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Cross-correlations and influence in world gold markets

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HIGHLIGHTS

- Multiscale cross-correlations and net cross-correlations among five major world gold markets are studied.
- Multiscale influence measures are proposed for quantify the influence of individual gold markets.
- The cross-correlations, net cross-correlations, and net influences vary across time scales.
- The cross-market correlation between London and New York at each time scale is intense and inherent.
- The London gold market significantly affects the other four gold markets and dominates the world-wide gold market.

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ABSTRACT

Using the detrended cross-correlation analysis (DCCA) coefficient and the detrended partial cross-correlation analysis (DPCCA) coefficient, we investigate cross-correlations and net cross-correlations among five major world gold markets (London, New York, Shanghai, Tokyo, and Mumbai) at different time scales. We propose multiscale influence measures for examining the influence of individual markets on other markets and on the entire system. We find (i) that the cross-correlations, net cross-correlations, and net influences among the five gold markets vary across time scales, (ii) that the cross-market correlation between London and New York at each time scale is intense and inherent, meaning that the influence of other gold markets on the London–New York market is negligible, (iii) that the remaining cross-market correlations (i.e., those other than London–New York) are greatly affected by other gold markets, and (iv) that the London gold market significantly affects the other four gold markets and dominates the world-wide gold market. Our multiscale findings give market participants and market regulators new information on cross-market linkages in the world-wide gold market.

1. Introduction

For thousands of years gold has been considered the ultimate storage of value and a safe haven in turbulent times. Because of its role in profit-taking and hedge fund activity, in recent years gold prices have been highly volatile [1,2]. Gold and its financial products, e.g., exchange-traded funds (ETFs), futures, and other derivatives, are traded on various organized exchanges and platforms around the world [3]. Although gold is a globally traded asset, according to O'Connor et al. [4] and GFMS (2015) [5], the current major trading centers are the London over-the-counter (OTC) market, the New York Commodity Exchange (COMEX), the Shanghai gold market including the Shanghai Futures Exchange (SHFE) and Shanghai

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Gold Exchange (SGE), the Tokyo Commodity Exchange (TOCOM), and the Mumbai Multi Commodity Exchange of India Ltd. (MCX). For example, in 2014 the net volume of gold transferred in the London OTC market was over 157,000 tons,[1] followed by the New York COMEX with a total volume of 126,028 tons, the Shanghai gold market with 33,994 tons,[2] the TOCOM with 8745 tons, and the Mumbai MCX with 3972 tons [5]. Cross-correlations across different financial agents is an important characteristic of the complex financial system [6,7]. Thus understanding cross-correlations across different gold markets has focused the attention of researchers because it can help investors construct a diversified portfolio to balance risk and optimize returns and help regulators monitor market stability and formulate effective policies. Our goal here is to investigate cross-correlations among the five major gold markets and detect their influence using the detrended partial cross-correlation analysis (DPCCA) coefficient from a multiscale (or multi-horizon) perspective.

Our work is related to the literature on relationships across different gold markets. For example, Xu and Fung [8] and Lin et al. [9] study cross-correlations between the New York and Tokyo gold markets using GARCH models. Xu and Fung [8] find that the New York gold market leads the Tokyo gold market in terms of the information flows, but Lin et al. [9] obtain a contrary conclusion. Kumar and Pandey [10] investigate cross-market linkages between the New York and Mumbai gold markets, finding that the New York market is a source of information flows to the Mumbai market. Lucey et al. [3] use the information share (IS) approach to examine relations between the London and New York gold markets. Using the vector error correction model (VECM) and the IS approach, Fuangkasem et al. [11] study cross-market linkages across three gold futures market, i.e., New York, Tokyo, and Mumbai. Lucey et al. [12] examine return and volatility spillover effects across four major gold markets (i.e., London, New York, Tokyo, and Shanghai) using a spillover index method. Following Lucey et al. [12], Wang et al. [1] investigate extreme risk spillover effects across the four major gold markets based on the Granger-causality risk test. Other related research includes, in particular, the work of Chang et al. [13], Hauptfleisch et al. [14], and Baklaci et al. [15]. Our study differs from the existing research in that the DPCCA coefficient allows us to analyze the net cross-correlations across different gold markets and detect their influence at different time scales.

The approaches used in our study are related to the literature on detrended fluctuation analysis (DFA) and detrended cross-correlation analysis (DCCA) and their extensions. The seminal work is done by Peng et al. [16] who proposed the DFA for analyzing long-range auto-correlations of time series. Kantelhardt et al. [17] extend the DFA to multifractal DFA (MF-DFA) to study the multifractal characterization of a time series. The DFA is extended to the DCCA by Podobnik and Stanley [18] to quantify long-range cross-correlations between two time series. To detect the multifractal feature in power-law cross-correlations, Zhou [19] proposes multifractal DCCA (MF-DCCA), which is a combination of MF-DFA and DCCA. Other related extensions include multifractal height cross-correlation analysis (MF-HXA) [20] and the multifractal cross-correlation analysis (MFCCA) [21]. An alternative approach to the DFA is the detrending moving-average (DMA) analysis [22,23], and its extensions include multifractal DMA (MF-DMA) [24] and multifractal detrending moving-average cross-correlation analysis (MF-X-DMA) [25]. Inspired by DFA and DCCA, Zebende [26] proposes a multiscale cross-correlation coefficient, the DCCA coefficient, that measures the strength of cross-correlations between two time series at different time scales.[3] The DCCA coefficient has been widely used to explore multiscale cross-correlations in financial markets (see, e.g., Refs. [29–32]), and we use it here to measure the cross-correlation level across the five major gold markets at different time scales.

