“Dynamic conditional correlation and volatility distributions in Tokyo, London, and New York gold markets”

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DYNAMIC CONDITIONAL CORRELATION AND VOLATILITY DISTRIBUTIONS IN TOKYO, LONDON, AND NEW YORK GOLD MARKETS

Abstract

This study investigates the volatility and co-movement of gold prices across Tokyo, London, and New York gold markets. Using a dynamic conditional correlation (DCC) model, the authors estimate the cross-correlation and volatility of gold in each pair among three markets over the period from 1993 to 2012. Both the time-varying correlations and realized distributions are explored. After estimating the DCC as well as the corresponding distributions of the DCC among the three markets, the results suggest that: (i) the DCC probability distribution of London and New York shows a higher volatility associated with a higher DCC value; (ii) the DCC probability distribution between London and New York as well as between Tokyo and London both express the similar and overlapping pattern, implying that these markets are almost equal, and neither dominates; and (iii) New York exhibits a spillover effect of Tokyo's variance, while the latter does not influence New York's variance. The shapes of the distributions show that the distribution of high DCC is wider than that of low DCC, meaning that risk increases with the dynamic correlation. The implications of these gold DCC probability distributions encourage investors to diversify their global portfolios and manage latent risks in different gold markets effectively. Besides, the volatility-threshold DCC model suggests that the correlations are more sensitive to extreme volatility thresholds in London and New York markets, whereas the correlation is significantly affected by all levels of volatility at 50%, 75%, 90%, and 95% thresholds in Tokyo and London markets. Investors may not be able to diversify portfolio risk by choosing London and New York at the same time once gold becomes volatile as a high correlation is observed in the extreme thresholds.

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INTRODUCTION

Gold possesses the attributes of both (quasi-) currency and commodity. It is regarded as a substitute currency and a strong safe haven during the turmoil period. Prior studies in this area have typically focused on the co-movements of equity prices among stock market indexes, while past researches on the synchronization of equity prices across different countries have explored the benefits of international diversification in reducing the systematic portion of portfolio risk (Ripley, 1973; Hilliard, 1979; Das & Uppal, 2004). Most recent, Reboredo (2013) and Reboredo and Rivera-Castro (2014) both found evidence of positive and significant dependence between gold and USD depreciation and suggested that gold was a haven against US dollar. Besides, researchers also found the co-movements of gold and other financial assets (stocks, bonds, real estate, and oil) during both economic expansion and contraction regimes (see, e.g., Poshakwale & Mandal, 2016; Baruník, Kočenda, & Vácha, 2016).

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As long as gold has been recognized as both commodity and currency, exploring micro-information about gold is a meaningful task. This study extends the existing literature by examining how the prices of the same commodity (gold) in different time zones interact with one another. Given the role gold has played as a major alternative investment, several interesting questions arise: Do gold prices in major national markets behave similarly regarding return and volatility? What are the Granger causality relationships in gold prices between these major markets? What is the probability distribution of returns and volatility among various time zone markets of gold? Are the markets integrated closely, and do they interact with one another in different time zones?

The remainder of the study is structured in four sections. Section 1 reviews the most relevant literature about this subject. Section 2 provides the data and methodology. Section 3 presents the empirical results and analysis and the last section concludes the study.

1. LITERATURE REVIEW

Taking into account the similar studies about probability distribution model, they are likely to apply weekly or monthly returns and found that the return correlations across countries were low or statistically insignificant. By contrast, this study employs daily data in a longer time horizon to better detect the movement and volatility of returns among three gold markets. Until now, many studies have investigated the issue of interdependency among various financial markets. For instance, some researchers have focused on the stock market interdependency regarding price and volatility spillovers. Eun and Shim (1989) examined the transmission mechanism of returns from the US to European markets, while Booth, Teppo, and Tse (1997) found weak evidence of price and volatility spillovers among four Scandinavian stock markets. Kanas (1998) explored the volatility transmission mechanism across the London, Frankfurt, and Paris stock markets.

