

Gold Markets Around the World – Who spills over what, to whom, when?

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Abstract

Gold is traded worldwide, mainly in London, New York, Tokyo and Shanghai. We apply the recently developed spillover index approach of Diebold and Yilmaz (2009) to investigate the degree to which these markets are integrated, and which are net senders or recipients of information. The evidence suggests that Shanghai remains isolated as a market both in terms of volatility and return spillovers. The strongest and most integrated pair of markets are the London Cash market and COMEX. Returns spill over more strongly than do volatilities. Spillovers show significant time variation

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Introduction

Gold is a liquid, globally traded asset. It is traded both over the counter, cash, centred in London and in futures markets round the globe. A good description of the historical emergence of the world gold markets post 1972 is O'Callaghan (1991). More regular updates on market situations can be found on the World Gold Council website, www.gold.org. Even with regard to the significant industrial and adornment usage, investment represented approximately 36% of the estimated 2011 demand, with 90% of this being for physical bullion (World Gold Council (2012)). Despite this, gold bullion has not been studied in the same depth that one might think warranted given the size of the market. The world market for gold in 2011 was of the order of 4,000 tonnes, equivalent to over \$200b, approximately the same gross size as the US---Australian or US – Canadian dollar foreign exchange markets (based on 2010 data in Bank for International Settlements (2011)). The largest pool of liquidity was and remains the London OTC market, whose benchmark price set by the London AM and PM fix is seen as the global benchmark. Murray (2011) suggests that 87% of global volume is settled in London, with just under 10% via COMEX in New York ; SHFE (Shanghai Futures Exchange) and TOCOM (Tokyo Commodity Exchange) share approximately 1% each. Similar results are discernable in GFMS Ltd (2012). Despite the small size of the far eastern markets, much speculation has emerged regarding the future role of these markets. A useful discussion on the Shanghai futures exchange is found in Skoyles (2013); a key point to note is that despite being very new, having commenced trading in 2009, the Shanghai Futures Exchange is now the second largest hub for gold futures trading worldwide, after COMEX in New York.

Given the worldwide nature of the trade, it is thus surprising that little research has emerged on the interrelationships. Some studies have examined the relationship between gold futures markets. Xu and Fung (2005) and Lin, Chiang, and Chen (2008) used GARCH models to examine the COMEX---TOCOM linkages, while Fuangkasem, Chunchachinda, and Nathaphan (2012) examine the COMEX---MIX (India)--- TOCOM markets. The general consensus of these papers is that COMEX dominates in terms of information flow. However, all of these papers concentrate on futures markets, missing the overwhelmingly dominant London cash bullion market. It is reasonable to assume that size alone does not imply dominance. It is well known that the transparency and ease of execution of organized derivative markets can allow (relatively) small markets to lead larger markets. See as examples and discussions Bohl, Salm, and Schuppli (2011) and Rosenberg and Traub (2009). One recent paper, Lucey, Larkin, and O'Connor (2013) does look at the COMEX---London relationship, using the Gonzalo and Granger (1995)

information shares approach, concluding that in general the London Cash market dominates but that this is time varying and dependent on real economic conditions.

We shed some further light on these relationships here. Using the integration index approach of Diebold and Yilmaz (2009), we examine all four markets at once. We surface heretofore un-discussed spillovers and examine the extent to which markets are net senders or recipients of spillovers in both volatility and returns. We specify volatility using the Garman and Klass (1980) range based volatility estimator.

Methodology

The model presented in this paper is drawn from Diebold and Yilmaz (2009), Diebold and Yilmaz (2012). These authors look at return and volatility spillovers using a Vector Autoregressive Models (VAR's) following Engle, Ito, and Lin (1990) but concentrate on variance decompositions. This gives one measure of spillover based on spillovers from a number of markets.

Consider a set of assets. For each asset i the shares of its forecast error variance coming from shocks to asset j , for all $j \neq i$, are summed. These are then added for all $i = 1, \dots, N$. Considered as a covariance stationary first-order two variable VAR it can be written as

$$x_t = \Phi x_{t-1} + \varepsilon_t \quad (1)$$

where $x_t = (x_{1t}, x_{2t})$ and Φ is a 2×2 parameter matrix. In this paper x_t will represent either a vector of gold returns or gold returns volatilities. Diebold and Yilmaz (2009) show that by covariance stationarity we can represent this VAR as a moving average given by equation (2) below.

$$x_t = \Theta(L)\varepsilon_t \quad (2)$$

Where $\Theta(L) = (I - \Phi L)$. This can be rewritten as below for ease.

$$x_t = A(L)\mu_t \quad (3)$$

Where $A(L) = \Theta(L)Q$, $\mu_t = Q'\varepsilon_t$, $E \begin{pmatrix} \mu_t \\ \mu_t' \end{pmatrix} = I$, and Q is a unique lower triangular Cholesky

factor of the covariance matrix of ε_t .