Thus our work is also related to the literature on the application of the MF-DFA, DCCA and MF-DCCA on gold markets. For example, Bolgorian et al. [33] investigate the multifractal features and scaling behavior of daily gold prices in the London OTC market during the 1968–2010 period using the MF-DFA. Ghosha et al. [34] divide the sample of daily gold prices in the London OTC market during the 1973–2011 period into subsamples with five years each and study the time variation of the level of multifractality. Unlike in Refs [33] and [34], Wang et al. [35] use the MF-DAF to examine the multifractality of daily gold prices in the New York COMEX market over the period from 13 July 1990 to 15 September 2009. Yuan et al. [36] study the time-varying cross-correlations between the gold spot and futures returns using the DCCA. Yuan et al. [37] investigate the price-volume cross-correlations in the Chinese gold spot and futures markets based on the MF-DCCA. They find significant multifractal properties between price and volume in the Chinese gold markets.

We also use the DPCCA coefficient to measure net cross-correlations and the influence of the five major gold markets at different time scales. Thus our paper is also related to the literature on partial cross-correlation analysis. There are three ways of computing the partial cross-correlation coefficient, (i) linear regression, (ii) the iterative method, and (iii) matrix inversion (see, Wang et al. [38]). Kenett et al. [39,40] use the iterative approach to estimate the partial cross-correlation coefficient and propose influence measures for analyzing the relationships among stocks. Fernandez [41] study the influence in commodity markets using the measures proposed by Kenett et al. [39,40]. Qian et al. [42] extend the DCCA to the DPCCA using the linear regression and also propose the relevant DPCCA coefficient. In contrast to Ref. [42], Yuan et al. [43] propose the DPCCA coefficient using matrix inversion.[4] Our study uses the DPCCA coefficient as in Ref. [43] to capture net cross-correlations

[1] According to GFMS (2015) [5], the net volume in the London OTC market is approximately one-third of its total volume.

[2] The total volume traded on the Shanghai gold market is the sum of volumes traded on SHFE and SGE, where the volume of gold futures traded on SHFE was 23,858 tons and the volumes of Au(T+D) futures and the physical spot contracts traded on SGE were 7576 tons and 2560 tons, respectively.

[3] Kristoufek [27] proposes a similar approach, i.e., the detrending moving-average cross-correlation analysis (DMCA) coefficient based on DMA and DMCA. Kwapień et al. [28] develop an extension of the DCCA coefficient based on the MF-DFA and MF-DCCA.

[4] Note that Yuan et al. [44] extend the DCCA and DPCCA into the temporal evolution of DCCA (TDCCA) and temporal evolution of DPCCA (TDPCCA), which are used to investigate cross-correlations on multi-time scales and over different periods. One possible extension for our work is to develop time-varying and multiscaling influence measures based on the TDCCA and TDPCCA for examining the dynamic influence of individual markets over different time scales.

across the five major gold markets, and it extends the influence measures of Kenett et al. [39,40] to multiscale influence measures to quantify each gold market's average influence at different time scales.

This paper is organized as follows. Section 2 introduces the methods including the DCCA coefficient, the DPCCA coefficient, and the relevant influence measures. Section 3 describes the data for five major gold markets and presents empirical results. Section 4 provides concluding remarks.

2. Methodology

In this section we first introduce the DCCA coefficient [26] for quantifying cross-correlations across different gold markets at different time scales and then present the DPCCA coefficient [43] for examining net cross-correlations. Finally we show the multiscale influence measures for detecting the average influence of each gold market.

Given two return series $\{r_X(t)\}$ and $\{r_Y(t)\}$ of gold markets X and Y of equal size T, we calculate two integrated series $R_X(k) = \sum_{t=1}^{k} r_X(t)$ and $R_Y(k) = \sum_{t=1}^{k} r_Y(t)$, where $k = 1, 2, \ldots, T$. We then divide both integrated series into $T - n$ overlapping boxes, each containing $n+1$ values. In each box starting at i and ending at $i+n$, we define the "local trends" $\tilde{R}_X^i(k)$ and $\tilde{R}_Y^i(k)\,(i \le k \le i+n)$ as the linear least-squares fittings of $R_X(k)$ and $R_Y(k)$. For each return series we define the "detrended walk" or the residual as the difference between the original walk and the "local trend", i.e., $\varepsilon_X(k) = R_X(k) - \tilde{R}_X^i(k)$ and $\varepsilon_Y(k) = R_Y(k) - \tilde{R}_Y^i(k)$. We compute the covariance of the residuals in each box to be $\mathrm{Cov}_{XY}(n,i) = 1/(n-1)\sum_{k=1}^{i+n} \varepsilon_X(k)\varepsilon_Y(k)$. We average over all $T - n$ overlapping boxes with scale n and obtain the scale-dependent (or detrended) covariance

$$\mathrm{Cov}_{XY}(n) = (T-n)^{-1} \sum_{i=1}^{T-n} \mathrm{Cov}_{XY}(n,i). \tag{1}$$

When only one return series is investigated, the DCCA reduces to the DFA, and the scale-dependent covariance reduces to the scale-dependent variance

$$\mathrm{Var}_M(n) = (T-n)^{-1} \sum_{i=1}^{T-n} \mathrm{Var}_M(n,i),\ M \in \{X, Y\}, \tag{2}$$

where $\mathrm{Var}_M(n,i) = 1/(n-1)\sum_{k=1}^{i+n} \varepsilon_M^2(k)$.

The DCCA coefficient of Zebende [26] is defined as the ratio of the scale-dependent covariance to two scale-dependent variances

$$\rho_{XY}^{\mathrm{DCCA}}(n) = \frac{\mathrm{Cov}_{XY}(n)}{\sqrt{\mathrm{Var}_X(n)\mathrm{Var}_Y(n)}}, \tag{3}$$

where $\rho_{XY}^{\mathrm{DCCA}}(n)$ is a dimensionless coefficient ranging from -1 to 1 at each time scale n.[5] We obtain a DCCA coefficient matrix for N gold markets, i.e.,

$$\boldsymbol{\rho}(n) = \left(\rho_{XY}^{\mathrm{DCCA}}(n)\right)_{N\times N}, \tag{4}$$

where $1 \le X, Y \le N$.

