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Gold market price spillover between COMEX, LBMA and SGE

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Abstract

In this paper, the author investigates spillover between the main markets from New York, London and Shanghai. Specific contract prices from the Commodity Exchange Inc. (COMEX), London Bullion Market Association (LBMA) and Shanghai Gold Exchange (SGE) were utilized. Results suggest that even with the increasing market influence of SGE, it still remains an isolated market, COMEX and LBMA maintain their dominant positions and act as the net spillover spreaders in the world gold market with almost equally strong market impacts.

1 Introduction

1.1 Background

Gold is one of the most homogeneous goods in the world. Due to it's fairly ideal preservation of value and easy storage, gold has been traded globally among exchanges and banks, both as a spot and/or future, as a commodity, and a financed asset. Three major gold trading centres are London, New York and Shanghai. CME Group (2017)

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Established in 1933, Commodity Exchange Inc. (COMEX) is the oldest among the three markets studied in this research. COMEX merged with the New York Mercantile Exchange (NYMEX) in 1996 and then joined the CME Group in 2008. Being the division responsible for metals trading, COMEX is no longer a separate institution but a primary futures and options market for trading metals such as gold, silver, copper and aluminium.

Established in 1987, London Bullion Market Association (LBMA) is a wholesale over-the-counter market for the trading of gold and silver. LBMA took over the London Gold Fix operates by the ICE Benchmark Administration (IBA) since 19. March 2015 and set the benchmark price twice daily (at 10:30 and 15:00 London BST) in US Dollars and is also available in a further sixteen currencies (indicative for settlements).

The youngest market in this paper is the Shanghai Gold Exchange (SGE). Despite its short history (founded in 2002), SGE has already become the largest commodity exchange in the People's Republic of China for trading in precious metals (gold, silver and platinum). Furthermore, the daily trading volume for gold and silver is at the second highest in the world and in 2017, exceeded the Shanghai Future Exchange (SHFE).

1.2 Motivation and research question

Take a panoramic view of the overall situation of the global precious metal exchanges. COMEX is still first with respect to trading volume in gold and silver. SHFE and Tokyo Commodity Exchange (TOCOM) are shrinking significantly since 2016, while Shanghai Gold Exchange (SGE) has climbed to second position in the world rankings. With the emerging market power in Asia, especially the internationalisation process of the Shanghai Gold Exchange (SGE), trading liquidity during the Asia hour has been increased significantly (CME Group 2017). Meanwhile, LBMA remains relatively stable as a dominating world OTC market (Shanghai Gold Exchange 2018). This new world ranking inspires the motivation for researching the latest markets interaction between the first three ranking exchanges, namely COMEX, LBMA and SGE. When SGE started its internationalisation in 2015, expectations increased over this newly emerged market. Chairman of Swiss-based refining group MKS, Marwan Shakarchi once presented his hypothesis to Reuters in early 2016 when SGE launched a Yuan-denominated gold benchmark on 19 April 2016:"(China) is a market of 1.2 billion people and simply cannot be neglected. I am convinced that in the future we won't say China is at a premium or discount to London, but vice versa"; however, even though the Chinese domestic market participants can begin their trading with local currency Chinese Yuan (CNY), the world players may not accept or even take consideration of this newly-developing market. Voice had been made from the side of SGE, expressing the concern that an adjusting process would be time-consuming, and not going to happen in the near future. Ananthalakshmi (2015)

Because of the short market history of SGE and the limitations of the existing econometric model, no research, to the best of the author's knowledge, has been done about the gold market daily price volatility spillover including SGE till now. Hence,

in this paper, the author would like to a) use a proper method to investigate the market impacts between the current top three markets being introduced in Section 1.1 and b) examine the dynamic trend of the interactions between these three markets, check if there has already been changes that have taken place or whether any signs can be defined from the recent observations. The result of this research might be helpful for the concerning exchanges to take a review of the strength and market impact in the recent years and develop a qualitative overview of the main market situation and trend during sequential initiatives and changes, either made by themselves or by their competitors and/or partners.

1.3 Literature reviews

The attributes of gold have been studied by a considerable amount of literature. Apart from those which focused on the industrial sector and jewellery sector (about mining and fashioning technique), we direct our attention to the monetary attributes of gold in this subsection. Worthington and Pahlavani (2007) provided solid evidence to prove the widely held view that an investment in gold can serve as an effective inflationary hedge. Later Ciner et al. (2013) examined the correlation between stocks, bonds, gold, oil and exchange rates using data from United States and United Kingdom. They found that gold can be regarded as a safe haven against exchange rates in both countries, which highlighted its role in the monetary assets.

With the world gold markets becoming more open and easily accessible, the interconnection between markets spurred researchers' interest to find a proper econometric method to quantify the connection strength as well as the direction of the spreading. Diebold and Yilmaz (2009) (henceforth DY09) first examined the different spillover behaviours between return and volatility using data from equity markets and coined the term connectedness using the Vector Autoregressive Regression model. They exhibited difference between return and volatility by measuring the time-varying and time-variation spillover intensity. According to Diebold and Yilmaz (2009, 2012, 2014), such a volatility connectedness can be treated as "fear connectedness" expressed by the traders during different market conditions and is particularly crisis sensitive (Diebold and Yilmaz 2014). In their 2012 research (Diebold and Yilmaz 2012) (henceforth DY12), they further improved the model from DY09, so that it is no longer sensitive to the VAR order by replacing the Cholesky decomposition, and is able to detect the direction of the connectedness flow (the so-called "directional spillover"). In the technical sense, DY12 can be treated as a robust version of DY09, which applied the decomposition approach from Koop et al. (1996) and Pesaran and Shin (1998). Additionally, Baruník and Křehlík (2018) realised that a long-term-effect shock has high power at the low frequencies, and thus they separated the long- and short-term connectedness by applying the frequency bands in order to mimic the spillover movements between 1 to 4 days as well as 4 days to a longer period.

According to the fact that most of the gold trading volume is still settled in London, Lucey et al. (2014) applied the method from Diebold and Yilmaz (2009) and studied the spillover effect of the spot gold prices between four markets, namely: LBMA, COMEX, SHFE and TOCOM. Results showed that SHFE as a newly emerged market has rarely any effect on the other three. However, Lucey et al. (2014) only researched

the future markets and applied Garman and Klass approach (Garman et al. 1980) approach for the volatility spillover estimation. Evidence from Rosenberg and Traub (2006) has shown, that in the foreign exchange future and spot markets, the latter one has the dominant information share. On the other hand, the Garman and Klass (1980) approach has been shown to underestimate the volatility because it ignores the overnight jump.[1] Furthermore, their application of DY09 only provided an overall insight of the return or volatility for the multiple markets as a whole, lacking exact directional spillover patterns between the specific markets due to technical restrictions. Addressing the directional spillover patterns is exactly the major contribution of this research paper.

1.4 Organisation of the paper

The goal of this paper is to determine the strength of the market impacts among three markets by examining their interactions, i.e. receive/give spillover from/to each other, in both qualitative and quantitative senses. This paper has been organized as follows: Section 2 provides detail on the methods we are going to apply for estimating the spillover, Section 3 introduces the data and the processing procedures to provide descriptive statistics of the sample data, Section 4 presents the main results, and Section 5 offers a conclusion.