The Wiener-Kolmogorov linear least-squares forecast is an optimal 1 step ahead forecast from the above can be shown as:

$$x_{t+1|t} = \Phi x_t \quad (4)$$

with a 1 step ahead error vector:

$$e_{t+1,t} = x_{t+1,t} - x_{t,t} = A_t \mu_{t+1,t} = \begin{bmatrix} a_{1,t+1,t} & a_{1,t+1,t}'' \\ a_{2,t+1,t} & a_{2,t+1,t}'' \end{bmatrix} \begin{bmatrix} \mu_{1,t+1,t} \\ \mu_{2,t+1,t} \end{bmatrix} \quad (5)$$

which has a covariance matrix of:

$$E(e_{t+1,t} e_{t+1,t}') = A_t A_t' \quad (6)$$

Using this approach allows us to say what proportion of the error variance in forecasting any particular x (a specific gold market e.g. London) is due to shocks to itself, or spillover from shocks to another market e.g. New York. Diebold and Yilmaz (2009) define *own variance shares* as “to be the fractions of the 1-step-ahead error variances in forecasting x_i due to shocks to x_i ” for all i and *cross variance shares*, or spillovers, to be “the fractions of the 1-step-ahead error variances in forecasting x_i due to shocks to x_j ” for all j , where $i \neq j$.

In this 2 variable illustration the variance of the one step ahead error in forecasting x_1 at time t is then $a_{1,t+1,t}^2 + a_{1,t+1,t}''^2$ from equation (5) above. $a_{1,t+1,t}''$ can then be thought of as a $x_{2,t}$'s spillover that effects the forecast error variance of $x_{1,t}$ and $a_{2,t+1,t}''$ can then be thought of as a $x_{1,t}$'s spillover that

effects the forecast error variance of $x_{2,t}$. Total spillover is then $a_{1,t+1,t}''^2 + a_{2,t+1,t}''^2$. Using these we can calculate a spillover index measure as total spillover divided by the total forecast error variation $\frac{a_{1,t+1,t}''^2 + a_{2,t+1,t}''^2}{a_{1,t+1,t}^2 + a_{1,t+1,t}''^2 + a_{2,t+1,t}^2 + a_{2,t+1,t}''^2} = \frac{A_t A_t' - \text{diag}(A_t A_t')}{A_t A_t'}$ as in (7).

$$S = \frac{\sum_{i=1}^n \sum_{j=1, j \neq i}^n (a_{i,j,t+1,t}''^2)}{\sum_{i=1}^n (a_{i,i,t+1,t}^2 + a_{i,i,t+1,t}''^2)} \times 100 \quad (7)$$

This first-order two variable case can be generalised into a p^{th} -order N -variable case using 1 step ahead forecasts giving:

$$S = \frac{\sum_{i=1}^N \sum_{j=1, j \neq i}^N (a_{i,j,t+1,t}''^2)}{\sum_{i=1}^N (a_{i,i,t+1,t}^2 + a_{i,i,t+1,t}''^2)} \times 100 \quad (8)$$

For a H -step ahead forecasts:

$$S = \frac{\sum_{i=1}^N \sum_{j=1, j \neq i}^N (a_{i,j,t+H,t}''^2)}{\sum_{i=1}^N (a_{i,i,t+H,t}^2 + a_{i,i,t+H,t}''^2)} \times 100 \quad (9)$$

While it is commonplace to measure asset volatility based on the standard deviation of the log difference across a regular time interval, we also utilise a more complex measure, the GKe measure, which incorporates information about the open, close, high and low prices *within* a particular time interval. As discussed in Molnár (2012) the GK Range based estimator is

amongst the most efficient estimators for volatility estimation. From Garman and Klass (1980) the GKe is:

$$GKe = \sigma^2 = 0.511(H-L)^2 - 0.019(C-O)(H+L-2C)(1-C) - 0.383(C-O)^2 \quad (10)$$

where H = log of interval high

L = log of interval low

O = log of interval open

C = log of interval close

Data

We collect data on a daily basis from 9 Jan 2008 to 9 October 2013. Data are collected on the daily high, low, open and close for the London cash market, and for TOCOM, SHFE and COMEX we collect this data for the nearest month future, on a continuous roll basis. This gives us 1501 usable observations. The data are sourced from Reuters. Some summary statistics are provided in [Table 1](#). Observing this we can see that the cash market shows the highest volatility, followed by COMEX. This is consistent with the volume ranking. Daily returns are remarkably similar as we might expect given the homogeneity of the product.