As in Ref. [43], we compute the DPCCA coefficient using a matrix inversion. The first step is to calculate the inverse matrix of $\rho(n)$, i.e.,

$$\boldsymbol{C}(n) = \boldsymbol{\rho}^{-1}(n) = (c_{XY}(n))_{N\times N}. \tag{5}$$

Then the DPCCA coefficient between two gold markets X and Y is defined

$$\rho_{XY}^{\mathrm{DPCCA}}(n) = -\frac{c_{XY}(n)}{\sqrt{c_{XX}(n)c_{YY}(n)}}, \tag{6}$$

where $c_{XX}(n)$ and $c_{YY}(n)$ are diagonal elements of $\boldsymbol{C}(n)$. The DPCCA coefficient $\rho_{XY}^{\mathrm{DPCCA}}(n)$ defined here allows us to characterize the net cross-correlation between two gold markets X and Y at time scale n.

We introduce a quantity $\Delta\rho_{XY}(n)$, defined as the difference between the DCCA coefficient and the DPCCA coefficient,

$$\Delta\rho_{XY}(n) = \rho_{XY}^{\mathrm{DCCA}}(n) - \rho_{XY}^{\mathrm{DPCCA}}(n), \tag{7}$$

which measures the influence from all the other markets to the market pair X and Y at time scale n. The quantity $\Delta\rho_{XY}(n)$ is large when a significant fraction of the cross-correlation between markets X and Y is caused by all the other markets. We propose another DPCCA coefficient, $\rho_{XY:Z}(n)$, between markets X and Y conditional on market Z, which is defined

$$\rho_{XY:Z}(n) = \frac{\rho_{XY}^{\mathrm{DCCA}}(n) - \rho_{XZ}^{\mathrm{DCCA}}(n)\rho_{YZ}^{\mathrm{DCCA}}(n)}{\sqrt{\left[1-(\rho_{XZ}^{\mathrm{DCCA}}(n))^2\right]\left[1-(\rho_{YZ}^{\mathrm{DCCA}}(n))^2\right]}}. \tag{8}$$

5 We follow Kantelhardt et al. [17] and set time scale n at the range $[4, T/4]$.

Table 1
Summary statistics of daily returns of the London, New York, Shanghai, Tokyo, and Mumbai gold markets during the period from 2008 to 2016. Notes: The Jarque–Bera statistic tests for the null hypothesis of normal distribution for the sample returns. Each Jarque–Bera statistic is significant at the 1% level, rejecting the null hypothesis of normal distribution for each returns.

	London	New York	Shanghai	Tokyo	Mumbai
Mean	0.0119	0.0115	0.0066	0.0143	0.0389
Maximum	6.8414	8.6432	5.8482	10.7623	10.4498
Minimum	−9.5962	−9.8206	−7.1333	−12.0816	−8.6577
Std. Dev.	1.2289	1.2344	1.2167	1.3104	1.0462
Skewness	−0.3267	−0.2287	−0.2780	−0.6943	−0.0790
Kurtosis	8.2767	8.5758	7.5369	13.7498	13.1879
Jarque–Bera	2749.2570	3043.8033	2031.8106	11 425.456	10 096.414

Following Kenett et al. [39,40], we introduce an influence quantity, defined as the difference between the DCCA coefficient $\rho_{XY}^{\mathrm{DCCA}}(n)$ of markets X and Y and the DPCCA coefficient $\rho_{XY:Z}(n)$ of markets X and Y conditional on market Z, i.e.,

$$d_{XY:Z}(n) = \rho_{XY}^{\mathrm{DCCA}}(n) - \rho_{XY:Z}(n), \tag{9}$$

which quantifies the influence of market Z on the market pair X and Y at time scale n. A large value of $d_{XY:Z}(n)$ means that a large proportion of the cross-market correlation between X and Y can be explained by market Z. When considering all possible market combinations for N gold markets, there are $N(N-1)(N-2)/2$ partial cross-correlation interactions $d_{XY:Z}(n)$. For simplicity, we define the average influence $d_{X:Z}(n)$ of market Z on the cross-correlations between market X and all the other markets as

$$d_{X:Z}(n) = \langle d_{XY:Z}(n)\rangle_{Y\neq X}, \tag{10}$$

which approximates the net influence from market Z to market X at time scale n.

By averaging over all X markets, we define the average influence $d_Z(n)$ of market Z on all the other markets to be

$$d_Z(n) = \langle d_{X:Z}(n)\rangle\,, \tag{11}$$

which represents the net influence of market Z on the system at time scale n.

3. Data and empirical results

Our study focuses on the top five gold trading centers, including the London OTC market, the New York COMEX market, the Shanghai gold market, the TOCOM market, and the Mumbai MCX market. For simplicity, we refer to these five trading centers as the London, New York, Shanghai, Tokyo, and Mumbai gold markets. Following Lucey et al. [3,12] and Wang et al. [1], we use the daily afternoon (3:00 PM) gold fixing prices in the London Bullion Market (LBMA) as the empirical data for the London gold market. For the other four futures markets, we use the gold futures prices in the New York COMEX market, the SHFE market, the TOCOM market, and the Mumbai MCX market as empirical data. In particular, the data for each futures market are the daily closing prices of the near-month futures contract on a continuous rolling basis. We collect the data for the five gold markets during the period from 9 January 2008 to 30 December 2016, available from Datastream. The daily return of gold market X is defined as $r_X(t) = 100\ln(P_X(t)/P_X(t-1))$, where $P_X(t)$ is the daily closing (fixing) price of gold market X on day t.[6] We set the beginning of the sample time period at 9 January 2008, which is the date the SHFE market launched its first gold futures contract.

Fig. 1 shows the daily returns of the five major gold markets during the entire period. We find that the five returns during the 2008–2009 global financial crisis show violent fluctuation. The possible reason is that a large number of market participants sought gold as a tool of risk-avoidance because the market was experiencing distress. Table 1 summarizes the daily return statistics for the five gold markets during the investigated period. The Mumbai gold market has the largest mean value of returns, followed by Tokyo, London, New York, and Shanghai. The Tokyo and Mumbai gold markets have the largest and smallest standard deviations, respectively, and the other three gold markets have a similar standard deviation. Each skewness value is negative and each kurtosis value is larger than three, suggesting that each return series obeys a leptokurtic distribution with a left tail and disobeys a normal distribution. Each Jarque–Bera statistic is significant at the 1% level, once again suggesting that each return series is not a normal distribution.