Besides, other related research explores the impacts of world factors on global stock markets (Bekaert & Harvey, 1997; Ng, 2000). Afterwards, the research by Fratzscher (2002) studied the spillovers of shocks from the US to European equity markets and concluded that the transmission of shocks from the euro area had shown more prominence than shocks from the US market. Skintzi and Refenes (2006) employed the dynamic correlation approach to examine the dynamic linkage among the European bond markets and suggested that the significant volatility spillovers exist from both the European and US bond markets to the individual European markets.

Research on market interdependence can be traced back to the 1980s where the links between international equity markets using high-frequency data are examined. As the first researchers, Jaffe and Westerfield (1985) used the daily closing prices of the five markets and found that correlations of return between the US and four other national markets-UK, Japan, Canada and Australia are positive and significant. Becker, Finnerty, and Gupta (1990) used the opening-to-closing price returns of the Japanese and US stock markets and found that the US market Granger-causes the Japanese market on the prices of metals, while the Japanese market has only a trivial impact on the US market.

Moreover, Lin, Engle, and Ito (1994) investigated the correlation of returns and the volatility of stock indexes between Tokyo and New York. They found that excluding a lagged return spillover from New York to Tokyo in the period after the crash, no significant lagged spillover had occurred in returns or volatilities. Ng (2000) examined how do the volatility spillover from Japan and the US affect the six Pacific Rim equity markets. Employing four different correlation specifications, the author constructed a volatility spillover model that distinguishes between a local, idiosyncratic shock, a regional shock (from Japan), and a global shock (from the US). It provided evidence of a significant spillover from the regional shock to the Pacific Rim economies. Andersen, Bollerslev, Diebold, and Ebens (2001a) found strong evidence that volatilities and correlations move together in a manner broadly consistent with the latent factor structure. Moreover, Andersen, Bollerslev, Diebold, and Labys (2001b) found that volatility movements were highly correlated across the Deutsche Mark and the yen against the US dollar. Furthermore, the correlation between the two exchange rates increases with volatility. Engle (2002) found evidence of the breakdown of correlations between the Deutsche mark, the British pound, and the Italian lira in August 1992, and that as the euro was launched, the estimated currency correlation was close to 1.

Recently, many researchers have documented the role of correlations as critical inputs for many common long-term economic relationships. For example, Kearney and Lombra (2009) investigated the behavior of gold prices over the last thirty years and found that gold and platinum prices were positively correlated from 1985 to 2006. However, the correlation turned out to be negative from positive in shorter periods. From a different viewpoint, Fleming, Kirby, and Ostdiek (1998) developed a model of speculative trading to explain the relationship between information and volatility. They suggested that volatility linkages arise from either common information or information spillover, which occurs when investors react to information in one market through cross-hedging to rebalance their portfolios.

Research involving multivariate GARCH models typically employs a constant covariance specification. However, numerous studies have shown that correlations between markets are time-varying. King and Wadhwani (1990) found that international correlations increase during periods of market crises. Andersen, Bollerslev, Diebold, and Ebens (2001a) found a high correlation between correlation and volatilities. However, their estimates of realized volatilities and correlations were not only model-free but also free of measurement error under general conditions. Kasch-Haroutounian (2005) indicated that the correlations of the developed markets are significantly affected by high volatility levels, while high volatility does not seem to have a direct impact on the correlations of the transition blue-chip indices with the rest of the markets.

Furthermore, Doong, Yang, and Wang (2005) examined dynamic relationships between stocks and exchange rates in six emerging Asian markets and found that a fall accompanied in stock prices accompanied currency depreciation. The conditional variance-covariance process of changes in stock prices and exchange rates is time-variant. Lanza, Manera, and McAleer (2006) estimated the dynamic conditional correlations in the daily returns on West Texas Intermediate (WTI) oil futures prices and found that dynamic conditional correlations vary dramatically. Chu (2006) investigated how volatility co-movement and spillover effects interacted with each other in the yen/dollar foreign exchange markets of Tokyo, London, and New York. Using daily returns of yen/dollar spot rate from 1994 to 2003, the paper found that high volatility is accompanied by high DCC value and that high DCC distribution is wider than low DCC distribution. Pérez-Rodríguez (2006) applied the multivariate DCC-GARCH technique to examine the structure of the short-run dynamics of volatility returns on the euro, yen, and British pound against the US dollar over the period from 1999 to 2004. Strong dynamic relationships were found between the currencies. Tastan (2006) used the multivariate GARCH model to capture the time-varying variance-covariance matrix and changes in euro-dollar exchange rates for stock market returns. Chiang, Tan, and Li (2007) employed the DCC model in the analysis of nine Asian daily stock-return series from 1990 to 2003. Their empirical evidence confirmed the presence of a contagion effect and the significance of herding behavior. Chiang and Lin (2005) examined A and B share market segmentation conditions by employing a dynamic multivariate GARCH model to analyze daily stock-return data for the period from 1996 to 2003. The statistics showed that stock returns in both A and B shares are positively correlated to daily changes in trading volume.