Table 1: Summary Statistics

	Mean	Max	Min	Median
Tokyo GK Volatility	0.147084	9.510868	---0.002493	0.061621
New York GK Volatility	0.409063	14.544554	---3.131144	0.188456
Shanghai GK Volatility	0.375592	21.854975	---10.961953	0.004194
London GK Volatility	0.657766	19.614311	---0.450762	0.376272
Tokyo Return	0.000269	0.107321	---0.117677	0.000795
New York Return	0.000264	0.086432	---0.098206	0.000396
Shanghai Return	0.000207	0.115374	---0.125066	0.000000
London Return	0.000265	0.103919	---0.088787	0.000732

Results

- Full sample analysis

Here we follow Diebold and Yilmaz (2009) in breaking down the overall spillover index for the four markets into all the forecast error variance components for a variable i (the returns or returns variance for a particular market) that comes from either itself or one other 3 markets (variables i to j).

Table 2 shows the return spillover of the full sample 2008 – 2013. In the next section we will look at how stable these estimates are over time using a rolling data window. The spillover index is shown in the bottom right corner cell. Each of the other cells is the contribution to the forecast error variance of market i by country j . The sum of the right hand column (Contribution from others) and row titled “Contribution to others” represents the numerator in equation (9) above. The sum of the last row (Contribution including own) is the denominator. Table 3 is structured in the same way for the return’s volatility spillovers.

From these we can see that New York and London are the dominant markets. New York contributes 26.7% of the error variance in forecasting Tokyo’s returns but Tokyo is responsible for only 3.4% of New York’s forecast error variance. Both New York and London contribute in roughly equal proportions to each other’s error variances (44.3% and 45.2% respectively).

Shanghai has a negligible effect on the other markets and Tokyo's is small relative to the two major trading centres. The spillover index indicates that over 45% of returns are as a result of spillovers from other markets. For volatility the picture is similar to returns, as shown in Table 2. London and New York are dominant with the strongest interlinkages between these two. Interestingly Shanghai is very disconnected from the other three markets with 98.7% of its forecast error variance coming from itself. The overall spillover index shows 32.4% of volatility coming from spillovers in these markets.

Table 2: Spillovers between gold markets' returns 2008---2013

	<u>From</u>				
<u>To</u>	Tokyo	New York	Shanghai	London	Others
Tokyo	40.7	26.7	0.7	31.8	59
New York	3.4	51.2	0.2	45.2	49
Shanghai	2.5	11.4	72.8	13.2	27
Cash	2.9	44.3	0.1	52.7	47
Others	9	82	1	90	183
Contribution including own	49	134	74	143	Spillover Index = 45.6%

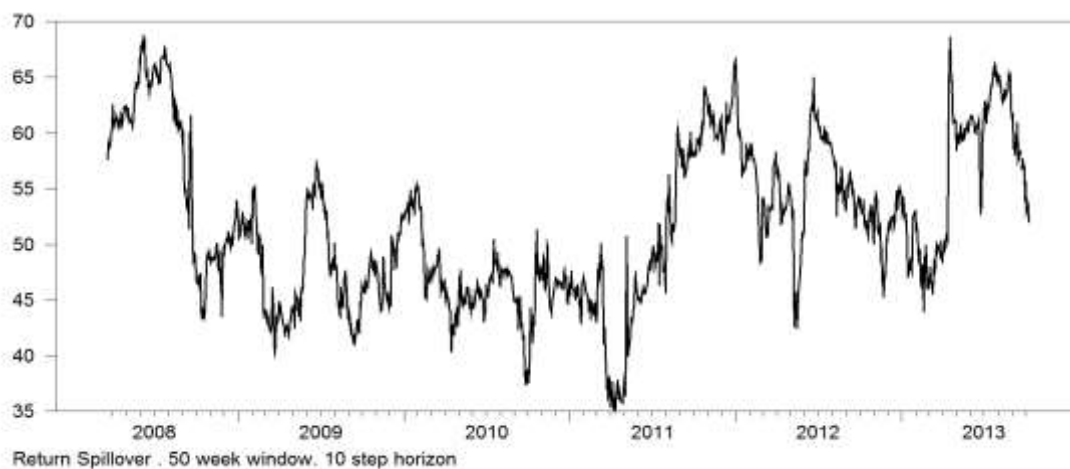
Table 3: Spillovers between gold markets' volatility 2008---2013

