D(FDI)	-0.062219	0.006738	-0.137612	-0.396903	0.042481

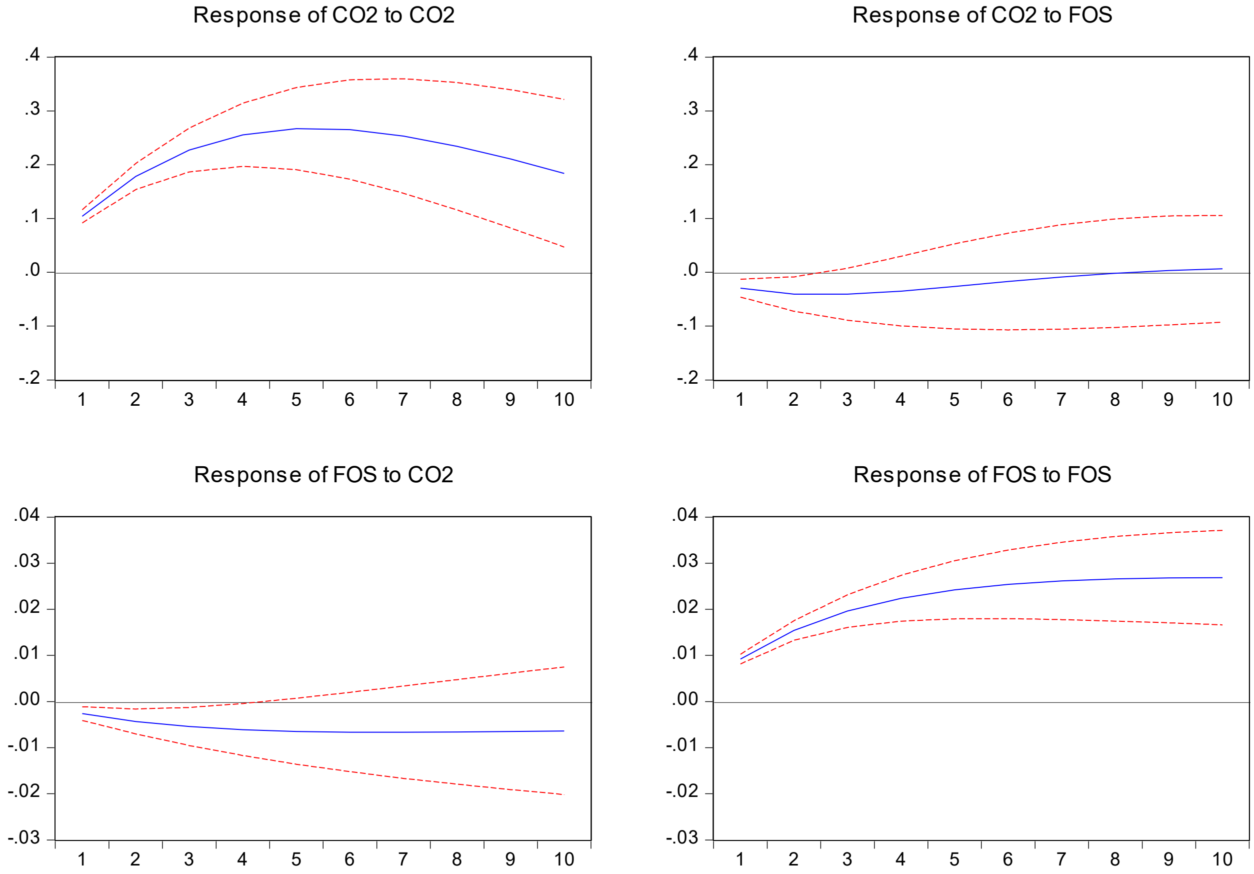
	(0.03081)	(0.00495)	(0.04118)	(0.32633)	(0.01601)
D(FOS)	-0.000473	6.49E-05	0.001707	-0.010036	0.000930
	(0.00106)	(0.00017)	(0.00142)	(0.01127)	(0.00055)
D(GDPG)	0.168500	0.004004	-0.071782	-1.491084	-0.117133
	(0.07423)	(0.01194)	(0.09921)	(0.78625)	(0.03858)
D(IP)	0.042749	0.005532	-0.008336	-0.189069	-0.004241
	(0.01555)	(0.00250)	(0.02078)	(0.16466)	(0.00808)

Impulse Response South Africa




Response to Generalized One S.D. Innovations ± 2 S.E.
Response of CO2 to CO2
Response of CO2 to FD
Response of CO2 to FDI
Response of CO2 to FOS
Response of CO2 to GDPG
Response of CO2 to IP
Response of FD to CO2
Response of FD to FD
Response of FD to FDI
Response of FD to FOS
Response of FD to GDPG
Response of FD to IP
Response of FDI to CO2
Response of FDI to FD
Response of FDI to FDI
Response of FDI to FOS
Response of FDI to GDPG
Response of FDI to IP
Response of FOS to CO2
Response of FOS to FD
Response of FOS to FDI
Response of FOS to FOS
Response of FOS to GDPG
Response of FOS to IP
Response of GDPG to CO2
Response of GDPG to FD
Response of GDPG to FDI
Response of GDPG to FOS
Response of GDPG to GDPG
Response of GDPG to IP
Response of IP to CO2
Response of IP to FD
Response of IP to FDI
Response of IP to FOS
Response of IP to GDPG
Response of IP to IP

Response to Generalized One S.D. Innovations ± 2 S.E.



Variance decompo South Africa

Variance Decomposition of CO2: Period	S.E.	CO2	FD	FDI	FOS	GDPG	IP
1	0.107127	100.0000	0.000000	0.000000	0.000000	0.000000	0.000000
2	0.222840	99.79681	0.011167	0.006041	0.046957	0.139022	2.44E-08
3	0.334856	99.06235	0.054167	0.075193	0.470853	0.337156	0.000278
4	0.438328	97.55625	0.143495	0.228004	1.479545	0.592513	0.000193
5	0.533910	95.47060	0.267021	0.446831	2.941035	0.873247	0.001269
6	0.623094	93.14457	0.400762	0.705153	4.590920	1.149434	0.009158
7	0.706912	90.87092	0.524741	0.979714	6.201703	1.392667	0.030256
8	0.785922	88.82487	0.628753	1.253653	7.638882	1.585971	0.067875
9	0.860421	87.07902	0.710323	1.516308	8.848481	1.724933	0.120934
10	0.930618	85.63957	0.771301	1.761510	9.827688	1.814913	0.185017

Variance Decomposition of FD: Period	S.E.	CO2	FD	FDI	FOS	GDPG	IP
1	1.468754	0.688463	99.31154	0.000000	0.000000	0.000000	0.000000
2	3.036120	0.861407	98.92173	0.010776	0.000371	0.203362	0.002359

3	4.599972	0.946721	98.32587	0.312629	0.006217	0.407535	0.001028
4	6.074712	0.974004	97.29831	1.024586	0.010695	0.683209	0.009197
5	7.430141	0.985112	96.02730	1.912533	0.012240	1.014654	0.048161
6	8.657147	1.000206	94.70552	2.742101	0.011868	1.398540	0.141763
7	9.759802	1.023889	93.43761	3.401636	0.010750	1.819128	0.306983
8	10.74996	1.053432	92.26230	3.872647	0.009557	2.253774	0.548288
9	11.64291	1.084235	91.19317	4.181592	0.008583	2.675209	0.857207
10	12.45441	1.112521	90.23777	4.368147	0.007956	3.058025	1.215583

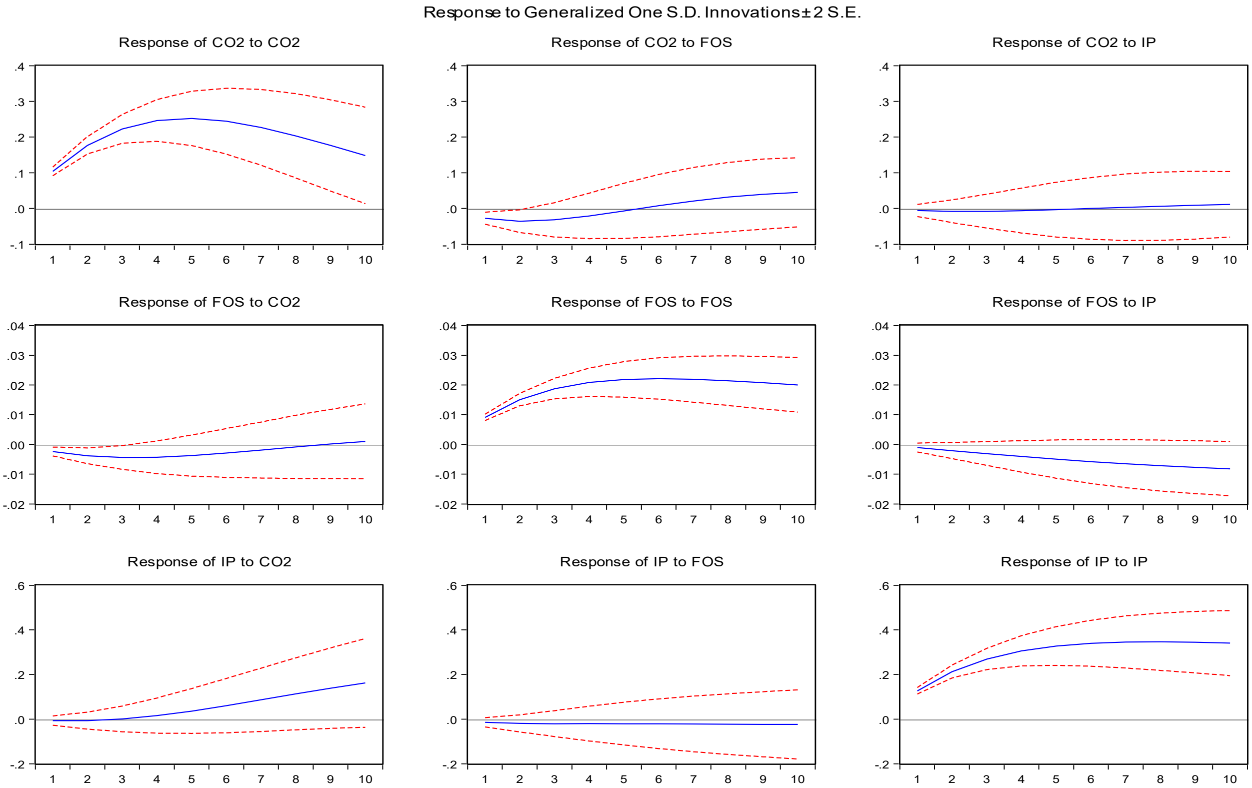
Variance Decomposition of FDI: Period	S.E.	CO2	FD	FDI	FOS	GDPG	IP
1	0.296403	0.393357	10.20748	89.39917	0.000000	0.000000	0.000000
2	0.599042	0.305595	9.991495	89.57972	0.048418	0.073076	0.001700
3	0.865701	0.363840	10.76804	88.62177	0.040593	0.189860	0.015897
4	1.086872	0.528191	11.90444	87.14598	0.027913	0.296259	0.097214
5	1.270664	0.775739	13.21592	85.34323	0.066055	0.359773	0.239281
6	1.426989	1.070040	14.63498	83.33753	0.166354	0.381091	0.410004
7	1.563573	1.370961	16.11973	81.23928	0.310760	0.375203	0.584065
8	1.685774	1.647508	17.62478	79.14883	0.473434	0.357573	0.747871
9	1.797197	1.882770	19.09912	77.15071	0.634077	0.338349	0.894975
10	1.900290	2.072317	20.49279	75.30821	0.781798	0.322906	1.021979

Variance Decomposition of FOS: Period	S.E.	CO2	FD	FDI	FOS	GDPG	IP
1	0.009157	7.472469	8.736987	6.740460	77.05008	0.000000	0.000000
2	0.018645	6.935470	9.124897	6.039085	77.79508	0.105442	2.63E-05
3	0.027453	6.304019	8.699742	4.753714	80.06538	0.172450	0.004693
4	0.035166	5.714774	7.877573	3.542018	82.56823	0.271032	0.026374
5	0.041894	5.219812	6.944440	2.622995	84.73659	0.410651	0.065516
6	0.047837	4.837920	6.052423	2.013650	86.39274	0.587459	0.115808
7	0.053170	4.564808	5.271759	1.657302	87.55820	0.777109	0.170824
8	0.058022	4.386249	4.621921	1.479361	88.33714	0.949873	0.225457
9	0.062490	4.284216	4.095273	1.411231	88.85129	1.082795	0.275191
10	0.066646	4.239557	3.673292	1.399782	89.20480	1.166456	0.316111

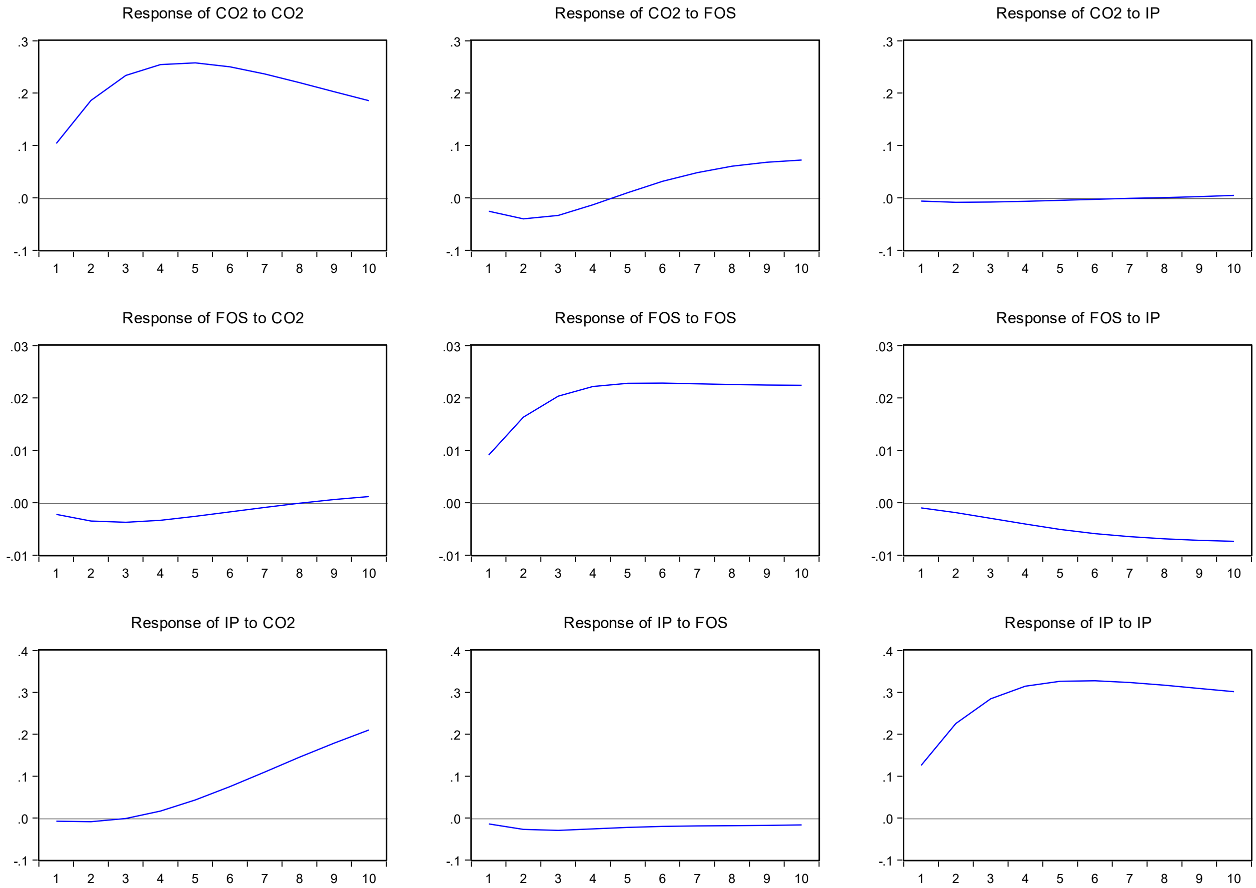
Variance Decomposition of GDPG: Period	S.E.	CO2	FD	FDI	FOS	GDPG	IP
1	0.705783	0.226297	0.131204	0.214314	0.223189	99.20500	0.000000
2	1.108043	0.767684	0.435160	0.583051	0.363288	97.68491	0.165907
3	1.437746	2.123231	0.599180	0.885091	0.816431	94.12684	1.449231
4	1.675189	4.334921	1.058695	1.518884	1.161086	88.17563	3.750781
5	1.854976	7.067897	2.167442	2.766808	1.199962	80.44220	6.355688
6	2.007435	9.689761	4.339804	4.839373	1.035864	71.71337	8.381829
7	2.158510	11.57226	7.680939	7.606617	1.006251	62.80583	9.328111
8	2.320686	12.44764	11.82476	10.61630	1.387346	54.46443	9.259512
9	2.493224	12.47879	16.14470	13.37668	2.198974	47.20448	8.596372
10	2.667901	12.02374	20.11327	15.60850	3.261397	41.23901	7.754075

Variance Decomposition of IP: Period	S.E.	CO2	FD	FDI	FOS	GDPG	IP
1	0.130316	0.899803	13.87530	5.159193	11.76987	0.192816	68.10301
2	0.270436	1.006395	13.59933	5.245577	11.92759	0.313991	67.90711
3	0.411534	0.933924	12.45060	5.850284	10.78369	0.416155	69.56535
4	0.547010	0.802971	11.06510	6.519066	9.395165	0.522925	71.69477
5	0.674555	0.667241	9.691720	6.936192	8.100302	0.625071	73.97947
6	0.793622	0.548105	8.433617	7.013536	6.984384	0.716162	76.30420
7	0.904509	0.451609	7.332628	6.812581	6.051237	0.790866	78.56108
8	1.007836	0.376693	6.398224	6.441377	5.281190	0.845476	80.65704
9	1.104258	0.319552	5.621862	5.996208	4.649242	0.878291	82.53484
10	1.194356	0.275988	4.985620	5.542918	4.131064	0.890104	84.17431
Cholesky Ordering: CO2 FD FDI FOS GDPG IP							

SOUTH AFRICA



Response to Generalized One S.D. Innovations



VARIANCE DECOMPO

Variance Decomposition of CO2: Period	S.E.	CO2	FOS	IP
1	0.103863	100.0000	0.000000	0.000000
2	0.213179	99.89959	0.077376	0.023031
3	0.317342	99.25642	0.656739	0.086840
4	0.410187	97.88030	1.932634	0.187067
5	0.490735	95.94226	3.750476	0.307263
6	0.559633	93.73046	5.838210	0.431329
7	0.618012	91.48676	7.962421	0.550814
8	0.667163	89.36099	9.974661	0.664353
9	0.708407	87.42377	11.80182	0.774412
10	0.743017	85.69378	13.42160	0.884617

Variance Decomposition of FOS: Period	S.E.	CO2	FOS	IP
1	0.009090	6.108490	93.89151	0.000000
2	0.018694	4.920279	95.07923	0.000493

3	0.027675	4.059549	95.89744	0.043008
4	0.035557	3.344700	96.47058	0.184717
5	0.042406	2.735845	96.84430	0.419858
6	0.048429	2.232020	97.06057	0.707406
7	0.053830	1.835312	97.15946	1.005229
8	0.058771	1.540044	97.17505	1.284905
9	0.063372	1.333091	97.13431	1.532599
10	0.067715	1.197646	97.05758	1.744772

Variance Decomposition of IP: Period	S.E.	CO2	FOS	IP
1	0.126021	0.347208	1.706592	97.94620
2	0.258516	0.201516	1.755326	98.04316
3	0.384979	0.091792	1.425470	98.48274
4	0.498797	0.165726	1.057379	98.77689
5	0.600197	0.625061	0.770343	98.60460
6	0.691721	1.642364	0.580303	97.77733
7	0.776353	3.301626	0.473559	96.22481
8	0.856701	5.577734	0.434707	93.98756
9	0.934694	8.354051	0.452406	91.19354
10	1.011549	11.46290	0.518255	88.01885