To examine the strength of cross-correlations among the five gold markets at different time scales, Fig. 2 shows DCCA coefficients $\rho_{XY}^{\mathrm{DCCA}}(n)$ between the ten gold market pairs. All DCCA coefficients between the ten gold market pairs vary across time scales. According to the trend of DCCA coefficients, the gold market ten pairs can be broadly classified into two groups. The first includes London–New York, London–Shanghai, and New York–Shanghai, whose cross-correlations increase as the time scale increases, a phenomenon known as the Epps effect [46]. The second group comprises the other of

6 To test the robustness, we follow Forbes and Rigobon [45] and use the two-day rolling-average returns to eliminate asynchronous market data caused by time-zone differences. Similar to Forbes and Rigobon [45], the results based on the two-day rolling-average returns are consistent with our findings.

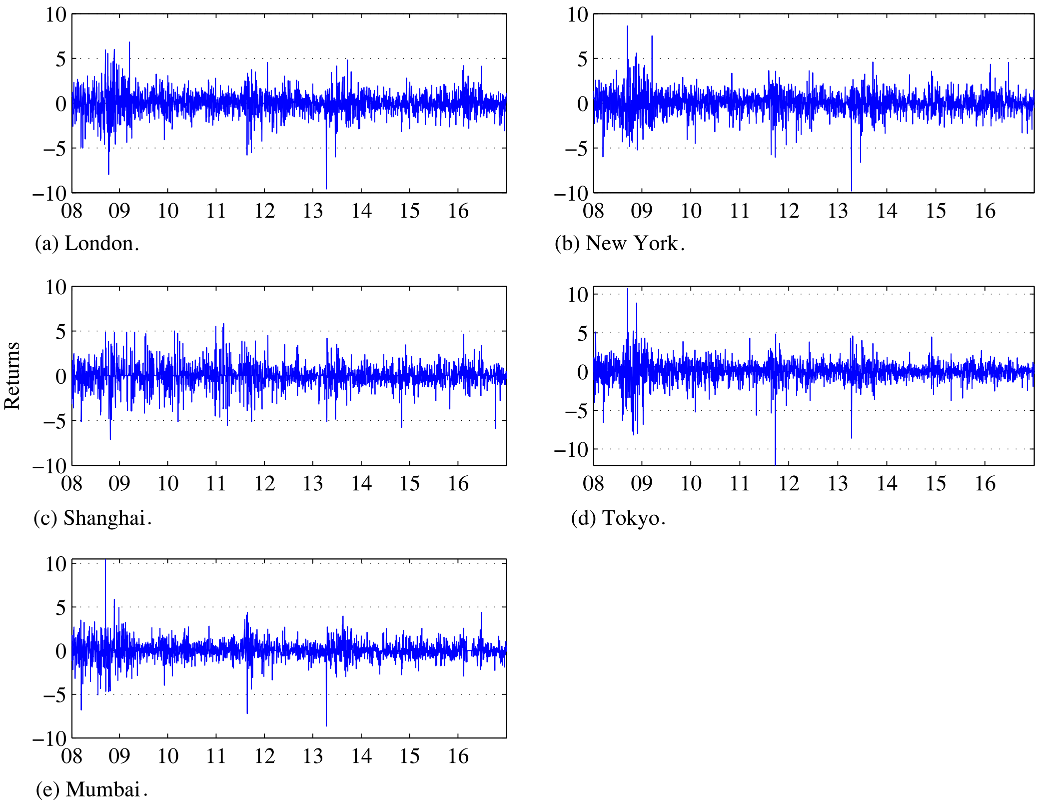

Fig. 1. Daily returns of the (a) London, (b) New York, (c) Shanghai, (d) Tokyo, and (e) Mumbai gold markets during the 2008–2016 period.

seven gold market pairs, and their cross-correlations increase as the time scale increases when time scale n is shorter than 100 days and declines otherwise. For all time scales, London–New York has the largest DCCA coefficient, suggesting that there is a strong relationship between the London and New York gold markets. With the exception of Tokyo–Mumbai, all other gold market pairs also show strong cross-correlations at large time scales, especially when the time scale is $n > 20$ days.

To quantify the net cross-correlations among the five gold markets at different time scales, Fig. 3 shows the DPCCA coefficients $\rho_{XY}^{\mathrm{DPCCA}}(n)$ between the ten gold market pairs. The DPCCA coefficient of London–New York at each time scale is always the largest and falls in a range from 0.7 to 0.9 with an increasing trend, suggesting that there is a high level of net cross-market correlation between London and New York. This also indicates that the cross-correlation between the London and New York gold markets is pure and less affected by other gold markets. The DPCCA coefficients at different time scales for the other nine gold market pairs are less than 0.3, and some coefficients are close to zero, implying that these nine pairs of net cross-market correlations are weak and are strongly influenced by other markets. For example, the DPCCA coefficients of New York–Shanghai, New York–Tokyo, and New York–Mumbai are close to zero, but their DCCA coefficients significantly differ from zero, indicating that the relations between New York and the other three gold markets are highly correlated with and affected by the London gold market. The trend of the DPCCA coefficient of Tokyo–Mumbai is unique because the variable $\rho_{XY}^{\mathrm{DPCCA}}$ between Tokyo and Mumbai is a monotonically-decreasing function of time scale n that decreases from 0.3 to -0.3 as the time scale increases. The negative net cross-correlation between the Tokyo and Mumbai gold markets when time scale $n > 100$ days provides a risk-hedging opportunity for market participants.