	<u>From</u>				
<u>To</u>	Tokyo	New York	Shanghai	Cash	Others
Tokyo	58.5	20.2	0.1	21.2	42
New York	4.3	54.0	0.2	41.5	46
Shanghai	0.6	0.3	98.7	0.4	1
Cash	3.7	37.0	0.1	59.2	41
Others	9	57	0	63	130
Contribution including own	67	112	99	122	Spillover Index = 32.4%

- Rolling window analysis

Below we show the evolving importance of spillovers to returns between the 4 markets through the spillover index in Figure 1 for returns and Figure 2 for volatility. We use an initial window of 50 weeks, and then update this by 10 observations each iteration. While the average result for the returns spillover index over the full sample given in the last section was 45%, we can see that this varies substantially over time. In mid---2008 the index is over 65 for a number of months and reaches a low of 35% in April 2011.

Figure 1 – Return Spillover Index



For figures 2---5 we show the net spillover to returns for each market separately following Diebold and Yilmaz (2012). A positive number indicates that on balance that market's returns are being driven by other markets (receiving spillover). A negative number shows a market that is spilling over onto others.

The first peak in the return spillover index is in February and March 2008. This corresponds to the first time gold has risen over the psychological barrier of \$1,000 per ounce (see Aggarwal and Lucey (2007) for a discussion of such barriers in gold). Examining the figures for net contribution we can see that New York and London are driving the other markets at this time. This period of high spillover from the London market (approx. 65%) also relates to the Northern Rock bank run.

Overall London is never a net recipient of spillovers and for New York the only significant occasion when it is a recipient is in March – May 2009. Here Shanghai goes through its only sustained period of net spillover to other markets. This may have been due to significant economic news coming from China including a 25% contraction in exports reported in March as opposed to an expected 5% decline. Real market contagion onto the gold market is an

understudied area, but in the context of the significant Chinese use of gold as part of reserves (see Williams (2013)) this would be a reasonable spillover conduit.