Cholesky Ordering: CO2 FOS IP

APPENDIX: 4 ARDL ESTIMATE FOR NIGERIA, GHANA, AND SOUTH AFRICA

Nigeria

	CO2	FD	FDI	FOS	GDPG	IP
Mean	0.610068	9.210868	1.528186	0.554622	3.518211	29.99289
Median	0.610025	8.144584	1.266578	0.538799	4.102091	29.85481
Maximum	0.928241	19.62560	5.790847	0.906598	15.87961	39.24509
Minimum	0.325560	4.957522	-1.150856	0.347140	-11.55525	18.17313
Std. Dev.	0.178221	3.619655	1.308790	0.133846	5.812052	5.525767
Skewness	-0.064903	1.174064	1.330622	1.259021	-0.551951	-0.241201
Kurtosis	1.858354	3.839329	5.513240	4.021076	3.771914	2.046490
Jarque-Bera	2.090323	9.845452	21.21445	11.68995	2.872881	1.807998
Probability	0.351635	0.007279	0.000025	0.002894	0.237773	0.404947
Sum	23.18259	350.0130	58.07107	21.07565	133.6920	1139.730
Sum Sq. Dev.	1.175216	484.7704	63.37848	0.662842	1249.858	1129.762
Observations	38	38	38	38	38	38

Ghana

	CO2	FD	FDI	FOS	GDPG	IP
Mean	7.240894	9.156950	2.916409	0.078274	4.484533	21.32333
Median	0.314521	10.22622	1.705456	0.059734	4.695101	23.72110
Maximum	268.6775	15.88200	9.517043	0.177078	13.44524	34.85998
Minimum	-4.471123	1.542268	0.045328	0.028909	-7.144235	6.247470
Std. Dev.	43.56386	5.301333	2.979765	0.045727	3.696774	6.993689
Skewness	5.915317	-0.088509	0.834145	0.859586	-1.120767	-0.264515
Kurtosis	36.00394	1.338776	2.344111	2.507326	6.501685	2.729325
Jarque-Bera	1946.271	4.419083	5.087851	5.063946	27.36993	0.559135
Probability	0.000000	0.109751	0.078557	0.079502	0.000001	0.756111
Sum	275.1540	347.9641	110.8235	2.974407	170.4123	810.2865
Sum Sq. Dev.	70218.96	1039.853	328.5229	0.077366	505.6471	1809.733
Observations	38	38	38	38	38	38

South Africa

	CO2	FD	FDI	FOS	GDPG	IP
Mean	8.922869	112.3904	0.903997	0.964020	2.339302	31.99790
Median	8.823257	115.9312	0.510649	0.926654	2.655457	29.62173
Maximum	9.979458	160.1248	5.983101	1.353412	6.533849	45.27759
Minimum	7.361072	53.96717	-0.766120	0.647961	-2.611739	26.02838
Std. Dev.	0.683839	33.60682	1.263622	0.222851	2.285522	5.722216
Skewness	-0.187261	-0.325638	2.048342	0.364743	-0.247764	0.747608
Kurtosis	2.293273	1.652252	8.185288	1.756954	2.472957	2.206747
Jarque-Bera	1.012907	3.547595	69.14421	3.289078	0.828594	4.536131
Probability	0.602629	0.169687	0.000000	0.193102	0.660805	0.103512
Sum	339.0690	4270.837	34.35190	36.63278	88.89349	1215.920
Sum Sq. Dev.	17.30252	41788.48	59.07943	1.837507	193.2735	1211.519
Observations	38	38	38	38	38	38

Unit root test

Without intercept and trend

Nigeria

Null Hypothesis: CO2 has a unit root
Exogenous: None
Lag Length: 5 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-0.719754	0.4033
Test critical values:	1% level	-2.581233	
	5% level	-1.943074	
	10% level	-1.615231	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(CO2)
Method: Least Squares
Date: 08/09/22 Time: 03:59
Sample (adjusted): 1981Q3 2017Q1
Included observations: 143 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
CO2(-1)	-0.001401	0.001946	-0.719754	0.4729
D(CO2(-1))	0.885586	0.072453	12.22283	0.0000
D(CO2(-2))	0.000739	0.089217	0.008287	0.9934
D(CO2(-3))	0.000739	0.089217	0.008287	0.9934
D(CO2(-4))	-0.692857	0.092366	-7.501203	0.0000
D(CO2(-5))	0.564392	0.077445	7.287688	0.0000

R-squared	0.700786	Mean dependent var	-0.001045
Adjusted R-squared	0.689866	S.D. dependent var	0.025640
S.E. of regression	0.014279	Akaike info criterion	-5.619057
Sum squared resid	0.027931	Schwarz criterion	-5.494742
Log likelihood	407.7626	Hannan-Quinn criter.	-5.568542
Durbin-Watson stat	1.920418		

Null Hypothesis: D(CO2) has a unit root
Exogenous: None
Lag Length: 4 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.153669	0.0018
Test critical values:	1% level	-2.581233	
	5% level	-1.943074	
	10% level	-1.615231	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(CO2,2)
Method: Least Squares
Date: 08/09/22 Time: 04:00
Sample (adjusted): 1981Q3 2017Q1
Included observations: 143 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(CO2(-1))	-0.235992	0.074831	-3.153669	0.0020
D(CO2(-1),2)	0.124548	0.074331	1.675585	0.0961
D(CO2(-2),2)	0.124548	0.074331	1.675585	0.0961
D(CO2(-3),2)	0.124548	0.074331	1.675585	0.0961
D(CO2(-4),2)	-0.567387	0.077198	-7.349800	0.0000

R-squared	0.452001	Mean dependent var	0.000432
Adjusted R-squared	0.436117	S.D. dependent var	0.018982
S.E. of regression	0.014254	Akaike info criterion	-5.629269
Sum squared resid	0.028037	Schwarz criterion	-5.525673
Log likelihood	407.4927	Hannan-Quinn criter.	-5.587173
Durbin-Watson stat	1.921458		

Null Hypothesis: FD has a unit root
Exogenous: None
Lag Length: 1 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-0.617442	0.4484
Test critical values:	1% level	-2.580788	
	5% level	-1.943012	
	10% level	-1.615270	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(FD)
Method: Least Squares
Date: 08/09/22 Time: 04:02
Sample (adjusted): 1980Q3 2017Q1
Included observations: 147 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
FD(-1)	-0.001655	0.002680	-0.617442	0.5379
D(FD(-1))	0.788393	0.047463	16.61083	0.0000

R-squared	0.655254	Mean dependent var	0.015179
Adjusted R-squared	0.652877	S.D. dependent var	0.536491
S.E. of regression	0.316085	Akaike info criterion	0.547901
Sum squared resid	14.48692	Schwarz criterion	0.588588
Log likelihood	-38.27076	Hannan-Quinn criter.	0.564433
Durbin-Watson stat	1.847966		

Null Hypothesis: D(FD) has a unit root
Exogenous: None
Lag Length: 0 (Automatic - based on SIC, maxlag=13)

	t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic	-4.500678	0.0000
Test critical values: 1% level	-2.580788	
5% level	-1.943012	
10% level	-1.615270	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(FD,2)
Method: Least Squares
Date: 08/09/22 Time: 04:03
Sample (adjusted): 1980Q3 2017Q1
Included observations: 147 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(FD(-1))	-0.212940	0.047313	-4.500678	0.0000

R-squared	0.121344	Mean dependent var	0.007940
Adjusted R-squared	0.121344	S.D. dependent var	0.336490
S.E. of regression	0.315415	Akaike info criterion	0.536922
Sum squared resid	14.52501	Schwarz criterion	0.557265
Log likelihood	-38.46375	Hannan-Quinn criter.	0.545187
Durbin-Watson stat	1.844148		

Null Hypothesis: FDI has a unit root
Exogenous: None
Lag Length: 5 (Automatic - based on SIC, maxlag=13)

	t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic	-1.659352	0.0916
Test critical values: 1% level	-2.581233	
5% level	-1.943074	
10% level	-1.615231	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(FDI)
Method: Least Squares
Date: 08/09/22 Time: 04:03
Sample (adjusted): 1981Q3 2017Q1
Included observations: 143 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
FDI(-1)	-0.015837	0.009544	-1.659352	0.0993
D(FDI(-1))	0.805625	0.078369	10.27984	0.0000
D(FDI(-2))	0.007821	0.091588	0.085389	0.9321
D(FDI(-3))	0.007821	0.091588	0.085389	0.9321
D(FDI(-4))	-0.556578	0.091650	-6.072879	0.0000
D(FDI(-5))	0.384007	0.078202	4.910427	0.0000

R-squared	0.623964	Mean dependent var	0.004263

Adjusted R-squared	0.610241	S.D. dependent var	0.342755
S.E. of regression	0.213984	Akaike info criterion	-0.204776
Sum squared resid	6.273128	Schwarz criterion	-0.080461
Log likelihood	20.64151	Hannan-Quinn criter.	-0.154261
Durbin-Watson stat	1.901012		

Null Hypothesis: D(FDI) has a unit root
Exogenous: None
Lag Length: 4 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-4.456272	0.0000
Test critical values:	1% level	-2.581233	
	5% level	-1.943074	
	10% level	-1.615231	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(FDI,2)
Method: Least Squares
Date: 08/09/22 Time: 04:04
Sample (adjusted): 1981Q3 2017Q1
Included observations: 143 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(FDI(-1))	-0.391560	0.087867	-4.456272	0.0000
D(FDI(-1),2)	0.193361	0.078224	2.471880	0.0147
D(FDI(-2),2)	0.193361	0.078224	2.471880	0.0147
D(FDI(-3),2)	0.193361	0.078224	2.471880	0.0147
D(FDI(-4),2)	-0.371251	0.078316	-4.740392	0.0000

R-squared	0.407697	Mean dependent var	-0.000243
Adjusted R-squared	0.390529	S.D. dependent var	0.275833
S.E. of regression	0.215339	Akaike info criterion	-0.198863
Sum squared resid	6.399207	Schwarz criterion	-0.095268
Log likelihood	19.21874	Hannan-Quinn criter.	-0.156767
Durbin-Watson stat	1.890669		

Null Hypothesis: FOS has a unit root
Exogenous: None
Lag Length: 9 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		0.675033	0.8605
Test critical values:	1% level	-2.581705	
	5% level	-1.943140	
	10% level	-1.615189	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(FOS)

Method: Least Squares
Date: 08/09/22 Time: 04:04
Sample (adjusted): 1982Q3 2017Q1
Included observations: 139 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
FOS(-1)	0.001121	0.001660	0.675033	0.5009
D(FOS(-1))	0.898586	0.077111	11.65317	0.0000
D(FOS(-2))	-0.000738	0.096576	-0.007639	0.9939
D(FOS(-3))	-0.000738	0.096576	-0.007639	0.9939
D(FOS(-4))	-0.762718	0.096674	-7.889611	0.0000
D(FOS(-5))	0.665180	0.102734	6.474806	0.0000
D(FOS(-6))	-0.000374	0.096509	-0.003878	0.9969
D(FOS(-7))	-0.000374	0.096509	-0.003878	0.9969
D(FOS(-8))	-0.594432	0.097354	-6.105851	0.0000
D(FOS(-9))	0.493893	0.078746	6.272009	0.0000

R-squared	0.724272	Mean dependent var	0.003005
Adjusted R-squared	0.705036	S.D. dependent var	0.018383
S.E. of regression	0.009984	Akaike info criterion	-6.306499
Sum squared resid	0.012858	Schwarz criterion	-6.095386
Log likelihood	448.3017	Hannan-Quinn criter.	-6.220709
Durbin-Watson stat	1.928507		

Null Hypothesis: D(FOS) has a unit root
Exogenous: None
Lag Length: 8 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.801147	0.0053
Test critical values:	1% level	-2.581705	
	5% level	-1.943140	
	10% level	-1.615189	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(FOS,2)
Method: Least Squares
Date: 08/09/22 Time: 04:04
Sample (adjusted): 1982Q3 2017Q1
Included observations: 139 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(FOS(-1))	-0.268288	0.095778	-2.801147	0.0059
D(FOS(-1),2)	0.176584	0.092830	1.902230	0.0594
D(FOS(-2),2)	0.176584	0.092830	1.902230	0.0594
D(FOS(-3),2)	0.176584	0.092830	1.902230	0.0594
D(FOS(-4),2)	-0.585896	0.093080	-6.294560	0.0000
D(FOS(-5),2)	0.089575	0.075233	1.190643	0.2360
D(FOS(-6),2)	0.089575	0.075233	1.190643	0.2360
D(FOS(-7),2)	0.089575	0.075233	1.190643	0.2360
D(FOS(-8),2)	-0.505906	0.076548	-6.609033	0.0000

R-squared	0.529921	Mean dependent var	6.13E-05
Adjusted R-squared	0.500994	S.D. dependent var	0.014104

S.E. of regression	0.009963	Akaike info criterion	-6.317362
Sum squared resid	0.012903	Schwarz criterion	-6.127360
Log likelihood	448.0567	Hannan-Quinn criter.	-6.240150
Durbin-Watson stat	1.937293		

Null Hypothesis: GDPG has a unit root
Exogenous: None
Lag Length: 9 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.364187	0.0180
Test critical values:	1% level	-2.581705	
	5% level	-1.943140	
	10% level	-1.615189	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(GDPG)
Method: Least Squares
Date: 08/09/22 Time: 04:05
Sample (adjusted): 1982Q3 2017Q1
Included observations: 139 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
GDPG(-1)	-0.034351	0.014530	-2.364187	0.0196
D(GDPG(-1))	0.688044	0.076696	8.971021	0.0000
D(GDPG(-2))	0.141583	0.077009	1.838519	0.0683
D(GDPG(-3))	0.061611	0.076281	0.807689	0.4208
D(GDPG(-4))	-1.099641	0.075816	-14.50399	0.0000
D(GDPG(-5))	0.758681	0.097006	7.820930	0.0000
D(GDPG(-6))	0.099362	0.076272	1.302724	0.1950
D(GDPG(-7))	0.038117	0.075785	0.502959	0.6159
D(GDPG(-8))	-0.434078	0.074810	-5.802372	0.0000
D(GDPG(-9))	0.299330	0.061403	4.874849	0.0000

R-squared	0.764647	Mean dependent var	0.053386
Adjusted R-squared	0.748227	S.D. dependent var	1.903953
S.E. of regression	0.955346	Akaike info criterion	2.815736
Sum squared resid	117.7364	Schwarz criterion	3.026850
Log likelihood	-185.6937	Hannan-Quinn criter.	2.901527
Durbin-Watson stat	2.063429		

Null Hypothesis: D(GDPG) has a unit root
Exogenous: None
Lag Length: 8 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-4.249455	0.0000
Test critical values:	1% level	-2.581705	
	5% level	-1.943140	
	10% level	-1.615189	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(GDPG,2)
Method: Least Squares
Date: 08/09/22 Time: 04:05
Sample (adjusted): 1982Q3 2017Q1
Included observations: 139 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(GDPG(-1))	-0.573664	0.134997	-4.249455	0.0000
D(GDPG(-1),2)	0.254639	0.128623	1.979724	0.0498
D(GDPG(-2),2)	0.377620	0.110947	3.403593	0.0009
D(GDPG(-3),2)	0.417849	0.103012	4.056325	0.0001
D(GDPG(-4),2)	-0.707820	0.099260	-7.130992	0.0000
D(GDPG(-5),2)	0.039975	0.081180	0.492431	0.6232
D(GDPG(-6),2)	0.135859	0.069879	1.944208	0.0540
D(GDPG(-7),2)	0.167812	0.064603	2.597598	0.0105
D(GDPG(-8),2)	-0.278748	0.061846	-4.507115	0.0000

R-squared	0.797456	Mean dependent var	0.011738
Adjusted R-squared	0.784992	S.D. dependent var	2.096364
S.E. of regression	0.972063	Akaike info criterion	2.843764
Sum squared resid	122.8378	Schwarz criterion	3.033766
Log likelihood	-188.6416	Hannan-Quinn criter.	2.920976
Durbin-Watson stat	2.033381		

Null Hypothesis: IP has a unit root
Exogenous: None
Lag Length: 13 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-1.119803	0.2379
Test critical values:	1% level	-2.582204	
	5% level	-1.943210	
	10% level	-1.615145	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(IP)
Method: Least Squares
Date: 08/09/22 Time: 04:06
Sample (adjusted): 1983Q3 2017Q1
Included observations: 135 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
IP(-1)	-0.001312	0.001172	-1.119803	0.2650
D(IP(-1))	0.881542	0.080920	10.89394	0.0000
D(IP(-2))	0.000966	0.103279	0.009351	0.9926
D(IP(-3))	0.000966	0.103279	0.009351	0.9926
D(IP(-4))	-0.618518	0.105167	-5.881299	0.0000
D(IP(-5))	0.516138	0.109018	4.734425	0.0000
D(IP(-6))	0.000664	0.101785	0.006520	0.9948
D(IP(-7))	0.000664	0.101785	0.006520	0.9948
D(IP(-8))	-0.761341	0.102534	-7.425270	0.0000

D(IP(-9))	0.651817	0.108582	6.003023	0.0000
D(IP(-10))	0.000349	0.103586	0.003367	0.9973
D(IP(-11))	0.000349	0.103586	0.003367	0.9973
D(IP(-12))	-0.479587	0.103620	-4.628313	0.0000
D(IP(-13))	0.361578	0.081194	4.453260	0.0000

R-squared	0.772175	Mean dependent var	-0.080446
Adjusted R-squared	0.747697	S.D. dependent var	0.763109
S.E. of regression	0.383307	Akaike info criterion	1.017964
Sum squared resid	17.77787	Schwarz criterion	1.319252
Log likelihood	-54.71256	Hannan-Quinn criter.	1.140399
Durbin-Watson stat	1.950216		

Null Hypothesis: D(IP) has a unit root
Exogenous: None
Lag Length: 12 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.206762	0.0015
Test critical values:	1% level	-2.582204	
	5% level	-1.943210	
	10% level	-1.615145	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(IP,2)
Method: Least Squares
Date: 08/09/22 Time: 04:06
Sample (adjusted): 1983Q3 2017Q1
Included observations: 135 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(IP(-1))	-0.395914	0.123462	-3.206762	0.0017
D(IP(-1),2)	0.291460	0.116640	2.498804	0.0138
D(IP(-2),2)	0.291460	0.116640	2.498804	0.0138
D(IP(-3),2)	0.291460	0.116640	2.498804	0.0138
D(IP(-4),2)	-0.327140	0.119259	-2.743103	0.0070
D(IP(-5),2)	0.200271	0.095347	2.100445	0.0377
D(IP(-6),2)	0.200271	0.095347	2.100445	0.0377
D(IP(-7),2)	0.200271	0.095347	2.100445	0.0377
D(IP(-8),2)	-0.561182	0.096644	-5.806666	0.0000
D(IP(-9),2)	0.105246	0.080333	1.310131	0.1926
D(IP(-10),2)	0.105246	0.080333	1.310131	0.1926
D(IP(-11),2)	0.105246	0.080333	1.310131	0.1926
D(IP(-12),2)	-0.374571	0.080444	-4.656275	0.0000

R-squared	0.528831	Mean dependent var	0.014656
Adjusted R-squared	0.482487	S.D. dependent var	0.533381
S.E. of regression	0.383706	Akaike info criterion	1.013459
Sum squared resid	17.96210	Schwarz criterion	1.293226
Log likelihood	-55.40848	Hannan-Quinn criter.	1.127149
Durbin-Watson stat	1.958743		