2 Methods

DY09 is the first research developing a model based on VAR (vector autoregressive model) framework and investigating the volatility spillover between different assets by Diebold and Yilmaz. When several assets (or equities) from different countries affect each other (i.e., have spillover effects on each other), DY09 can detect the total volatility among all those assets, define how much volatilities in the fluctuation are actually caused by the spillovers between them. However, as the author Diebold and Yilmaz later in their 2012 research (Diebold and Yilmaz 2012) coined, there are two main methodological drawbacks. Namely that a) DY09 depends fairly strong on the variable ordering because of the Cholesky identification applied for a VAR decomposition, and b) DY09 can only address the *total* spillover among all the assets being estimated. In practice, one might be more interested in a separated directional spillover from a specific asset to another specific one. In DY12, the authors followed the general idea of DY09 and computed the total overall spillover index and an unconditional full-sample static average spillover table. Their innovative initiative was using the decomposition from Koop et al. (1996) and Pesaran and Shin (1998) (henceforth KPPS) in order to avoid the sensitivity of the variable ordering caused by the Cholesky approach they previously used in DY09. Since the result from DY12 no longer depends on the VAR ordering, we can treat DY12 as a more robust version of

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[1]See Yang and Zhang (2000). The Journal of Business, volume 73, number, p481, "Therefore. ignoring opening jumps will underestimate the volatility."

DY09 which fills the gap of DY09 and an advanced model being able to detect the *direction* of the spillover between every each single assets.

Thus, in this section, DY09 is first introduced until the "overall spillover index" is reached. Thereafter, new improvements have been contributed by DY12, from where we turn to the method of DY12 and present all formulae for the further directional spillover estimation.

DY09 investigated the connectedness using VAR and first created the concept of "spillover index". For a two-variable vector of stationary first-order series x_t, it can be written as:

$$x_t = \Phi x_{t-1} + \varepsilon_t \tag{1}$$

where x_t is a vector of either returns or volatilities, here x_t is a 2×1 vector and Φ is a 2×2 parameter matrix. Expression (1) can be represented in the following form:

$$(I - \Phi L)x_t = \varepsilon_t \tag{2}$$

$$\Phi(L)x_t = \varepsilon_t \tag{3}$$

$\Phi(L)$ is a 2×2 matrix polynomial in L. Then the equation can be written as:

$$x_t = \Theta(L)\varepsilon_t = A(L)\mu_t \tag{4}$$

where $\Theta(L) = (I - \Phi L)^{-1}$ and $A(L) = \Theta(L)Q_t^{-1}$. Q_t^{-1} stands for a unique lower triangular Cholesky factor of ε_t, with μ being defined as $\mu = Q_t\varepsilon_t$ and $E(\mu_t\mu_t') = I$. One can show that the one-step-ahead Wiener-Kolmogorov linear least-square forecast as:

$$x_{t+1,t} = \Theta x_t \tag{5}$$

with a corresponding one-step-ahead error vector:

$$e_{t+1,t} = x_{t+1} - x_{t+1,t} = A_0 u_{t+1} = \begin{bmatrix} a_{0,11} & a_{0,12} \\ a_{0,21} & a_{0,22} \end{bmatrix} \begin{bmatrix} u_{1,t+1} \\ u_{2,t+1} \end{bmatrix} \tag{6}$$

Thus the covariance matrix can be written as:

$$E(e_{t+1,t}e_{t+1,t}') = A_0 A_0' \tag{7}$$

The advantage of using this approach is being able to split the forecast error variances into two parts, namely the one-step-ahead error for $x_{1,t}$ as $a_{0,11}^2 + a_{0,12}^2$, and $a_{0,21}^2 + a_{0,22}^2$ for $x_{2,t}$. By doing this, one can be informed on which proportion of the error variance has been contributed by the shock to itself (in a 2-variable case, this can be x_1), the so-called *own variance shares*, or by the shock to the others (x_2 in this case), the *cross variance shares*, which is also the *spillover* we want to examine. The total forecast error variation is defined as:

$$a_{0,11}^2 + a_{0,12}^2 + a_{0,21}^2 + a_{0,22}^2 = trace(A_0 A_0') \tag{8}$$

The spillover as a percentage ratio to the total forecast error variation leads to the formula of the *spillover index* for the basic first-order two-variable case:

$$S = \frac{a_{0,12}^2 + a_{0,21}^2}{trace(A_0 A_0')} \times 100 \tag{9}$$

Analogously the case of pth-order N-variable VAR with H-step-ahead forecast *spillover index* can be immediately deduced as:

$$S = \frac{\sum_{h=0}^{H-1}\sum_{\substack{i,j=1\\i\neq j}}^{N}a_{h,ij}^2}{\sum_{h=0}^{H-1}trace(A_h A_h')} \times 100 \tag{10}$$

However, there are certain limitations to the use of this method from DY09. Firstly, the variance decomposition resulting from the Cholesky factorisation leads to a strong dependency on the ordering of the variables. The second methodological limitation comes when one has more than 2 markets and would like to detect the *directional* spillovers. With DY09, only a total spillover is identified. By exploiting an order-invariant variance decomposition raised by KPPS, DY12 produced a new approach based on the general idea from DY09. An H-step-ahead forecast error variance decomposition being denoted by $\theta_{ij}^g(H)$ for $H = 1, 2, ...$ has the following representation:

$$\theta_{ij}^g(H) = \frac{\sigma_{jj}^{-1}\sum_{h=0}^{H-1}(e_i' A_h \Lambda e_j)^2}{\sum_{h=0}^{H-1}(e_i' A_h \Lambda A_h' e_i)} \tag{11}$$

$$where\ e_i = \begin{cases} 1 & i^{th}\ element \\ 0 & otherwise \end{cases}$$

e_i is a selection vector which equals 1 for the ith items and 0 otherwise. Λ stands for the variance matrix for the error vector ε and σ_{jj} represents the standard deviation of the error term for the jth equation. Realising that each entry of the variance decomposition matrix can be normalised by the row sum as: $\tilde{\theta}_{ij}^g(H) = \frac{\theta_{ij}^g(H)}{\sum_{j=1}^{N}\theta_{ij}^g(H)}$ with $\sum_{N}^{j=1}\tilde{\theta}_{ij}^g(H) = 1$ and $\sum_{N}^{i,j=1}\tilde{\theta}_{ij}^g(H) = N$ by construction, we then have the expression for *total spillover*, which is the KPPS analogue based on the DY09 total spillover as formula (10):

$$S^g(H) = \frac{\sum_{\substack{i,j=1\\i\neq j}}^{N}\tilde{\theta}_{ij}^g(H)}{\sum_{i,j=1}^{N}\tilde{\theta}_{ij}^g(H)} \times 100 = \frac{\sum_{\substack{i,j=1\\i\neq j}}^{N}\tilde{\theta}_{ij}^g(H)}{N} \times 100 \tag{12}$$

Thus in DY12, the following exclusively further spillovers have been deduced: Directional volatility spillover **received** by market i **from** all other markets j:

$$S_{i.}^g(H) = \frac{\sum_{\substack{j=1\\j\neq i}}^{N}\tilde{\theta}_{ij}^g(H)}{\sum_{i,j=1}^{N}\tilde{\theta}_{ij}^g(H)} \times 100 = \frac{\sum_{\substack{j=1\\j\neq 1}}^{N}\tilde{\theta}_{ij}^g(H)}{N} \times 100 \tag{13}$$

