

TESTING THE VOLATILITY TRANSMISSION AMONG THE PRECIOUS METAL ETFs AND FUTURES

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Abstract

In this study, multivariate generalized autoregressive conditional heteroskedasticity (MGARCH) models are applied to examine conditional correlations and to analyze the robust check for the volatility spillovers between the precious metal (base metal) exchange-traded funds (ETFs) and futures indices. Three different MGARCH models, namely, the Baba, Engle, Kraft, and Kroner (BEKK), the constant conditional correlation, and the dynamic conditional correlation models, are utilized and compared. BEKK is recognized to fit data the best, and it represents long-run persistence. The shocks on the volatility of the precious (base) metal ETFs may affect their futures contracts through a long-time range. Significance results indicate the lagged covariances and cross-products of the shocks. Therefore, the volatilities of the precious metal (base metal) ETF returns influence their futures returns. This finding suggests that investors and traders should consider the return volatility trends of the precious metal (base metal) ETFs when studying the volatility of their futures market.

Key words: *precious metal etf, base metal etf, futures indexes, volatility dynamics, mgarch model*

1. INTRODUCTION

Exchange-traded funds (ETFs) are known as the index funds that track the performance of underlying indices. They have been considered a financial innovation in recent decades because of their advantages in comparison with mutual funds, such as having lower expenses and tax benefits and being an effective instrument for diversified strategies. The integration trends in international financial markets attract financial market participants and policy makers to be aware of the shocks and the volatility transmitted across financial markets over time. A few papers have considered the volatility transmission across different ETF markets. For instance, Chen and Huang (2008) examined ETFs in emerging and developed markets; Datar et al. (2008) evaluated Standard & Poor's Depositary Receipts (SPY) and the Japan Index Fund (EWJ); Wang et al. (2009) considered the leading role of stock index and ETFs in the Taiwanese market; Kim (2011) focused on ETFs in the United States and Asia-Pacific stock markets; and Chen (2011) investigated ethical and non-ethical ETFs. Nevertheless, most of these papers have focused on different ETFs, and no formal work has been conducted on the volatility transmission between the precious metal ETFs (base metal ETFs) and the precious metal (base metal) futures indices.

After a long time of decreasing and maintaining at a low price, the precious metals have been considered by investors and speculators recently, particularly when the economy has to face shocks or financial crises. The uncertainty in the economy that induces the demand to store the precious metals, the dearth of natural resources, and the increase in the precious metal usage in different industries have caused the precious metal prices to increase sharply in the recent decade. With this trend, investors and fund managers tend to diversify their portfolios into commodity indices and the precious metal ETF as several of their favored items. According to the category of the ETF database website, commodity index ETFs are divided into five groups: agricultural commodities, commodities, metals, oil and gas, and the precious metal ETFs. The precious metal ETFs have the largest market capitalization and are the most traded among commodity indices.

Financial volatility and transmission in financial variables have been mentioned in many recent studies, such as in Worthington and Higgs (2004), Hammoudeh et al. (2009), Buttner and Hayo (2011), and Lean and Teng (2013) on the stock markets and in Worthington et al. (2005), Moon et al. (2009), and Chang et al. (2010) on different commodity markets. To estimate the source and magnitude of price and

price volatility spillover among Australian electricity markets, Worthington et al. (2005) applied the multivariate generalized autoregressive conditional heteroskedasticity (MGARCH)-constant conditional correlation (CCC), vector autoregressive moving average (VARMA)-generalized autoregressive conditional heteroskedasticity (GARCH), and VARMA-asymmetric GARCH (VARMA-AGARCH) models. They not only identified the volatility spillovers and asymmetric effects, but also forecast the conditional correlation between oil markets. Chkili et al. (2012) compared the univariate GARCH with MGARCH for estimating the conditional volatilities of stock returns and exchange rate. Buttner and Hayo (2011) found integration among European stock markets when dynamic conditional correlations (DCCs) were taken from the bivariate CCC-GARCH model and discovered the determinants that influenced the integration.

The MGARCH model is designed to show the conditional covariance matrix of different time series and to provide appropriate information on spillover effects, forecasting, and risk measurement of a set of financial tools. To the authors' knowledge, a detailed study of the application of MGARCH to the precious metal ETFs (base metal ETFs) to futures indices has not yet been undertaken. Therefore, the motivation of this study is to investigate the volatility dynamics of the precious metal ETFs (base metal ETFs) and futures contracts through three popular MGARCH models, namely, Baba, Engle, Kraft and Kroner (BEKK), CCC, and DCC. The results of the three models are compared to determine the most consistent model for the precious and base metal ETFs. Volatility is one of the factors that investors always consider carefully when investigating the financial market, but it is difficult to observe. Volatility spillover can widely exist in a financial market. Therefore, the spillover effect exists when changes in return and volatility in this market create a lagged influence on the return or volatility of other markets. The spillover effect and the leverage asymmetry between the precious metal ETFs (base metal ETFs) and futures contracts are important for constructing hedging ratio, optimal portfolio diversification, inter-ETF prediction, and regulation. The advantages of the MGARCH model of Engle and Kroner (1995) are the recognition of different behaviors in financial return that assembles time-varying volatility, persistence, and clustering of volatility. The MGARCH model can capture shocks to return dynamic interdependence both at risk and conditional correlations. This finding helps to identify the major determinants to construct optimal portfolio diversification and to test bias and efficient market hypotheses. Therefore, this information may be useful for policy makers, traders, portfolio managers, and individual investors.

This study aims to extend the univariate GARCH model to the MGARCH model. The awareness of the MGARCH approach involves the parameterization of conditional cross-moments. Application of the dynamic MGARCH models to the precious metal ETFs is the core motivation. When shocks and volatility transmission exist across financial markets, considering how these shocks can affect other markets and their integration is necessary. Engle (1982) introduced MGARCH methods emanating from the univariate autoregressive conditional heteroskedasticity (ARCH) and GARCH models. MGARCH models comprise a parameter influenced by a conditional moment (Bollerslev et al., 1992). They are widely applied to model the volatility spillover effects among different financial time-series variables.