Nigeria

Intercept and trend

Null Hypothesis: CO2 has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 5 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.170557	0.5019
Test critical values:	1% level	-4.023506	
	5% level	-3.441552	
	10% level	-3.145341	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(CO2)
Method: Least Squares
Date: 08/09/22 Time: 04:22
Sample (adjusted): 1981Q3 2017Q1
Included observations: 143 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
CO2(-1)	-0.016339	0.007528	-2.170557	0.0317
D(CO2(-1))	0.874912	0.072262	12.10753	0.0000
D(CO2(-2))	0.008602	0.088263	0.097454	0.9225
D(CO2(-3))	0.008602	0.088263	0.097454	0.9225
D(CO2(-4))	-0.683770	0.091390	-7.481897	0.0000
D(CO2(-5))	0.566425	0.077400	7.318146	0.0000
C	0.008361	0.005632	1.484418	0.1400
@TREND("1980Q1")	1.63E-05	3.01E-05	0.541435	0.5891

R-squared	0.711978	Mean dependent var	-0.001045
Adjusted R-squared	0.697044	S.D. dependent var	0.025640
S.E. of regression	0.014112	Akaike info criterion	-5.629208
Sum squared resid	0.026887	Schwarz criterion	-5.463455
Log likelihood	410.4884	Hannan-Quinn criter.	-5.561854
F-statistic	47.67355	Durbin-Watson stat	1.942594
Prob(F-statistic)	0.000000		

Null Hypothesis: D(CO2) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 4 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.275768	0.0745
Test critical values:	1% level	-4.023506	
	5% level	-3.441552	
	10% level	-3.145341	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(CO2,2)
Method: Least Squares
Date: 08/09/22 Time: 04:23
Sample (adjusted): 1981Q3 2017Q1
Included observations: 143 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(CO2(-1))	-0.254780	0.077777	-3.275768	0.0013
D(CO2(-1),2)	0.132815	0.075291	1.764035	0.0800
D(CO2(-2),2)	0.132775	0.075287	1.763591	0.0800
D(CO2(-3),2)	0.132735	0.075283	1.763146	0.0801
D(CO2(-4),2)	-0.556375	0.078309	-7.104906	0.0000
C	-0.002498	0.002623	-0.952342	0.3426
@TREND("1980Q1")	3.01E-05	2.98E-05	1.011159	0.3137

R-squared	0.456147	Mean dependent var	0.000432
Adjusted R-squared	0.432153	S.D. dependent var	0.018982
S.E. of regression	0.014304	Akaike info criterion	-5.608891
Sum squared resid	0.027825	Schwarz criterion	-5.463857
Log likelihood	408.0357	Hannan-Quinn criter.	-5.549956
F-statistic	19.01124	Durbin-Watson stat	1.916527
Prob(F-statistic)	0.000000		

Null Hypothesis: FD has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 1 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-4.095785	0.0080
Test critical values:	1% level	-4.021691	
	5% level	-3.440681	
	10% level	-3.144830	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(FD)
Method: Least Squares
Date: 08/09/22 Time: 04:24
Sample (adjusted): 1980Q3 2017Q1
Included observations: 147 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
FD(-1)	-0.045667	0.011150	-4.095785	0.0001
D(FD(-1))	0.780546	0.045813	17.03782	0.0000
C	0.220067	0.070507	3.121200	0.0022
@TREND("1980Q1")	0.002732	0.000919	2.972753	0.0035

R-squared	0.691034	Mean dependent var	0.015179
Adjusted R-squared	0.684553	S.D. dependent var	0.536491
S.E. of regression	0.301318	Akaike info criterion	0.465535
Sum squared resid	12.98336	Schwarz criterion	0.546907
Log likelihood	-30.21681	Hannan-Quinn criter.	0.498597
F-statistic	106.6116	Durbin-Watson stat	1.951333
Prob(F-statistic)	0.000000		

Null Hypothesis: D(FD) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-4.385233	0.0031
Test critical values:	1% level	-4.021691	
	5% level	-3.440681	
	10% level	-3.144830	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(FD,2)
Method: Least Squares
Date: 08/09/22 Time: 04:24
Sample (adjusted): 1980Q3 2017Q1
Included observations: 147 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(FD(-1))	-0.211423	0.048213	-4.385233	0.0000
C	0.020257	0.053621	0.377775	0.7062
@TREND("1980Q1")	-0.000144	0.000625	-0.230224	0.8182

R-squared	0.122467	Mean dependent var	0.007940
Adjusted R-squared	0.110279	S.D. dependent var	0.336490
S.E. of regression	0.317394	Akaike info criterion	0.562854
Sum squared resid	14.50645	Schwarz criterion	0.623883
Log likelihood	-38.36979	Hannan-Quinn criter.	0.587651
F-statistic	10.04819	Durbin-Watson stat	1.849237
Prob(F-statistic)	0.000082		

Null Hypothesis: FDI has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 5 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.522156	0.0408
Test critical values:	1% level	-4.023506	
	5% level	-3.441552	
	10% level	-3.145341	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(FDI)
Method: Least Squares
Date: 08/09/22 Time: 04:24
Sample (adjusted): 1981Q3 2017Q1
Included observations: 143 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.

FDI(-1)	-0.065370	0.018560	-3.522156	0.0006
D(FDI(-1))	0.810620	0.076507	10.59543	0.0000
D(FDI(-2))	0.032285	0.089422	0.361044	0.7186
D(FDI(-3))	0.032285	0.089422	0.361044	0.7186
D(FDI(-4))	-0.533139	0.089446	-5.960460	0.0000
D(FDI(-5))	0.411215	0.077203	5.326433	0.0000
C	0.099476	0.043335	2.295540	0.0232
@TREND("1980Q1")	0.000108	0.000439	0.245334	0.8066

R-squared	0.649566	Mean dependent var	0.004263
Adjusted R-squared	0.631396	S.D. dependent var	0.342755
S.E. of regression	0.208096	Akaike info criterion	-0.247316
Sum squared resid	5.846033	Schwarz criterion	-0.081563
Log likelihood	25.68310	Hannan-Quinn criter.	-0.179962
F-statistic	35.74811	Durbin-Watson stat	1.941870
Prob(F-statistic)	0.000000		

Null Hypothesis: D(FDI) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 4 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-4.465025	0.0024
Test critical values:	1% level	-4.023506	
	5% level	-3.441552	
	10% level	-3.145341	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(FDI,2)
Method: Least Squares
Date: 08/09/22 Time: 04:25
Sample (adjusted): 1981Q3 2017Q1
Included observations: 143 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(FDI(-1))	-0.400101	0.089608	-4.465025	0.0000
D(FDI(-1),2)	0.198198	0.079138	2.504442	0.0134
D(FDI(-2),2)	0.198188	0.079137	2.504375	0.0134
D(FDI(-3),2)	0.198179	0.079135	2.504307	0.0135
D(FDI(-4),2)	-0.366207	0.079266	-4.619968	0.0000
C	0.022008	0.038872	0.566160	0.5722
@TREND("1980Q1")	-0.000252	0.000445	-0.565987	0.5723

R-squared	0.409174	Mean dependent var	-0.000243
Adjusted R-squared	0.383108	S.D. dependent var	0.275833
S.E. of regression	0.216646	Akaike info criterion	-0.173389
Sum squared resid	6.383244	Schwarz criterion	-0.028355
Log likelihood	19.39731	Hannan-Quinn criter.	-0.114454
F-statistic	15.69772	Durbin-Watson stat	1.889438
Prob(F-statistic)	0.000000		

Null Hypothesis: FOS has a unit root

Exogenous: Constant, Linear Trend
Lag Length: 9 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.561242	0.2988
Test critical values:	1% level	-4.025426	
	5% level	-3.442474	
	10% level	-3.145882	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(FOS)
Method: Least Squares
Date: 08/09/22 Time: 04:25
Sample (adjusted): 1982Q3 2017Q1
Included observations: 139 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
FOS(-1)	-0.032724	0.012776	-2.561242	0.0116
D(FOS(-1))	0.914019	0.076149	12.00302	0.0000
D(FOS(-2))	0.021572	0.095044	0.226966	0.8208
D(FOS(-3))	0.021572	0.095044	0.226966	0.8208
D(FOS(-4))	-0.742807	0.095061	-7.814021	0.0000
D(FOS(-5))	0.693813	0.101572	6.830719	0.0000
D(FOS(-6))	0.010965	0.094706	0.115775	0.9080
D(FOS(-7))	0.010965	0.094706	0.115775	0.9080
D(FOS(-8))	-0.589932	0.095469	-6.179290	0.0000
D(FOS(-9))	0.537012	0.079271	6.774414	0.0000
C	0.012943	0.005331	2.427904	0.0166
@TREND("1980Q1")	7.24E-05	3.24E-05	2.236898	0.0270

R-squared	0.739123	Mean dependent var	0.003005
Adjusted R-squared	0.716528	S.D. dependent var	0.018383
S.E. of regression	0.009787	Akaike info criterion	-6.333088
Sum squared resid	0.012165	Schwarz criterion	-6.079752
Log likelihood	452.1496	Hannan-Quinn criter.	-6.230139
F-statistic	32.71091	Durbin-Watson stat	1.997228
Prob(F-statistic)	0.000000		

Null Hypothesis: D(FOS) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 8 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.972151	0.1439
Test critical values:	1% level	-4.025426	
	5% level	-3.442474	
	10% level	-3.145882	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(FOS,2)
Method: Least Squares

Date: 08/09/22 Time: 04:26
Sample (adjusted): 1982Q3 2017Q1
Included observations: 139 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(FOS(-1))	-0.313751	0.105563	-2.972151	0.0035
D(FOS(-1),2)	0.206578	0.097483	2.119111	0.0360
D(FOS(-2),2)	0.206583	0.097485	2.119126	0.0360
D(FOS(-3),2)	0.206587	0.097486	2.119140	0.0360
D(FOS(-4),2)	-0.555073	0.097970	-5.665746	0.0000
D(FOS(-5),2)	0.104702	0.076866	1.362140	0.1755
D(FOS(-6),2)	0.104708	0.076867	1.362191	0.1755
D(FOS(-7),2)	0.104713	0.076868	1.362242	0.1755
D(FOS(-8),2)	-0.488440	0.078623	-6.212461	0.0000
C	0.000123	0.001874	0.065633	0.9478
@TREND("1980Q1")	9.74E-06	2.17E-05	0.449960	0.6535

R-squared	0.533913	Mean dependent var	6.13E-05
Adjusted R-squared	0.497500	S.D. dependent var	0.014104
S.E. of regression	0.009998	Akaike info criterion	-6.297113
Sum squared resid	0.012794	Schwarz criterion	-6.064889
Log likelihood	448.6494	Hannan-Quinn criter.	-6.202743
F-statistic	14.66270	Durbin-Watson stat	1.925200
Prob(F-statistic)	0.000000		

Null Hypothesis: GDPG has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 9 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.405811	0.0547
Test critical values:	1% level	-4.025426	
	5% level	-3.442474	
	10% level	-3.145882	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(GDPG)
Method: Least Squares
Date: 08/09/22 Time: 04:26
Sample (adjusted): 1982Q3 2017Q1
Included observations: 139 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
GDPG(-1)	-0.082086	0.024102	-3.405811	0.0009
D(GDPG(-1))	0.700250	0.075284	9.301439	0.0000
D(GDPG(-2))	0.159718	0.076788	2.079989	0.0395
D(GDPG(-3))	0.087564	0.075677	1.157082	0.2494
D(GDPG(-4))	-1.063323	0.075501	-14.08354	0.0000
D(GDPG(-5))	0.776351	0.094707	8.197427	0.0000
D(GDPG(-6))	0.096937	0.074701	1.297679	0.1967
D(GDPG(-7))	0.042872	0.073965	0.579628	0.5632
D(GDPG(-8))	-0.416523	0.073172	-5.692396	0.0000
D(GDPG(-9))	0.330912	0.060643	5.456750	0.0000
C	0.209581	0.188859	1.109719	0.2692

@TREND("1980Q1")	0.001822	0.002648	0.687966	0.4927

R-squared	0.781099	Mean dependent var	0.053386
Adjusted R-squared	0.762139	S.D. dependent var	1.903953
S.E. of regression	0.928576	Akaike info criterion	2.772047
Sum squared resid	109.5063	Schwarz criterion	3.025383
Log likelihood	-180.6573	Hannan-Quinn criter.	2.874996
F-statistic	41.19740	Durbin-Watson stat	2.147279
Prob(F-statistic)	0.000000		

Null Hypothesis: D(GDPG) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 8 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-4.616669	0.0014
Test critical values:	1% level	-4.025426	
	5% level	-3.442474	
	10% level	-3.145882	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(GDPG,2)
Method: Least Squares
Date: 08/09/22 Time: 04:26
Sample (adjusted): 1982Q3 2017Q1
Included observations: 139 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(GDPG(-1))	-0.641221	0.138893	-4.616669	0.0000
D(GDPG(-1),2)	0.310609	0.131247	2.366601	0.0195
D(GDPG(-2),2)	0.415073	0.112058	3.704100	0.0003
D(GDPG(-3),2)	0.445457	0.103440	4.306439	0.0000
D(GDPG(-4),2)	-0.684262	0.099454	-6.880159	0.0000
D(GDPG(-5),2)	0.059175	0.081333	0.727561	0.4682
D(GDPG(-6),2)	0.139540	0.069489	2.008093	0.0467
D(GDPG(-7),2)	0.162986	0.064269	2.536005	0.0124
D(GDPG(-8),2)	-0.286095	0.061600	-4.644389	0.0000
C	0.359015	0.191146	1.878222	0.0626
@TREND("1980Q1")	-0.003824	0.002149	-1.779448	0.0775

R-squared	0.802946	Mean dependent var	0.011738
Adjusted R-squared	0.787551	S.D. dependent var	2.096364
S.E. of regression	0.966259	Akaike info criterion	2.845060
Sum squared resid	119.5080	Schwarz criterion	3.077285
Log likelihood	-186.7317	Hannan-Quinn criter.	2.939430
F-statistic	52.15689	Durbin-Watson stat	2.068745
Prob(F-statistic)	0.000000		

Null Hypothesis: IP has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 13 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.611844	0.2759
Test critical values:	1% level	-4.027463	
	5% level	-3.443450	
	10% level	-3.146455	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(IP)
Method: Least Squares
Date: 08/09/22 Time: 04:27
Sample (adjusted): 1983Q3 2017Q1
Included observations: 135 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
IP(-1)	-0.044109	0.016888	-2.611844	0.0102
D(IP(-1))	0.891376	0.079535	11.20736	0.0000
D(IP(-2))	0.032580	0.101701	0.320347	0.7493
D(IP(-3))	0.032580	0.101701	0.320347	0.7493
D(IP(-4))	-0.587730	0.103708	-5.667140	0.0000
D(IP(-5))	0.540796	0.107384	5.036120	0.0000
D(IP(-6))	0.022370	0.099844	0.224053	0.8231
D(IP(-7))	0.022370	0.099844	0.224053	0.8231
D(IP(-8))	-0.740149	0.100648	-7.353824	0.0000
D(IP(-9))	0.667860	0.106431	6.275051	0.0000
D(IP(-10))	0.011554	0.101335	0.114014	0.9094
D(IP(-11))	0.011554	0.101335	0.114014	0.9094
D(IP(-12))	-0.468494	0.101375	-4.621388	0.0000
D(IP(-13))	0.387345	0.080502	4.811615	0.0000
C	1.712884	0.650801	2.631965	0.0096
@TREND("1980Q1")	-0.005203	0.001880	-2.767960	0.0065

R-squared	0.785983	Mean dependent var	-0.080446
Adjusted R-squared	0.759006	S.D. dependent var	0.763109
S.E. of regression	0.374618	Akaike info criterion	0.985068
Sum squared resid	16.70033	Schwarz criterion	1.329397
Log likelihood	-50.49207	Hannan-Quinn criter.	1.124993
F-statistic	29.13543	Durbin-Watson stat	2.003368
Prob(F-statistic)	0.000000		

Null Hypothesis: D(IP) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 12 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.469635	0.0468
Test critical values:	1% level	-4.027463	
	5% level	-3.443450	
	10% level	-3.146455	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(IP,2)
Method: Least Squares

Date: 08/09/22 Time: 04:27
Sample (adjusted): 1983Q3 2017Q1
Included observations: 135 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(IP(-1))	-0.472182	0.136090	-3.469635	0.0007
D(IP(-1),2)	0.349272	0.124353	2.808712	0.0058
D(IP(-2),2)	0.349289	0.124355	2.808801	0.0058
D(IP(-3),2)	0.349306	0.124357	2.808889	0.0058
D(IP(-4),2)	-0.273544	0.126100	-2.169264	0.0320
D(IP(-5),2)	0.237334	0.099574	2.383497	0.0187
D(IP(-6),2)	0.237343	0.099575	2.383570	0.0187
D(IP(-7),2)	0.237352	0.099575	2.383644	0.0187
D(IP(-8),2)	-0.526752	0.100482	-5.242279	0.0000
D(IP(-9),2)	0.123595	0.081503	1.516437	0.1320
D(IP(-10),2)	0.123568	0.081502	1.516136	0.1321
D(IP(-11),2)	0.123541	0.081500	1.515834	0.1322
D(IP(-12),2)	-0.356877	0.081562	-4.375546	0.0000
C	0.024351	0.076564	0.318040	0.7510
@TREND("1980Q1")	-0.000809	0.000858	-0.942096	0.3480

R-squared	0.536816	Mean dependent var	0.014656
Adjusted R-squared	0.482778	S.D. dependent var	0.533381
S.E. of regression	0.383598	Akaike info criterion	1.025995
Sum squared resid	17.65768	Schwarz criterion	1.348804
Log likelihood	-54.25469	Hannan-Quinn criter.	1.157176
F-statistic	9.934039	Durbin-Watson stat	1.958130
Prob(F-statistic)	0.000000		

Ghana

Without intercept and trend

Null Hypothesis: CO2 has a unit root
Exogenous: None
Lag Length: 13 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		1.303851	0.9510
Test critical values:	1% level	-2.582204	
	5% level	-1.943210	
	10% level	-1.615145	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(CO2)
Method: Least Squares
Date: 08/09/22 Time: 05:20
Sample (adjusted): 1983Q3 2017Q1
Included observations: 135 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
CO2(-1)	0.124529	0.095508	1.303851	0.1948
D(CO2(-1))	0.718186	0.135539	5.298737	0.0000

D(CO2(-2))	-0.123355	0.131341	-0.939193	0.3495
D(CO2(-3))	-0.123355	0.131341	-0.939193	0.3495
D(CO2(-4))	6.237998	0.301177	20.71203	0.0000
D(CO2(-5))	-5.774786	0.677139	-8.528212	0.0000
D(CO2(-6))	-0.128268	0.799057	-0.160524	0.8727
D(CO2(-7))	-0.128268	0.799057	-0.160524	0.8727
D(CO2(-8))	-47.99254	0.911074	-52.67689	0.0000
D(CO2(-9))	40.25864	4.067005	9.898843	0.0000
D(CO2(-10))	-0.071903	4.730990	-0.015198	0.9879
D(CO2(-11))	-0.071903	4.730990	-0.015198	0.9879
D(CO2(-12))	-35.91328	4.806656	-7.471574	0.0000
D(CO2(-13))	26.32899	4.373002	6.020805	0.0000

R-squared	0.999244	Mean dependent var	1.988131
Adjusted R-squared	0.999162	S.D. dependent var	11.43223
S.E. of regression	0.330879	Akaike info criterion	0.723798
Sum squared resid	13.24723	Schwarz criterion	1.025086
Log likelihood	-34.85636	Hannan-Quinn criter.	0.846233
Durbin-Watson stat	1.877338		