Based on the prior theoretical foundations and empirical findings on financial market linkages, this study extends the existing literature by examining the interdependence of commodity markets using the dynamic conditional correlation (DCC) model. In recent years, commodity markets have experienced dramatic growth in trading volume, the variation of contracts, and range of underlying commodities, thereby enjoying an impressive bull run. With little exception, commodity prices have increased significantly and outperformed traditional investments. Some scholars have examined the relationships between gold and other assets and proven that gold is an effective hedge for stocks (Baur & Lucey, 2010; Baur & McDermott, 2010; Hood & Malik, 2013; Ciner, Gurdgiev, & Lucey, 2013). Further, gold has continued to attract a growing array of financial investors, such as hedge funds and sovereign wealth

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funds, who increasingly realize gold as a diversifying asset. Overall, previous research on the interactions and integrations of financial markets showed that the degree of interdependence among national financial markets increases over time. However, studies on the specific commodity are still lacking. Therefore, the study aims to answer two important questions for investors: Firstly, how do time-varying correlations and the associated distributions influence the price of gold? Secondly. based on the volatility-threshold DCC model suggested by Kasch and Caporin (2013), are the high-volatility values (exceeding a specified threshold) of assets associated with the increasing correlation in gold?

2. DATA AND METHODOLOGY

The data employed in this study consist of a time series of the daily closing prices of gold in Tokyo, London, and New York in the period between January 1, 1933 and December 31, 2012. This information was obtained from the website of Johnson Matthey.

To account for the possible effects of time-varying correlation, we follow Engle (2002) and Cappiello (2006) in the calculation of the conditional variance as follows:

$$H_{\tau,t} = D_{\tau,t} V_{\tau,t} D_{\tau,t}, \tag{1}$$

where $V_{\tau,t}$ is the conditional correlation matrix of the residuals, and $D_{\tau,t} = diag\sqrt{\sigma^2_{\tau,ii,t}}$. The subscript τ indicates the frequency of the data observed. To deal with the problem of heteroskedasticity, the residuals are standardized by way of $\eta_{\tau,i,t} = \varepsilon_{\tau,i,t} \big/ \sqrt{\sigma^2_{\tau,ii,t}}$ and $\eta_{\tau,i,t}$ is used to estimate the parameters of the conditional correlation. Equations (2) and (3) show how the methods are employed in the estimation of variance and covariance:

$$\sigma^2_{\tau,ii,t} = c_{\tau,i} + \alpha_{\tau,i}\varepsilon^2_{\tau,i,t-1} + \beta_{\tau,i}\sigma^2_{\tau,i,t-1}, \quad i = 1, 2, \tag{2}$$

$$Q_{\tau,t} = (1-\alpha_{\tau,i} - \beta_{\tau,i})\bar{Q}_\tau + \alpha_{\tau,i}\eta_{\tau,i,t-1}\eta'_{\tau,i,t-1} + \beta_{\tau,i}Q_{\tau,t-1}, \tag{3}$$

where $Q_{\tau,t} = \left(q_{\tau,ij,t}\right)$. is the time-varying covariance matrix of $\eta_{\tau,i,t-1}$, and $\bar{Q}_\tau$ is the unconditional variance matrix of $\eta_{\tau,i,t-1}$. Parameters are assumed to satisfy $\alpha_{\tau,i} + \beta_{\tau,i} < 1$.