This essay provides various findings to the literature. First, BEKK is found to be the best model among the other models. This study provides evidence that the lagged covariances and cross-products of shocks are present when studying the correlation between the precious metal (base metal) ETFs and futures indices. Cross-volatility spillovers are higher than own volatility spillovers. Therefore, past volatility shocks have a stronger effect on futures volatility than the past volatility shocks in an individual market. Second, the conditional variances and covariances from the DCC model emphasize a high time-varying correlation between the precious (base) metal ETFs and futures prices. These results suggest useful implications for the investing community when they hedge, create, diversify, and restructure their investment portfolios.

2. LITERATURE REVIEW

In the recent two decades, MGARCH has been widely applied by many researchers and scholars in the financial field. This model was developed by Bollerslev et al. (1992) and applied by Bera and Higgins (1993) to capture the time-varying variances in time-series data. The demand to understand the correlation and the volatility among financial variables is significant not only for scholars but also for practitioners when they aim to make decisions on derivative pricing, portfolio optimization, risk management, and hedging. The volatility spillover effects among different markets are recorded directly through the MGARCH model based on its conditional variance or indirectly on conditional covariance. Spillover effects enable the volatility of a market effect on the volatility of other markets, vice versa, and the transmission assets among different markets.

Worthington and Higgs (2004) used the MGARCH method to document the significant equity returns and volatility transmission among nine Asian stock markets. All the Asian stock markets showed evidence of high integration by testing the conditional mean return formulas. However, the spillover effects between developed and emerging markets were not similar. Hammoudeh et al. (2009) utilized the vector autoregressive (VAR)(1)–GARCH(1,1) model to estimate the dynamic volatility and volatility transmission among service, banking, and insurance sectors in four Arab stock markets. The past volatility of stock markets strongly affected the futures volatility of these sectors. Buttner and Hayo (2011) and Lean and Teng (2013) applied DCC–MGARCH to track the effects of shocks on volatility through time in bivariate time series. Buttner and Hayo (2011) found the increasing tendency of integration among European markets and determined that such factors as interest rate spread, exchange rate risk, market capitalization, and the business cycle could influence this integration. Lean and Teng (2013) also found integration of the two largest markets and two emerging markets in the Malaysian stock market. The strongest integration was between the Indian and Malaysian markets, whereas the weakest one was between the Chinese and Japanese markets. MGRACH models are also used to show the volatility transmissions and shocks on economic sector variables, such as in the studies of Ho et al. (2009). They detected volatility asymmetry and time-varying correlations in five major sectorial indices of industrial production in the United States, such as consumer goods, investment goods, manufacturing, non-durables, and raw materials.

Worthington et al. (2005) examined the electricity spot market in Australia and found the spillover effects among five electricity spot prices. The existence of significant ARCH and GARCH effects implies that the shocks in an individual market affect the volatility of other markets. Chang et al. (2010) found that crude oil price volatility in the forms on the spot, forward, and futures markets describe the volatility spillover and asymmetric effects on four crude oil markets. They applied three alternative models, namely, CCC, VARMA–GARCH, and VARMA–AGARCH. Moon et al. (2009) used other alternative models, such as diagonal vector error correction, matrix diagonal, BEKK, and CCC models, to determine whether dynamic hedging models outperform the conventional ordinary least square model in consideration of the Korean stock and futures markets.

The MGARCH approach is also applied to find the transmission among different financial variables. Zhao (2010) analyzed the correlation between exchange rate and stock price in China and found evidence of bidirectional volatility spillovers between foreign exchange and stock markets. Therefore, past shocks of a stock market may affect the volatility of exchange rate. Datar et al. (2008) found evidence of intraday spillover in the mean, volatility, and depth of SPY and EWJ using the VAR model. Through the contemporaneous trading between SPY and EWJ indices, they also showed the integration between the American and Japanese markets. Wang et al. (2009) examined the co-integrating relationships between the spot index and the ETF indices in Taiwan using the VAR model. The guiding relationship in the spot index proves that the spot index presents a leading role in ETFs. Kim (2011) used the MGARCH model to detect the co-integration and spillover effects in nine ETFs in the United States and Asia-Pacific stock markets with the sub-samples before and after the global financial crisis. This study showed evidence of the co-integration and spillover effects, which had become stronger in these markets. Diaz (2012) applied MGARCH models (diagonal BEKK, CCC, and DCC models) to examine the presence of time-varying correlations among seven commodity exchange-traded notes

(ETNs) and the futures market. The BEKK model was found to be the most accurate among the different MGARCH models on the basis of log-likelihood values.

To further apply volatility transmission, portfolio design, and hedging effectiveness, Arouri et al. (2011) considered the correlation between the oil and stock markets in Europe and the United States. A strong volatility interaction between the oil and stock market sectors was exhibited, but the volatility transmission from oil to stock was more manifested than that from stock for oil price in Europe. The VAR–GARCH model was tested to find the effective portfolio weights and hedging between stocks and oil risk.

The precious and base metal issues have been considered in many previous studies. Xu and Fung (2005) examined the market information flows across the precious metal futures trading in both the American and Japanese markets by applying the MGARCH model. They emphasized that the intraday pricing information transmission between the two markets is strong and fast. The American market played a leading role in the Japanese market in returns. Wahab (2006) observed conditional dynamics and optimal spreading in gold and silver futures markets to examine the potential profit. The daily price return and volatility exhibited significantly cross-serial dependence on the first lag. The means and variances of the forecast changes may be used to calculate optimal spread ratios conditional on a constant correlation assumption. Batten et al. (2010) determined the major macroeconomic factors that influence the price returns of the precious metal indices. Three economic factors, namely, business cycle, monetary environment, and financial market, were proved to insignificantly influence the volatility of the precious metals. The precious metals presented evidence of being distinct metals. Hammoudeh et al. (2010) used the VARMA–GARCH and VARMA–DCC approaches to estimate conditional own and spillover volatilities and correlations across the precious metals and exchange rates. The two models outperformed the BEKK model in explaining the parameters and convergence complications. Optimal portfolio weights and hedging ratios were formulated according to these methods. The precious metal price was strongly sensitive to the shocks in their own group, but was insignificantly influenced by news from base metals. Sari et al. (2010) evaluated the co-movements and dynamic transmission among four the precious metals, crude oil, and exchange rate. They concluded a weak, long-run equilibrium relationship, but strong short-run transmissions among them. The market feedback for the precious metals was strongly influenced by the volatility in other metal markets and exchange rate but only temporarily. Hammoudeh et al. (2011) used the value-at-risk (VaR) model to investigate the risk of the precious metals to help investors create optimal portfolios. They suggested that portfolio managers should consider VaR with different methods that would yield inconsiderable violation even with low profitability. Mutafoğlu et al. (2012) used the VAR model and the Granger causality tests to determine whether trader positions could forecast futures the precious metal market curves. They recognized that market return plays a significant role in explaining trader positions in the precious metal markets. However, the net position of a trader is not a determinant that leads to the market return.