Directional volatility spillover **transmitted** by market i **to** all other markets j:

$$S_{.i}^g(H) = \frac{\sum_{\substack{j=1\\j\neq i}}^{N}\tilde{\theta}_{ji}^g(H)}{\sum_{i,j=1}^{N}\tilde{\theta}_{ji}^g(H)} \times 100 = \frac{\sum_{\substack{j=1\\j\neq 1}}^{N}\tilde{\theta}_{ij}^g(H)}{N} \times 100 \tag{14}$$

Net volatility spillovers **from** market i **to** all other markets j:

$$S_i^g(H) = S_{.i}^g(H) - S_{i.}^g(H) \tag{15}$$

Net pairwise spillovers **between** markets i and j (from i to j):

$$S_{ij}^g(H) = \left(\frac{\tilde{\theta}_{ji}^g(H)}{\sum_{i,k=1}^N \tilde{\theta}_{ik}^g(H)} - \frac{\tilde{\theta}_{ij}^g(H)}{\sum_{j,k=1}^N \tilde{\theta}_{jk}^g(H)} \right) \times 100$$

$$= \left(\frac{\tilde{\theta}_{ji}^g(H) - \tilde{\theta}_{ij}^g(H)}{N} \right) \times 100 \tag{16}$$

In the following sections, those formulae will be applied to the data introduced in Section 3 for return and volatility specifically. The results will be shown in Section 4 in the form of tables as well as rolling-window dynamic plots.

3 Data

Daily data which includes open, close, high and low information for COMEX, LBMA and SGE has been applied from 23. November 2012 to 15. August 2018.

Within COMEX, gold (product ticker GC) has been traded with 100 troy ounces contract size. The minimum tick is $0.10 per troy ounce. For one tick, the dollar value is hence 10$. Trading hours are from Sunday to Friday, 5:00 pm till 4:00 pm the next day depends on the North American Central Time Zone (CT). For each trading day, there is only one hour break from 4:00 pm to 5:00 pm. Contracts are only monthly signed within 23- or 72-monthly period for Feb, Apr, Aug & Oct or Jun & Dec respectively. In order to compare the gold future prices from COMEX with other spot price series, "forwards Panama adjusted price roll on last trading day" (GC1) (Stevens Analytics 2019) has been used from Quandl.[2]

LBMA daily gold price data is provided by Bloomberg Terminal. ICE Benchmark Administration (IBA) is the current operator of the LBMA price setting. The trading is 24 hours and the prices are set twice daily at 10:30 am and 3:00 pm London BST in US Dollar and 16 other currencies adjusted at the spot exchange rate as indicative prices for settlements only. In this paper we use the afternoon setting benchmark in US Dollar as the closing price for the node of one day.

For SGE, we are going to use the spot deferred contract Au(T+D) first introduced by Shanghai Gold Exchange in 2004. Au(T+D) allows the traders to postpone their contract made on t^{th} day by d ($d \geq 0$) day(s) through a deferral payment, which only

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[2]This method is sometimes also called "first-true method". By rolling the price forwardly from the oldest history contract to the latest one, one achieves a smoothed contract price series without jumps due to the maturities. The price of the oldest contract will therefore be the "true" as the rolling base of the series, thus the name "first-true method". Original data and this method are provided by Stevens Analytics.

amounts to 10%(as margin level) of the contract value. We also note that Au(T+D) is
not a future contract, but a special type of spot contract. Gold futures have fixed deliv-
ery dates, while a position of Au(T+D) can always be held without a fixed delivery
date. Furthermore, Au(T+D) has night trading hours, which brings another advan-
tage to the trading flexibility. The reason for choosing this contract instead of using
the pure spot contract AU9999 from SGE is for its contract attributes, it can avoid
the incentive of man-made manipulation. Having no boundary for daily volatility, the
price of AU(T+D) contract reflects more about the true spot value balanced by real
demand and supply from the market, unlike the settlement price for AU9999, which is
typically anchored to the daily LBMA fixing. Besides, Au(T+D) also has the largest
trading volume among all gold contracts in SGE during our sample period.[3] Data is
traced from Wind Financial Terminal. The trading unit is 1kg with Yuan/gram as the
unit of quotation and the minimum tick is 0.01 Yuan/gram. Trading hours have been
separated into three periods: 9:00 to 11:30 am, 1:30 to 3:30 pm, 8:00 to 2:30 am (next
day).[4]

The continuously compounded return or *log return* will be calculated using daily
close-to-close price through the following approach.

$$r_t = \ln(1 + R_t) = \ln \frac{P_t}{P_{t-1}} = p_t - p_{t-1}$$

where $p_t = \ln(P_t)$

By using the log return, one can easily achieve a normalisation and avoid the
originating from price series of unequal units and/or quoting currencies. Gold being
traded in COMEX and LBMA are both quoted in US Dollar, the only omitted exter-
nal changing variable is the exchange rate between US Dollar and Chinese Yuan.
Since gold is highly homogenous, the possibility of arbitrage does not incentivise the
investors due to the law of one price.

Volatilities have been obtained by applying the Yang and Zhang (2000) measure-
ment fully using daily open, close, high, low information. Yang-Zhang measurement
also takes the overnight jumps and volatility drift into considerations. An once-
difference have been taken on it afterwards to reach a stationary time series.[5] The
formula is as follow, where notations h, l, o and c stand for logged daily high, low,
open and close respectively:

$$Volatility_{Yang-Zhang} = \sigma^2_{YZ}$$
$$= \sigma^2_{overnight\ volatility} + k\sigma^2_{open\ to\ close\ volatility} + (1-k)\sigma^2_{RS}$$

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[3]Au(T+D) trading volume amounts to 34.43% of the total gold trading volume in 2017.

[4]There have been sequential changes in margin level and trading hours. The latest information in December
2019 indicates a 6% margin ratio and a longer trading hour with two periods: 9:00 - 15:30 and 19:50 -
2:30 (next day)

[5]There is no overnight jump for the COMEX since it runs 24 hours around the clock. LBMA closes for
only one hour with slight jumps most of the time. In contrast, there is always a gap for the SGE since the
closing time is much longer than the other two.

Table 1 Descriptive Statistics, Daily Log Return, 23. Nov. 2012 - 15. Aug. 2018

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
COMEX	1,351	−0.0003	0.009	−0.094	−0.005	0.004	0.044
LBMA	1,351	−0.0002	0.009	−0.095	−0.005	0.005	0.046
SGE	1,351	−0.0002	0.008	−0.071	−0.005	0.004	0.044

where $k = \dfrac{0.34}{1.34 + \frac{N+1}{N-1}}$

$$\sigma^2_{overnight\ volatility} = \frac{1}{N-1} \sum_{i=1}^{N} \left[ln\left(\frac{o_i}{c_{i-1}}\right) - \overline{ln\left(\frac{o_i}{c_{i-1}}\right)} \right]^2$$

$$\sigma^2_{open\ to\ close\ volatility} = \frac{1}{N-1} \sum_{i=1}^{N} \left[ln\left(\frac{c_i}{o_i}\right) - \overline{ln\left(\frac{c_i}{o_i}\right)} \right]^2$$

σ^2_{RS} refers to the Rogers and Satchell (1991) volatility with the following expression:

$$\sigma_{RS} = \sqrt{\frac{1}{N}} \sqrt{\sum_{i=1}^{N} \left[ln\left(\frac{o_i}{c_{i-1}}\right) \right]^2 + \frac{1}{2} \left[ln\left(\frac{h_i}{l_i}\right) \right]^2 - [2ln(2) - 1] \left[ln\left(\frac{c_i}{o_i}\right) \right]^2}$$

After omitting the first 5 observations which have been used for generating the Yang-Zhang volatility and eliminating the entries where the market is not opened, 1351 observations remain. The descriptive statistics for both returns and volatility are provided in Tables 1 and 2.