The correlation matrix $V_{\tau,t}$ can be expressed in the following equation:

$$V_{\tau,t} = \left(diag\left(Q_{\tau,t}\right)\right)^{1/2} Q_{\tau,t} \left(diag\left(Q_{\tau,t}\right)\right)^{1/2}, \tag{4}$$

where

$$diag\left(Q_{\tau,t}\right)^{-1/2} = diag\left(1\big/\sqrt{q_{\tau,11,t}}, 1\big/\sqrt{q_{\tau,22,t}}\right).$$

A typical element of $V_{\tau,t}$ is in the form of the following equation:

$$\rho_{\tau,12,t} = q_{\tau,12,t} \big/ \sqrt{q_{\tau,11,,t}q_{\tau,22,,t}}. \tag{5}$$

To break down the various patterns present in the different subperiods, we employ the volatility threshold model suggested by Kasch and Caporin (2013) to see if increasing volatility comes with an increasing correlation. The volatility threshold DCC model is shown as follows:

$$q_{ij,t} = \left(1-\alpha^2-\beta^2\right)\bar{q}_{i,j} + \gamma_i\gamma_j\bar{v}_{ij} + \alpha^2\varepsilon_{i,t-1}\varepsilon_{j,t-1} + \beta^2 q_{ij,t-1} + \gamma_i\gamma_j v_{ij,t}, \tag{6}$$

where $v_{ij,t}$ is a dummy variable matrix defined as:

$$v_{ij,t} = \begin{cases} 1 \text{ if } h_{i,t} > fh_i\left(k\right) \text{ or } h_{j,t} > fh_j\left(k\right) \\ 0 \text{ otherwise} \end{cases}, \tag{7}$$

where $fh_i\left(k\right)$ is the k fraction of the volatility series.

3. EMPIRICAL RESULTS OF DYNAMIC CONDITIONAL CORRELATION

The returns for gold in the three markets are shown in Table 1. The statistics indicate that the Tokyo market exhibited the lowest returns, while the London and New York markets exhibited very similar returns.

Table 1. Summary statistics of daily gold returns in Tokyo, London, and New York

Spot	Tokyo	London	New York
Mean	0.00010	0.00013	0.00013
Median	0.00010	0.00003	0
Max	0.03268	0.03404	0.03043
Min	−0.03014	−0.03720	−0.03462
Standard Dev	0.00482	0.00427	0.00432
Skewness	−0.11740	−0.01668	0.05759
Kurtosis	7.65985	9.48119	9.83605

Table 2 presents the simple correlation matrix. The results show that the three markets are highly correlated, with the coefficients of correlation exceeding 0.7.

Table 2. The correlation of gold among Tokyo, London, and New York

Gold Market	Tokyo	London	New York
Tokyo	1	–	–
London	0.7412	1	–
New York	0.7796	0.8134	1

Table 3 presents the estimation results of the dynamic correlations of returns across the Tokyo, London, and New York markets, and Table 4 reports the results of the DCC-GARCH model. As the null hypothesis of the scalar dynamic conditional correlation is rejected based on the likelihood ratio test. Table 4 shows the $(\alpha+\beta)$ in the variance equation is close to 1 for all three cases, implying that volatility tends to be highly persistent. Figure 1 shows the distribution of dynamic conditional correlations for the Tokyo, London, and New York markets over the sample period.

Table 3. DCC conditional correlation estimates: three markets[a]

	α	β
DCC	0.0534** (10.8424)	0.9404** (158.3246)

Note: a. The t-statistics are indicated in parentheses, ** represents the significance at 0.05 level.

To analyze the effects of volatility on the correlation, we ranked the sequence of the volatility based on the empirical results. Table 5 shows the panels of volatility and dynamic conditional correlation. We found evidence that higher volatility comes with greater DCC in all three cases.