Quantifying the influence of all the other gold markets on the two targeted gold market pairs, Fig. 4 shows the $\Delta\rho_{XY}(n)$ values among the ten gold market pairs, defined as the difference between $\rho_{XY}^{\mathrm{DCCA}}(n)$ and $\rho_{XY}^{\mathrm{DPCCA}}(n)$. In each time scale, the $\Delta\rho_{XY}(n)$ value of the London–New York pair is <0.1, indicating that the influence from the other three gold markets on the cross-correlation between the London and New York gold markets is negligible. The $\Delta\rho_{XY}(n)$ values of the remaining nine gold market pairs show that the influence of all other gold markets on the cross-market linkages of the nine pairs is strong. The trend of $\Delta\rho_{XY}(n)$ values indicates that the remaining nine gold market pairs fall into two groups. The first includes New York–Shanghai, Shanghai–Tokyo, and Shanghai–Mumbai in which the $\Delta\rho_{XY}(n)$ values increase as the time scale increases. This means that the influence of all other markets on this group's cross-market correlations increases with the time scale. The second group is made up of the remaining six gold market pairs for which each $\Delta\rho_{XY}(n)$ curve is a downward-opening

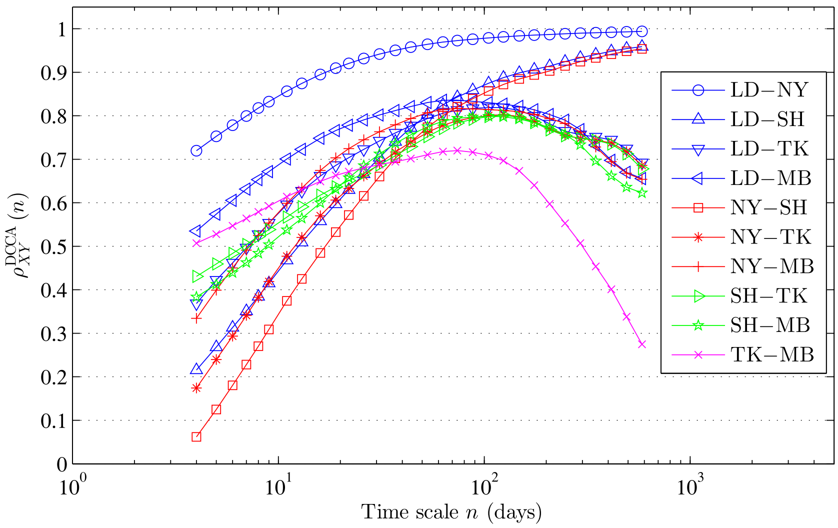

Fig. 2. (Color online) DCCA coefficients $\rho_{XY}^{\mathrm{DCCA}}(n)$ across five major gold markets, i.e., London (LD), New York (NY), Shanghai (SH), Tokyo (TK), and Mumbai (MB), at different time scales. The DCCA coefficient $\rho_{XY}^{\mathrm{DCCA}}(n)$ measures the strength of the cross-correlation between two gold markets X and Y at time scale n.

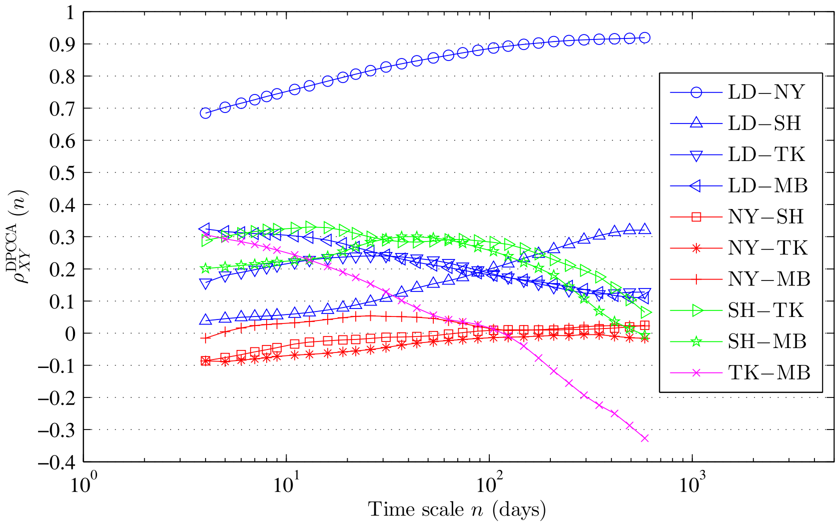

Fig. 3. (Color online) DPCCA coefficients $\rho_{XY}^{\mathrm{DPCCA}}(n)$ across five major gold markets, i.e., London (LD), New York (NY), Shanghai (SH), Tokyo (TK), and Mumbai (MB), at different time scales. The DPCCA coefficient $\rho_{XY}^{\mathrm{DPCCA}}(n)$ quantifies the strength of the net cross-correlation between two gold markets X and Y at time scale n.

parabola, i.e., the value of $\Delta\rho_{XY}(n)$ first increases as the time scale increases, then decreases after reaching its maximum. The crossover time scale for the $\Delta\rho_{XY}(n)$ curve is close to 100 days.

Quantifying the net influence of one gold market on another, Fig. 5 shows the values of the average influence $d_{X:Z}(n)$ of market Z on the cross-correlations between market X and all the other markets. We find that $d_{X:Z}(n)$ is not equal to $d_{Z:X}(n)$, e.g., the $d_{X:Z}(n)$ value from London to New York is always larger than the $d_{Z:X}(n)$ value from New York to London at each time scale n, indicating that the net influence between two gold markets is asymmetrical. The influence of London on New York (i.e., LD→NY shown in Fig. 5) has the largest $d_{Z:X}(n)$ value at each time scale, followed by the influence of London on Mumbai, on Tokyo, and on Shanghai, indicating that the London gold market strongly affects these four gold markets and dominates the world-wide gold market. The $d_{X:Z}(n)$ values indicate that the net influence of a given market on the other four markets shows a similar pattern. For example, the $d_{X:Z}(n)$ value of London, New York, or Shanghai on other markets increases as the time scale increases, indicating the net influence of these three markets on other markets increases as the time scale increases. The curve of net influence of the Tokyo or Mumbai market on other markets is a downward-opening