Table 1 is the daily log return of the three markets. With 1351 observations, the mean values for returns are all slightly negative, with similar standard deviations. Minimum returns from COMEX and LBMA are lower than SGE, while their first, third quantile and maximum values are quite close to the others. This similarity is highlighted in Fig. 1: it shows that the three stationary return series have been performing in immensely similar patterns over time. This fact also meets the expectation, given that gold as a product has an exceedingly high homogeneity.

Table 2 describes the Yang-Zhang volatility of the three markets. LBMA is the only market that has a slightly positive mean value whereas both COMEX and SGE are insignificantly negative on average. SGE has a larger standard deviation compares to COMEX and LBMA. With the same interquartile range (all three series

Table 2 Descriptive Statistics, Daily Yang-Zhang Volatility, once-differenced, 23. Nov. 2012 - 15. Aug. 2018

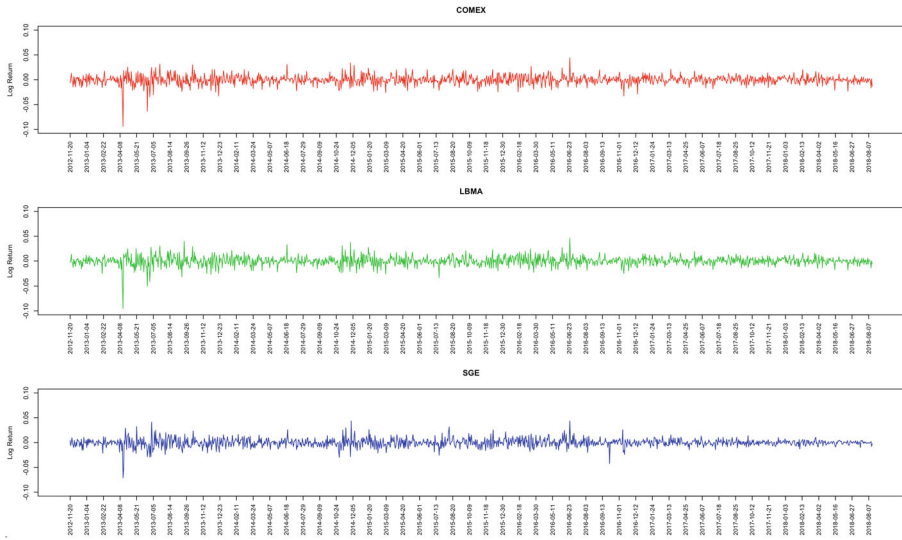| Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
COMEX	1,351	−0.00004	0.003	−0.030	−0.001	0.001	0.030
LBMA	1,351	0.00001	0.003	−0.035	−0.001	0.001	0.035
SGE	1,351	−0.00004	0.005	−0.050	−0.001	0.001	0.060

Fig. 1 Daily Log Returns, 23. Nov. 2012 - 15. Aug. 2018

have -0.001 and 0.001 as the first and the third quarter), both SGE's minimum and maximum values are further from mean than the other two markets.

Figure 2 illustrates all three stationary volatility series. Volatility clustering can be identified from all three dynamic series, namely "large changes tend to be followed by large changes, of either sign, and small changes tend to be followed by
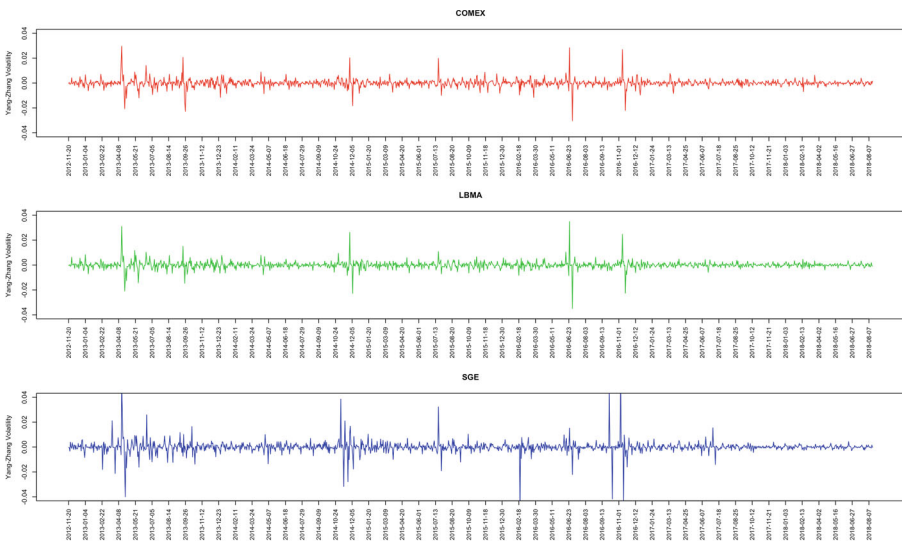

Fig. 2 Daily Yang-Zhang volatility, 23. Nov. 2012 - 15. Aug. 2018

small changes".[6] LBMA and COMEX share more similarity in the volatility pattern. Distinctions of SGE are reflected in two aspects. Firstly, SGE has a fluctuation at the same slots as the other two but with different scales, for example in April 2013, December and June 2014 as well as November 2016. The second aspect can be concluded as an exclusive fluctuation unique to SGE, for example in February 2016 and June 2017. These differences may be caused by partial shocks burst only in one market, however with different international influences to the others. Fluctuations from 2013 April may come from the announcement made by North Korea that a plutonium-producing reactor plan had been restarted. During November 2014, the Asia-Pacific Economic Cooperation (APEC) Leaders Meeting took place in Beijing, China from 5th to 11th, and later from the 15th to 16th, the G20 Leaders Summit was held in Brisbane, Australia. This can, to some extent, explain an early emerged fluctuation in China, then a later one in the other two markets. The large downward shock only occurred in the Chinese market in 2016 February might be the result of a continuous appreciation of the Chinese Yuan against the US Dollar, onshore CNY created a record of the largest increase since 2005 while offshore CNY rose 704 basis points from February 8th to February 12th. In June 2016, the shock caused by the British voters' decision to withdraw from the EU in a referendum on 23rd, happened simultaneously to the three markets, thereof LBMA had the largest fluctuation, then to COMEX, and SGE was affected the least. A grand shock exclusively in the Chinese market happened in October 2016, this was because since October 1st, 2016, the Chinese Yuan has been officially included in the International Monetary Fund's Special Drawing Rights (SDR) currency baskets, becoming one of the official reserve currencies of the International Monetary Fund. Then in the beginning of November, the election of US president affected the three markets at the same time.

4 Result

The results will be divided into four parts. First, we consider unconditional spillover, in which we summarise an average spillover index for the whole time period. Later we examine the dynamic variation using the rolling window estimation as the time progresses. The rolling window results will be divided into three parts: overall, gross directional and net directional.[7]

4.1 Unconditional full-sample spillover tables

We first treat the entire data sample from November 2012 to August 2018 as a whole and generate the following tables using the DY12 approach for both return and volatility in each of the three markets.

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[6]The term "volatility clustering" has been first noted by Mandelbrot (1963), this quotation also comes from the same resource.

[7]During the computation, the author has the set the correlation between variables (markets) no equal to zero, by not manually setting the off-diagonal in the covariance matrix be zero, since one can not assume that three markets are fully-independent from each other.