3. DATA AND METHODOLOGY

To investigate the evidence of the spillover and leverage effects of the precious metal (base metal) ETFs, we use the daily closing prices of four precious metal (base metal) ETFs versus four the precious metal (base metal) futures. The data of the precious metal and base metal ETFs are collected from the Yahoo Finance website from different inception dates of ETFs until June 30, 2013. The gold, silver, platinum, palladium, and copper futures contracts are collected from COMEX. The precious metal futures transactions are conducted in two divisions: i.e., the gold and silver futures are transacted in the COMEX division, and the platinum and palladium futures are transacted in the New York Mercantile Exchange division. The base metal futures, such as tin, nickel, and aluminum, are traded on the London Metal Exchange¹.

Based on the applications of Bollerslev et al. (1992), Bera and Higgins (1993), and Chua (2012), the MGARCH model is widely used in the financial field. In the MGARCH approach, a time series

¹ Information is based on the cnyes website: <http://www.cnyes.com/futures>

comprises the volatility interdependence and transmission mechanisms among different time series. The present study uses three MGARCH models to identify the spillover and leverage effects between the precious metal (base metal) ETFs and futures. The MGARCH approach typically examines financial volatility by using a non-parametric model and by extending CCC to a more adaptive model. According to the literature review, we use the three MGARCH models of BEKK, CCC, and DCC.

The mean equation used to estimate an individual return series is

$$y_{i,t} = \mu_i + \alpha y_{i,t-1} + \varepsilon_{it}, \quad (1)$$

where $y_{i,t}$ is the return on the index i between time $t-1$ and time t ,

μ_i is the long-run drift coefficient, and

ε_{it} is the error term for the return on variable i at time t .

According to Engle (1982), the expression of GARCH is derived from a test in Equation (1). The estimation results of the series show an ARCH process. A variant of the MGARCH method is implemented to evaluate both the possibility of volatility transmission among different variables and the persistence of volatility within each variable.

3.1. BEKK model

The BEKK model was designed by Engle and Kroner (1995) to estimate the dynamic conditional variance–covariance matrices that are positive definite. This estimation is a necessary requirement to ensure non-negative estimated variance. The conditional variance–covariance matrices are affected by the squares and cross-products of innovation ε_t and volatility H_t for each market with lag one. The major feature of the BEKK model is to enable the conditional variance–covariance matrices of the effects of the precious metal (base metal) ETFs and futures on each other without the need to estimate a large number of parameters. To simplify the equation, this study uses the BEKK model for MGARCH(1,1), which is exhibited as follows:

$$H_t = C'C + A'\varepsilon_{t-1}\varepsilon_t'A + BH_{t-1}B. \quad (2)$$

The individual elements included in the C, A, and B matrices are expressed as follows:

$$A = \begin{bmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{31} & a_{33} \end{bmatrix}, B = \begin{bmatrix} b_{11} & b_{12} & b_{13} \\ b_{21} & b_{22} & b_{23} \\ b_{31} & b_{31} & b_{33} \end{bmatrix}, C = \begin{bmatrix} c_{11} & c_{12} & c_{13} \\ c_{21} & c_{22} & c_{23} \\ c_{31} & c_{31} & c_{33} \end{bmatrix}.$$

$$\sum_{j=1}^q \sum_{k=1}^K (A_{kj} \otimes A_{kj}) + \sum_{j=1}^q \sum_{k=1}^K (B_{kj} \otimes B_{kj}),$$

where C represents a 3×3 low triangular matrix with six parameters.

A denotes a 3×3 square matrix of parameters and indicates the correlation between conditional variances and past square errors. The factors of matrix A provide the influence of good news or bad news on conditional variances. B stands for a 3×3 square matrix of parameters and presents the effect of past conditional variances on the current degrees of conditional variances. $\otimes$ denotes the Kronecker product of the three matrices.

Chang et al. (2010) found that the conditional variance features are lagged values and squared return shocks, whereas the conditional covariance features are lagged covariances and cross-products of the corresponding return shocks from the diagonal equation. These conditions are used to ensure that volatility H_t is positive definite at all times t .

Caporin and McAleer (2008) pointed out that $N(5N + 1)/2$ parameters are given in the BEKK–GARCH(1,1) model. In the formula $B = AD$, D is a diagonal matrix of the reduced number of estimated parameters. Equation (1) is rewritten as follows:

$$H_t = C'C + A'\varepsilon_{t-1}\varepsilon_t'A + DE[A'\varepsilon_{t-1}\varepsilon_t'D], \quad (3)$$

where $\alpha_{ii}^2 + b_{ii}^2 < 1$, (where $i = 1, 2$, and is a stationary sequence).

The subsequent parameters of the two variance equations ($h_{ij,t}$) create the parameters for the covariance equation ($h_{ij}, i \neq j$).

3.2. CCC model

This study applies the CCC multivariate model introduced by Bollerslev et al. (1992) to capture non-parametric models. Caporin and McAleer (2008) indicated that CCC is not influenced by dimension compared with the BEKK model. The CCC model has been widely applied in recent studies to test CCC.

$$y_t = E(y_t|F_{t-1}) + \varepsilon_t, \varepsilon_t = D_t \eta_t, \quad (4)$$

$$\text{var}(\varepsilon_t|F_{t-1}) = D_t \Gamma D_t,$$

where $y_t = (y_{1t}, \dots, y_{mt})'$ and $\eta_t = (\eta_{1t}, \dots, \eta_{mt})'$ are the series of independent and identically distributed (i.i.d.) random vectors,

F_t is the forward specific information at particular time 1,

$$D_t = \text{diag}(h_1^{1/2}, \dots, h_m^{1/2}),$$

where m is the number of returns, and $t = 1, \dots, n$.