Figure 2 – Net Return Spillovers --- Shanghai

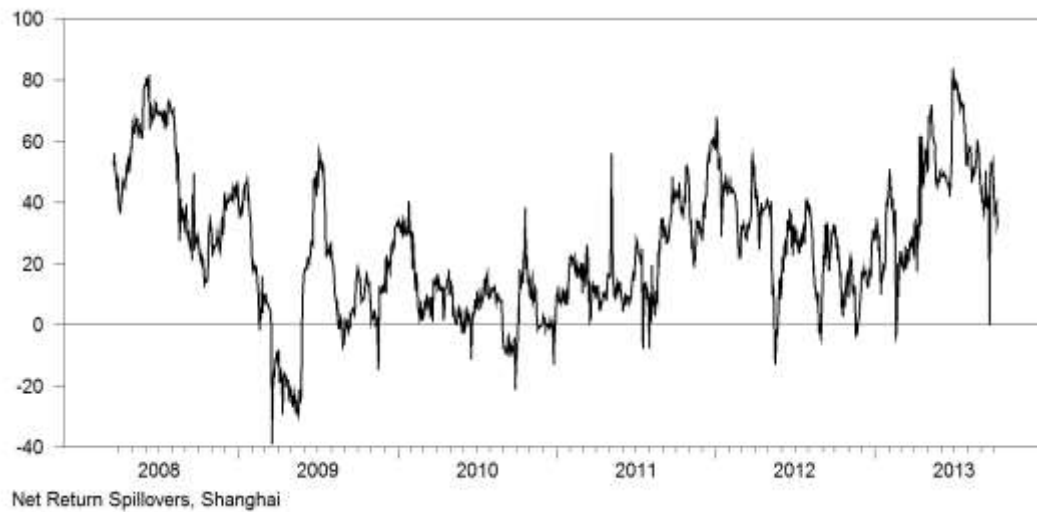


Figure 3 – Net Return Spillovers --- New York

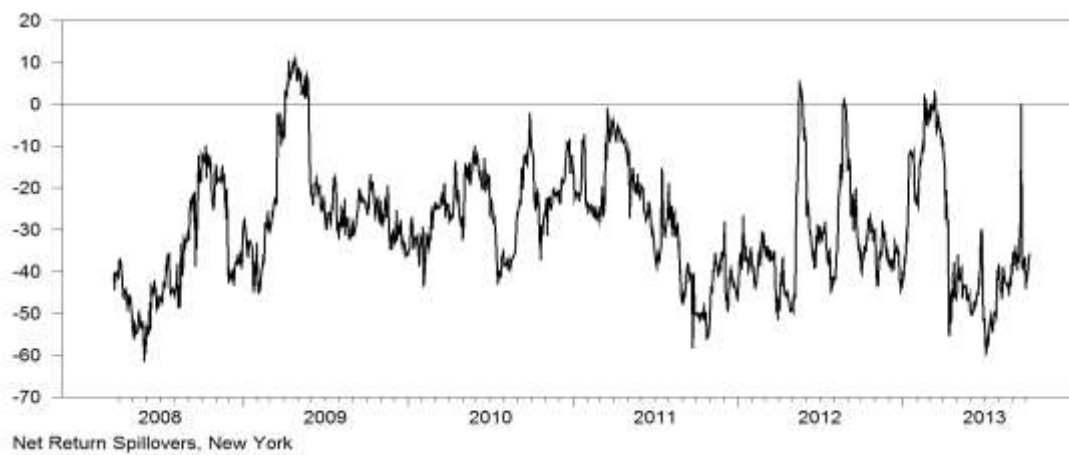


Figure 4 – Net Return Spillovers --- Tokyo

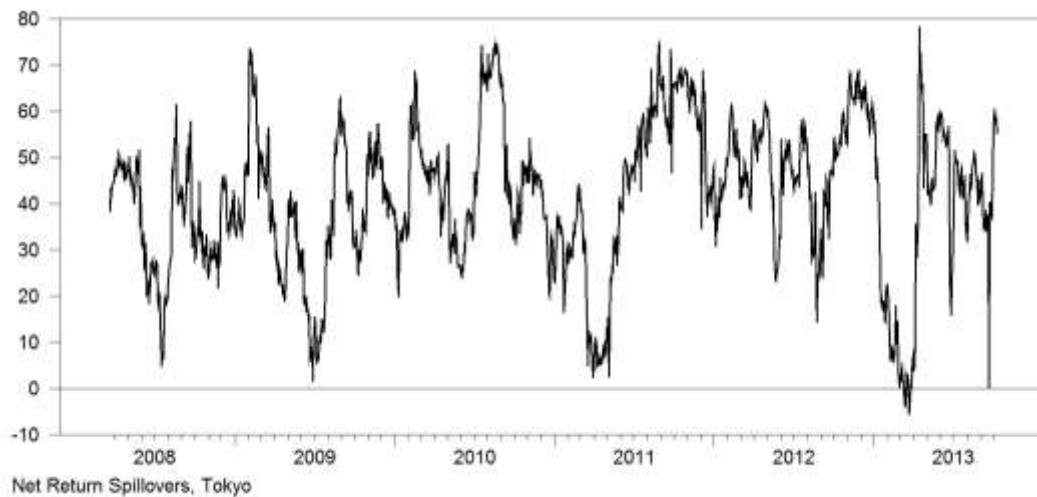


Figure 5 – Net Return Spillovers --- London

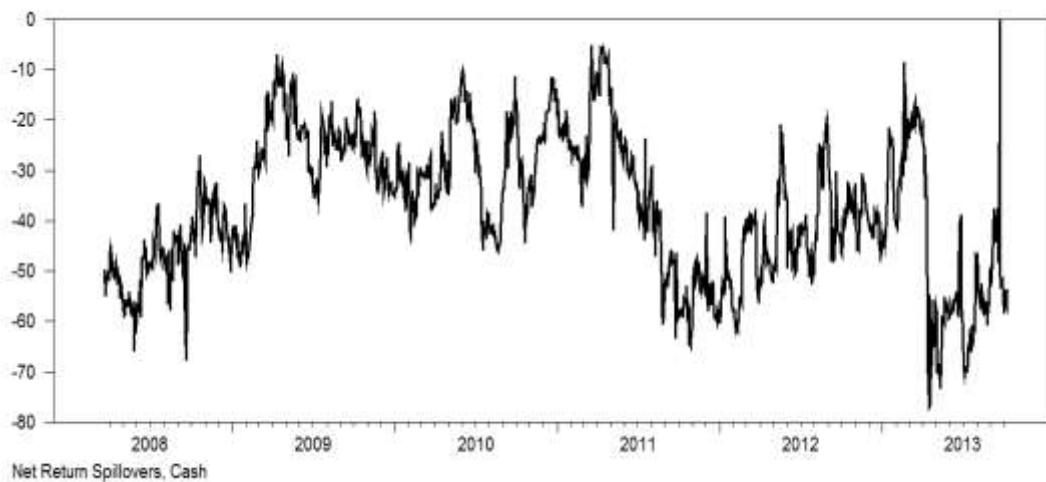


Figure 6 shows a similar picture for volatility with spillovers varying in size over time. In general there appears to be a trend towards a higher level of volatility spillovers as compared to return spillovers during the sample. Volatility spillover peaks at 70% of all volatility being as a result of spillover in March 2012. From Figures 8 and 10 we can see that these correlate to events in both London and New York

A massive spillover of volatility occurs in late June 2008 coming from the London market. This drives all other markets at that time, with even New York receiving net spillovers for that time. It dwarfs New York's largest spillover which is about half as large and occurs at the end of February 2012.