Table 3 Return spillover, 23. Nov. 2012 - 15. Aug. 2018

| Return spillover using DY12 | From (Percentage) | | | |
To (Percentage)	COMEX	LBMA	SGE	Contribution from others
COMEX	51.12	42.14	6.75	16.29
LBMA	42.48	51.93	5.60	16.02
SGE	30.59	35.90	33.51	22.16
				Spillover Index
Contribution to others	24.36	26.01	4.11	54.48

Tables 3 and 4 are the so-called spillover tables for return and volatility respectively, which describes an "input-output decomposition" of the spillover index.[8] The ijth entry estimates the percentage forecast error variance which has been contributed from the ith market and transferred to the jth market.[9] Entries on the diagonal indicate the proportion of return or volatility forecast error variances of themselves. The off-diagonal entries remaining in each row or column thus sum up to the spillover index among those markets.[10] Using the difference between "Contribution to others" and "Contribution from others", the net directional spillover can also be derived.

First consider the return spillover Table 3. For all three markets, the forecast variance errors mainly come from themselves, 51.12% of COMEX, 51.93% of LBMA, 33.51% of SGE. While SGE has a smaller percentage of self-spillover, it receives a larger contribution (22.16%) of the total spillover from other markets.[11] This disparity is even larger when we look at their "Contribution to others". Both COMEX and LBMA create around a quarter of the total spillover to the others, while SGE has only a small contribution of 4.11%. More than half of the return forecast error variance in total is caused by the spillovers between markets, mainly contributed by COMEX and LBMA. Combining both contributions, a conclusion can be made, that whereas COMEX and LBMA are net spillover givers, SGE is purely a spillover receiver.

The volatility spillover Table 4 is obviously different from the situation of the return spillover in the column of "Contribution from others". In the case of volatility spillover here, approximately 40% forecast error variance comes from the spillovers, in which almost three quarters from COMEX and LBMA, whereas SGE receives in this case less spillover than the other two markets (11.33%). Nevertheless, when we examine the "Contribution to others" row, SGE still spreads less spillover than COMEX and LBMA. The largest value (66.01%) in this table is the percentage

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[8]This term has been coined by Diebold and Yilmaz (2009, 2012).

[9]The results for return spillover are based on the vector autoregressions with 1 order and 10-day-ahead forecast errors. As being mentioned in Diebold and Yilmaz (2009), the total spillover results are not sensitive to the order of the VAR or the choice of the forecast horizon.

[10]Different from the Diebold and Yilmaz (2009, 2012), the percentage value here is the proportion of the whole three markets, not the proportion in the specific market of this row or column.

[11]22-16% is remained by summing up 30.59% from COMEX and 35.90% from LBMA and divided by 3.

Table 4 Volatility spillover, 23. Nov. 2012 - 15. Aug. 2018

Volatility spillover using DY12	From (Percentage)			
To (Percentage)	COMEX	LBMA	SGE	Contribution from others
COMEX	55.48	39.46	5.06	14.84
LBMA	38.96	55.57	5.47	14.81
SGE	16.56	17.43	66.01	11.33
				Spillover Index
Contribution to others	18.51	18.96	3.51	40.98

volatility forecast error variance of SGE being descended from its own innovation. This indicates, SGE is more self-dependent in the sense of volatility than in terms of return (Table 3). Subtract the "contribution from others" from "contribution to others" we have the net spillover. As in the previous case, SGE is a net receiver and the other two are spillover spreaders.

DY09 mentioned, that the spillovers for return and volatility are distinguished from each other. In both cases, whether in return or volatility, the same observation can be concluded as a relatively much weaker frequency connectedness as well as market power of SGE compared to the other two markets. With the main part of its forecast error resulting from its own innovation, SGE receives a lot of shock affections from the others. On the other hand, the innovations taking place in SGE have a weaker transmission power to COMEX and LBMA.

All in all, LBMA and COMEX are performing dominating roles with the strongest inter-linkages between them. However the argument from Lucey et al. (2014) that "Shanghai is very *disconnected* from the other markets with 98.7% of its forecast error variance coming from itself" no longer holds from a later estimation in this research.

4.2 Conditional dynamic overall spillover rolling window plots

A serious weakness with the full-sample spillover tables, however, is the missing fact that many dynamic transforms have taken place during the time horizon. Simply treating the total sample as a whole and only examining the average would not be adequate to capture the changes and dynamic movements of the spillover pattern within the sample period. In the following estimation, the rolling window dynamic patterns of 200 days and 10 days ahead are plotted.[12]

Figures 3 and 4 depict the dynamic variations of overall spillovers for return and volatility respectively (of which the averages are simply the numbers at the lower right corner of Tables 3 and 4). First consider the overall return spillover. The value

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[12]Plotting results are based on the VAR of orders 1 and 5 for return and volatility respectively. As it has been proved in the DY12, the overall spillover plot is not sensitive to the choice of the order of the VAR or the choices of the forecast horizon.
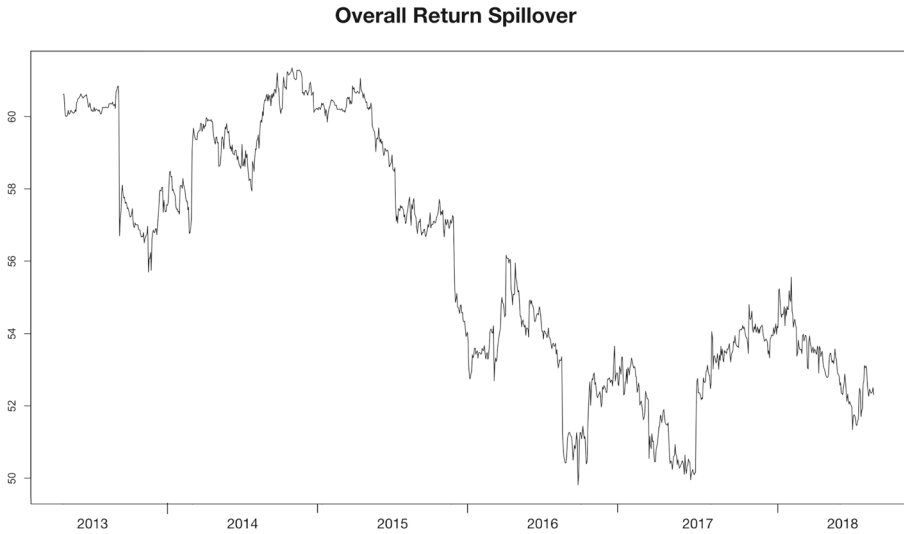
Overall Return Spillover

Fig. 3 Total Return Spillover, three markets, 23. Nov. 2012 - 15. Aug. 2018

started from over 60% at the beginning of our sample period in 2013, then a sudden drop from mid-late 2013 till mid-2014, the lowest value during this drop fell even below 56%. Afterwards, the overall return spillover rose again and exceeded the initial 60% till early-2015. Then after two cyclical downward-moves in 2016, the overall return spillover hit bottom during the second half of 2016, with the value even lower than 50%. From end-2016 till early-2017, overall return spillover was modestly stronger than 52% but plunged again in the first half of 2017. From mid-2017