Table 4. Estimation results from DCC-GARCH model[a]

Gold market	Mean equation constant	α	β	Persistence
Tokyo	0.0001 (1.2419)	0.0746** (6.6111)	0.9131** (78.1996)	0.9877**
London	3.08e-05 (0.6081)	0.0769** (6.3781)	0.9123** (73.2002)	0.9892**
New York	1.69e-05 (0.3820)	0.0758** (6.4876)	0.9252** (91.6599)	1.001

Note: a. The persistence level of the variance is calculated as the sum of the coefficients in the variance equations $(\alpha+\beta)$. The z-statistic is indicated in parentheses. The Ljung-Box Q-statistic tests the serial correlation of the residuals. ** Denotes significance at 0.05 level.

Table 5. DCC distributions of gold among Tokyo, London, and New York markets

Level	Mean	Std. dev.	Skewness	Kurtosis
Panel A. DCC between Tokyo and London gold market volatility				
0%–10%	0.6945	0.1206	−0.5634	2.2513
10%–20%	0.7488	0.0836	−0.7737	2.7539
20%–30%	0.6536	0.1265	−0.4729	2.9606
30%–40%	0.5639	0.1890	−0.4672	2.0867
40%–50%	0.4705	0.2325	−0.0058	2.0534
50%–60%	0.7511	0.1123	−1.5951	6.2191
60%–70%	0.6892	0.0927	−0.8438	3.8053
70%–80%	0.8469	0.1159	−1.2383	3.5861
80%–90%	0.8225	0.0775	−1.0887	3.6506
90%–100%	0.7222	0.0991	−1.0246	4.5338
Panel B. DCC between London and New York gold market volatility				
0%–10%	0.7139	0.1542	−0.6917	2.1545
10%–20%	0.5797	0.1942	−0.7568	2.6739
20%–30%	0.6788	0.1332	−0.5777	2.7256
30%–40%	0.7864	0.0762	−0.1548	2.1283
40%–50%	0.5971	0.2067	−0.0848	2.1394
50%–60%	0.7461	0.0913	−0.7894	3.6583
60%–70%	0.7037	0.0944	−0.6518	2.8536
70%–80%	0.8084	0.1526	−1.3631	4.3817
80%–90%	0.8986	0.0243	−1.0070	4.4094
90%–100%	0.8110	0.0692	−0.2882	2.0552
Panel C. DCC between New York and Tokyo gold market volatility				
0%–10%	0.6629	0.1788	−0.9503	2.9098
10%–20%	0.4780	0.1935	−0.7195	2.9199
20%–30%	0.6152	0.1342	−0.8039	2.9868
30%–40%	0.5184	0.2202	−0.3271	1.5477
40%–50%	0.7298	0.0917	0.0342	2.5171
50%–60%	0.7447	0.0807	−0.5674	3.0931
60%–70%	0.7454	0.0961	−0.8709	3.3564
70%–80%	0.8161	0.1164	−1.0912	2.8295
80%–90%	0.8386	0.0606	−1.2007	5.6804
90%–100%	0.8142	0.0531	−0.3017	2.8399