Null Hypothesis: D(CO2) has a unit root
Exogenous: None
Lag Length: 12 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.028587	0.0027
Test critical values:	1% level	-2.582204	
	5% level	-1.943210	
	10% level	-1.615145	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(CO2,2)
Method: Least Squares
Date: 08/09/22 Time: 05:21
Sample (adjusted): 1983Q3 2017Q1
Included observations: 135 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(CO2(-1))	-14.64997	4.837228	-3.028587	0.0030
D(CO2(-1),2)	14.51190	4.792075	3.028312	0.0030
D(CO2(-2),2)	14.51190	4.792075	3.028312	0.0030
D(CO2(-3),2)	14.51190	4.792075	3.028312	0.0030
D(CO2(-4),2)	20.85642	4.725855	4.413258	0.0000
D(CO2(-5),2)	15.08987	5.014109	3.009481	0.0032
D(CO2(-6),2)	15.08987	5.014109	3.009481	0.0032
D(CO2(-7),2)	15.08987	5.014109	3.009481	0.0032
D(CO2(-8),2)	-32.80143	4.915105	-6.673597	0.0000
D(CO2(-9),2)	8.458880	4.365173	1.937811	0.0550
D(CO2(-10),2)	8.458880	4.365173	1.937811	0.0550
D(CO2(-11),2)	8.458880	4.365173	1.937811	0.0550
D(CO2(-12),2)	-27.43457	4.302297	-6.376726	0.0000

R-squared	0.996898	Mean dependent var	0.497588
Adjusted R-squared	0.996593	S.D. dependent var	5.684697
S.E. of regression	0.331827	Akaike info criterion	0.722935

Sum squared resid	13.43335	Schwarz criterion	1.002702
Log likelihood	-35.79813	Hannan-Quinn criter.	0.836625
Durbin-Watson stat	1.885549		

Null Hypothesis: FD has a unit root
Exogenous: None
Lag Length: 9 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		0.725246	0.8704
Test critical values:	1% level	-2.581705	
	5% level	-1.943140	
	10% level	-1.615189	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(FD)
Method: Least Squares
Date: 08/09/22 Time: 05:21
Sample (adjusted): 1982Q3 2017Q1
Included observations: 139 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
FD(-1)	0.001472	0.002029	0.725246	0.4696
D(FD(-1))	0.893505	0.081939	10.90454	0.0000
D(FD(-2))	-0.001003	0.104960	-0.009551	0.9924
D(FD(-3))	-0.001003	0.104960	-0.009551	0.9924
D(FD(-4))	-0.813231	0.105708	-7.693183	0.0000
D(FD(-5))	0.692257	0.112651	6.145174	0.0000
D(FD(-6))	-0.000483	0.105258	-0.004590	0.9963
D(FD(-7))	-0.000483	0.105258	-0.004590	0.9963
D(FD(-8))	-0.498687	0.106145	-4.698151	0.0000
D(FD(-9))	0.385481	0.083951	4.591719	0.0000

R-squared	0.689757	Mean dependent var	0.087196
Adjusted R-squared	0.668112	S.D. dependent var	0.397030
S.E. of regression	0.228728	Akaike info criterion	-0.043346
Sum squared resid	6.748810	Schwarz criterion	0.167767
Log likelihood	13.01253	Hannan-Quinn criter.	0.042445
Durbin-Watson stat	1.939481		

Null Hypothesis: D(FD) has a unit root
Exogenous: None
Lag Length: 8 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.016074	0.0028
Test critical values:	1% level	-2.581705	
	5% level	-1.943140	
	10% level	-1.615189	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(FD,2)
Method: Least Squares
Date: 08/09/22 Time: 05:21
Sample (adjusted): 1982Q3 2017Q1
Included observations: 139 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(FD(-1))	-0.304829	0.101068	-3.016074	0.0031
D(FD(-1),2)	0.207630	0.101125	2.053196	0.0421
D(FD(-2),2)	0.207630	0.101125	2.053196	0.0421
D(FD(-3),2)	0.207630	0.101125	2.053196	0.0421
D(FD(-4),2)	-0.603373	0.101665	-5.934886	0.0000
D(FD(-5),2)	0.100057	0.081362	1.229772	0.2210
D(FD(-6),2)	0.100057	0.081362	1.229772	0.2210
D(FD(-7),2)	0.100057	0.081362	1.229772	0.2210
D(FD(-8),2)	-0.396799	0.082338	-4.819172	0.0000

R-squared	0.492351	Mean dependent var	-0.002248
Adjusted R-squared	0.461111	S.D. dependent var	0.311011
S.E. of regression	0.228310	Akaike info criterion	-0.053665
Sum squared resid	6.776327	Schwarz criterion	0.136337
Log likelihood	12.72973	Hannan-Quinn criter.	0.023547
Durbin-Watson stat	1.945554		

Null Hypothesis: FDI has a unit root
Exogenous: None
Lag Length: 1 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-1.111075	0.2412
Test critical values:	1% level	-2.580788	
	5% level	-1.943012	
	10% level	-1.615270	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(FDI)
Method: Least Squares
Date: 08/09/22 Time: 05:23
Sample (adjusted): 1980Q3 2017Q1
Included observations: 147 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
FDI(-1)	-0.004323	0.003891	-1.111075	0.2684
D(FDI(-1))	0.797362	0.051261	15.55490	0.0000

R-squared	0.621181	Mean dependent var	0.035087
Adjusted R-squared	0.618569	S.D. dependent var	0.312203
S.E. of regression	0.192817	Akaike info criterion	-0.440642
Sum squared resid	5.390850	Schwarz criterion	-0.399955
Log likelihood	34.38715	Hannan-Quinn criter.	-0.424110
Durbin-Watson stat	1.832775		

Null Hypothesis: D(FDI) has a unit root
Exogenous: None
Lag Length: 0 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-4.119484	0.0001
Test critical values:	1% level	-2.580788	
	5% level	-1.943012	
	10% level	-1.615270	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(FDI,2)
Method: Least Squares
Date: 08/09/22 Time: 05:23
Sample (adjusted): 1980Q3 2017Q1
Included observations: 147 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(FDI(-1))	-0.209706	0.050906	-4.119484	0.0001

R-squared	0.104085	Mean dependent var	-0.001450
Adjusted R-squared	0.104085	S.D. dependent var	0.203873
S.E. of regression	0.192971	Akaike info criterion	-0.445769
Sum squared resid	5.436746	Schwarz criterion	-0.425426
Log likelihood	33.76404	Hannan-Quinn criter.	-0.437504
Durbin-Watson stat	1.813395		

Null Hypothesis: FOS has a unit root
Exogenous: None
Lag Length: 5 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		2.820025	0.9988
Test critical values:	1% level	-2.581233	
	5% level	-1.943074	
	10% level	-1.615231	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(FOS)
Method: Least Squares
Date: 08/09/22 Time: 05:24
Sample (adjusted): 1981Q3 2017Q1
Included observations: 143 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
FOS(-1)	0.004009	0.001422	2.820025	0.0055
D(FOS(-1))	0.851680	0.079550	10.70628	0.0000
D(FOS(-2))	-0.001992	0.097025	-0.020530	0.9837

D(FOS(-3))	-0.001992	0.097025	-0.020530	0.9837
D(FOS(-4))	-0.546008	0.099495	-5.487813	0.0000
D(FOS(-5))	0.383129	0.083491	4.588839	0.0000

R-squared	0.679604	Mean dependent var	0.001021
Adjusted R-squared	0.667911	S.D. dependent var	0.001528
S.E. of regression	0.000880	Akaike info criterion	-11.19121
Sum squared resid	0.000106	Schwarz criterion	-11.06689
Log likelihood	806.1715	Hannan-Quinn criter.	-11.14069
Durbin-Watson stat	1.912616		

Null Hypothesis: D(FOS) has a unit root
Exogenous: None
Lag Length: 4 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.314895	0.0204
Test critical values:	1% level	-2.581233	
	5% level	-1.943074	
	10% level	-1.615231	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(FOS,2)
Method: Least Squares
Date: 08/09/22 Time: 05:24
Sample (adjusted): 1981Q3 2017Q1
Included observations: 143 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(FOS(-1))	-0.117513	0.050764	-2.314895	0.0221
D(FOS(-1),2)	0.058390	0.074700	0.781668	0.4357
D(FOS(-2),2)	0.058390	0.074700	0.781668	0.4357
D(FOS(-3),2)	0.058390	0.074700	0.781668	0.4357
D(FOS(-4),2)	-0.476146	0.078608	-6.057227	0.0000

R-squared	0.299158	Mean dependent var	-9.29E-06
Adjusted R-squared	0.278844	S.D. dependent var	0.001063
S.E. of regression	0.000902	Akaike info criterion	-11.14877
Sum squared resid	0.000112	Schwarz criterion	-11.04517
Log likelihood	802.1370	Hannan-Quinn criter.	-11.10667
Durbin-Watson stat	1.959803		

Null Hypothesis: GDPG has a unit root
Exogenous: None
Lag Length: 12 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-0.476344	0.5077
Test critical values:	1% level	-2.582076	
	5% level	-1.943193	
	10% level	-1.615157	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(GDPG)
Method: Least Squares
Date: 08/09/22 Time: 05:26
Sample (adjusted): 1983Q2 2017Q1
Included observations: 136 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
GDPG(-1)	-0.005373	0.011280	-0.476344	0.6347
D(GDPG(-1))	0.641253	0.088053	7.282579	0.0000
D(GDPG(-2))	0.246807	0.105306	2.343716	0.0207
D(GDPG(-3))	0.097409	0.107007	0.910306	0.3644
D(GDPG(-4))	-1.225551	0.103075	-11.88988	0.0000
D(GDPG(-5))	0.658183	0.126570	5.200150	0.0000
D(GDPG(-6))	0.254160	0.139189	1.826004	0.0703
D(GDPG(-7))	0.109643	0.139269	0.787276	0.4326
D(GDPG(-8))	-0.888629	0.127067	-6.993399	0.0000
D(GDPG(-9))	0.346595	0.101460	3.416076	0.0009
D(GDPG(-10))	0.139612	0.105683	1.321045	0.1889
D(GDPG(-11))	0.072595	0.104154	0.696994	0.4871
D(GDPG(-12))	-0.337630	0.087203	-3.871750	0.0002

R-squared	0.686536	Mean dependent var	0.112302
Adjusted R-squared	0.655954	S.D. dependent var	1.195703
S.E. of regression	0.701344	Akaike info criterion	2.219071
Sum squared resid	60.50174	Schwarz criterion	2.497486
Log likelihood	-137.8968	Hannan-Quinn criter.	2.332212
Durbin-Watson stat	1.685952		

Null Hypothesis: D(GDPG) has a unit root
Exogenous: None
Lag Length: 11 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-5.627340	0.0000
Test critical values:	1% level	-2.582076	
	5% level	-1.943193	
	10% level	-1.615157	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(GDPG,2)
Method: Least Squares
Date: 08/09/22 Time: 05:26
Sample (adjusted): 1983Q2 2017Q1
Included observations: 136 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(GDPG(-1))	-0.916898	0.162936	-5.627340	0.0000
D(GDPG(-1),2)	0.556896	0.155113	3.590264	0.0005
D(GDPG(-2),2)	0.800542	0.150259	5.327731	0.0000
D(GDPG(-3),2)	0.893615	0.148169	6.031043	0.0000

D(GDPG(-4),2)	-0.337944	0.131945	-2.561244	0.0116
D(GDPG(-5),2)	0.320748	0.134752	2.380276	0.0188
D(GDPG(-6),2)	0.573388	0.133023	4.310444	0.0000
D(GDPG(-7),2)	0.679874	0.130104	5.225633	0.0000
D(GDPG(-8),2)	-0.214955	0.087837	-2.447192	0.0158
D(GDPG(-9),2)	0.132404	0.090487	1.463234	0.1459
D(GDPG(-10),2)	0.271568	0.090141	3.012693	0.0031
D(GDPG(-11),2)	0.342365	0.086364	3.964190	0.0001

R-squared	0.681108	Mean dependent var	0.027366
Adjusted R-squared	0.652819	S.D. dependent var	1.186576
S.E. of regression	0.699155	Akaike info criterion	2.206208
Sum squared resid	60.61335	Schwarz criterion	2.463207
Log likelihood	-138.0221	Hannan-Quinn criter.	2.310646
Durbin-Watson stat	1.688901		

Null Hypothesis: IP has a unit root
Exogenous: None
Lag Length: 1 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		0.277354	0.7650
Test critical values:	1% level	-2.580788	
	5% level	-1.943012	
	10% level	-1.615270	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(IP)
Method: Least Squares
Date: 08/09/22 Time: 05:27
Sample (adjusted): 1980Q3 2017Q1
Included observations: 147 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
IP(-1)	0.000420	0.001514	0.277354	0.7819
D(IP(-1))	0.818670	0.048143	17.00503	0.0000

R-squared	0.662702	Mean dependent var	0.133282
Adjusted R-squared	0.660376	S.D. dependent var	0.692457
S.E. of regression	0.403545	Akaike info criterion	1.036456
Sum squared resid	23.61307	Schwarz criterion	1.077142
Log likelihood	-74.17950	Hannan-Quinn criter.	1.052987
Durbin-Watson stat	1.836453		

Null Hypothesis: D(IP) has a unit root
Exogenous: None
Lag Length: 0 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.791103	0.0002
Test critical values:	1% level	-2.580788	
	5% level	-1.943012	

	10% level	-1.615270	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(IP,2)
Method: Least Squares
Date: 08/09/22 Time: 05:27
Sample (adjusted): 1980Q3 2017Q1
Included observations: 147 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(IP(-1))	-0.178901	0.047190	-3.791103	0.0002

R-squared	0.089206	Mean dependent var	0.008953
Adjusted R-squared	0.089206	S.D. dependent var	0.421507
S.E. of regression	0.402268	Akaike info criterion	1.023381
Sum squared resid	23.62560	Schwarz criterion	1.043724
Log likelihood	-74.21848	Hannan-Quinn criter.	1.031646
Durbin-Watson stat	1.839015		

Intercept and trend

Null Hypothesis: CO2 has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 13 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.025628	0.1292
Test critical values:	1% level	-4.027463	
	5% level	-3.443450	
	10% level	-3.146455	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(CO2)
Method: Least Squares
Date: 08/09/22 Time: 06:00
Sample (adjusted): 1983Q3 2017Q1
Included observations: 135 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
CO2(-1)	-3.994446	1.320204	-3.025628	0.0030
D(CO2(-1))	4.786456	1.310606	3.652095	0.0004
D(CO2(-2))	3.956364	1.310589	3.018767	0.0031
D(CO2(-3))	3.956364	1.310589	3.018767	0.0031
D(CO2(-4))	10.14608	1.274212	7.962627	0.0000
D(CO2(-5))	-1.331628	1.544360	-0.862253	0.3903
D(CO2(-6))	4.122229	1.562066	2.638959	0.0094
D(CO2(-7))	4.122229	1.562066	2.638959	0.0094
D(CO2(-8))	-44.01761	1.533329	-28.70721	0.0000
D(CO2(-9))	41.75698	3.997422	10.44598	0.0000
D(CO2(-10))	2.301644	4.625620	0.497586	0.6197

D(CO2(-11))	2.301644	4.625620	0.497586	0.6197
D(CO2(-12))	-34.07061	4.670347	-7.295091	0.0000
D(CO2(-13))	29.19367	4.341676	6.724055	0.0000
C	0.766700	0.275670	2.781221	0.0063
@TREND("1980Q1")	0.006946	0.002088	3.326805	0.0012

R-squared	0.999308	Mean dependent var	1.988131
Adjusted R-squared	0.999221	S.D. dependent var	11.43223
S.E. of regression	0.319124	Akaike info criterion	0.664412
Sum squared resid	12.11897	Schwarz criterion	1.008740
Log likelihood	-28.84778	Hannan-Quinn criter.	0.804337
F-statistic	11456.60	Durbin-Watson stat	1.948759
Prob(F-statistic)	0.000000		

Null Hypothesis: D(CO2) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 12 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.436811	0.0508
Test critical values:	1% level	-4.027463	
	5% level	-3.443450	
	10% level	-3.146455	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(CO2,2)
Method: Least Squares
Date: 08/09/22 Time: 06:01
Sample (adjusted): 1983Q3 2017Q1
Included observations: 135 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(CO2(-1))	-17.25575	5.020861	-3.436811	0.0008
D(CO2(-1),2)	17.08384	4.972761	3.435483	0.0008
D(CO2(-2),2)	17.08377	4.972754	3.435475	0.0008
D(CO2(-3),2)	17.08370	4.972747	3.435466	0.0008
D(CO2(-4),2)	23.46928	4.914617	4.775404	0.0000
D(CO2(-5),2)	17.91653	5.221176	3.431512	0.0008
D(CO2(-6),2)	17.91777	5.221319	3.431655	0.0008
D(CO2(-7),2)	17.91900	5.221462	3.431798	0.0008
D(CO2(-8),2)	-29.90502	5.136363	-5.822217	0.0000
D(CO2(-9),2)	9.773406	4.405131	2.218642	0.0284
D(CO2(-10),2)	9.772658	4.405094	2.218490	0.0284
D(CO2(-11),2)	9.771909	4.405057	2.218339	0.0284
D(CO2(-12),2)	-25.99507	4.351728	-5.973506	0.0000
C	-0.042976	0.068402	-0.628294	0.5310
@TREND("1980Q1")	0.001096	0.000814	1.345966	0.1809

R-squared	0.996986	Mean dependent var	0.497588
Adjusted R-squared	0.996634	S.D. dependent var	5.684697
S.E. of regression	0.329789	Akaike info criterion	0.723709
Sum squared resid	13.05126	Schwarz criterion	1.046518
Log likelihood	-33.85037	Hannan-Quinn criter.	0.854889
F-statistic	2835.367	Durbin-Watson stat	1.876531
Prob(F-statistic)	0.000000		

Null Hypothesis: FD has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 9 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-1.564021	0.8022
Test critical values:	1% level	-4.025426	
	5% level	-3.442474	
	10% level	-3.145882	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(FD)
Method: Least Squares
Date: 08/09/22 Time: 06:01
Sample (adjusted): 1982Q3 2017Q1
Included observations: 139 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
FD(-1)	-0.022398	0.014321	-1.564021	0.1203
D(FD(-1))	0.881714	0.082370	10.70433	0.0000
D(FD(-2))	0.015343	0.104040	0.147473	0.8830
D(FD(-3))	0.015343	0.104040	0.147473	0.8830
D(FD(-4))	-0.799742	0.104581	-7.647072	0.0000
D(FD(-5))	0.685936	0.112530	6.095594	0.0000
D(FD(-6))	0.007399	0.103985	0.071157	0.9434
D(FD(-7))	0.007399	0.103985	0.071157	0.9434
D(FD(-8))	-0.493946	0.104778	-4.714225	0.0000
D(FD(-9))	0.387634	0.084596	4.582190	0.0000
C	0.064198	0.045110	1.423127	0.1572
@TREND("1980Q1")	0.002245	0.001782	1.260114	0.2099

R-squared	0.702517	Mean dependent var	0.087196
Adjusted R-squared	0.676751	S.D. dependent var	0.397030
S.E. of regression	0.225731	Akaike info criterion	-0.056569
Sum squared resid	6.471232	Schwarz criterion	0.196767
Log likelihood	15.93151	Hannan-Quinn criter.	0.046380
F-statistic	27.26501	Durbin-Watson stat	1.949563
Prob(F-statistic)	0.000000		

Null Hypothesis: D(FD) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 8 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.520867	0.0410
Test critical values:	1% level	-4.025426	
	5% level	-3.442474	
	10% level	-3.145882	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(FD,2)
Method: Least Squares
Date: 08/09/22 Time: 06:02
Sample (adjusted): 1982Q3 2017Q1
Included observations: 139 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(FD(-1))	-0.408626	0.116058	-3.520867	0.0006
D(FD(-1),2)	0.277302	0.108188	2.563138	0.0115
D(FD(-2),2)	0.277285	0.108188	2.563004	0.0115
D(FD(-3),2)	0.277268	0.108187	2.562869	0.0115
D(FD(-4),2)	-0.534456	0.108296	-4.935159	0.0000
D(FD(-5),2)	0.132730	0.083140	1.596464	0.1129
D(FD(-6),2)	0.132721	0.083140	1.596357	0.1129
D(FD(-7),2)	0.132711	0.083139	1.596249	0.1129
D(FD(-8),2)	-0.364928	0.083810	-4.354217	0.0000
C	0.071832	0.045098	1.592794	0.1137
@TREND("1980Q1")	-0.000438	0.000484	-0.905997	0.3666