Figure 6 – Volatility Spillovers Index

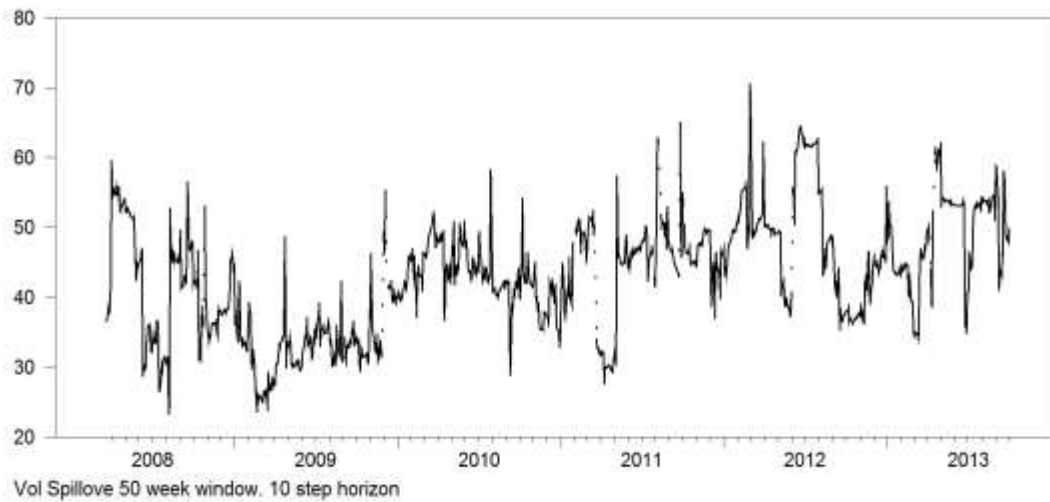


Figure 7 – Net Volatility Spillovers--- Shanghai

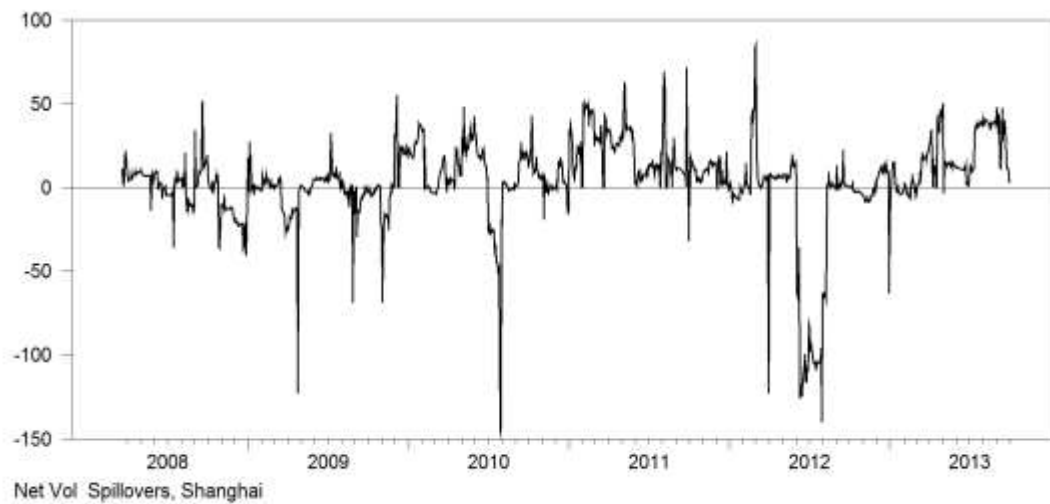