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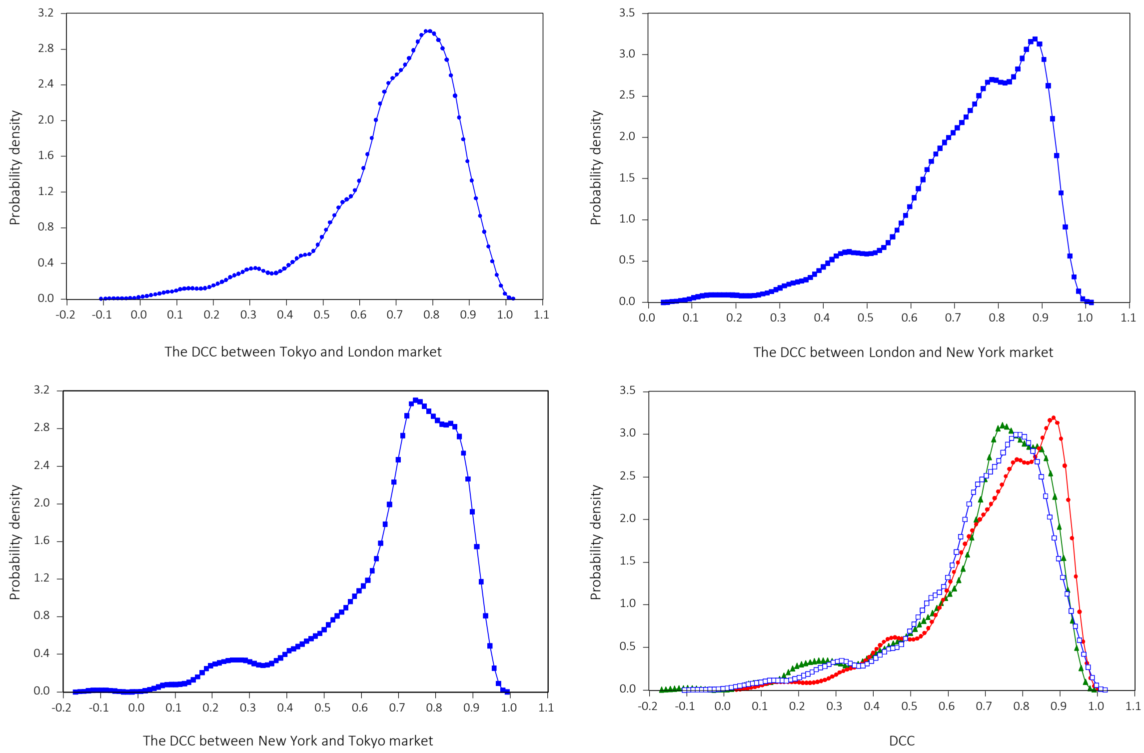

Figure 1. Distributions of dynamic conditional correlations for the Tokyo, London, and New York gold markets over the sample period

To further analyze the effect of volatility on the correlation, we classified the volatility into two groups: low volatility (less than 10%) and high volatility (larger than 90%). Then, we ranked the sequence of the volatility based on the results. Figure 2(a-c) reports the DCC distributions for low-volatility and high-volatility days.

From Figure 2(a-c), we found that the distributions of DCC for the low-volatility days' approximate leptokurtic distributions, while the high-volatility days approximate platykurtic distributions. Second, the average DCCs of the low-volatility days are greater than those observed in the high-volatility days between the Tokyo and London markets. This condition implies that the correlation between the Tokyo and London markets decreases with the increasing volatility. However, this fact is not immediately obvious in the other two cases. The London and New York markets exhibited two peaks in the distribution of DCCs of the high-volatility days, making it difficult to tell whether the average of the DCCs of the low-volatility days was higher or lower than that of the high-volatility days. In the New York and Tokyo markets, the average of the DCCs of the low-volatility days was less than that of the high-volatility days, which implies that the correlation between the New York and Tokyo markets increases with the increasing volatility.

The estimation results of the threshold DCC model are shown in Table 6. The estimation was based on 50%, 75%, 90%, and 95% threshold levels. As we were interested in the analysis of the heterogeneous impact of volatilities on correlations of different markets in our sample, we did not consider the scalar model. We can observe that the correlation between Tokyo and London markets is significantly affected by all levels of volatility at 50%, 75%, 90%, and 95% levels, implying the sensitivity of correlation of both markets are the same at all levels of volatility. However, in the case of the London and New York markets, the correlations are more sensitive to extreme volatility values which shows the significance only at 50% and 95% levels. As for New York and Tokyo markets, the correlation is increasing with the increasing volatility thresholds at 50%, 90%, and 95%.

Investors may not be able to diversify the risk by choosing London and NY in the meantime, once gold becomes volatile as the high correlation is observed for both in the extreme thresholds.