Overall Volatility Spillover
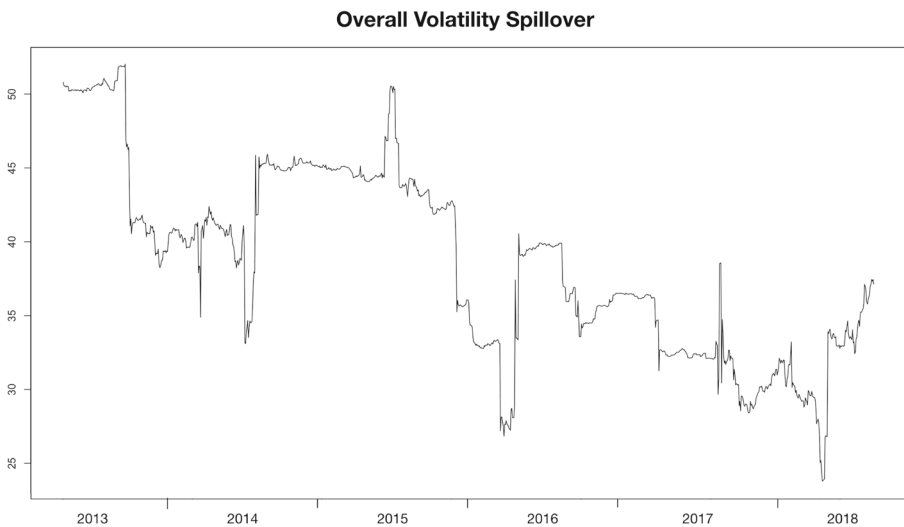
Fig. 4 Total Volatility Spillover, three markets, 23. Nov. 2012 - 15. Aug. 2018

till the end of our sample period, the value remained between 52% and 54% most of the time.

The volatility plot shown in Fig. 4 has a much smoother fluctuation than the return plot with similar movement patterns. The overall volatility spillover was slightly above 50% at the beginning of the sample period, which indicates, in the early half of 2013, more than half of the variance forecast error comes from the spillover. Then it suddenly slid to 40%. After a deep sink at mid-2014, it climbed back to approximately 45% and remained at that level for most of the time until end-2015. The second drop appeared at early 2016, overall volatility spillover fell underneath 30% level and bounced back again for a short time afterwards. From early-2016 till mid-2018, the overall trend for volatility spillover was a downward movement. The nadir took place in 2018 with a value even lower than 25%. Finally, a small upward trend can be observed before the end of our data sample.

4.3 Conditional directional return spillover dynamic rolling window plots

4.3.1 Directional *from* return spillover

The directional *from* return spillover plot (Fig. 5) describes the return forecast variance error resulting from receiving the spillovers from other markets. Among the whole data period, the spillover received by SGE is always larger than for the other two markets, even its lowest value (around 18%) in early to middle of 2017 was just about the upper boundaries of the percentage spillovers received by COMEX and LBMA during the five years. Yet the overall trend demonstrates a slowly decreasing receiving of SGE. The same downward trends also appeared in COMEX and LBMA and became more obvious since 2016.
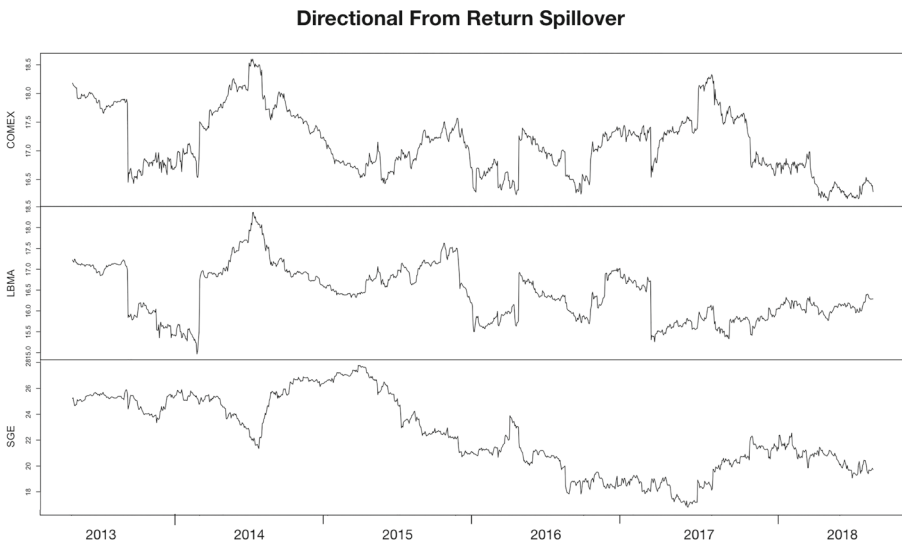
Directional From Return Spillover

Fig. 5 Directional from Return Spillover, three markets, 23. Nov. 2012 - 15. Aug. 2018

4.3.2 Directional *to* return spillover

The directional *to* spillover plot is illustrated in Fig. 6. With the same vertical axis ranging from approximately 15% to 18.5% of COMEX and LBMA in the *from* plot, they have in this case both stronger spillover spreading abilities, which were mainly between an interval from 20% to 30%. Two stages can be easily identified from the plot, namely before and after 2016. The return spillovers before 2016 were most of the time above 24% for COMEX and 26% for LBMA. Then a downturn occurred subsequently. Both of them had an all-time-low concurrently during the middle of 2016. SGE had a positive spillover jump up to 10% from time to time. Nevertheless, this influence from SGE is not at all comparable to either COMEX or LBMA.

4.3.3 *Net* return spillover

Subtracting the *from* values from the *to* results leads to Fig. 7 of *net* return spillover. Value intervals from the ordinate axis provide the roles all three markets are playing, i.e. COMEX and LBMA are the spillover net givers while SGE is a spillover net receiver. But since the dynamic plotting was getting less negative with time, the market influence of SGE among the three was also slightly growing. We might expect a positive net spillover soon.

4.3.4 *Pairwise* return spillover

In addition to treating all three markets as a whole, spillover between the pairs i.e. COMEX and LBMA, LBMA and SGE as well as COMEX and SGE was also considered. The pairwise spillover plot enables us to investigate the relationship between

Directional To Return Spillover

Fig. 6 Directional To Return Spillover, three markets, 23. Nov. 2012 - 15. Aug. 2018
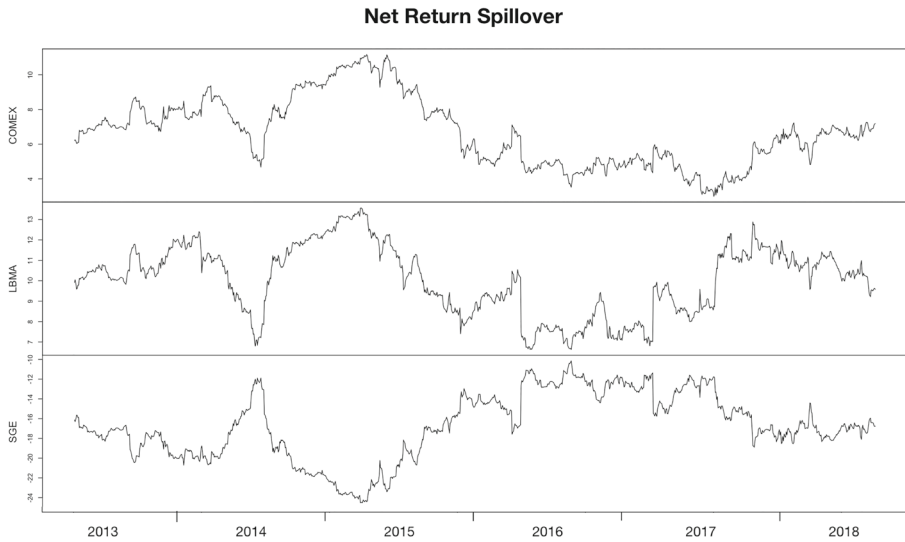
Net Return Spillover