Figure 8 – Net Volatility Spillovers – New York

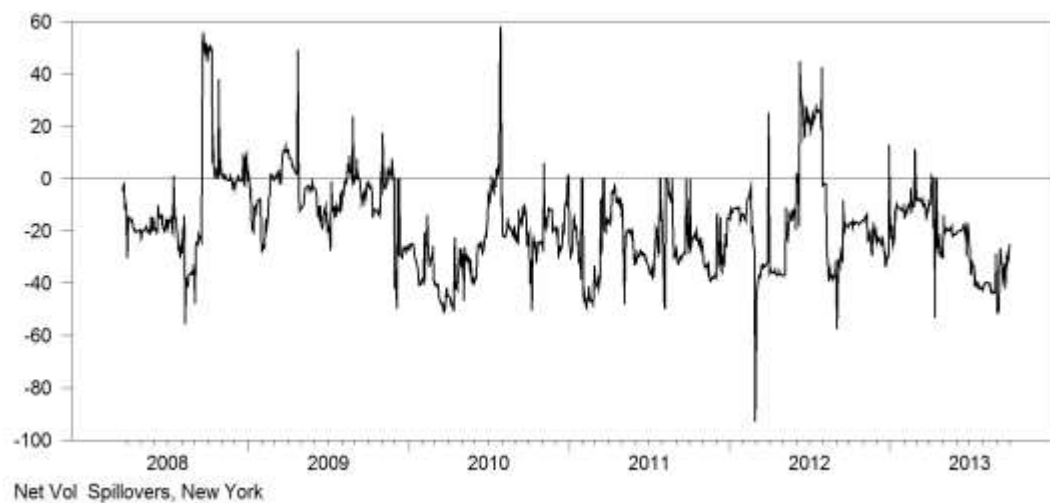


Figure 9 – Net Volatility Spillovers --- Tokyo

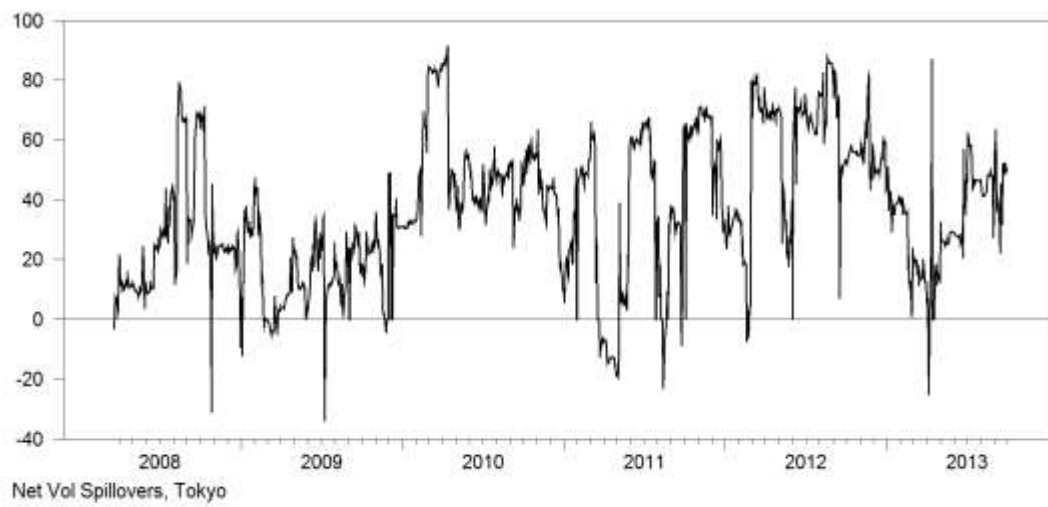
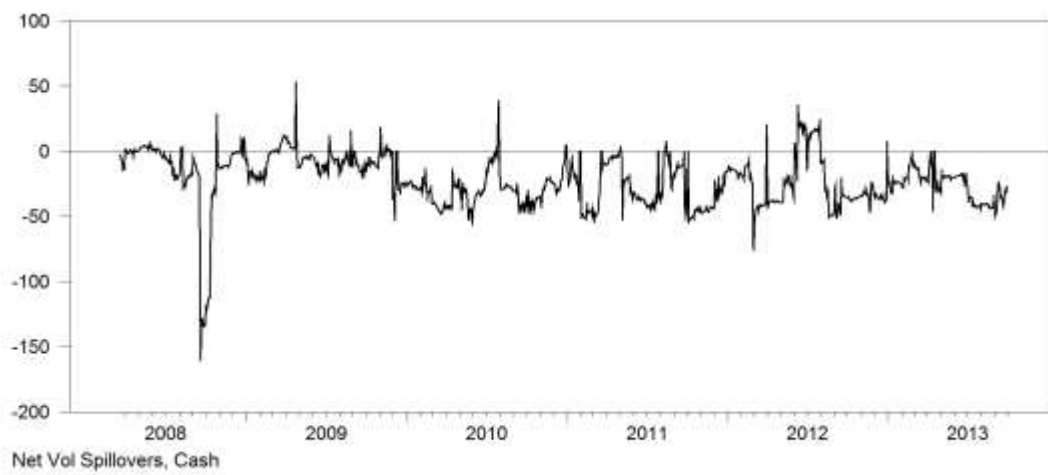