R-squared	0.505869	Mean dependent var	-0.002248
Adjusted R-squared	0.467265	S.D. dependent var	0.311011
S.E. of regression	0.227003	Akaike info criterion	-0.051879
Sum squared resid	6.595875	Schwarz criterion	0.180346
Log likelihood	14.60559	Hannan-Quinn criter.	0.042491
F-statistic	13.10407	Durbin-Watson stat	1.934757
Prob(F-statistic)	0.000000		

Null Hypothesis: FDI has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 1 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.417297	0.0530
Test critical values:	1% level	-4.021691	
	5% level	-3.440681	
	10% level	-3.144830	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(FDI)
Method: Least Squares
Date: 08/09/22 Time: 06:03
Sample (adjusted): 1980Q3 2017Q1
Included observations: 147 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
FDI(-1)	-0.033107	0.009688	-3.417297	0.0008
D(FDI(-1))	0.803592	0.049979	16.07866	0.0000
C	-0.035451	0.034193	-1.036820	0.3016
@TREND("1980Q1")	0.001836	0.000663	2.768512	0.0064

R-squared	0.647231	Mean dependent var	0.035087
Adjusted R-squared	0.639830	S.D. dependent var	0.312203

S.E. of regression	0.187366	Akaike info criterion	-0.484675
Sum squared resid	5.020142	Schwarz criterion	-0.403303
Log likelihood	39.62365	Hannan-Quinn criter.	-0.451613
F-statistic	87.45485	Durbin-Watson stat	1.920511
Prob(F-statistic)	0.000000		

Null Hypothesis: D(FDI) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-4.109410	0.0076
Test critical values:	1% level	-4.021691	
	5% level	-3.440681	
	10% level	-3.144830	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(FDI,2)
Method: Least Squares
Date: 08/09/22 Time: 06:03
Sample (adjusted): 1980Q3 2017Q1
Included observations: 147 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(FDI(-1))	-0.211976	0.051583	-4.109410	0.0001
C	0.010644	0.032564	0.326864	0.7442
@TREND("1980Q1")	-5.80E-05	0.000377	-0.153633	0.8781

R-squared	0.105179	Mean dependent var	-0.001450
Adjusted R-squared	0.092751	S.D. dependent var	0.203873
S.E. of regression	0.194188	Akaike info criterion	-0.419781
Sum squared resid	5.430106	Schwarz criterion	-0.358751
Log likelihood	33.85387	Hannan-Quinn criter.	-0.394984
F-statistic	8.463020	Durbin-Watson stat	1.811607
Prob(F-statistic)	0.000335		

Null Hypothesis: FOS has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 5 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-1.096471	0.9253
Test critical values:	1% level	-4.023506	
	5% level	-3.441552	
	10% level	-3.145341	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(FOS)
Method: Least Squares

Date: 08/09/22 Time: 06:04
Sample (adjusted): 1981Q3 2017Q1
Included observations: 143 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
FOS(-1)	-0.006027	0.005497	-1.096471	0.2748
D(FOS(-1))	0.841371	0.079273	10.61352	0.0000
D(FOS(-2))	0.002946	0.096471	0.030541	0.9757
D(FOS(-3))	0.002946	0.096471	0.030541	0.9757
D(FOS(-4))	-0.535763	0.099077	-5.407557	0.0000
D(FOS(-5))	0.380111	0.083219	4.567614	0.0000
C	-1.97E-05	0.000157	-0.125136	0.9006
@TREND("1980Q1")	1.05E-05	5.55E-06	1.898780	0.0597

R-squared	0.688108	Mean dependent var	0.001021
Adjusted R-squared	0.671936	S.D. dependent var	0.001528
S.E. of regression	0.000875	Akaike info criterion	-11.19014
Sum squared resid	0.000103	Schwarz criterion	-11.02438
Log likelihood	808.0949	Hannan-Quinn criter.	-11.12278
F-statistic	42.54893	Durbin-Watson stat	1.924138
Prob(F-statistic)	0.000000		

Null Hypothesis: D(FOS) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 4 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-4.019982	0.0101
Test critical values:	1% level	-4.023506	
	5% level	-3.441552	
	10% level	-3.145341	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(FOS,2)
Method: Least Squares
Date: 08/09/22 Time: 06:04
Sample (adjusted): 1981Q3 2017Q1
Included observations: 143 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(FOS(-1))	-0.333911	0.083063	-4.019982	0.0001
D(FOS(-1),2)	0.171661	0.080607	2.129605	0.0350
D(FOS(-2),2)	0.171639	0.080604	2.129413	0.0350
D(FOS(-3),2)	0.171616	0.080600	2.129221	0.0350
D(FOS(-4),2)	-0.371397	0.082900	-4.480064	0.0000
C	-3.79E-05	0.000156	-0.242503	0.8088
@TREND("1980Q1")	4.96E-06	2.21E-06	2.244936	0.0264

R-squared	0.349447	Mean dependent var	-9.29E-06
Adjusted R-squared	0.320746	S.D. dependent var	0.001063
S.E. of regression	0.000876	Akaike info criterion	-11.19526
Sum squared resid	0.000104	Schwarz criterion	-11.05022
Log likelihood	807.4609	Hannan-Quinn criter.	-11.13632
F-statistic	12.17550	Durbin-Watson stat	1.913882

Prob(F-statistic)	0.000000

Null Hypothesis: GDPG has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 9 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-4.711700	0.0010
Test critical values:	1% level	-4.025426	
	5% level	-3.442474	
	10% level	-3.145882	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(GDPG)
Method: Least Squares
Date: 08/09/22 Time: 06:05
Sample (adjusted): 1982Q3 2017Q1
Included observations: 139 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
GDPG(-1)	-0.135973	0.028859	-4.711700	0.0000
D(GDPG(-1))	0.697750	0.083657	8.340604	0.0000
D(GDPG(-2))	0.251782	0.088413	2.847788	0.0051
D(GDPG(-3))	0.149993	0.090914	1.649826	0.1014
D(GDPG(-4))	-0.906415	0.091734	-9.880895	0.0000
D(GDPG(-5))	0.695298	0.113354	6.133861	0.0000
D(GDPG(-6))	0.142325	0.088382	1.610335	0.1098
D(GDPG(-7))	0.076531	0.089220	0.857772	0.3926
D(GDPG(-8))	-0.466489	0.088756	-5.255840	0.0000
D(GDPG(-9))	0.383163	0.083806	4.572010	0.0000
C	0.315371	0.139052	2.268011	0.0250
@TREND("1980Q1")	0.004865	0.001977	2.461025	0.0152

R-squared	0.683442	Mean dependent var	0.109114
Adjusted R-squared	0.656024	S.D. dependent var	1.183159
S.E. of regression	0.693916	Akaike info criterion	2.189445
Sum squared resid	61.15305	Schwarz criterion	2.442781
Log likelihood	-140.1664	Hannan-Quinn criter.	2.292394
F-statistic	24.92643	Durbin-Watson stat	2.003685
Prob(F-statistic)	0.000000		

Null Hypothesis: D(GDPG) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 11 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-6.049611	0.0000
Test critical values:	1% level	-4.026942	
	5% level	-3.443201	
	10% level	-3.146309	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(GDPG,2)
Method: Least Squares
Date: 08/09/22 Time: 06:05
Sample (adjusted): 1983Q2 2017Q1
Included observations: 136 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(GDPG(-1))	-1.044643	0.172679	-6.049611	0.0000
D(GDPG(-1),2)	0.656696	0.161046	4.077702	0.0001
D(GDPG(-2),2)	0.891513	0.155165	5.745560	0.0000
D(GDPG(-3),2)	0.980497	0.152558	6.427059	0.0000
D(GDPG(-4),2)	-0.259056	0.136059	-1.903994	0.0593
D(GDPG(-5),2)	0.375813	0.136034	2.762631	0.0066
D(GDPG(-6),2)	0.621892	0.133701	4.651371	0.0000
D(GDPG(-7),2)	0.724096	0.130446	5.550914	0.0000
D(GDPG(-8),2)	-0.183277	0.088242	-2.076995	0.0399
D(GDPG(-9),2)	0.152348	0.090024	1.692297	0.0931
D(GDPG(-10),2)	0.287923	0.089486	3.217528	0.0017
D(GDPG(-11),2)	0.354593	0.085591	4.142889	0.0001
C	0.308178	0.145648	2.115910	0.0364
@TREND("1980Q1")	-0.002714	0.001613	-1.682953	0.0949

R-squared	0.693268	Mean dependent var	0.027366
Adjusted R-squared	0.660583	S.D. dependent var	1.186576
S.E. of regression	0.691293	Akaike info criterion	2.196744
Sum squared resid	58.30215	Schwarz criterion	2.496576
Log likelihood	-135.3786	Hannan-Quinn criter.	2.318588
F-statistic	21.21084	Durbin-Watson stat	1.704436
Prob(F-statistic)	0.000000		

Null Hypothesis: IP has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 1 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.293379	0.0714
Test critical values:	1% level	-4.021691	
	5% level	-3.440681	
	10% level	-3.144830	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(IP)
Method: Least Squares
Date: 08/09/22 Time: 06:06
Sample (adjusted): 1980Q3 2017Q1
Included observations: 147 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
IP(-1)	-0.025803	0.007835	-3.293379	0.0012
D(IP(-1))	0.825848	0.046724	17.67515	0.0000
C	0.347778	0.114170	3.046134	0.0028

@TREND("1980Q1")	0.003107	0.001237	2.512224	0.0131

R-squared	0.688317	Mean dependent var	0.133282
Adjusted R-squared	0.681779	S.D. dependent var	0.692457
S.E. of regression	0.390623	Akaike info criterion	0.984685
Sum squared resid	21.81982	Schwarz criterion	1.066057
Log likelihood	-68.37434	Hannan-Quinn criter.	1.017747
F-statistic	105.2667	Durbin-Watson stat	1.946531
Prob(F-statistic)	0.000000		

Null Hypothesis: D(IP) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.886949	0.0149
Test critical values:	1% level	-4.021691	
	5% level	-3.440681	
	10% level	-3.144830	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(IP,2)
Method: Least Squares
Date: 08/09/22 Time: 06:06
Sample (adjusted): 1980Q3 2017Q1
Included observations: 147 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(IP(-1))	-0.187058	0.048125	-3.886949	0.0002
C	0.040330	0.067937	0.593642	0.5537
@TREND("1980Q1")	-0.000108	0.000785	-0.137954	0.8905

R-squared	0.095018	Mean dependent var	0.008953
Adjusted R-squared	0.082449	S.D. dependent var	0.421507
S.E. of regression	0.403757	Akaike info criterion	1.044189
Sum squared resid	23.47482	Schwarz criterion	1.105218
Log likelihood	-73.74790	Hannan-Quinn criter.	1.068986
F-statistic	7.559627	Durbin-Watson stat	1.836095
Prob(F-statistic)	0.000755		

South Africa

Without intercept and trend

Null Hypothesis: CO2 has a unit root
Exogenous: None
Lag Length: 5 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-0.637396	0.4396
Test critical values:	1% level	-2.581233	

	5% level	-1.943074
	10% level	-1.615231

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(CO2)
Method: Least Squares
Date: 08/09/22 Time: 07:04
Sample (adjusted): 1981Q3 2017Q1
Included observations: 143 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
CO2(-1)	-0.000502	0.000788	-0.637396	0.5249
D(CO2(-1))	0.869155	0.072199	12.03825	0.0000
D(CO2(-2))	0.000288	0.087670	0.003290	0.9974
D(CO2(-3))	0.000288	0.087670	0.003290	0.9974
D(CO2(-4))	-0.849203	0.101152	-8.395359	0.0000
D(CO2(-5))	0.677513	0.091748	7.384514	0.0000

R-squared	0.709593	Mean dependent var	-0.010820
Adjusted R-squared	0.698994	S.D. dependent var	0.153795
S.E. of regression	0.084378	Akaike info criterion	-2.065964
Sum squared resid	0.975395	Schwarz criterion	-1.941649
Log likelihood	153.7165	Hannan-Quinn criter.	-2.015449
Durbin-Watson stat	1.920828		

Null Hypothesis: D(CO2) has a unit root
Exogenous: None
Lag Length: 4 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.521637	0.0005
Test critical values:	1% level	-2.581233	
	5% level	-1.943074	
	10% level	-1.615231	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(CO2,2)
Method: Least Squares
Date: 08/09/22 Time: 07:05
Sample (adjusted): 1981Q3 2017Q1
Included observations: 143 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(CO2(-1))	-0.305087	0.086632	-3.521637	0.0006
D(CO2(-1),2)	0.175116	0.079366	2.206425	0.0290
D(CO2(-2),2)	0.175116	0.079366	2.206425	0.0290
D(CO2(-3),2)	0.175116	0.079366	2.206425	0.0290
D(CO2(-4),2)	-0.676484	0.091536	-7.390359	0.0000

R-squared	0.470002	Mean dependent var	-0.004843
Adjusted R-squared	0.454640	S.D. dependent var	0.114012

S.E. of regression	0.084196	Akaike info criterion	-2.076989
Sum squared resid	0.978287	Schwarz criterion	-1.973393
Log likelihood	153.5047	Hannan-Quinn criter.	-2.034893
Durbin-Watson stat	1.918086		

Null Hypothesis: FD has a unit root
Exogenous: None
Lag Length: 5 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		0.988514	0.9143
Test critical values:	1% level	-2.581233	
	5% level	-1.943074	
	10% level	-1.615231	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(FD)
Method: Least Squares
Date: 08/09/22 Time: 07:06
Sample (adjusted): 1981Q3 2017Q1
Included observations: 143 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
FD(-1)	0.001016	0.001027	0.988514	0.3246
D(FD(-1))	0.862025	0.080985	10.64424	0.0000
D(FD(-2))	-0.000507	0.101881	-0.004976	0.9960
D(FD(-3))	-0.000507	0.101881	-0.004976	0.9960
D(FD(-4))	-0.465545	0.102124	-4.558628	0.0000
D(FD(-5))	0.326253	0.081572	3.999580	0.0001

R-squared	0.627394	Mean dependent var	0.617137
Adjusted R-squared	0.613795	S.D. dependent var	2.185457
S.E. of regression	1.358161	Akaike info criterion	3.491193
Sum squared resid	252.7106	Schwarz criterion	3.615508
Log likelihood	-243.6203	Hannan-Quinn criter.	3.541709
Durbin-Watson stat	1.930734		

Null Hypothesis: D(FD) has a unit root
Exogenous: None
Lag Length: 4 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.604552	0.0004
Test critical values:	1% level	-2.581233	
	5% level	-1.943074	
	10% level	-1.615231	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(FD,2)

Method: Least Squares
Date: 08/09/22 Time: 07:06
Sample (adjusted): 1981Q3 2017Q1
Included observations: 143 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(FD(-1))	-0.251558	0.069789	-3.604552	0.0004
D(FD(-1),2)	0.125564	0.080014	1.569263	0.1189
D(FD(-2),2)	0.125564	0.080014	1.569263	0.1189
D(FD(-3),2)	0.125564	0.080014	1.569263	0.1189
D(FD(-4),2)	-0.340256	0.080326	-4.235959	0.0000

R-squared	0.282794	Mean dependent var	0.003251
Adjusted R-squared	0.262005	S.D. dependent var	1.580844
S.E. of regression	1.358049	Akaike info criterion	3.484315
Sum squared resid	254.5130	Schwarz criterion	3.587911
Log likelihood	-244.1285	Hannan-Quinn criter.	3.526411
Durbin-Watson stat	1.936145		

Null Hypothesis: FDI has a unit root
Exogenous: None
Lag Length: 13 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-1.181481	0.2162
Test critical values:	1% level	-2.582204	
	5% level	-1.943210	
	10% level	-1.615145	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(FDI)
Method: Least Squares
Date: 08/09/22 Time: 07:07
Sample (adjusted): 1983Q3 2017Q1
Included observations: 135 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
FDI(-1)	-0.014208	0.012025	-1.181481	0.2397
D(FDI(-1))	0.866486	0.076565	11.31697	0.0000
D(FDI(-2))	0.010898	0.088904	0.122584	0.9026
D(FDI(-3))	0.010898	0.088904	0.122584	0.9026
D(FDI(-4))	-1.043032	0.088949	-11.72614	0.0000
D(FDI(-5))	0.898081	0.113543	7.909641	0.0000
D(FDI(-6))	0.007119	0.113572	0.062681	0.9501
D(FDI(-7))	0.007119	0.113572	0.062681	0.9501
D(FDI(-8))	-0.875656	0.113859	-7.690733	0.0000
D(FDI(-9))	0.727315	0.114196	6.368984	0.0000
D(FDI(-10))	0.003343	0.088836	0.037634	0.9700
D(FDI(-11))	0.003343	0.088836	0.037634	0.9700
D(FDI(-12))	-0.690423	0.088879	-7.768101	0.0000
D(FDI(-13))	0.555433	0.077008	7.212704	0.0000

R-squared	0.822879	Mean dependent var	0.002907
Adjusted R-squared	0.803849	S.D. dependent var	0.397344

S.E. of regression	0.175980	Akaike info criterion	-0.538975
Sum squared resid	3.747223	Schwarz criterion	-0.237687
Log likelihood	50.38083	Hannan-Quinn criter.	-0.416540
Durbin-Watson stat	1.907443		

Null Hypothesis: D(FDI) has a unit root
Exogenous: None
Lag Length: 12 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.326365	0.0010
Test critical values:	1% level	-2.582204	
	5% level	-1.943210	
	10% level	-1.615145	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(FDI,2)
Method: Least Squares
Date: 08/09/22 Time: 07:07
Sample (adjusted): 1983Q3 2017Q1
Included observations: 135 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(FDI(-1))	-0.618828	0.186037	-3.326365	0.0012
D(FDI(-1),2)	0.474681	0.155840	3.045950	0.0028
D(FDI(-2),2)	0.474681	0.155840	3.045950	0.0028
D(FDI(-3),2)	0.474681	0.155840	3.045950	0.0028
D(FDI(-4),2)	-0.578952	0.156240	-3.705530	0.0003
D(FDI(-5),2)	0.310068	0.123049	2.519868	0.0130
D(FDI(-6),2)	0.310068	0.123049	2.519868	0.0130
D(FDI(-7),2)	0.310068	0.123049	2.519868	0.0130
D(FDI(-8),2)	-0.571997	0.124046	-4.611155	0.0000
D(FDI(-9),2)	0.145617	0.076623	1.900435	0.0597
D(FDI(-10),2)	0.145617	0.076623	1.900435	0.0597
D(FDI(-11),2)	0.145617	0.076623	1.900435	0.0597
D(FDI(-12),2)	-0.547900	0.076868	-7.127842	0.0000

R-squared	0.753207	Mean dependent var	-0.001148
Adjusted R-squared	0.728932	S.D. dependent var	0.338553
S.E. of regression	0.176265	Akaike info criterion	-0.542320
Sum squared resid	3.790452	Schwarz criterion	-0.262553
Log likelihood	49.60658	Hannan-Quinn criter.	-0.428630
Durbin-Watson stat	1.894111		

Null Hypothesis: FOS has a unit root
Exogenous: None
Lag Length: 13 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		0.780853	0.8807
Test critical values:	1% level	-2.582204	
	5% level	-1.943210	