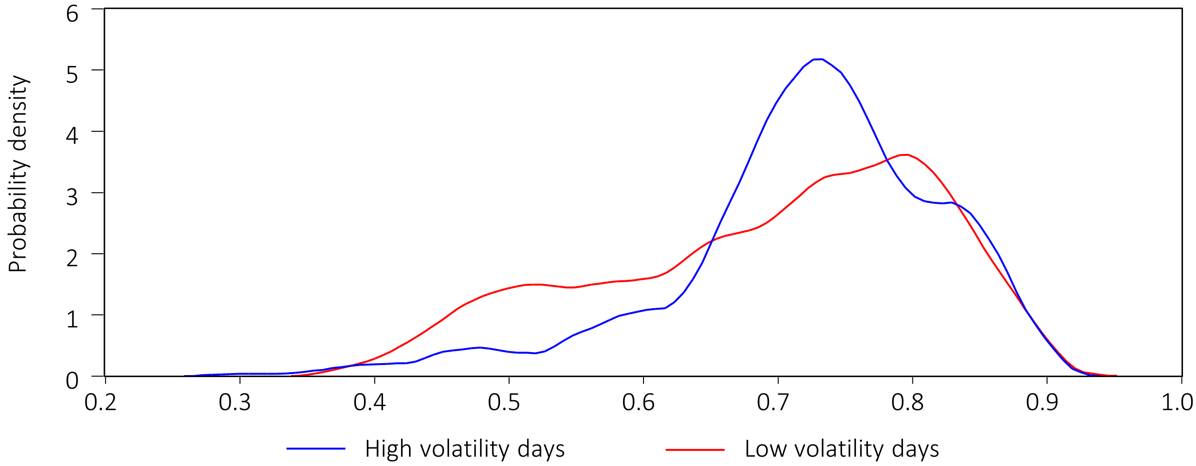

Figure 2(a). Distributions of DCC between Tokyo and London gold markets on low and high volatility days

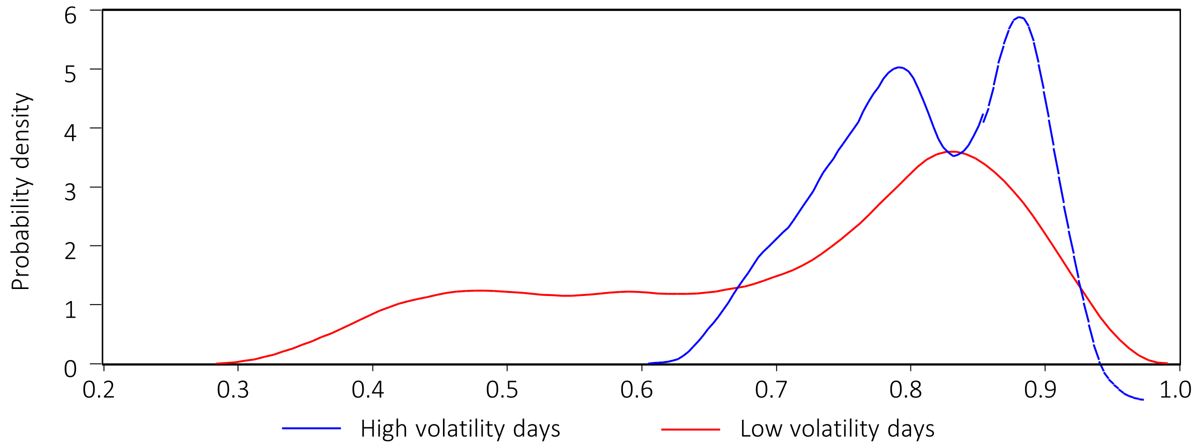

Figure 2(b). Distributions of DCC between London and New York gold markets on low and high volatility days