The CCC matrix of unconditional shocks, η_t , is similar to the constant conditional covariance matrix of conditional shocks, ε_t . From Equation (3), $\varepsilon_t \varepsilon_t' = D_t \eta_t \eta_t' D_t$, $D_t = (\text{diag } Q_t)^{1/2}$, and $E(\varepsilon_t \varepsilon_t' | F_{t-1}) = Q_t = D_t \Gamma D_t$,

with $\Gamma = E(\eta_t \eta_t' | F_{t-1}) = E(\eta_t \eta_t')$, where $\Gamma = \{\rho_{ij}\}$ for $i, j = 1, \dots, m$, and Q_t identifies the conditional covariance matrix. Q_t is positive definite when the conditional variances and Γ are positive.

As a constant conditional variance for each return, $h_{it}, i = 1, \dots, m$ indicates a univariate GARCH model and has expressed as

$$h_{it} = \omega_i + \sum_{j=1}^r \alpha_{ij} \varepsilon_{i,t-j}^2 + \sum_{j=1}^s \beta_{ij} h_{i,t-j}^2, \quad (5)$$

where α_{ij} is the ARCH effect or the short-run persistence of shocks to return i ,

β_{ij} is the GARCH effect, and

$\sum_{j=1}^r \alpha_{ij} + \sum_{j=1}^s \beta_{ij}$ represents long-term persistence.

In the MGARCH model, the restriction is assumed to eliminate the number of parameters. Bollerslev et al. (1992) assumed that the conditional correlation matrix in the CCC model is constantly progressive over time. According to Tse (2000), a test for constant correlations with the null hypothesis is $h_{ijt} = \rho_{ij} \sqrt{h_{iit} h_{jtt}}$, where the conditional variances are the GARCH models. H_1 is hypothesized as follows: $h_{ijt} = \rho_{ijt} \sqrt{h_{iit} h_{jtt}}$. The Lagrange multiplier (LM) test is conducted under the null hypothesis with asymptotically $X^2(\frac{N(N-1)}{2})$.

Engle and Sheppard (2001) conducted another test for the conditional correlation in the DDC model. The null hypothesis is $R_t = \bar{R}$, $\forall t$, and H_1 is $\text{vech}(R_t) = \text{vech}(\bar{R}) + \beta_1^* \text{vech}(R_{t-1}) + \dots + \beta_p^* \text{vech}(R_{t-p})$. The null hypothesis indicates that $X_t = \beta_0^* + \beta_1^* X_{t-1} + \dots + \beta_p^* X_{t-p} + u_t^*$ is equal to zero, and $X_t = \text{vech}^u(\hat{z}_t \hat{z}_t' - I_N)$, vech^u only identifies the elements under the main diagonal.

3.3. DCC model

The DCC approach was applied and developed by Engle (2002) to investigate a financial time series with time-varying volatility. The integration among variables is estimated through a time-varying correlation. The integration becomes strong when the conditional correlation increases over time. Through a direct or an indirect approach, the conditional variance in the DCC model can determine the

volatility across markets. The volatility spillover from this market to other markets is also recognized through this model. The DCC model is described as follows:

$$y_t | F_{t-1} + \varepsilon_t, \varepsilon_t = D_t \eta_t \sim N(0, Q_t), t = 1, 2, \dots, n, \quad (6)$$

$$Q_t = D_t \Gamma_t D_t, \quad (7)$$

where $D_t = \text{diag}(h_1^2, \dots, h_m^2)$ is the diagonal matrix of conditional variances, and F_t is the information set at time t .

The conditional variance, h_{it} , in a univariate GARCH process is exhibited as

$$h_{it} = \omega_t + \sum_{k=1}^p \alpha_{ik} \varepsilon_{i,t-k}^2 + \sum_{l=1}^q \beta_{ij} h_{i,t-l}^2. \quad (8)$$

We assume that η_t identifies a vector of i.i.d. random variables with zero mean and unit variance. η_t is used to estimate in the DCC model and has expressed as

$$\Gamma_t = \{\text{diag}(Q_t)^{-1/2}\} Q_t \{\text{diag}(Q_t)^{-1/2}\}, \quad (9)$$

where Q_t is the conditional covariance matrix, and

$k \times k$ is the symmetric positive definite matrix. Q_t is computed as

$$Q_t = (1 - \theta_1 - \theta_2) \bar{Q} + \theta_1 \eta_{t-1} \eta'_{t-1} + \theta_2 Q_{t-1}, \quad (10)$$

where θ_1 stands for the scalar parameters used to illustrate the effects of past shocks on current conditional correlations.

θ_2 denotes the scalar parameters to describe the effects of past correlations. When θ_1 and θ_2 are significant statistics, a parameter, in which conditional correlations are not constant can be found. Otherwise, non-negative scalar parameters exist under the conditions of $\theta_1 + \theta_2 < 1$ and $Q_t > 0$.

Given that Q_t is a conditional covariance matrix, $\theta_1 = \theta_2 = 0$, and $\bar{Q}$ stands for $k \times k$, which is the unconditional variance matrix of η_t . According to Lean and Teng (2013), the DCC model is applied to a nonlinear series and can be implemented in a two-step process. The first step is that the univariate GARCH (1,1) model is estimated for an individual return series in the multivariate system. The second step is that standardized residuals are obtained by maximizing the likelihood to estimate the parameters.

4. EMPIRICAL RESULTS

Table 1 presents the descriptive statistics for each return series with the sample means, standard deviations, skewness, kurtosis, Jarque–Bera statistics, and p-value for daily the precious metal (base metal) ETFs and futures indices. The highest mean returns are the gold futures price (0.446%) and the palladium futures price (0.313%), whereas the lowest are the nickel futures price (−12.174%) and the aluminum futures index (−0.733%). The returns are also higher across the three the precious metal ETFs and their futures prices than in the base metal ETFs and their futures prices. Conversely, volatility, which is measured by standard deviation, is higher in the base metal futures prices. The two base metal futures prices provide levels of 503.605 (nickel) and 430.280 (tin). The standard deviations of the precious metal ETFs and their futures prices have a range from 0.544 (SLV) to 21.085 (platinum futures price). For both the precious and base metals, the futures indices normally have higher volatility than their ETFs.