	10% level	-1.615145	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(FOS)
Method: Least Squares
Date: 08/09/22 Time: 07:08
Sample (adjusted): 1983Q3 2017Q1
Included observations: 135 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
FOS(-1)	0.000617	0.000791	0.780853	0.4364
D(FOS(-1))	0.951640	0.075258	12.64500	0.0000
D(FOS(-2))	-0.000476	0.098607	-0.004832	0.9962
D(FOS(-3))	-0.000476	0.098607	-0.004832	0.9962
D(FOS(-4))	-1.040611	0.098918	-10.51996	0.0000
D(FOS(-5))	0.982084	0.115987	8.467199	0.0000
D(FOS(-6))	-0.000307	0.120610	-0.002544	0.9980
D(FOS(-7))	-0.000307	0.120610	-0.002544	0.9980
D(FOS(-8))	-0.860508	0.120854	-7.120245	0.0000
D(FOS(-9))	0.800436	0.117851	6.791913	0.0000
D(FOS(-10))	-0.000144	0.103399	-0.001389	0.9989
D(FOS(-11))	-0.000144	0.103399	-0.001389	0.9989
D(FOS(-12))	-0.664383	0.104321	-6.368665	0.0000
D(FOS(-13))	0.612541	0.081714	7.496125	0.0000

R-squared	0.788217	Mean dependent var	0.004117
Adjusted R-squared	0.765464	S.D. dependent var	0.012709
S.E. of regression	0.006155	Akaike info criterion	-7.245209
Sum squared resid	0.004584	Schwarz criterion	-6.943921
Log likelihood	503.0516	Hannan-Quinn criter.	-7.122774
Durbin-Watson stat	1.959271		

Null Hypothesis: D(FOS) has a unit root
Exogenous: None
Lag Length: 12 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-1.634606	0.0962
Test critical values:	1% level	-2.582204	
	5% level	-1.943210	
	10% level	-1.615145	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(FOS,2)
Method: Least Squares
Date: 08/09/22 Time: 07:08
Sample (adjusted): 1983Q3 2017Q1
Included observations: 135 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(FOS(-1))	-0.143473	0.087772	-1.634606	0.1047

D(FOS(-1),2)	0.110720	0.097129	1.139929	0.2565
D(FOS(-2),2)	0.110720	0.097129	1.139929	0.2565
D(FOS(-3),2)	0.110720	0.097129	1.139929	0.2565
D(FOS(-4),2)	-0.930761	0.097722	-9.524572	0.0000
D(FOS(-5),2)	0.071298	0.095669	0.745258	0.4575
D(FOS(-6),2)	0.071298	0.095669	0.745258	0.4575
D(FOS(-7),2)	0.071298	0.095669	0.745258	0.4575
D(FOS(-8),2)	-0.787621	0.095777	-8.223471	0.0000
D(FOS(-9),2)	0.033373	0.075799	0.440290	0.6605
D(FOS(-10),2)	0.033373	0.075799	0.440290	0.6605
D(FOS(-11),2)	0.033373	0.075799	0.440290	0.6605
D(FOS(-12),2)	-0.633211	0.077184	-8.203899	0.0000

R-squared	0.661675	Mean dependent var	-4.22E-05
Adjusted R-squared	0.628397	S.D. dependent var	0.010081
S.E. of regression	0.006145	Akaike info criterion	-7.254997
Sum squared resid	0.004607	Schwarz criterion	-6.975230
Log likelihood	502.7123	Hannan-Quinn criter.	-7.141308
Durbin-Watson stat	1.978210		

Null Hypothesis: GDPG has a unit root
Exogenous: None
Lag Length: 13 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-1.239474	0.1969
Test critical values:	1% level	-2.582204	
	5% level	-1.943210	
	10% level	-1.615145	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(GDPG)
Method: Least Squares
Date: 08/09/22 Time: 07:09
Sample (adjusted): 1983Q3 2017Q1
Included observations: 135 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
GDPG(-1)	-0.018371	0.014822	-1.239474	0.2176
D(GDPG(-1))	0.736811	0.083677	8.805383	0.0000
D(GDPG(-2))	0.153924	0.083417	1.845240	0.0674
D(GDPG(-3))	0.054607	0.084045	0.649733	0.5171
D(GDPG(-4))	-1.275737	0.083777	-15.22783	0.0000
D(GDPG(-5))	0.928200	0.127328	7.289837	0.0000
D(GDPG(-6))	0.130189	0.101584	1.281584	0.2024
D(GDPG(-7))	0.039320	0.101374	0.387866	0.6988
D(GDPG(-8))	-1.035997	0.100491	-10.30936	0.0000
D(GDPG(-9))	0.722514	0.118809	6.081330	0.0000
D(GDPG(-10))	0.073462	0.080439	0.913259	0.3629
D(GDPG(-11))	0.019032	0.080262	0.237126	0.8130
D(GDPG(-12))	-0.473123	0.078974	-5.990833	0.0000
D(GDPG(-13))	0.300826	0.072722	4.136650	0.0001

R-squared	0.770159	Mean dependent var	0.023725
Adjusted R-squared	0.745465	S.D. dependent var	0.896564

S.E. of regression	0.452330	Akaike info criterion	1.349114
Sum squared resid	24.75689	Schwarz criterion	1.650401
Log likelihood	-77.06517	Hannan-Quinn criter.	1.471548
Durbin-Watson stat	2.041780		

Null Hypothesis: D(GDPG) has a unit root
Exogenous: None
Lag Length: 12 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.970476	0.0001
Test critical values:	1% level	-2.582204	
	5% level	-1.943210	
	10% level	-1.615145	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(GDPG,2)
Method: Least Squares
Date: 08/09/22 Time: 07:10
Sample (adjusted): 1983Q3 2017Q1
Included observations: 135 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(GDPG(-1))	-0.731015	0.184113	-3.970476	0.0001
D(GDPG(-1),2)	0.456376	0.154312	2.957487	0.0037
D(GDPG(-2),2)	0.599564	0.154739	3.874679	0.0002
D(GDPG(-3),2)	0.640553	0.157687	4.062181	0.0001
D(GDPG(-4),2)	-0.650674	0.158892	-4.095081	0.0001
D(GDPG(-5),2)	0.267685	0.115108	2.325500	0.0217
D(GDPG(-6),2)	0.393435	0.115618	3.402879	0.0009
D(GDPG(-7),2)	0.425193	0.118907	3.575860	0.0005
D(GDPG(-8),2)	-0.620794	0.119500	-5.194932	0.0000
D(GDPG(-9),2)	0.094172	0.073911	1.274120	0.2050
D(GDPG(-10),2)	0.166961	0.073490	2.271890	0.0248
D(GDPG(-11),2)	0.183284	0.074494	2.460404	0.0153
D(GDPG(-12),2)	-0.294632	0.072709	-4.052180	0.0001

R-squared	0.781406	Mean dependent var	0.000697
Adjusted R-squared	0.759905	S.D. dependent var	0.925158
S.E. of regression	0.453323	Akaike info criterion	1.346916
Sum squared resid	25.07122	Schwarz criterion	1.626683
Log likelihood	-77.91680	Hannan-Quinn criter.	1.460605
Durbin-Watson stat	2.029943		

Null Hypothesis: IP has a unit root
Exogenous: None
Lag Length: 5 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.543712	0.0111
Test critical values:	1% level	-2.581233	
	5% level	-1.943074	

	10% level	-1.615231

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(IP)
Method: Least Squares
Date: 08/09/22 Time: 07:10
Sample (adjusted): 1981Q3 2017Q1
Included observations: 143 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
IP(-1)	-0.001085	0.000426	-2.543712	0.0121
D(IP(-1))	0.834371	0.080935	10.30919	0.0000
D(IP(-2))	0.000459	0.100668	0.004561	0.9964
D(IP(-3))	0.000459	0.100668	0.004561	0.9964
D(IP(-4))	-0.445121	0.100685	-4.420910	0.0000
D(IP(-5))	0.307641	0.078455	3.921247	0.0001

R-squared	0.637991	Mean dependent var	-0.111374
Adjusted R-squared	0.624779	S.D. dependent var	0.192441
S.E. of regression	0.117880	Akaike info criterion	-1.397239
Sum squared resid	1.903726	Schwarz criterion	-1.272924
Log likelihood	105.9026	Hannan-Quinn criter.	-1.346723
Durbin-Watson stat	1.929827		

Null Hypothesis: D(IP) has a unit root
Exogenous: None
Lag Length: 8 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-1.921759	0.0525
Test critical values:	1% level	-2.581705	
	5% level	-1.943140	
	10% level	-1.615189	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(IP,2)
Method: Least Squares
Date: 08/09/22 Time: 07:11
Sample (adjusted): 1982Q3 2017Q1
Included observations: 139 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(IP(-1))	-0.101104	0.052610	-1.921759	0.0568
D(IP(-1),2)	0.057043	0.074400	0.766707	0.4446
D(IP(-2),2)	0.057043	0.074400	0.766707	0.4446
D(IP(-3),2)	0.057043	0.074400	0.766707	0.4446
D(IP(-4),2)	-0.611001	0.074424	-8.209687	0.0000
D(IP(-5),2)	0.023177	0.068872	0.336527	0.7370
D(IP(-6),2)	0.023177	0.068872	0.336527	0.7370
D(IP(-7),2)	0.023177	0.068872	0.336527	0.7370
D(IP(-8),2)	-0.363169	0.069292	-5.241117	0.0000

R-squared	0.438485	Mean dependent var	-0.001019
Adjusted R-squared	0.403931	S.D. dependent var	0.129921
S.E. of regression	0.100306	Akaike info criterion	-1.698623
Sum squared resid	1.307971	Schwarz criterion	-1.508622
Log likelihood	127.0543	Hannan-Quinn criter.	-1.621412
Durbin-Watson stat	1.968259		

Intercept and trend

Null Hypothesis: CO2 has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 5 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.645093	0.2613
Test critical values:	1% level	-4.023506	
	5% level	-3.441552	
	10% level	-3.145341	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(CO2)
Method: Least Squares
Date: 08/09/22 Time: 07:14
Sample (adjusted): 1981Q3 2017Q1
Included observations: 143 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
CO2(-1)	-0.033821	0.012786	-2.645093	0.0091
D(CO2(-1))	0.874276	0.071344	12.25441	0.0000
D(CO2(-2))	0.019351	0.086402	0.223960	0.8231
D(CO2(-3))	0.019351	0.086402	0.223960	0.8231
D(CO2(-4))	-0.839733	0.099608	-8.430400	0.0000
D(CO2(-5))	0.699669	0.091391	7.655779	0.0000
C	0.311657	0.117593	2.650315	0.0090
@TREND("1980Q1")	-0.000153	0.000172	-0.889509	0.3753

R-squared	0.724043	Mean dependent var	-0.010820
Adjusted R-squared	0.709734	S.D. dependent var	0.153795
S.E. of regression	0.082859	Akaike info criterion	-2.089030
Sum squared resid	0.926862	Schwarz criterion	-1.923276
Log likelihood	157.3656	Hannan-Quinn criter.	-2.021676
F-statistic	50.60095	Durbin-Watson stat	1.961745
Prob(F-statistic)	0.000000		

Null Hypothesis: D(CO2) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 4 (Automatic - based on SIC, maxlag=13)

	t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic	-3.518072	0.0412

Test critical values:	1% level	-4.023506
	5% level	-3.441552
	10% level	-3.145341

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(CO2,2)
Method: Least Squares
Date: 08/09/22 Time: 07:16
Sample (adjusted): 1981Q3 2017Q1
Included observations: 143 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(CO2(-1))	-0.309352	0.087932	-3.518072	0.0006
D(CO2(-1),2)	0.174993	0.080052	2.186005	0.0305
D(CO2(-2),2)	0.174959	0.080048	2.185676	0.0306
D(CO2(-3),2)	0.174924	0.080044	2.185345	0.0306
D(CO2(-4),2)	-0.671375	0.092742	-7.239158	0.0000
C	0.003094	0.015142	0.204315	0.8384
@TREND("1980Q1")	-8.49E-05	0.000174	-0.488592	0.6259

R-squared	0.471839	Mean dependent var	-0.004843
Adjusted R-squared	0.448537	S.D. dependent var	0.114012
S.E. of regression	0.084666	Akaike info criterion	-2.052488
Sum squared resid	0.974898	Schwarz criterion	-1.907454
Log likelihood	153.7529	Hannan-Quinn criter.	-1.993553
F-statistic	20.24951	Durbin-Watson stat	1.916426
Prob(F-statistic)	0.000000		

Null Hypothesis: D(FD) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 4 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.979902	0.0114
Test critical values:	1% level	-4.023506	
	5% level	-3.441552	
	10% level	-3.145341	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(FD,2)
Method: Least Squares
Date: 08/09/22 Time: 07:18
Sample (adjusted): 1981Q3 2017Q1
Included observations: 143 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(FD(-1))	-0.305500	0.076761	-3.979902	0.0001
D(FD(-1),2)	0.153034	0.081476	1.878266	0.0625
D(FD(-2),2)	0.153032	0.081476	1.878249	0.0625
D(FD(-3),2)	0.153030	0.081476	1.878233	0.0625
D(FD(-4),2)	-0.312639	0.081807	-3.821669	0.0002
C	0.357177	0.255634	1.397220	0.1646
@TREND("1980Q1")	-0.002209	0.002795	-0.790504	0.4306

R-squared	0.297141	Mean dependent var	0.003251
Adjusted R-squared	0.266132	S.D. dependent var	1.580844
S.E. of regression	1.354247	Akaike info criterion	3.492080
Sum squared resid	249.4219	Schwarz criterion	3.637115
Log likelihood	-242.6837	Hannan-Quinn criter.	3.551015
F-statistic	9.582555	Durbin-Watson stat	1.927997
Prob(F-statistic)	0.000000		

Null Hypothesis: FDI has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 13 (Automatic - based on SIC, maxlag=13)

	t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic	-2.281254	0.4409

Test critical values:	1% level	-4.027463	
	5% level	-3.443450	
	10% level	-3.146455	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(FDI)
Method: Least Squares
Date: 08/09/22 Time: 07:18
Sample (adjusted): 1983Q3 2017Q1
Included observations: 135 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
FDI(-1)	-0.071293	0.031252	-2.281254	0.0243
D(FDI(-1))	0.909835	0.079794	11.40231	0.0000
D(FDI(-2))	0.054694	0.090847	0.602042	0.5483
D(FDI(-3))	0.054694	0.090847	0.602042	0.5483
D(FDI(-4))	-0.997707	0.091098	-10.95207	0.0000
D(FDI(-5))	0.932939	0.114427	8.153136	0.0000
D(FDI(-6))	0.035753	0.113477	0.315073	0.7533
D(FDI(-7))	0.035753	0.113477	0.315073	0.7533
D(FDI(-8))	-0.843383	0.114029	-7.396232	0.0000
D(FDI(-9))	0.760186	0.114898	6.616199	0.0000
D(FDI(-10))	0.016815	0.088298	0.190431	0.8493
D(FDI(-11))	0.016815	0.088298	0.190431	0.8493
D(FDI(-12))	-0.675676	0.088397	-7.643620	0.0000
D(FDI(-13))	0.578281	0.077700	7.442474	0.0000
C	-0.008743	0.037385	-0.233862	0.8155
@TREND("1980Q1")	0.000957	0.000658	1.454119	0.1485

R-squared	0.828936	Mean dependent var	0.002907
Adjusted R-squared	0.807373	S.D. dependent var	0.397344
S.E. of regression	0.174391	Akaike info criterion	-0.544144
Sum squared resid	3.619067	Schwarz criterion	-0.199816
Log likelihood	52.72975	Hannan-Quinn criter.	-0.404219
F-statistic	38.44311	Durbin-Watson stat	1.944354
Prob(F-statistic)	0.000000		

Null Hypothesis: D(FDI) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 12 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.353512	0.0623
Test critical values:	1% level	-4.027463	
	5% level	-3.443450	
	10% level	-3.146455	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(FDI,2)
Method: Least Squares
Date: 08/09/22 Time: 07:18
Sample (adjusted): 1983Q3 2017Q1

Included observations: 135 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(FDI(-1))	-0.635067	0.189374	-3.353512	0.0011
D(FDI(-1),2)	0.486951	0.158323	3.075678	0.0026
D(FDI(-2),2)	0.486949	0.158323	3.075672	0.0026
D(FDI(-3),2)	0.486947	0.158322	3.075666	0.0026
D(FDI(-4),2)	-0.566995	0.158688	-3.573026	0.0005
D(FDI(-5),2)	0.317980	0.124655	2.550890	0.0120
D(FDI(-6),2)	0.317972	0.124653	2.550848	0.0120
D(FDI(-7),2)	0.317964	0.124652	2.550806	0.0120
D(FDI(-8),2)	-0.564842	0.125593	-4.497388	0.0000
D(FDI(-9),2)	0.149031	0.077393	1.925641	0.0565
D(FDI(-10),2)	0.149021	0.077392	1.925534	0.0565
D(FDI(-11),2)	0.149011	0.077391	1.925427	0.0565
D(FDI(-12),2)	-0.544773	0.077624	-7.018085	0.0000
C	0.021136	0.035623	0.593321	0.5541
@TREND("1980Q1")	-0.000255	0.000395	-0.644998	0.5202

R-squared	0.754061	Mean dependent var	-0.001148
Adjusted R-squared	0.725368	S.D. dependent var	0.338553
S.E. of regression	0.177420	Akaike info criterion	-0.516156
Sum squared resid	3.777336	Schwarz criterion	-0.193348
Log likelihood	49.84056	Hannan-Quinn criter.	-0.384976
F-statistic	26.28041	Durbin-Watson stat	1.893326
Prob(F-statistic)	0.000000		

Null Hypothesis: FOS has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 13 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.847114	0.1834
Test critical values:	1% level	-4.027463	
	5% level	-3.443450	
	10% level	-3.146455	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(FOS)
Method: Least Squares
Date: 08/09/22 Time: 07:20
Sample (adjusted): 1983Q3 2017Q1
Included observations: 135 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
FOS(-1)	-0.035603	0.012505	-2.847114	0.0052
D(FOS(-1))	0.949579	0.073342	12.94722	0.0000
D(FOS(-2))	0.027727	0.096457	0.287458	0.7743
D(FOS(-3))	0.027727	0.096457	0.287458	0.7743
D(FOS(-4))	-1.011092	0.096828	-10.44216	0.0000
D(FOS(-5))	0.978827	0.112898	8.670013	0.0000
D(FOS(-6))	0.018417	0.117558	0.156666	0.8758
D(FOS(-7))	0.018417	0.117558	0.156666	0.8758
D(FOS(-8))	-0.843035	0.117765	-7.158607	0.0000

D(FOS(-9))	0.807070	0.114738	7.034029	0.0000
D(FOS(-10))	0.008513	0.100674	0.084555	0.9328
D(FOS(-11))	0.008513	0.100674	0.084555	0.9328
D(FOS(-12))	-0.653437	0.101621	-6.430122	0.0000
D(FOS(-13))	0.627430	0.079705	7.871860	0.0000
C	0.020702	0.007000	2.957436	0.0037
@TREND("1980Q1")	0.000178	6.52E-05	2.732323	0.0072

R-squared	0.802726	Mean dependent var	0.004117
Adjusted R-squared	0.777860	S.D. dependent var	0.012709
S.E. of regression	0.005990	Akaike info criterion	-7.286548
Sum squared resid	0.004270	Schwarz criterion	-6.942219
Log likelihood	507.8420	Hannan-Quinn criter.	-7.146623
F-statistic	32.28148	Durbin-Watson stat	2.023873
Prob(F-statistic)	0.000000		