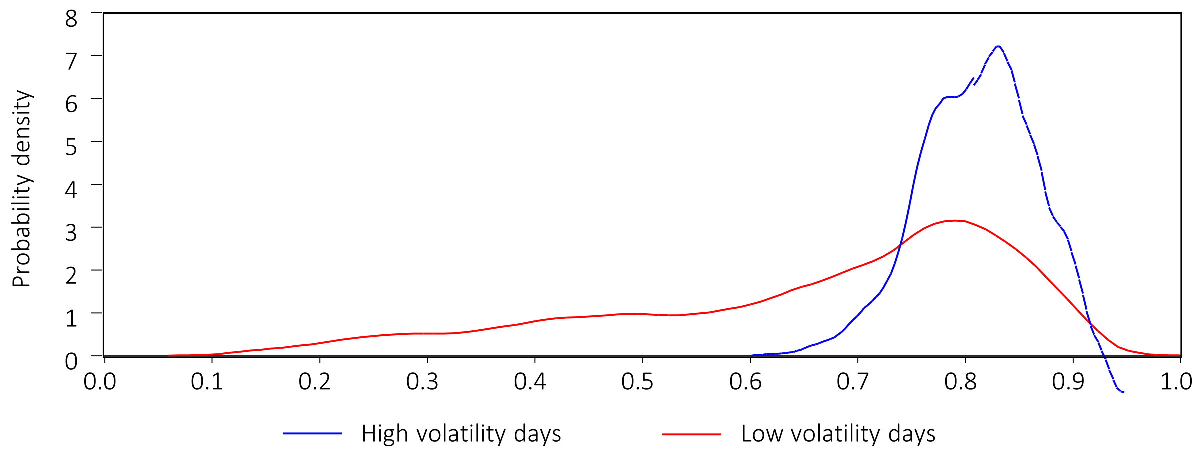

Figure 2(c). Distributions of DCC between New York and Tokyo gold markets on low and high volatility days

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Table 6. Volatility threshold and dynamic conditional correlation [a]

Threshold	50%	75%	90%	95%
Panel A. Tokyo and London gold markets				
α^2	0.822 (2.110)	0.706 (2.489)*	0.560 (2.626)*	0.810 (4.258)*
β^2	0.099 (0.233)	0.321 (1.171)	0.443 (0.049)	0.246 (–0.357)
$\gamma_{Tokyo}\gamma_{London}$	0.086 (2.186)*	–0.052 (–2.567)*	–0.069 (–3.414)*	–0.110 (1.398)*
Panel B. London and New York gold markets				
α^2	0.916 (5.701)*	0.543 (2.557)*	0.350 (2.867)	0.859 (4.960)*
β^2	0.004 (0.022)	0.475 (2.285)	0.626 (4.674)	0.226 (1.455)
$\gamma_{London}\gamma_{NewYork}$	0.174 (5.455)*	–0.035 (–3.416)	0.046 (1.862)	–0.131 (–0.373)*
Panel C. New York and Tokyo gold markets				
α^2	1.302 (6.860)*	0.645 (2.877)*	0.460 (3.049)*	0.457 (2.465)*
β^2	–0.108 (–0.669)	0.335 (1.439)	0.553 (2.744)	0.577 (3.199)
$\gamma_{NewYork}\gamma_{Tokyo}$	0.281 (6.025)*	0.044 (2.011)	–0.063 (–3.411)*	–0.104 (–3.215)*

Note: a. This table presents the quasi-maximum likelihood estimates of volatility threshold dynamic conditional correlation. The t-statistics are indicated in parentheses, * denotes the significance at 0.1 level.

CONCLUSION AND IMPLICATIONS

This study investigates whether the price transmission effect exists in the gold markets across Tokyo, London, and New York. Using DCC, DCC probability distribution and volatility-threshold DCC model, the following conclusions should be made:

Firstly, the correlations between each pair of the three gold markets are found to be time-varying instead of constant. As such, while considering the mean and standard deviation of gold, investors need to follow the co-movement in gold across different markets to improve portfolio hedging and risk management decisions.

Secondly, the distributions of DCC for the low-volatility approximate leptokurtic distributions, while the high-volatility approximate platykurtic distributions.

Thirdly, by employing the volatility-threshold DCC model, we find out the DCC of each pair of the gold markets is increasing in accordance with the volatility, indicating that the distribution of DCC shifts rightward when volatility increases. We also find out that the correlation between Tokyo and London markets is significantly affected by the all levels of volatility at 50%, 75%, 90% and 95%, implying the sensitive of correlation of both markets are the same at all levels of volatility. However, in the case of the London and New York markets, the correlations are more sensitive to extreme volatility values at 50% and 95% thresholds. As for New York and Tokyo markets, the correlation is increasing with the increasing volatility thresholds at 50%, 90%, and 95%. Investors may not be able to diversify the risk by choosing London and New York at the meantime once gold becomes volatile as a high correlation is observed in the high threshold.

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