Figure 10 – Net Volatility Spillovers --- London



Conclusion

Gold spillovers, in both return and volatility, are concentrated as originating from London and New York. Despite recent growth in the SHFE in particular there is little evidence that it as yet has an impact on the world gold market. It rarely provides spillovers to the other market either in returns or in volatility. The changes in returns and volatility spillovers can be matched, in a qualitative manner, to a number of events.

Bibliography

Aggarwal, R, and B M Lucey, 2007, Psychological barriers in gold prices?, *Review of Financial Economics* 16, 217–230.

Bank for International Settlements, 2011, Triennial central bank survey report on global foreign exchange market activity in 2010.

Bohl, M T, C A Salm, and M Schuppli, 2011, Price discovery and investor structure in stock index futures, *Journal of Futures Markets* 31, 282–306.

Diebold, Francis X, and Kamil Yilmaz, 2009, Measuring financial asset return and volatility spillovers, with application to global equity markets, *The Economic Journal* 119, 158–171.

Diebold, Francis X., and Kamil Yilmaz, 2012, Better to give than to receive: predictive directional measurement of volatility spillovers, *International Journal of Forecasting*.

Engle, Robert F., Takatoshi Ito, and Wen---Ling Lin, 1990, Meteor showers or heat waves? heteroskedastic intra---daily volatility in the foreign exchange market, *Econometrica* 58, 525.

Fuangkasem, Rapeesorn, Pornchai Chunchinda, and Sarayut Nathaphan, 2012, Information transmission among world major gold futures markets: evidence from high frequency synchronous trading data, *SSRN Electronic Journal*.

Garman, Mark B., and Michael J. Klass, 1980, On the estimation of security price volatilities from historical data, *The Journal of Business*.

GFMS ltd, 2012, Gold survey 2012.

Gonzalo, J, and C W J Granger, 1995, Estimation of common long---memory components in cointegrated systems, *Journal of Business and Economic Statistics* 13, 27–35.

Lin, Hui---Na, Shu---Mei Chiang, and Kun---Hong Chen, 2008, The dynamic relationships between gold futures markets: evidence from comex and tocom, *Applied Financial Economics Letters* 4, 19–24.

Lucey, Brian M., Charles Larkin, and Fergal A. O'Connor, 2013, London or new york: where and when does the gold price originate?, *Applied Economics Letters* 20, 813–817.

Molnár, P, 2012, Properties of range---based volatility estimators, *International Review of Financial Analysis* 23, 20–29.

Murray, Stuart, 2011, Loco london liquidity survey, *Alchemist* 63, 9–10.

O'Callaghan, Gary, 1991, The structure and operation of the world gold market, (IMF, New York).

Rosenberg, J.V.a, and L.G.b Traub, 2009, Price discovery in the foreign currency futures and spot market, *Journal of Derivatives* 17, 7–25.

Skoyles, Jan, 2013, Investigating shanghai's gold futures, *Safehaven.com*.

Williams, Lawrence, 2013, Playing the long game: how big are china's real gold reserves? --- seeking alpha, *Seeking Alpha*.

World Gold Council, 2012, Gold demand trends second quarter 2012.

Xu, Xiaoqing Eleanor, and Hung---Gay Fung, 2005, Cross---market linkages between u s and japanese precious metals futures trading, *Journal of International Financial Markets, Institutions and Money* 15, 107-124.