Fig. 7 Net Return Spillover of three markets, 23. Nov. 2012 - 15. Aug. 2018

only two markets as if all the others do not exist. The first row in Fig. 8 shows the spillover strength from LBMA to COMEX, which was mainly close to zero with slight fluctuation before mid-2016. From late-2016 till almost end-2017, LBMA transferred a series of spillover to COMEX. The reason might be Brexit in 2016. Apart from that occasion, the spillover between COMEX and LBMA were evenly matched. However, the relationship between SGE and either COMEX or LBMA is

Pairwise Return Spillover
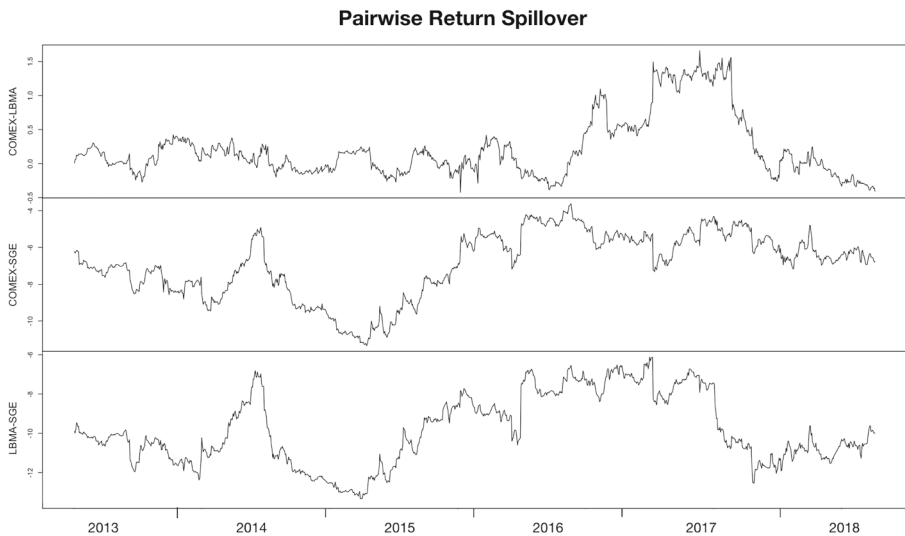
Fig. 8 Pairwise Return Spillover of three markets, 23. Nov. 2012 - 15. Aug. 2018

entirely disparate. The second row presents the net spillover from SGE to COMEX. Remarkably, the whole dynamic rolling estimation results are lying in the negative dimension, from -4% to -12%. It began with a 6% return spillover from COMEX to SGE, then this spillover effect turned stronger in a stepwise fashion until early-2015. After that, the effectiveness of return spillover of SGE pushed the percentage back to approximately -5% and remained at that level without other large change. Till the end of the sample period, there is no sign of a positive spillover from SGE to COMEX. Finally, the last row describes the relationship between SGE and LBMA, which is also an one-sided spillover transmission from London to Shanghai, the percentage scale was floating -6% to -14%. The pattern was similar to the one between SGE and COMEX before mid-2017. From then on, COMEX-SGE pairwise spillover remained around -6% while a stronger tendency of a percentage spillover higher than 10% from LBMA to SGE appeared in the LBMA-SGE pairwise pattern.

4.4 Conditional directional volatility spillover dynamic rolling window plots

As Diebold and Yilmaz (2009) mentioned, spillover intensity is indeed time-varying and the nature of the time-variation is strikingly different for return and volatility. Using a dynamic rolling window plot, it was already shown that static tables cannot fully summarise the dynamic of spillover pattern. Now we move to the spillover plots of volatility and examine the latter argument.

4.4.1 Directional *from* volatility spillover

As for the return estimations, one first generates the directional *from* volatility spillover in Fig. 9, which illustrates the spillover received by the respective market on the ordinate from the other two markets. In general, COMEX and LBMA receive more volatility spillover (both scales are from around 10% to above 16%, and lie above 15% for most often) than SGE (scale from 5% to approximately 20%, but the major part lies underneath the 15% line). Different from the previous cases, volatility dynamics are not as volatile as the returns'. Apart from minor-inconsistencies at some specific time points, it stays fairly constant during most of the time. This is the first point which distinguishes from the return spillover. The big change was quite similar to the return estimation, namely a lower stage after the beginning high level spillover from late-2013 till mid-2014. Then, COMEX jumped back to its previous high-level of approximately 15%, LBMA also went back to a flat level slightly lower than the first high stage. In contrast to them, SGE didn't bounce back, the spillover strength decreased slowly even when there was another low at mid-2014 and small spike mid-2016. Finally, after several steps, SGE reached its nadir in 2017, the spillover was even lower than 5% during late-2016 and the first two-thirds of 2017. On the other hand, COMEX and LBMA did not have an obvious medium trend. After their second spillover plateaux from mid-2014 to late-2015, another large decrease followed in early-2016, which lasted only for a short period and both spillover strengths jumped back to their previous level directly afterwards. The third drop in COMEX and LBMA appeared in 2017 (from approximately 15% to 11%) while for SGE it was
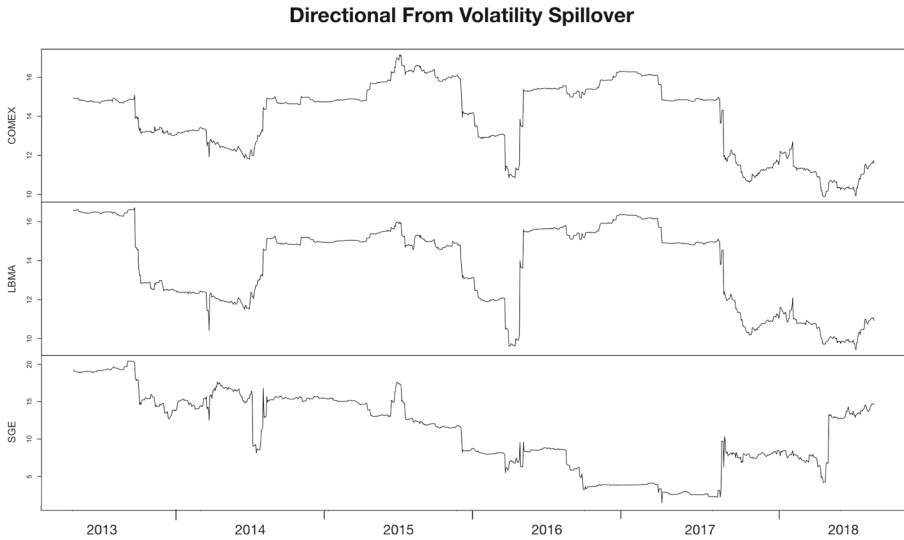
Directional From Volatility Spillover

Fig. 9 Directional From Volatility Spillover, three markets, 23. Nov. 2012 - 15. Aug. 2018

an accompanying upheaval. The biggest reason for this change was a sudden rising exchange rate of the Chinese Yuan during the end of August till mid-September 2017.