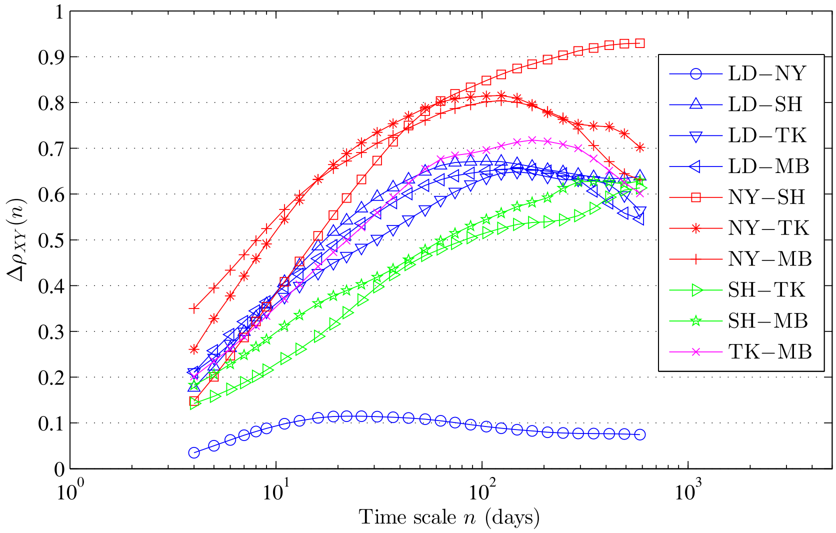

Fig. 4. (Color online) Values of $\Delta\rho_{XY}(n)$ across five major gold markets, i.e., London (LD), New York (NY), Shanghai (SH), Tokyo (TK), and Mumbai (MB), at different time scales. The quantity $\Delta\rho_{XY}(n)$ is defined as the difference between the DCCA coefficient $\rho_{XY}^{\rm DCCA}(n)$ and the DPCCA coefficient $\rho_{XY}^{\rm DPCCA}(n)$ at time scale n, which measures the influence from all the other markets to the pair of markets X and Y.

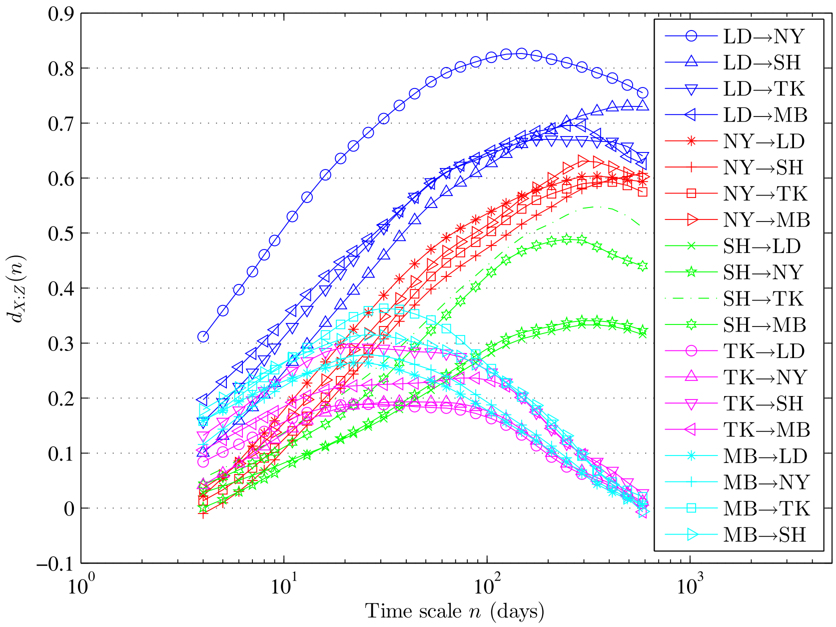

Fig. 5. (Color online) Average influence $d_{X:Z}(n)$ of market Z on the cross-correlations between market X and all the other markets for five major gold markets, i.e., London (LD), New York (NY), Shanghai (SH), Tokyo (TK), and Mumbai (MB), at different time scales. The quantity $d_{X:Z}(n)$ approximates the net influence from market Z to market X at time scale n. In the legend, $Z \to X$ represents the net influence from market Z to market X.

parabola, i.e., $d_{X:Z}(n)$ first increases to a peak when time scale n approaches 30 days, and then declines monotonically to zero, indicating that these two gold markets lose their net influence on other markets at a long time scale (e.g., 600 days).

Quantifying the net influence of a given gold market on the entire system, Fig. 6 shows the values of the average influence $d_Z(n)$ of market Z on all other markets. At each time scale, the London gold market has the strongest average influence $d_Z(n)$, once again confirming that the London gold market leads the world gold markets. The trend in $d_Z(n)$ values in individual markets is similar to the trend in $d_{X:Z}(n)$ values. Note that the net influence of individual markets on the entire system in descending order is London, Mumbai, Tokyo, New York, and Shanghai at small time scales ($n < 20$ days). This order changes when the time scale $n > 60$ days and becomes London, New York, Shanghai, Mumbai, and Tokyo.