In the distribution, all indices have negative skewness. However, the kurtosis exceeds three, which suggests a leptokurtic distribution. The final statistics presented in Table 1 is the Jarque–Bera statistics and the corresponding p-value used to examine the null hypothesis of whether the daily distribution of returns is normal. All p-values significant at the 1% level indicate that the null hypothesis is rejected for all time series and can be well estimated by the normal distribution.

Table 2 describes the unit root, LM, and ARMA–LM tests for eight time-series variables. The augmented Dickey–Fuller unit-root test is implemented to test the null hypothesis that time series is stationary. The optimal ARMA and GARCH models are selected on the basis of the Akaike information

criterion. The Breusch–Godfrey LM test is utilized to verify the null hypothesis that time series is correlated. All results are insignificant. Therefore, we cannot reject the null hypothesis that no serial correlation exists for all the precious metal (base metal) ETFs and their futures index returns. Engle (1982) applied the ARCH–LM test to validate the null hypothesis that no autoregressive conditional heteroscedasticity exists in time series. The significance results show that the null hypothesis is rejected for time series. Therefore, no ARCH effects occur in all univariate samples.

4.1. BEKK model results

Table 3 shows the coefficient of the variance–covariance matrix of the diagonal BEKK model for eight variables of the precious metal (base metal) ETFs and futures indices. Hosking (1980) and Li and McLeod (1981) developed a test to examine whether a time series produced MGARCH effects. All values of samples that are significant at the 1% level indicate that the MGARCH model can be used for the sample with the application of the diagonal BEKK model. For base metal, the significant values are found at the 1% level in all factors of A and B parameter matrices in the diagonal BEKK model. With the alpha values in A matrix, conditional covariances depend only on their own lags, and the return volatilities of base metal ETFs and futures indices can be captured by their lag values. By contrast, the conditional covariances in the A matrix of the precious metals are mostly significant statistics, except that of palladium. The beta values in the B matrix show that the conditional covariances of the precious metal (base metal) ETFs and futures prices have a feature of the lagged variances and cross-products of shocks. Therefore, volatilities are influenced by both their own lagged value and the cross-volatility spillovers between ETFs and futures contracts. The highest degree of relationship is found between the DJ-UBS Copper Total Return Sub-Index ETN and futures contracts based on its highest log-likelihood value. The diagonal BEKK exhibits a higher log-likelihood value than the CCC and DCC models. Therefore, the diagonal BEKK model is considered the best among the MGARCH models. This finding is in accordance with those of Worthington et al. (2005) and Chang et al. (2010).

Own volatility spillovers in all markets present large and significant ARCH effects. Large own volatility spillover effects are found in the ETFs of physical platinum share (0.376) in the precious metal market and in the DJ-UBS Tin Total Return Sub-Index ETN (0.753) in the base metal market. Therefore, investors should focus on the own lagged volatilities of these items. For cross-volatility spillover effects, the highest relationship between ETF and futures prices is found in GLD/FGLD (0.959) and SLV/FSLV (0.935) in the precious metal market and in JJN/FJJN (0.963) and JJU/FJJU (0.977) in the base metal market. High significance of cross-volatility spillovers is found in almost all markets, except the platinum ETF market. This result may help investors consider that the volatility of ETF returns influences futures price returns. Cross-volatility spillovers are higher than own volatility spillovers. This finding suggests that past cross-volatility shocks have a stronger effect on futures volatility than the past volatility shocks in an individual market. By considering the own volatility spillover effects and the cross-volatility spillover effects, investors and speculators may generate a suitable hedging method to reduce risks and may have an opportunity to increase their profits.

4.2. CCC model results

Table 4 demonstrates the estimation of the CCC model for the precious and base metal time series. In this model, the tests of Tse (2000) and Engle and Sheppard (2001) are utilized to verify the existence of MGARCH effects for constant correlations. All significant results indicate that samples have multivariate ARCH effects and can be estimated with ARCH effects. The ARCH (α) and GARCH (β) effects for the CCC model are almost significant for both ETFs and futures contracts. The highest degrees of persistence are 0.177 (Ishare Silver trust) for ARCH effects and 0.987 (DJ-UBS Copper Total Return Sub-Index ETN) for GARCH effects, which seem to dominate ARCH effects. This finding implies that conditional volatility can be predicted from past data and is consistent with the finding of Hammoudeh et al. (2010). This finding also assures the presence of long-run fluctuation in samples. Therefore, changes and shocks in the volatilities of the precious and base metal ETFs may affect futures counterparts in the long run. The results are useful for investors and traders when they aim to restructure their investment portfolios to look for realizing returns.

All moment conditions represent the results in $\alpha + \beta < 1$ to ensure a sufficient condition for the consistency of the quasi maximum likelihood estimator for GARCH model. These results agree with those of Chang et al. (2010) in the oil markets. The highest significant CCC coefficient is the copper ETF pairs of 0.987 for the entire sample, and the highest CCC for the precious metal pairs is the palladium ETF (0.920). Therefore, the copper and palladium ETFs are the most widely traded among the precious and base metal ETFs. The lowest correlation is found in the aluminum pairs (0.521), and thus this ETF is the least traded. The higher CCC in the base metal ETF market indicates that the base metal ETFs are transacted more frequently than the precious metal ETFs. Therefore, fund managers and investors can consider the movement of these ETFs to hedge the liquidity risk or to make a profit. The result of the CCC model also supports that of the BEKK model that the correlation between the precious metal (base metal) ETF returns and futures contracts can be predicted. This finding is in accordance with those of Hammoudeh et al. (2010) and Chang et al. (2010).