4.4.2 Directional *to* volatility spillover

Figure 10 illustrates the directional *to* volatility spillover. One still observes similar pattern from COMEX and LBMA, in which both have spillover range between 12%

Directional To Volatility Spillover
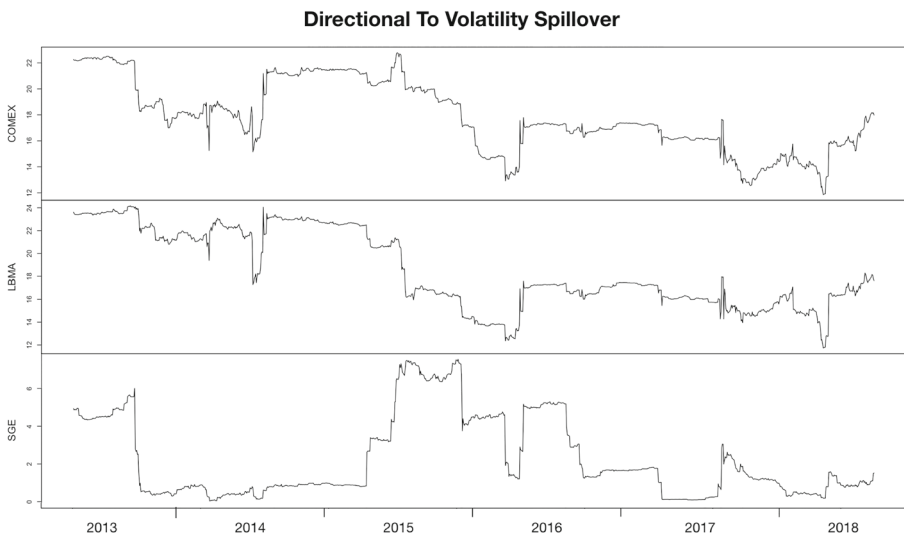
Fig. 10 Directional To Volatility Spillover of three markets, 23. Nov. 2012 - 15. Aug. 2018

to 24%, whereas the SGE's spillover keeps in single digits, even close to zero for most of the time. For COMEX and LBMA, a slightly decreasing trend can be identified, but for SGE, there is no clear movement tendency.

4.4.3 *Net* volatility spillover

Again we use the difference between "directional to" and "directional from" to compute the "net volatility spillover", which is shown in Fig. 11. Here we observe a mirror spillover pattern between SGE and the other two markets. While both COMEX and LBMA experience a decreasing phase between mid-2015 and early-2018, there was an inversely increasing stage for SGE. However, this "increasing stage" in the net spillover of SGE is actually a "less negative stage" after all. The total net volatility spillover for SGE stays entirely in the negative dimension. Just as in the case of return spillover, COMEX and LBMA are the net spreaders among the three markets while SGE plays the role of a net receiver.

4.4.4 *Pairwise* volatility spillover

Finally, Fig. 12 examines the pairwise spillovers between any two of the three markets. As can be observed from the first plot window, COMEX and LBMA were again mostly even with the volatility spillover staying around 0 within most of the time period. The spillovers from COMEX and LBMA to SGE have similar patterns. However, the pairwise spillover between LBMA and SGE is marginally stronger than the one between COMEX and SGE. During mid-2015 and late-2017, SGE pushed both spillovers from COMEX and LBMA fairly close to zero, probably due to the internationalisation of SGE during that period.
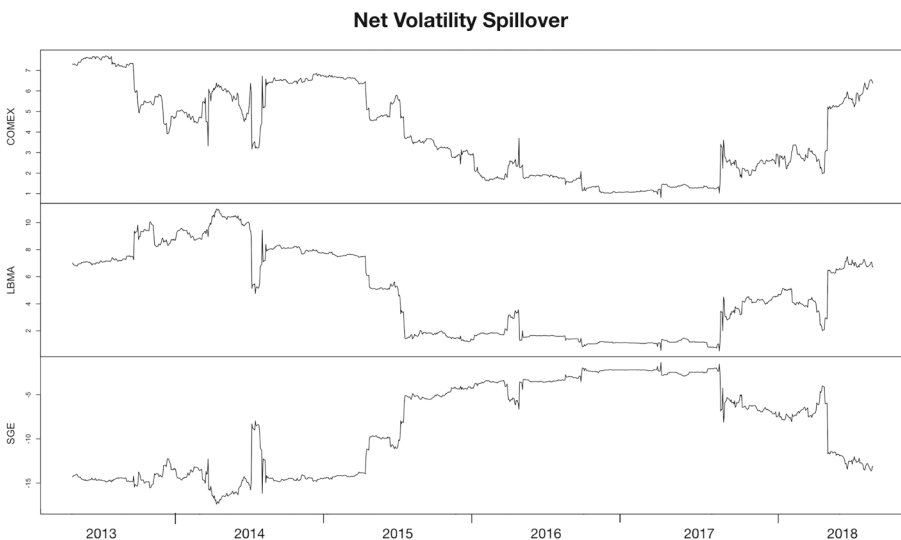

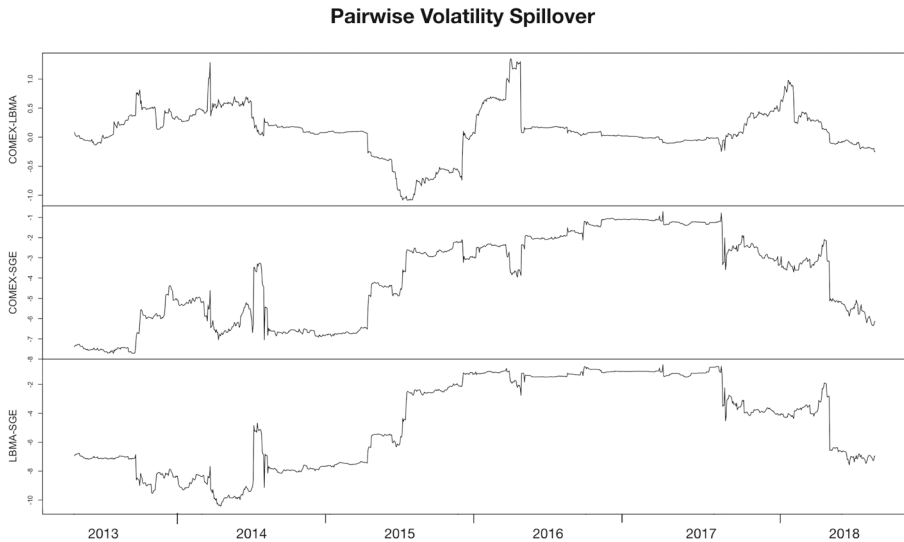**Fig. 11** Net Volatility Spillover of three markets, 23. Nov. 2012 - 15. Aug. 2018

Pairwise Volatility Spillover

Fig. 12 Pairwise Volatility Spillover of three markets, 23. Nov. 2012 - 15. Aug. 2018

5 Conclusions

In this paper, the spillover strength between COMEX, LBMA and SGE was examined using the method from Diebold and Yilmaz (2012). Both static, as well as dynamic results, prove that the spillover strength of SGE is still comparably minor, and SGE as an emerging exchange remains isolated as compared to COMEX and LBMA. Nevertheless, through the dynamic rolling-window plot, an increasing spillover can be observed since mid-2015, when SGE started its internationalization: however, there does not appear to be any definite signs of SGE becoming as strong as the other two older markets in the short term, and the current situation is far from building a tripartite confrontation between those three exchanges. COMEX and LBMA are still the dominant spillover players in the gold markets presumably because of their stronger invest confidence which is based on their more solid foundations, longer trading windows as well as larger trading volume.

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