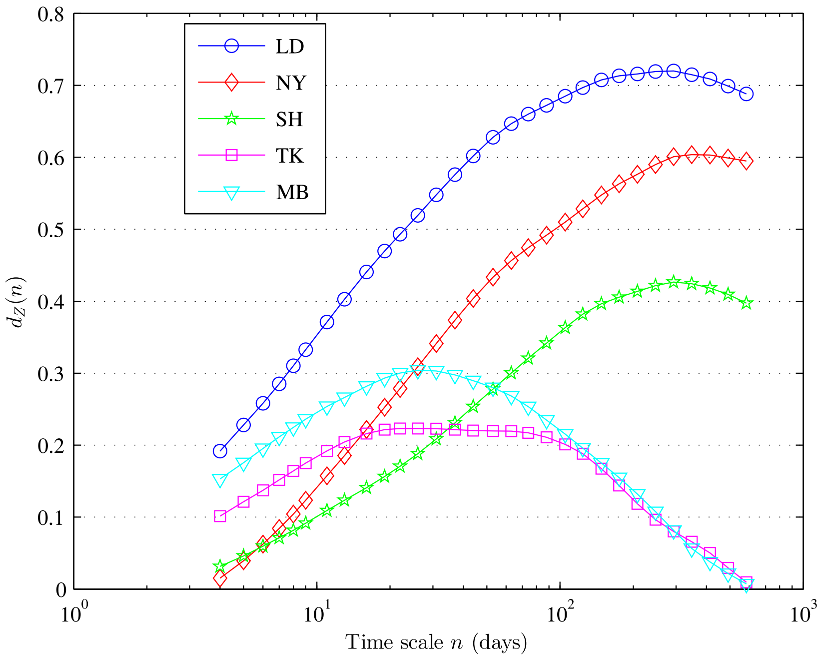

Fig. 6. (Color online) Average influence $d_Z(n)$ of market Z on all the other markets for five major gold markets, i.e., London (LD), New York (NY), Shanghai (SH), Tokyo (TK), and Mumbai (MB), at different time scales. The quantity $d_Z(n)$ represents the net influence of market Z on the system at time scale n.

4. Conclusion

We have studied the cross-correlations and influences among five major gold markets, i.e., those of London, New York, Shanghai, Tokyo, and Mumbai. We analyze multiscale cross-correlations and net cross-correlations across the five gold markets using the DCCA coefficient and the DPCCA coefficient. We find (i) that the cross-correlations and net cross-correlations between different gold markets vary across time scales, (ii) that London–New York has the largest DCCA and DPCCA coefficients and has a negligible $\Delta\rho(n)$ value at each time scale, indicating that the cross-market correlation between London and New York is strong and inherent, and (iii) that other cross-market correlations are significantly affected by other markets. Using multiscale influence measures, we have investigated the net influence of one market on another and on the entire system, and we find (i) that the net influence changes across time scales, (ii) that the London gold market greatly influences the other four gold markets and dominates the world-wide market, and (iii) that the net influence of Tokyo and Mumbai on other markets and on the entire system is negligible at long time scales. Our work contributes to the literature on cross-market linkages between gold markets, and it provides new information for market participants building a diversified portfolio and regulators analyzing the co-movement across different gold markets. Specifically, our study provides the following information for the international gold investors or hedgers: (i) the cross-correlations and net cross-correlations between different gold markets vary across time scales, suggesting that construing gold portfolios should change over different time horizons, (ii) because the London gold market dominates the world gold markets, investors should pay much attention to its gold price fluctuation and timely adjust the asset portfolio, and (iii) the decreasing cross-correlations and negative net cross-correlations between the Tokyo and Mumbai gold markets at long time scales suggest that investors or hedgers could benefit from the gold portfolio from these two markets with a long investment or hedging horizon.

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References

[1] G.-J. Wang, C. Xie, Z.-Q. Jiang, H.E. Stanley, Extreme risk spillover effects in world gold markets and the global financial crisis, Int. Rev. Econ. Finance 46 (2016) 55–77.