4.3. DCC model results

The results of the DCC model are presented in Table 5. Before estimating the DCC model, the Hosking (1980) and Li and McLeod (1981) tests are implemented to capture the dynamic properties of the conditional correlation series estimated above. The null hypothesis of DCC is rejected at the 1% significance level. This finding indicates that dynamic properties exist in the correlation series. As detailed in Table 5, most of the ARCH (α) and GARCH (β) effects are found to be significant. A long-run fluctuation is also observed through the DCC model for the time series. In consideration of the DCC results, short-run persistence and long-run persistence are captured by DCC_{E1} and DCC_{E2} , respectively. According to the DCC_{E1} parameter, a short-run persistence is indicated for all ETF pairs with the highest values being nickel (0.152) and silver (0.146), which are significant at 1%, except the gold ETF pairs. DCC_{E2} is used to capture the long-run persistence. Significant long-run persistence is detected in all samples, except Ishare Silver trust (SLV) and ETF physical platinum share (PPLT). For the precious metal ETF market, this study finds that the correlation between SPDR Gold Shares and futures prices has long-run persistence, and silver and platinum ETF pairs present existing short-run persistence. The correlation between physical palladium shares and futures contracts indicates both short-run and long-run persistence. For the base metal ETF market, the significance of existing time-varying correlation in all time series is highlighted at the 1% level. In comparison with the CCC model, the DCC model performs better estimation based on the higher log-likelihood values. This finding is in accordance with that of Sadorsky (2012).

5. CONCLUSIONS

This study uses three MGARCH models, namely, diagonal BEKK, CCC, and DCC, to investigate the correlations and volatility spillover effects between the precious metal (base metal) ETFs and futures contracts. On the basis of the empirical results, this essay contributes to the following issues. First, the empirical results indicate that BEKK is the best model among the MGARCH models, and this result is consistent with that of Chang et al. (2010). The significance of each pair of series proves the lagged covariances and cross-products of shocks. Therefore, the volatilities of ETF returns influence their futures price returns in the case of the precious metal (base metal) ETFs. This finding suggests that investors and traders should consider the return volatility trends of the precious metal (base metal) ETFs when studying the volatility of their futures market.

Second, the CCC model result indicates the presence of long-run persistence in samples. Therefore, changes and shocks in the volatilities of the precious and base metal ETFs may affect their futures counterparts in the long term. The conditional variances and covariances from the DCC model also emphasize the high time-varying correlation between the precious (base) metal ETFs and futures prices. The evidence for both short-run persistence and long-run persistence in the DCC model indicates that the DCC model is more efficient than the CCC model.

These findings have economic implications. Fund managers and investors can build on the movement of these ETFs and the lagged covariances and cross-products of shocks to hedge and restructure their investment portfolios. The degree of financial integration between the precious metal (base metal) ETF

markets and futures markets suggests that investors and traders should diversify their portfolios and help minimize volatility in their portfolios.

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Table 1. Summary statistics

	ETFs and future indexes	Period	Obs.	Mean	Std. Dev.	Skew.	Kurt.	J-Bera
<i>The precious metal ETFs</i>								
1	SPDR Gold Shares (GLD)/ Gold future price (FGLD)	2004/11/18- 2013/5/31	2127 2127	0.042 0.446	1.381 14.427	-0.807 -1.003	11.284 13.184	6313.219*** 9548.9***
2	Ishare Silver trust (SLV)/ Silver future price (FSLV)	2006/04/21- 2013/5/31	1763 1763	0.004 0.005	0.544 0.570	-1.557 -1.775	16.138 18.137	13390.79*** 17756.17***
3	Physical palladium shares (PALL)/ Palladium future price index (FPALL)	2010/01/08- 2013/5/31	856 856	0.031 0.313	1.309 13.329	-0.390 -0.586	4.090 4.296	61.082*** 108.791***
4	ETFs physical platinum share (PPLT)/ Platinum future price (FPPLT)	2010/1/8- 2013/5/31	853 853	-0.019 -0.129	2.017 21.085	-0.471 -0.685	4.517 4.814	113.215*** 183.062***
<i>Base metal ETFs</i>								
1	DJ-UBS Copper Total Return Sub-Index ETN (JJC)/ Copper future price (FJC)	2007/10/23- 2013/5/31	1392 1392	-0.007 0.000	0.863 0.063	-0.224 -0.173	3.982 3.982	67.620*** 62.863***
2	DJ-UBS Nickel Total Return Sub-Index ETN (JJN) Nickel future price (FJJN)	2007/10/23- 2013/5/31	1382 1382	-0.021 -12.174	0.777 503.065	-0.252 -0.177	5.440 5.428	357.321*** 346.623***
3	DJ-UBS Tin Total Return Sub-Index ETN (JJT) Tin future price (FJJT)	2008/06/24- 2013/5/31	1210 1210	0.000 -0.992	1.002 430.280	-0.504 -0.325	6.579 4.992	697.205*** 221.401***
4	DJ-UBS Aluminum Total Return Sub-Index ETN (JJU) Aluminum future index (FJJU)	2008/06/24- 2013/5/31	1209 1209	-0.024 -0.733	0.538 30.077	-0.982 -0.357	10.302 6.919	2880.687*** 797.805***

Source: Yahoo Finance <<http://finance.yahoo.com>>

Note: *, ** and *** are significance at 10, 5 and 1% levels, respectively.

Table 2. Summary statistics of unit root, LM, ARMA-LM tests

ETFs/Indices		ADF	ARMA	AIC	LM	ARCH-LM	GARCH	AIC	ARCH-LM
The precious metal ETFs									
1	GLD/	-46.228***	(3,3)	3.503	0.116	101.379***	(3,2)	3.014	3.755
	FGLD	-45.920***	(1,1)	8.176	1.196	110.892***	(3,2)	7.758	3.906
2	SLV/	-18.578***	(2,2)	1.666	0.215	309.016***	(3,3)	1.088	3.223
	FSLV	-40.76***	(3,3)	1.701	1.495	207.393***	(2,3)	1.167	2.720
3	PALL/	-17.709***	(2,1)	3.332	1.010	21.658***	(3,2)	3.284	2.120
	FPALL	-27.059***	(1,2)	8.013	0.058	22.481***	(3,2)	7.963	2.118
4	PPLT/	-26.209***	(3,2)	4.226	0.305	30.549***	(3,3)	4.190	1.399
	FPPLT	-26.474***	(3,2)	8.927	2.209	54.29***	(3,3)	8.839	0.199
Base metal ETFs									
1	JJC/	-39.797***	(2,3)	2.538	0.501	25.062***	(3,2)	2.455	0.457
	FJJC	-39.406***	(3,3)	-2.710	0.050	44.955***	(1,1)	-2.776	0.206
2	JJN/	-21.869***	(3,3)	2.312	2.085	66.095***	(3,3)	2.159	2.976
	FJJN	-37.591***	(3,2)	15.273	0.668	44.471***	(3,3)	15.107	0.606
3	JJT/	-33.445***	(2,2)	2.838	0.995	26.221***	(2,3)	2.772	0.018
	FJJT	-23.087***	(3,3)	14.961	1.896	37.488***	(1,2)	14.871	0.148
4	JJU/	-36.860***	(3,3)	1.561	0.559	1.561	(1,3)	1.424	0.184
	FJJU	-41.981***	(1,2)	9.596	1.723	11.229***	(3,3)	9.510	0.465