Null Hypothesis: D(FOS) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 12 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-1.845578	0.6769
Test critical values:	1% level	-4.027463	
	5% level	-3.443450	
	10% level	-3.146455	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(FOS,2)
Method: Least Squares
Date: 08/09/22 Time: 07:20
Sample (adjusted): 1983Q3 2017Q1
Included observations: 135 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(FOS(-1))	-0.239353	0.129690	-1.845578	0.0674
D(FOS(-1),2)	0.185387	0.122929	1.508075	0.1342
D(FOS(-2),2)	0.185382	0.122932	1.508004	0.1342
D(FOS(-3),2)	0.185377	0.122934	1.507933	0.1342
D(FOS(-4),2)	-0.854952	0.124440	-6.870409	0.0000
D(FOS(-5),2)	0.121657	0.108663	1.119585	0.2651
D(FOS(-6),2)	0.121643	0.108669	1.119392	0.2652
D(FOS(-7),2)	0.121628	0.108675	1.119199	0.2653
D(FOS(-8),2)	-0.738407	0.108033	-6.835013	0.0000
D(FOS(-9),2)	0.056699	0.079496	0.713226	0.4771
D(FOS(-10),2)	0.056694	0.079497	0.713160	0.4771
D(FOS(-11),2)	0.056690	0.079498	0.713094	0.4772
D(FOS(-12),2)	-0.607885	0.081727	-7.438028	0.0000
C	0.001097	0.001295	0.847085	0.3986
@TREND("1980Q1")	-3.52E-06	1.38E-05	-0.254928	0.7992

R-squared	0.665074	Mean dependent var	-4.22E-05
Adjusted R-squared	0.625999	S.D. dependent var	0.010081
S.E. of regression	0.006165	Akaike info criterion	-7.235465
Sum squared resid	0.004561	Schwarz criterion	-6.912656
Log likelihood	503.3939	Hannan-Quinn criter.	-7.104284

F-statistic	17.02056	Durbin-Watson stat	1.957050
Prob(F-statistic)	0.000000		

Null Hypothesis: GDPG has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 13 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.471541	0.3417
Test critical values:	1% level	-4.027463	
	5% level	-3.443450	
	10% level	-3.146455	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(GDPG)
Method: Least Squares
Date: 08/09/22 Time: 07:21
Sample (adjusted): 1983Q3 2017Q1
Included observations: 135 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
GDPG(-1)	-0.083623	0.033834	-2.471541	0.0149
D(GDPG(-1))	0.772726	0.085444	9.043704	0.0000
D(GDPG(-2))	0.197924	0.084639	2.338450	0.0210
D(GDPG(-3))	0.106291	0.086231	1.232630	0.2201
D(GDPG(-4))	-1.217532	0.086943	-14.00386	0.0000
D(GDPG(-5))	0.958448	0.127259	7.531448	0.0000
D(GDPG(-6))	0.154189	0.100742	1.530531	0.1285
D(GDPG(-7))	0.071198	0.100992	0.704990	0.4822
D(GDPG(-8))	-0.995075	0.100842	-9.867646	0.0000
D(GDPG(-9))	0.750377	0.118314	6.342225	0.0000
D(GDPG(-10))	0.080986	0.079427	1.019628	0.3100
D(GDPG(-11))	0.032369	0.079385	0.407750	0.6842
D(GDPG(-12))	-0.450790	0.078528	-5.740490	0.0000
D(GDPG(-13))	0.328783	0.072920	4.508798	0.0000
C	0.162216	0.096595	1.679348	0.0957
@TREND("1980Q1")	0.000380	0.001124	0.338156	0.7358

R-squared	0.780048	Mean dependent var	0.023725
Adjusted R-squared	0.752323	S.D. dependent var	0.896564
S.E. of regression	0.446194	Akaike info criterion	1.334762
Sum squared resid	23.69164	Schwarz criterion	1.679091
Log likelihood	-74.09642	Hannan-Quinn criter.	1.474687
F-statistic	28.13519	Durbin-Watson stat	2.073517
Prob(F-statistic)	0.000000		

Null Hypothesis: D(GDPG) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 12 (Automatic - based on SIC, maxlag=13)

	t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic	-3.981771	0.0115

Test critical values:	1% level	-4.027463	
	5% level	-3.443450	
	10% level	-3.146455	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(GDPG,2)
Method: Least Squares
Date: 08/09/22 Time: 07:21
Sample (adjusted): 1983Q3 2017Q1
Included observations: 135 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(GDPG(-1))	-0.738201	0.185395	-3.981771	0.0001
D(GDPG(-1),2)	0.455868	0.155389	2.933723	0.0040
D(GDPG(-2),2)	0.600734	0.155746	3.857136	0.0002
D(GDPG(-3),2)	0.642648	0.158680	4.049975	0.0001
D(GDPG(-4),2)	-0.648244	0.159864	-4.054976	0.0001
D(GDPG(-5),2)	0.261504	0.116206	2.250353	0.0262
D(GDPG(-6),2)	0.390608	0.116429	3.354910	0.0011
D(GDPG(-7),2)	0.424345	0.119631	3.547123	0.0006
D(GDPG(-8),2)	-0.620319	0.120176	-5.161768	0.0000
D(GDPG(-9),2)	0.089591	0.074590	1.201115	0.2321
D(GDPG(-10),2)	0.164500	0.073979	2.223597	0.0280
D(GDPG(-11),2)	0.182230	0.074913	2.432548	0.0165
D(GDPG(-12),2)	-0.294340	0.073084	-4.027423	0.0001
C	0.074136	0.091671	0.808718	0.4203
@TREND("1980Q1")	-0.000903	0.001018	-0.887186	0.3768

R-squared	0.782831	Mean dependent var	0.000697
Adjusted R-squared	0.757494	S.D. dependent var	0.925158
S.E. of regression	0.455593	Akaike info criterion	1.370005
Sum squared resid	24.90779	Schwarz criterion	1.692813
Log likelihood	-77.47533	Hannan-Quinn criter.	1.501185
F-statistic	30.89748	Durbin-Watson stat	2.026655
Prob(F-statistic)	0.000000		

Null Hypothesis: IP has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 5 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-0.782128	0.9641
Test critical values:	1% level	-4.023506	
	5% level	-3.441552	
	10% level	-3.145341	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(IP)
Method: Least Squares
Date: 08/09/22 Time: 07:22
Sample (adjusted): 1981Q3 2017Q1
Included observations: 143 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
IP(-1)	-0.004585	0.005862	-0.782128	0.4355
D(IP(-1))	0.811470	0.082224	9.869075	0.0000
D(IP(-2))	0.001937	0.100396	0.019297	0.9846
D(IP(-3))	0.001937	0.100396	0.019297	0.9846
D(IP(-4))	-0.443876	0.100422	-4.420091	0.0000
D(IP(-5))	0.282771	0.080164	3.527395	0.0006
C	0.106472	0.242375	0.439288	0.6612
@TREND("1980Q1")	1.27E-05	0.000759	0.016681	0.9867

R-squared	0.645441	Mean dependent var	-0.111374
Adjusted R-squared	0.627057	S.D. dependent var	0.192441
S.E. of regression	0.117522	Akaike info criterion	-1.390062
Sum squared resid	1.864546	Schwarz criterion	-1.224308
Log likelihood	107.3894	Hannan-Quinn criter.	-1.322707
F-statistic	35.10786	Durbin-Watson stat	1.922596
Prob(F-statistic)	0.000000		

Null Hypothesis: D(IP) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 4 (Automatic - based on SIC, maxlag=13)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-4.520428	0.0020
Test critical values:	1% level	-4.023506	
	5% level	-3.441552	
	10% level	-3.145341	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(IP,2)
Method: Least Squares
Date: 08/09/22 Time: 07:22
Sample (adjusted): 1981Q3 2017Q1
Included observations: 143 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(IP(-1))	-0.354369	0.078393	-4.520428	0.0000
D(IP(-1),2)	0.165118	0.080054	2.062575	0.0411
D(IP(-2),2)	0.164982	0.080036	2.061352	0.0412
D(IP(-3),2)	0.164846	0.080017	2.060128	0.0413
D(IP(-4),2)	-0.281331	0.080029	-3.515375	0.0006
C	-0.081661	0.029720	-2.747715	0.0068
@TREND("1980Q1")	0.000564	0.000281	2.006295	0.0468

R-squared	0.307770	Mean dependent var	0.003308
Adjusted R-squared	0.277230	S.D. dependent var	0.138038
S.E. of regression	0.117354	Akaike info criterion	-1.399527
Sum squared resid	1.872995	Schwarz criterion	-1.254492
Log likelihood	107.0662	Hannan-Quinn criter.	-1.340592
F-statistic	10.07774	Durbin-Watson stat	1.922155
Prob(F-statistic)	0.000000		

Bound test

South Africa

ARDL Bounds Test
Date: 08/10/22 Time: 03:16
Sample: 1982Q2 2017Q1
Included observations: 140
Null Hypothesis: No long-run relationships exist

Test Statistic	Value	k
F-statistic	4.830366	5

Critical Value Bounds

Significance	I0 Bound	I1 Bound
10%	2.26	3.35
5%	2.62	3.79
2.5%	2.96	4.18
1%	3.41	4.68

Test Equation:
Dependent Variable: D(CO2)
Method: Least Squares
Date: 08/10/22 Time: 03:16
Sample: 1982Q2 2017Q1
Included observations: 140

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(CO2(-1))	0.762650	0.071069	10.73113	0.0000
D(CO2(-2))	0.048819	0.078689	0.620409	0.5363
D(CO2(-3))	0.041640	0.078645	0.529469	0.5975
D(CO2(-4))	-0.679361	0.100958	-6.729120	0.0000
D(CO2(-5))	0.486475	0.094816	5.130741	0.0000
D(FD)	-0.012079	0.006616	-1.825749	0.0706
D(FD(-1))	0.013064	0.006399	2.041385	0.0436
D(FDI)	0.001030	0.031675	0.032512	0.9741
D(FDI(-1))	-0.038053	0.037070	-1.026529	0.3069
D(FDI(-2))	-0.028093	0.036775	-0.763932	0.4465
D(FDI(-3))	-0.032503	0.036610	-0.887813	0.3766
D(FDI(-4))	-0.188952	0.046283	-4.082539	0.0001
D(FDI(-5))	0.074020	0.042440	1.744114	0.0839
D(FDI(-6))	-0.011868	0.036188	-0.327949	0.7436
D(FDI(-7))	-0.015573	0.036091	-0.431496	0.6670
D(FDI(-8))	-0.101007	0.032752	-3.084008	0.0026
D(FOS)	-4.085356	0.941426	-4.339541	0.0000
D(FOS(-1))	3.085904	0.896261	3.443085	0.0008
D(GDPG)	0.003727	0.009469	0.393640	0.6946
D(GDPG(-1))	0.006672	0.009132	0.730666	0.4665
D(GDPG(-2))	-0.012412	0.009166	-1.354056	0.1785
D(GDPG(-3))	-0.013923	0.009051	-1.538328	0.1268
D(IP)	-0.116000	0.053375	-2.173299	0.0319

C	-1.068623	0.363363	-2.940921	0.0040
FD(-1)	0.004413	0.001451	3.040745	0.0030
FDI(-1)	0.029799	0.013661	2.181330	0.0313
FOS(-1)	0.005818	0.102829	0.056581	0.9550
GDPG(-1)	0.021396	0.006039	3.542849	0.0006
IP(-1)	0.035901	0.008961	4.006378	0.0001
CO2(-1)	-0.073457	0.017969	-4.087926	0.0001

R-squared	0.821167	Mean dependent var	-0.013932
Adjusted R-squared	0.774020	S.D. dependent var	0.153943
S.E. of regression	0.073180	Akaike info criterion	-2.204367
Sum squared resid	0.589092	Schwarz criterion	-1.574015
Log likelihood	184.3057	Hannan-Quinn criter.	-1.948211
F-statistic	17.41723	Durbin-Watson stat	1.834449
Prob(F-statistic)	0.000000		

Long and short run

South Africa

ARDL Cointegrating And Long Run Form
Dependent Variable: CO2
Selected Model: ARDL(6, 2, 9, 2, 4, 1)
Date: 08/10/22 Time: 03:18
Sample: 1980Q1 2017Q1
Included observations: 140

Cointegrating Form

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(CO2(-1))	0.762650	0.071069	10.731134	0.0000
D(CO2(-2))	0.048819	0.078689	0.620409	0.5363
D(CO2(-3))	0.041640	0.078645	0.529469	0.5975
D(CO2(-4))	-0.679361	0.100958	-6.729120	0.0000
D(CO2(-5))	0.486475	0.094816	5.130741	0.0000
D(FD)	-0.012079	0.006616	-1.825749	0.0706
D(FD(-1))	0.013064	0.006399	2.041385	0.0436
D(FDI)	0.001030	0.031675	0.032512	0.9741
D(FDI(-1))	-0.009960	0.061544	-0.161835	0.8717
D(FDI(-2))	0.004409	0.061256	0.071985	0.9427
D(FDI(-3))	0.156449	0.067667	2.312028	0.0226
D(FDI(-4))	-0.262971	0.076141	-3.453739	0.0008
D(FDI(-5))	0.085887	0.066112	1.299112	0.1966
D(FDI(-6))	0.003705	0.062151	0.059614	0.9526
D(FDI(-7))	0.085434	0.059536	1.434991	0.1541
D(FDI(-8))	-0.101007	0.032752	-3.084008	0.0026
D(FOS)	-4.085356	0.941426	-4.339541	0.0000
D(FOS(-1))	3.085904	0.896261	3.443085	0.0008
D(GDPG)	0.003727	0.009469	0.393640	0.6946
D(GDPG(-1))	0.019084	0.014242	1.340008	0.1830
D(GDPG(-2))	0.001511	0.013996	0.107969	0.9142
D(GDPG(-3))	-0.013923	0.009051	-1.538328	0.1268
D(IP)	-0.116000	0.053375	-2.173299	0.0319
CointEq(-1)	-0.073457	0.017969	-4.087926	0.0001

Cointeq = CO2 - (0.0601*FD + 0.4057*FDI + 0.0792*FOS + 0.2913*GDPG + 0.4887*IP -14.5477)

Long Run Coefficients				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
FD	0.060070	0.020735	2.896973	0.0045
FDI	0.405665	0.202671	2.001595	0.0478
FOS	0.079205	1.391243	0.056931	0.9547
GDPG	0.291280	0.078252	3.722314	0.0003
IP	0.488740	0.103490	4.722585	0.0000
C	-1.457675	5.040447	-2.886188	0.0047

Post estimation

South Africa

Heteroskedasticity Test: Breusch-Pagan-Godfrey

F-statistic	1.518143	Prob. F(31,108)	0.1606
Obs*R-squared	42.49088	Prob. Chi-Square(31)	0.0819
Scaled explained SS	73.77636	Prob. Chi-Square(31)	0.0000

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 08/10/22 Time: 04:01
Sample: 1982Q2 2017Q1
Included observations: 140

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.093899	0.048837	1.922708	0.0572
CO2(-1)	0.026299	0.010058	2.614642	0.0102
CO2(-2)	-0.024897	0.017228	-1.445153	0.1513
CO2(-3)	0.000635	0.017295	0.036688	0.9708
CO2(-4)	0.007595	0.019370	0.392081	0.6958
CO2(-5)	-0.001785	0.023199	-0.076947	0.9388
CO2(-6)	-0.003752	0.012209	-0.307339	0.7592
FD	0.001422	0.000854	1.665834	0.0986
FD(-1)	-0.002692	0.001518	-1.774013	0.0789
FD(-2)	0.000818	0.000833	0.981858	0.3284
FDI	0.007839	0.004114	1.905236	0.0594
FDI(-1)	-0.016064	0.007603	-2.112670	0.0369
FDI(-2)	0.009134	0.007885	1.158328	0.2493
FDI(-3)	-0.000132	0.007864	-0.016815	0.9866
FDI(-4)	0.014598	0.008803	1.658240	0.1002
FDI(-5)	-0.026736	0.009794	-2.729815	0.0074
FDI(-6)	0.011749	0.008534	1.376767	0.1714
FDI(-7)	2.14E-05	0.007976	0.002680	0.9979
FDI(-8)	0.002150	0.007735	0.277934	0.7816
FDI(-9)	-0.002763	0.004270	-0.646973	0.5190
FOS	0.249604	0.121913	2.047399	0.0430
FOS(-1)	-0.445736	0.220708	-2.019569	0.0459
FOS(-2)	0.167728	0.127798	1.312449	0.1922
GDPG	0.000103	0.001350	0.076581	0.9391
GDPG(-1)	-0.001097	0.002023	-0.542070	0.5889
GDPG(-2)	0.000461	0.001826	0.252674	0.8010

GDPG(-3)	-5.22E-05	0.001806	-0.028893	0.9770
GDPG(-4)	3.14E-05	0.001950	0.016111	0.9872
GDPG(-5)	-0.000593	0.001282	-0.462616	0.6446
IP	0.012659	0.007025	1.801847	0.0744
IP(-1)	-0.014726	0.007467	-1.972133	0.0512
@TREND	0.000275	0.000171	1.605846	0.1112

R-squared	0.303506	Mean dependent var	0.004085
Adjusted R-squared	0.103587	S.D. dependent var	0.009903
S.E. of regression	0.009376	Akaike info criterion	-6.303696
Sum squared resid	0.009494	Schwarz criterion	-5.631320
Log likelihood	473.2587	Hannan-Quinn criter.	-6.030462
F-statistic	1.518143	Durbin-Watson stat	2.229999
Prob(F-statistic)	0.060628		

Breusch-Godfrey Serial Correlation LM Test:

F-statistic	2.426424	Prob. F(2,106)	0.3932
Obs*R-squared	6.128834	Prob. Chi-Square(2)	0.0467

Test Equation:
Dependent Variable: RESID
Method: ARDL
Date: 08/10/22 Time: 04:04
Sample: 1982Q2 2017Q1
Included observations: 140
Presample missing value lagged residuals set to zero.