[2] L. Xian, K. He, K.K. Lai, Gold price analysis based on ensemble empirical model decomposition and independent component analysis, Physica A 454 (2016) 11–23.
[3] B.M. Lucey, C. Larkin, F.A. O'Connor, London or New York: Where and when does the gold price originate, Appl. Econ. Lett. 20 (8) (2013) 813–817.
[4] F.A. O'Connor, B.M. Lucey, J.A. Batten, D.G. Baur, The financial economics of gold—A survey, Int. Rev. Financ. Anal. 41 (2015) 186–205.
[5] GFMS, GFMS Gold Survey 2015, Thomson Reuters, London, 2015.
[6] G.-J. Wang, C. Xie, Cross-correlations between Renminbi and four major currencies in the Renminbi currency basket, Physica A 392 (6) (2013) 1418–1428.
[7] G.-J. Wang, C. Xie, Cross-correlations between the CSI 300 spot and futures markets, Nonlinear Dynam. 73 (3) (2013) 1687–1696.
[8] X.E. Xu, H.-G. Fung, Cross-market linkages between U.S. and Japanese precious metals futures trading, J. Int. Financ. Mark. Inst. Money 15 (2) (2005) 107–124.
[9] H.-N. Lin, S.-M. Chiang, K.-H. Chen, The dynamic relationships between gold futures markets: evidence from COMEX and TOCOM, Appl. Financ. Econ. Lett. 4 (1) (2008) 19–24.
[10] B. Kumar, A. Pandey, International linkages of the Indian commodity futures markets, Modern Econ. 2 (3) (2011) 213–227.
[11] R. Fuangkasem, P. Chunhachinda, S. Nathaphan, Information transmission among world major gold futures markets: Evidence from high frequency synchronous trading data, J. US-China Public Adm. 11 (3) (2014) 255–269.
[12] B.M. Lucey, C. Larkin, F. O'Connor, Gold markets around the world—Who spills over what, to whom, when, Appl. Econ. Lett. 21 (13) (2014) 887–892.
[13] C.-L. Chang, J.-C. Della Chang, Y.-W. Huang, Dynamic price integration in the global gold market, North Amer. J. Econ. Financ. 26 (2013) 227–235.
[14] M. Hauptfleisch, T.J. Putniņš, B. Lucey, Who sets the price of gold? London or New York, J. Futures Mark. 36 (6) (2016) 564–586.
[15] H.F. Baklaci, O. Süer, T. Yelkenci, A.A. Drakos, Price linkages among emerging gold futures markets, Singap. Econ. Rev. 62 (2) (2016) 1650020.
[16] C.K. Peng, S.V. Buldyrev, S. Havlin, M. Simons, H.E. Stanley, A.L. Goldberger, Mosaic organization of DNA nucleotides, Phys. Rev. E 49 (2) (1994) 1685–1689.
[17] J.W. Kantelhardt, S.A. Zschiegner, E. Koscielny-Bunde, S. Havlin, A. Bunde, H.E. Stanley, Multifractal detrended fluctuation analysis of nonstationary time series, Physica A 316 (1–4) (2002) 87–114.
[18] B. Podobnik, H.E. Stanley, Detrended cross-correlation analysis: A new method for analyzing two nonstationary time series, Phys. Rev. Lett. 100 (8) (2008) 084102.
[19] W.-X. Zhou, Multifractal detrended cross-correlation analysis for two nonstationary signals, Phys. Rev. E 77 (6) (2008) 066211.
[20] L. Kristoufek, Multifractal height cross-correlation analysis: A new method for analyzing long-range cross-correlations, Europhys. Lett. 95 (6) (2011) 68001.
[21] P. Oświęcimka, S. Drozdz, M. Forczek, S. Jadach, J. Kwapień, Detrended cross-correlation analysis consistently extended to multifractality, Phys. Rev. E 89 (2) (2014) 023305.
[22] N. Vandewalle, M. Ausloos, Crossing of two mobile averages: A method for measuring the roughness exponent, Phys. Rev. E 58 (5) (1998) 6832–6834.
[23] E. Alessio, A. Carbone, G. Castelli, V. Frappietro, Second-order moving average and scaling of stochastic time series, Eur. Phys. J. B 27 (2) (2002) 197–200.
[24] G.-F. Gu, W.-X. Zhou, Detrending moving average algorithm for multifractals, Phys. Rev. E 82 (1) (2010) 011136.
[25] Z.-Q. Jiang, W.-X. Zhou, Multifractal detrending moving-average cross-correlation analysis, Phys. Rev. E 84 (1) (2011) 016106.
[26] G.F. Zebende, DCCA cross-correlation coefficient: Quantifying level of cross-correlation, Physica A 390 (4) (2011) 614–618.
[27] L. Kristoufek, Detrending moving-average cross-correlation coefficient: Measuring cross-correlations between non-stationary series, Physica A 406 (2014) 169–175.
[28] J. Kwapień, P. Oświęcimka, S. Drozdz, Detrended fluctuation analysis made flexible to detect range of cross-correlated fluctuations, Phys. Rev. E 95 (2) (2015) 052815.
[29] B. Podobnik, Z.-Q. Jiang, W.-X. Zhou, H.E. Stanley, Statistical tests for power-law cross-correlated processes, Phys. Rev. E 84 (6) (2011) 066118.
[30] G.-J. Wang, C. Xie, L.-Y. He, S. Chen, Detrended minimum-variance hedge ratio: A new method for hedge ratio at different time scales, Physica A 405 (2014) 70–79.
[31] L. Kristoufek, Detrended fluctuation analysis as a regression framework: Estimating dependence at different scales, Phys. Rev. E 91 (2) (2015) 022802.
[32] G.-J. Wang, C. Xie, M. Lin, H.E. Stanley, Stock market contagion during the global financial crisis: A multiscale approach, Financ. Res. Lett. 22 (2017) 163–168.
[33] M. Bolgorian, Z. Gharli, A multifractal detrended fluctuation analysis of gold price fluctuations, Acta Phys. Polon. B 42 (1) (2011) 159–169.
[34] D. Ghosh, S. Dutta, S. Samanta, Fluctuation of gold price: A multifractal approach, Acta Phys. Polon. B 43 (6) (2012) 1261–1274.
[35] Y. Wang, Y. Wei, C. Wu, Analysis of the efficiency and multifractality of gold markets based on multifractal detrended fluctuation analysis, Physica A 390 (5) (2011) 817–827.
[36] Q. Ruan, Y. Huang, W. Jiang, The exceedance and cross-correlations between the gold spot and futures markets, Physica A 463 (2016) 139–151.
[37] Q. Ruan, W. Jiang, G. Ma, Cross-correlations between price and volume in Chinese gold markets, Physica A 451 (2016) 10–22.
[38] G.-J. Wang, C. Xie, H.E. Stanley, Correlation structure and evolution of world stock markets: Evidence from pearson and partial correlation-based networks, Comput. Econ. (2016) http://dx.doi.org/10.1007/s10614-016-9627-7.
[39] D.Y. Kenett, M. Tumminello, A. Madi, G. Gur-Gershgoren, R.N. Mantegna, E. Ben-Jacob, Dominating clasp of the financial sector revealed by partial correlation analysis of the stock market, PloS One 5 (12) (2010) e15032.
[40] D.Y. Kenett, X. Huang, I. Vodenska, S. Havlin, H.E. Stanley, Partial correlation analysis: Applications for financial markets, Quant. Finance 15 (4) (2015) 569–578.
[41] V. Fernandez, Influence in commodity markets: Measuring co-movement globally, Res. Policy 45 (2015) 151–164.
[42] X.-Y. Qian, Y.-M. Liu, Z.-Q. Jiang, B. Podobnik, W.-X. Zhou, H.E. Stanley, Detrended partial cross-correlation analysis of two nonstationary time series influenced by common external forces, Phys. Rev. E 91 (6) (2015) 062816.
[43] N. Yuan, Z. Fu, H. Zhang, L. Piao, E. Xoplaki, J. Luterbacher, Detrended partial-cross-correlation analysis: A new method for analyzing correlations in complex system, Sci. Rep. 5 (2015) 8143.
[44] N. Yuan, E. Xoplaki, C. Zhu, J. Luterbacher, A novel way to detect correlations on multi-time scales, with temporal evolution and for multi-variables, Sci. Rep. 6 (2016) 27707.
[45] K.J. Forbes, R. Rigobon, No contagion, only interdependence: Measuring stock market comovements, J. Finance 57 (5) (2002) 2223–2261.
[46] T.W. Epps, Comovements in stock prices in the very short run, J. Amer. Statist. Assoc. 74 (366a) (1979) 291–298.