Note: *, ** and *** are significance at 10, 5 and 1% levels, respectively; p-values are in parentheses.

Table 3. BEKK estimations

	ETFs/ Futures	Model	AIC	Multivariate ARCH test		C ₁₁	C ₁₂	C ₂₂	a ₁₁	a ₂₂	b ₁₁	b ₂₂	Log likely- hood
				Hosking (1980)	L&M (1981)								
The precious metal ETFs													
1	GLD/ FGLD	(1,2)	9.197	468.578 (0.000)***	468.345 (0.000)***	0.090 (0.2124)	0.783 (0.333)	0.0000 (0.107)	0.303 (0.000)***	0.223 (0.000)***	0.942 (0.000)***	0.959 (0.000)***	-9761.59
2	SLV/ FSLV	(1,2)	0.071	547.740 (0.000)***	547.422 (0.000)***	0.077 (0.000)***	0.074 (0.000)***	0.009 (0.017)**	0.267 (0.000)***	0.258 (0.000)***	0.952 (0.000)***	0.953 (0.000)***	-38.5834
3	PALL/ FPALL	(1,3)	9.083	283.448 (0.000)***	283.169 (0.000)***	0.868 (0.295)	7.621 (0.319)	0.0001 (0.576)	0.223 (0.092)*	0.032 (0.761)	0.722 (0.232)	0.801 (0.054)**	-3876.73
4	PPLT/ FPPLT	(1,3)	10.932	266.128 (0.000)***	265.822 (0.000)***	1.814 (0.000)***	19.454 (0.000)***	3.989 (0.126)	0.3566 (0.000)***	0.376 (0.000)***	0.371 (0.295)	0.194 (0.610)	-4638.55
Base metal ETFs													
1	JJC/ FJJC	(1,3)	-2.631	346.550 (0.000)***	346.263 (0.000)***	0.203 (0.000)***	0.016 (0.000)***	0.00000 (0.212)	0.251 (0.000)***	0.237 (0.000)***	0.942 (0.000)***	0.936 (0.000)***	1851.42
2	JJN/ FJJN	(1,1)	15.728	358.440 (0.000)***	358.185 (0.000)***	0.1152 (0.058)**	63.990 (0.096)*	32.824 (0.086)*	0.240 (0.000)***	0.232 (0.000)***	0.958 (0.000)***	0.963 (0.000)***	-10848
3	JJT/ FJJT	(1,1)	16.603	228.630 (0.000)***	228.422 (0.000)***	0.705 (0.000)***	299.793 (0.000)***	246.026 (0.000)***	0.6705 (0.010)***	0.753 (0.002)***	0.742 (0.000)***	0.658 (0.000)***	-10022.7
4	JJU/ FJJU	(1,1)	10.412	118.656 (0.000)***	118.554 (0.000)***	0.068 (0.026)**	9.563 (0.016)**	0.000002 (0.994)	0.181 (0.000)***	0.351 (0.000)***	0.977 (0.000)***	0.883 (0.000)***	-6272.2

Note: *, ** and *** are significance at 10, 5 and 1% levels, respectively; p-values are in parentheses.

Table 4. CCC estimations

ETFs/ Futures	Model	AIC	Multivariate ARCH test		alpha		beta		a+b	CCC	Log likelihood
			Tse (2000)	E&S (2001)							
GLD/ FGLD	(0,3)	9.831	112.502 (0.000)***	46.478 (0.000)***	α_3	0.344 (0.000)***	β_3		0.837	0.866 (0.000)***	-10435.76
					α_2	0.279 (0.000)***	β_2				
					α_1	0.214 (0.001)***	β_1				
									0.805		
					α_3	0.173 (0.005)***	β_3				
					α_2	0.252 (0.000)***	β_2				
					α_1	0.380 (0.000)***	β_1				
SLV/ FSLV	(3,1)	0.297	209.067 (0.000)***	585.422 (0.000)***	α_3		β_3	0.313 (0.055)**	0.989	0.915 (0.000)***	-235.766
					α_2		β_2	0.395 (0.000)***			
					α_1	0.177 (0.000)***	β_1	0.104 (0.558)			
									0.988		
					α_3		β_3	0.306 (0.070)***			
					α_2		β_2	0.451 (0.000)***			
					α_1	0.168 (0.000)***	β_1	0.063 (0.759)			
PALL/ FPALL	(1,2)	9.352	152.725(0.000)***	314.373(0.000)***	α_2	-0.091 (0.082)*	β_2		0.981	0.920 (0.000)***	-3994
					α_1	0.129 (0.013)**	β_1	0.942 (0.000)***			
					α_2	-0.022 (0.617)	β_2		0.969		
					α_1	0.073 (0.061)*	β_1	0.918 (0.000)***			
PPLT/ FPPLT	(1,2)	11.236	152.479 (0.000)***	99.445 (0.000)***	α_2	-0.051 (0.374)	β_2		0.878	0.915 (0.000)***	-4769.99
					α_1	0.137 (0.012)***	β_1	0.792 (0.000)***			
					α_2	0.032 (0.657)	β_2		0.720		
					α_1	0.112 (0.017)***	β_1	0.576 (0.010)***			
JJC/ FIJC	(3,1)	-2.420	179.744 (0.000)***	22.833 (0.018)**	α_3		β_3	0.830 (0.000)***	0.987	0.935 (0.000)***	1704.09
					α_2		β_2	-0.898 (0.000)***			
					α_1	0.0698 (0.000)***	β_1	0.984 (0.000)***			
									0.974		
					α_3		β_3	0.748 (0.000)***			
					α_2		β_2	-0.835 (0.000)***			
					α_1	0.074 (0.000)***	β_1	0.987 (0.000)***			
JJN/ FIJN	(2,1)	15.976	133.292(0.000)***	19.176 (0.058)**	α_2		β_2	0.059 (0.604)	0.990	0.846 (0.000)***	-11017.3
					α_1	0.071 (0.003)***	β_1	0.860 (0.000)***			
					α_2		β_2	0.193 (0.188)	0.988		
					α_1	0.108 (0.000)***	β_1	0.687 (0.000)***			
JJT/ FIJT	(2,1)	16.776	149.515(0.000)***	26.071 (0.006)***	α_2		β_2	0.073 (0.503)	0.964	0.656 (0.000)***	-10125.7
					α_1	0.062 (0.012)**	β_1	0.829 (0.000)***			
					α_2		β_2	0.561 (0.001)***	0.958		
					α_1	0.095 (0.000)***	β_1	0.302 (0.090)*			
JJU/ FIJU	(1,1)	10.449	34.471 (0.000)***	10.650 (0.099)*	α_1	0.028 (0.126)	β_1	0.967 (0.000)***	0.994	0.521 (0.000)***	-6294.5
					α_1	0.111 (0.000)***	β_1	0.763 (0.000)***	0.874		