Variable	Coefficient	Std. Error	t-Statistic	Prob.
CO2(-1)	-0.233332	0.133686	-1.745367	0.0838
CO2(-2)	0.258420	0.201721	1.281078	0.2030
CO2(-3)	0.026195	0.171499	0.152739	0.8789
CO2(-4)	-0.049639	0.155237	-0.319762	0.7498
CO2(-5)	-0.120295	0.185919	-0.647031	0.5190
CO2(-6)	0.099445	0.103866	0.957436	0.3405
FD	-0.002933	0.006676	-0.439363	0.6613
FD(-1)	0.002137	0.011670	0.183082	0.8551
FD(-2)	0.001832	0.006446	0.284223	0.7768
FDI	0.004300	0.031637	0.135916	0.8921
FDI(-1)	-0.011468	0.058479	-0.196097	0.8449
FDI(-2)	0.003564	0.060686	0.058720	0.9533
FDI(-3)	0.003349	0.060452	0.055398	0.9559
FDI(-4)	-0.018061	0.067935	-0.265865	0.7909
FDI(-5)	-0.010156	0.075175	-0.135104	0.8928
FDI(-6)	0.030033	0.067421	0.445463	0.6569
FDI(-7)	0.004128	0.062030	0.066550	0.9471
FDI(-8)	-0.025522	0.060464	-0.422100	0.6738
FDI(-9)	0.020474	0.034007	0.602044	0.5484
FOS	-0.111725	0.935475	-0.119432	0.9052
FOS(-1)	-0.681347	1.719678	-0.396206	0.6927
FOS(-2)	0.966312	1.073650	0.900025	0.3701
GDPG	0.000939	0.010353	0.090654	0.9279
GDPG(-1)	0.003065	0.015563	0.196910	0.8443
GDPG(-2)	0.002651	0.014043	0.188748	0.8507
GDPG(-3)	-0.001712	0.013869	-0.123432	0.9020
GDPG(-4)	-0.001495	0.014966	-0.099867	0.9206
GDPG(-5)	0.005125	0.010096	0.507667	0.6127
IP	-0.032434	0.055796	-0.581297	0.5623

IP(-1)	0.035415	0.059419	0.596032	0.5524
C	-0.107281	0.377462	-0.284217	0.7768
@TREND	-0.001524	0.001485	-1.026372	0.3071
RESID(-1)	0.320204	0.161485	1.982872	0.0500
RESID(-2)	0.179650	0.142982	1.256450	0.2117

R-squared	0.043777	Mean dependent var	1.58E-15
Adjusted R-squared	-0.253915	S.D. dependent var	0.064142
S.E. of regression	0.071826	Akaike info criterion	-2.221642
Sum squared resid	0.546844	Schwarz criterion	-1.507243
Log likelihood	189.5149	Hannan-Quinn criter.	-1.931332
F-statistic	0.147056	Durbin-Watson stat	1.945804
Prob(F-statistic)	1.000000		

Nigeria

Bound test

ARDL Bounds Test
Date: 08/10/22 Time: 03:52
Sample: 1981Q2 2017Q1
Included observations: 144
Null Hypothesis: No long-run relationships exist

Test Statistic	Value	k
F-statistic	4.009444	5

Critical Value Bounds

Significance	I0 Bound	I1 Bound
10%	2.26	3.35
5%	2.62	3.79
2.5%	2.96	4.18
1%	3.41	4.68

Test Equation:
Dependent Variable: D(CO2)
Method: Least Squares
Date: 08/10/22 Time: 03:52
Sample: 1981Q2 2017Q1
Included observations: 144

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(CO2(-1))	0.736427	0.077991	9.442480	0.0000
D(CO2(-2))	0.006609	0.094508	0.069930	0.9444
D(CO2(-3))	0.008635	0.094568	0.091313	0.9274
D(CO2(-4))	-0.188762	0.083884	-2.250271	0.0262
D(FDI)	-0.023992	0.005906	-4.062147	0.0001
D(FDI(-1))	0.026265	0.005505	4.771537	0.0000
D(IP)	0.003020	0.002763	1.093011	0.2765
D(IP(-1))	-0.002224	0.003275	-0.678969	0.4984
D(IP(-2))	0.000934	0.003277	0.284937	0.7762

D(IP(-3))	0.000875	0.003276	0.266985	0.7899
D(IP(-4))	0.005287	0.002742	1.928143	0.0561
C	0.130839	0.038580	3.391365	0.0009
FD(-1)	-0.001406	0.000746	-1.885350	0.0617
FDI(-1)	-0.004558	0.001439	-3.167429	0.0019
FOS(-1)	-0.028239	0.016059	-1.758441	0.0811
GDPG(-1)	-0.000423	0.000277	-1.526404	0.1294
IP(-1)	-0.002227	0.000717	-3.106213	0.0023
CO2(-1)	-0.044638	0.011215	-3.980248	0.0001

R-squared	0.703666	Mean dependent var	-0.001084
Adjusted R-squared	0.663684	S.D. dependent var	0.025554
S.E. of regression	0.014820	Akaike info criterion	-5.469265
Sum squared resid	0.027672	Schwarz criterion	-5.098038
Log likelihood	411.7871	Hannan-Quinn criter.	-5.318419
F-statistic	17.59972	Durbin-Watson stat	1.829625
Prob(F-statistic)	0.000000		

Nigeria

Long and short run

ARDL Cointegrating And Long Run Form
Dependent Variable: CO2
Selected Model: ARDL(5, 0, 2, 0, 0, 5)
Date: 08/10/22 Time: 03:54
Sample: 1980Q1 2017Q1
Included observations: 144

Cointegrating Form

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(CO2(-1))	0.736027	0.078173	9.415320	0.0000
D(CO2(-2))	0.007153	0.094693	0.075537	0.9399
D(CO2(-3))	0.019778	0.095588	0.206914	0.8364
D(CO2(-4))	-0.198347	0.083775	-2.367618	0.0194
D(FD)	-0.001378	0.000732	-1.881987	0.0621
D(FDI)	-0.024354	0.005903	-4.125486	0.0001
D(FDI(-1))	0.025826	0.005549	4.654279	0.0000
D(FOS)	-0.026152	0.015500	-1.687229	0.0940
D(GDPG)	-0.000377	0.000275	-1.370702	0.1729
D(IP)	0.002969	0.002781	1.067622	0.2877
D(IP(-1))	-0.003181	0.005653	-0.562649	0.5747
D(IP(-2))	0.000272	0.005663	0.048118	0.9617
D(IP(-3))	-0.004874	0.005375	-0.906825	0.3662

D(IP(-4))	0.005438	0.002772	1.961728	0.0520
CointEq(-1)	-0.062948	0.010950	-3.922231	0.0001

Cointeq = CO2 - (-0.0321*FD -0.1065*FDI -0.6089*FOS -0.0088*GDPG -0.0498*IP + 2.9281)

Long Run Coefficients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
FD	-0.032097	0.015805	-2.030750	0.0444
FDI	-0.106512	0.033837	-3.147787	0.0021
FOS	-0.608931	0.298375	-2.040827	0.0434
GDPG	-0.008783	0.006378	-1.377089	0.1709
IP	-0.049763	0.013521	-3.680437	0.0003
C	2.928082	0.596063	4.912372	0.0000

Nigeria

Post estimation

Heteroskedasticity Test: Breusch-Pagan-Godfrey

F-statistic	1.091698	Prob. F(17,126)	0.3690
Obs*R-squared	18.48711	Prob. Chi-Square(17)	0.3588
Scaled explained SS	51.95660	Prob. Chi-Square(17)	0.0000

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 08/10/22 Time: 03:55
Sample: 1981Q2 2017Q1
Included observations: 144

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.001152	0.001308	0.880840	0.3801
CO2(-1)	-0.001359	0.002818	-0.482257	0.6305
CO2(-2)	0.001565	0.005447	0.287306	0.7744
CO2(-3)	0.000255	0.005748	0.044316	0.9647
CO2(-4)	-0.001982	0.005578	-0.355411	0.7229
CO2(-5)	0.001416	0.002942	0.481232	0.6312
FD	-2.47E-05	2.57E-05	-0.961292	0.3382
FDI	0.000645	0.000207	3.112038	0.0023
FDI(-1)	-0.001112	0.000351	-3.167344	0.0019
FDI(-2)	0.000465	0.000195	2.384311	0.0186
FOS	-0.000138	0.000544	-0.254106	0.7998
GDPG	-7.14E-06	9.67E-06	-0.738248	0.4617
IP	0.000231	9.77E-05	2.363267	0.0196
IP(-1)	-0.000445	0.000186	-2.388687	0.0184
IP(-2)	0.000196	0.000199	0.986176	0.3259
IP(-3)	5.86E-08	0.000199	0.000295	0.9998
IP(-4)	8.13E-05	0.000189	0.430791	0.6674
IP(-5)	-8.12E-05	9.74E-05	-0.834307	0.4057

R-squared	0.128383	Mean dependent var	0.000193
Adjusted R-squared	0.010784	S.D. dependent var	0.000524

S.E. of regression	0.000521	Akaike info criterion	-12.16410
Sum squared resid	3.42E-05	Schwarz criterion	-11.79288
Log likelihood	893.8155	Hannan-Quinn criter.	-12.01326
F-statistic	1.091698	Durbin-Watson stat	2.157999
Prob(F-statistic)	0.368957		

Breusch-Godfrey Serial Correlation LM Test:

F-statistic	5.895593	Prob. F(2,124)	0.2036
Obs*R-squared	12.50398	Prob. Chi-Square(2)	0.0019

Test Equation:
Dependent Variable: RESID
Method: ARDL
Date: 08/10/22 Time: 03:56
Sample: 1981Q2 2017Q1
Included observations: 144
Presample missing value lagged residuals set to zero.

Variable	Coefficient	Std. Error	t-Statistic	Prob.
CO2(-1)	-0.473562	0.180077	-2.629779	0.0096
CO2(-2)	0.489814	0.321740	1.522388	0.1305
CO2(-3)	0.204473	0.288982	0.707563	0.4805
CO2(-4)	-0.353094	0.198088	-1.782511	0.0771
CO2(-5)	0.107457	0.086583	1.241094	0.2169
FD	-0.000645	0.000731	-0.882264	0.3793
FDI	0.004182	0.005823	0.718178	0.4740
FDI(-1)	-0.014219	0.010511	-1.352727	0.1786
FDI(-2)	0.007990	0.005866	1.362139	0.1756
FOS	-0.014569	0.015523	-0.938589	0.3498
GDPG	-0.000350	0.000284	-1.231636	0.2204
IP	0.000953	0.002694	0.353607	0.7242
IP(-1)	0.000160	0.005118	0.031186	0.9752
IP(-2)	-0.002759	0.005586	-0.493962	0.6222
IP(-3)	-0.000727	0.005596	-0.129834	0.8969
IP(-4)	0.004765	0.005380	0.885658	0.3775
IP(-5)	-0.003507	0.002859	-1.226599	0.2223
C	0.067063	0.040858	1.641344	0.1033
RESID(-1)	0.536868	0.199279	2.694050	0.0080
RESID(-2)	0.403161	0.179318	2.248302	0.0263

R-squared	0.086833	Mean dependent var	3.01E-16
Adjusted R-squared	-0.053087	S.D. dependent var	0.013932
S.E. of regression	0.014297	Akaike info criterion	-5.529243
Sum squared resid	0.025347	Schwarz criterion	-5.116769
Log likelihood	418.1055	Hannan-Quinn criter.	-5.361637
F-statistic	0.620589	Durbin-Watson stat	1.913044
Prob(F-statistic)	0.884777		

Ghana

Bound test

ARDL Bounds Test
Date: 08/12/22 Time: 05:02

Sample: 1982Q3 2017Q1
Included observations: 139
Null Hypothesis: No long-run relationships exist

Test Statistic	Value	k
F-statistic	8.966069	5

Critical Value Bounds

Significance	I0 Bound	I1 Bound
10%	2.26	3.35
5%	2.62	3.79
2.5%	2.96	4.18
1%	3.41	4.68

Test Equation:
Dependent Variable: D(CO2)
Method: Least Squares
Date: 08/12/22 Time: 05:02
Sample: 1982Q3 2017Q1
Included observations: 139

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(CO2(-1))	7.343976	1.267119	5.795808	0.0000
D(CO2(-2))	6.697675	1.254330	5.339643	0.0000
D(CO2(-3))	6.706986	1.254877	5.344737	0.0000
D(CO2(-4))	13.91858	1.195924	11.63835	0.0000
D(CO2(-5))	2.791413	1.481780	1.883824	0.0622
D(CO2(-6))	7.668392	1.494990	5.129395	0.0000
D(CO2(-7))	7.524536	1.483817	5.071069	0.0000
D(CO2(-8))	-44.89318	1.409906	-31.84126	0.0000
D(CO2(-9))	33.33922	3.367412	9.900548	0.0000
D(FD)	0.280976	0.110264	2.548211	0.0122
D(FD(-1))	-0.117708	0.132874	-0.885861	0.3776
D(FD(-2))	-0.031533	0.127681	-0.246964	0.8054
D(FD(-3))	0.266827	0.107716	2.477127	0.0147
D(FOS)	-110.2700	33.17185	-3.324206	0.0012
D(FOS(-1))	68.73535	33.55319	2.048549	0.0428
D(GDPG)	-0.097112	0.031927	-3.041642	0.0029
D(GDPG(-1))	0.186109	0.032162	5.786586	0.0000
D(GDPG(-2))	0.025727	0.033449	0.769146	0.4434
D(GDPG(-3))	0.065626	0.032487	2.020049	0.0458
D(IP)	-0.159554	0.048696	-3.276516	0.0014
C	1.185360	0.288480	4.108990	0.0001
FD(-1)	0.012366	0.017284	0.715435	0.4758
FDI(-1)	0.025666	0.022313	1.150256	0.2525
FOS(-1)	10.66856	2.314905	4.608640	0.0000
GDPG(-1)	-0.047565	0.014748	-3.225224	0.0017
IP(-1)	0.014305	0.007779	1.838865	0.0686
CO2(-1)	-6.839509	1.280474	-5.341387	0.0000

R-squared	0.999362	Mean dependent var	1.930979
Adjusted R-squared	0.999214	S.D. dependent var	11.27025
S.E. of regression	0.315963	Akaike info criterion	0.706129
Sum squared resid	11.18123	Schwarz criterion	1.276135
Log likelihood	-22.07595	Hannan-Quinn criter.	0.937764
F-statistic	6748.764	Durbin-Watson stat	2.175225

Prob(F-statistic)	0.000000

ARDL Cointegrating And Long Run Form
Dependent Variable: CO2
Selected Model: ARDL(10, 4, 0, 2, 4, 1)
Date: 08/12/22 Time: 05:03
Sample: 1980Q1 2017Q1
Included observations: 139

Cointegrating Form

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(CO2(-1))	7.271876	1.257503	5.782791	0.0000
D(CO2(-2))	6.626709	1.244256	5.325839	0.0000
D(CO2(-3))	6.635965	1.244804	5.330932	0.0000
D(CO2(-4))	13.847717	1.188171	11.654653	0.0000
D(CO2(-5))	2.721030	1.468832	1.852513	0.0666
D(CO2(-6))	7.586719	1.484259	5.111453	0.0000
D(CO2(-7))	7.445013	1.473018	5.054257	0.0000
D(CO2(-8))	-44.970759	1.403156	-32.049726	0.0000
D(CO2(-9))	33.281458	3.366656	9.885614	0.0000
D(FD)	0.273559	0.110136	2.483837	0.0145
D(FD(-1))	-0.087722	0.223349	-0.392759	0.6952
D(FD(-2))	-0.295134	0.209333	-1.409881	0.1613
D(FD(-3))	0.264181	0.107762	2.451517	0.0158
D(FDI)	0.026814	0.021667	1.237572	0.2185
D(FOS)	-111.076593	33.169115	-3.348796	0.0011
D(FOS(-1))	7.169302	33.425336	2.099285	0.0380
D(GDPG)	-0.097947	0.031946	-3.065988	0.0027
D(GDPG(-1))	0.160674	0.052997	3.031731	0.0030
D(GDPG(-2))	-0.039672	0.050107	-0.791754	0.4302
D(GDPG(-3))	0.065379	0.032406	2.017460	0.0460
D(IP)	-0.156815	0.048616	-3.225581	0.0016
CointEq(-1)	-0.676027	1.270203	-5.327515	0.0000

Cointeq = CO2 - (0.0017*FD + 0.0040*FDI + 1.5612*FOS -0.0071*GDPG + 0.0022*IP + 0.1725)

Long Run Coefficients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
FD	0.001664	0.002376	0.700408	0.4851
FDI	0.003962	0.003215	1.232345	0.2204
FOS	1.561169	0.384761	4.057500	0.0001
GDPG	-0.007054	0.002117	-3.331696	0.0012
IP	0.002180	0.001195	1.823331	0.0709
C	0.172468	0.018082	9.538058	0.0000

Ghana short and long run

Heteroskedasticity Test: Breusch-Pagan-Godfrey

F-statistic	1.669440	Prob. F(26,112)	0.3354
Obs*R-squared	38.82332	Prob. Chi-Square(26)	0.0507
Scaled explained SS	91.41484	Prob. Chi-Square(26)	0.0000

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 08/12/22 Time: 05:04
Sample: 1982Q3 2017Q1
Included observations: 139

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.576302	0.185258	3.110801	0.0024
CO2(-1)	-0.200314	0.042234	-4.743003	0.0000
CO2(-2)	0.154518	0.044394	3.480636	0.0007
CO2(-3)	0.004094	0.018124	0.225862	0.8217
CO2(-4)	-0.021380	0.181346	-0.117897	0.9064
CO2(-5)	1.405133	0.504136	2.787212	0.0062
CO2(-6)	-1.074457	0.564846	-1.902213	0.0597
CO2(-7)	-0.082375	0.490868	-0.167816	0.8670
CO2(-8)	-0.007282	0.616593	-0.011810	0.9906
CO2(-9)	-10.59867	2.248822	-4.712987	0.0000
CO2(-10)	8.206777	2.181156	3.762582	0.0003
FD	-0.066441	0.071354	-0.931150	0.3538
FD(-1)	0.205980	0.141088	1.459935	0.1471
FD(-2)	-0.150811	0.144701	-1.042226	0.2996
FD(-3)	0.158284	0.135620	1.167114	0.2456
FD(-4)	-0.148561	0.069816	-2.127895	0.0355
FDI	0.020010	0.014037	1.425468	0.1568
FOS	25.56230	21.48928	1.189537	0.2367
FOS(-1)	-59.97845	39.11632	-1.533336	0.1280
FOS(-2)	38.45928	21.65528	1.775977	0.0785
GDPG	-0.020786	0.020697	-1.004317	0.3174
GDPG(-1)	0.000492	0.032567	0.015100	0.9880
GDPG(-2)	0.038294	0.034335	1.115304	0.2671
GDPG(-3)	0.002853	0.032463	0.087892	0.9301
GDPG(-4)	-0.026908	0.020995	-1.281642	0.2026
IP	-0.041876	0.031497	-1.329543	0.1864
IP(-1)	0.037795	0.031003	1.219076	0.2254

R-squared	0.279304	Mean dependent var	0.080293
Adjusted R-squared	0.112000	S.D. dependent var	0.217029
S.E. of regression	0.204515	Akaike info criterion	-0.163839
Sum squared resid	4.684542	Schwarz criterion	0.406166
Log likelihood	38.38684	Hannan-Quinn criter.	0.067796
F-statistic	1.669440	Durbin-Watson stat	1.830339
Prob(F-statistic)	0.035354		

Breusch-Godfrey Serial Correlation LM Test:

F-statistic	0.912657	Prob. F(2,110)	0.4045
Obs*R-squared	2.268883	Prob. Chi-Square(2)	0.3216

Test Equation:
Dependent Variable: RESID
Method: ARDL
Date: 08/12/22 Time: 05:06

Sample: 1982Q3 2017Q1
Included observations: 139
Presampe missing value lagged residuals set to zero.

Variable	Coefficient	Std. Error	t-Statistic	Prob.
CO2(-1)	0.042699	0.099149	0.430660	0.6676
CO2(-2)	-0.046333	0.096764	-0.478824	0.6330
CO2(-3)	0.002979	0.028134	0.105875	0.9159
CO2(-4)	-0.014901	0.280372	-0.053148	0.9577
CO2(-5)	-0.303326	0.950955	-0.318970	0.7504
CO2(-6)	0.379053	1.022500	0.370712	0.7116
CO2(-7)	-0.069827	0.760683	-0.091795	0.9270
CO2(-8)	-0.020359	0.953852	-0.021344	0.9830
CO2(-9)	2.236898	5.211738	0.429204	0.6686
CO2(-10)	-2.268783	4.828335	-0.469889	0.6394
FD	0.016201	0.111127	0.145787	0.8844
FD(-1)	-0.037887	0.220024	-0.172196	0.8636
FD(-2)	0.027299	0.224489	0.121607	0.9034
FD(-3)	-0.013451	0.210059	-0.064033	0.9491
FD(-4)	0.010639	0.110062	0.096662	0.9232
FDI	-0.002338	0.022270	-0.104990	0.9166
FOS	1.392782	33.38671	0.041717	0.9668
FOS(-1)	0.179615	60.46150	0.002971	0.9976
FOS(-2)	-1.879444	34.08431	-0.055141	0.9561
GDPG	0.002108	0.032222	0.065413	0.9480
GDPG(-1)	0.004307	0.050587	0.085138	0.9323
GDPG(-2)	-0.010722	0.055148	-0.194416	0.8462
GDPG(-3)	0.000695	0.050169	0.013861	0.9890
GDPG(-4)	0.006018	0.034702	0.173425	0.8626
IP	0.004761	0.049299	0.096580	0.9232
IP(-1)	-0.005401	0.048807	-0.110665	0.9121
C	0.018517	0.296213	0.062513	0.9503
RESID(-1)	-0.126018	0.141108	-0.893063	0.3738
RESID(-2)	0.062511	0.114620	0.545381	0.5866

R-squared	0.016323	Mean dependent var	-2.37E-15
Adjusted R-squared	-0.234068	S.D. dependent var	0.284385
S.E. of regression	0.315919	Akaike info criterion	0.716610
Sum squared resid	10.97852	Schwarz criterion	1.328838
Log likelihood	-20.80440	Hannan-Quinn criter.	0.965403
F-statistic	0.065190	Durbin-Watson stat	2.001011
Prob(F-statistic)	1.000000		

APPENDIX 3: GUIDE FOR MULTIVARIATE MODELS