Note: *, ** and *** are significance at 10, 5 and 1% levels, respectively; p-values are in parentheses.

Table 5. Dynamic conditional correlation estimation of Engle (2002)

ETFs/ Futures	Model	AIC	Multivariate ARCH test		alpha		beta		a+b	DCC _E 1	DCC _E 2	Log likelihood							
			Hosking (1980)	L&M (1981)															
GLD/ FGLD	(0,3)	9.757	423.233 (0.000)***	422.703 (0.000)***	α_3	0.344 (0.000)***	β_3		0.837	0.099 (0.008)***	0.612 (0.000)***	-10355.2							
					α_2	0.279 (0.000)***	β_2												
					α_1	0.214 (0.001)***	β_1												
													0.805						
					α_3	0.380 (0.000)***	β_3												
					α_2	0.252 (0.000)***	β_2												
					α_1	0.173 (0.005)***	β_1												
SLV/ FSLV	(3,1)	0.249	505.305 (0.000)***	505.035 (0.000)***	α_3		β_3	0.313 (0.055)**	0.989	0.146 (0.000)***	0.000 (1.000)	-191.723							
					α_2		β_2	0.395 (0.000)***											
					α_1	0.177 (0.000)***	β_1	0.104 (0.558)											
													0.988						
					α_3		β_3	0.306 (0.070)***											
					α_2		β_2	0.451 (0.000)***											
					α_1	0.168 (0.000)***	β_1	0.063 (0.759)											
PALL/ FPALL	(1,2)	9.341	265.510 (0.000)***	265.310 (0.000)***	α_2	-0.091 (0.082)*	β_2		0.981	0.005 (0.028)**	0.988 (0.000)***	-3987.16							
					α_1	0.129 (0.013)**	β_1	0.942 (0.000)***											
													0.969						
					α_2	-0.022 (0.617)	β_2												
					α_1	0.073 (0.061)*	β_1	0.918 (0.000)***											
PPLT/ FPPLT	(1,2)	11.199	241.379 (0.000)***	240.999 (0.000)***	α_2	-0.051 (0.374)	β_2		0.878	0.13 (0.000)***	0.108 (0.235)	-4752.52							
					α_1	0.137 (0.012)***	β_1	0.792 (0.000)***											
													0.720						
					α_2	0.032 (0.657)	β_2												
					α_1	0.112 (0.017)***	β_1	0.576 (0.010)***											
JJC/ FIJC	(3,1)	-2.464	310.577 (0.000)***	310.323 (0.000)***	α_3		β_3	0.830 (0.000)***	0.987	0.151 (0.000)***	0.321 (0.015)**	1737.24							
					α_2		β_2	-0.897 (0.000)***											
					α_1	0.069 (0.000)***	β_1	0.984 (0.000)***											
													0.974						
					α_3		β_3	0.748 (0.000)***											
					α_2		β_2	-0.835 (0.000)***											
					α_1	0.074 (0.000)***	β_1	0.987 (0.000)***											
JJN/ FIJN	(1,3)	15.912	264.348 (0.000)***	264.143 (0.000)***	α_3	-0.113 (0.009)***	β_3		0.99	0.152 (0.005)***	0.589 (0.030)**	-10969.1							
					α_2	0.033 (0.607)	β_2												
					α_1	0.118 (0.014)**	β_1	0.957 (0.000)***											
													0.999						
					α_3	-0.107 (0.017)**	β_3												
					α_2	-0.016 (0.808)	β_2												
					α_1	0.143 (0.001)***	β_1	0.978 (0.000)***											

JJT/ FIJT	(2,3)	16.684	228.444 (0.000)***	228.151 (0.000)***	α_3	-0.168 (0.011)***	β_3		0.989	0.064 (0.002)***	0.917 (0.000)***	-10063.6
					α_2	0.122 (0.157)	β_2	-0.193 (0.425)				
					α_1	0.067 (0.086)*	β_1	1.162 (0.000)***				
					α_3	-0.111 (0.020)***	β_3					
					α_2	0.043 (0.000)***	β_2	0.927 (0.000)***				
					α_1	0.147 (0.003)***	β_1	-0.039 (0.007)***				
JJU/ FIJU	(1,1)	10.439	92.417 (0.000)***	92.396 (0.000)***	α_1	0.028 (0.126)***	β_1	0.967 (0.000)***	0.994	0.032 (0.004)***	0.916 (0.000)***	-6286.46
					α_1	0.111 (0.000)***	β_1	0.763 (0.000)***				

Note: *, ** and *** are significance at 10, 5 and 1% levels, respectively; p-values are in parentheses.