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What Drives the Volatility of Metal Market? The Role of World Oil Price and US Factors Volatility

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ABSTRACT

This paper examines the effect of world oil price and the US factors volatility on the volatility of returns for three precious metals (gold, silver, and copper) using daily data for the period of January 2010 to April 2017. The volatility of all variables was constructed using a generalized autoregressive conditional heteroskedasticity (GARCH) approach. Next, an autoregressive distributed lag (ARDL) model was used in examining the relationship between the volatility of returns for these three metals on the volatility of world oil prices and US factors. The main results revealed that there was a cointegration relationship (long-run co-movement) between the volatility of returns (gold, silver, and copper) and the volatility of world oil price and US factors. In the long run, the volatility of the US factors was statistically significant in influencing the volatility of all metals, however the volatility of world oil price only significant to influence the volatility of silver and copper, but not the volatility of gold. In the short run, the volatility of world oil price and US factors were statistically significant in influencing the volatility of gold, whereas, for silver, all variables were significant except for the US Dollar Index. For copper, all variables were statistically significant except for world oil prices and the US Dollar Index. Therefore, these results have provided more essential information for investors, fund managers,

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businesses and central bankers in managing their portfolio diversification, hedging purposes, and international reserve.

Keywords: ARCH, ARDL, GARCH, metals volatility, oil price volatility, US factors volatility

INTRODUCTION

Precious metals (gold, silver, and copper) have received much attention by the investors and researchers due to the fact that the world metal prices have increased at a historically high level during a commodities boom (the year 2006-2012). These three coinage metals are most traded in the global metals market in terms of their turnover. In particular, gold and silver have been important coinage metals before the 19th century and later replaced with nickel-made coins and paper notes. Now, they are used in jewelry and also serves as an international reserve and investment assets for investors.

The high uncertainty in the world financial markets over three decades ago has witnessed that international investors have to rebalance their portfolio investment to a safe asset like precious metal. The main attractiveness of investment in precious metals is they have a low correlation with other assets. In addition, since investors have lost their confidence for investment in the stock markets due to suffered steep losses, the panic of high volatility and contagion effect in the world financial markets, thus this development has led the investors to consider alternative instruments to hedge increasing risk in their portfolio. In fact, the European sovereign debt crisis and the role of China and Russia are also playing an important role in the world metal market, in particular, an investment in gold in order to stabilize their economy.

Given this current development in the world metal market, therefore there are several reasons why this study is important. First, gold, silver, and copper are counted among the most valuable commodities worldwide, in which these precious metals also can be used as an industrial commodity or as an investment. Second, investors include gold and silver in their portfolio because it is durable and acts as a hedging tool or safe haven against the uncertainty of financial assets especially after the global financial crisis in 2007/2008. This is because, after the global financial crisis the demand for the precious metal has increased due to the uncertainty in the world financial asset and a significant decline in the world equity markets value in 2000, and most recently as a result of the credit and stock market instability following the global financial crisis of 2007. Therefore, investors had switched their portfolio investment from financial assets to precious metals, in which they believed that investment in metals was relatively stable and more lucrative than a financial asset (stock and bond).

Third, gold and silver are used as coinage metals, and the gold reserve is held by the central banks of many countries worldwide in order to store value or for use as a redemption medium. Therefore, the central bank has also held a significant proportion of gold as an international reserve in strengthening diversification and insurance against unexpected market turmoil (Tully & Lucey, 2007). The idea behind this procedure is that gold reserves will help secure and stabilize the countries' respective currencies. Thus, a good understanding of what drives the volatility of precious metal is important to the investors in managing their investment portfolio (example, diversify their portfolio), and to the central bank in managing their international reserves in stabilizing their currency and international settlement. Fourth, for copper, it carries a major role in global economic growth and copper price act as one of the leading economic indicators to market participants. Copper has been widely used in the making of electrical conductors and one of the essential construction materials because of its electrical conductivity and corrosion-resistant properties.

Thus, based on these motivations, the focal point of this paper is to examine the determinants of volatility for three precious metals (gold, silver, and copper) by focusing on the role of world oil price and US factors volatility. The major contributions of this paper have three aspects. First, this study used all the family of ARCH-GARCH model in constructing the more accurate of the conditional variance (volatility) for all variables of interest. Second, this paper considers the role of world oil price and the US factors volatility in modeling the determinants of metal return volatility for three precious metal markets (gold, silver, and copper) using a most recent data set. Third, this study uses the ARDL model in modeling the determinants of volatility for each metal market to examine the long-run co-movement (cointegration), and long-run and short-run effect of the volatility of the world oil price and US factors upon the volatility of returns for each metal market.

This paper is organized as follows. Section 2 provides a brief discussion of the literature review, whereas section 3 describes the research methodology used in this study namely GARCH methodology and ARDL model. Section 4 summarized the main empirical findings, and finally, section 5 concludes and discusses some related policy implications.

LITERATURE REVIEW

The past literature on the volatility of metal markets has gained special attention from the previous researcher especially during the recent commodities boom from 2006 to 2012. For example, Hammoudeh and Yuan (2008) examined the volatility behavior of three precious metal namely gold, silver and copper, in the presence of crude oil and interest rate shocks. The main results using standard GARCH models suggested that gold and silver had almost the same nature of volatility (persistence) in which is greater than the volatility of copper. However, using the EGARCH models, the main results suggested that the leverage effect was present and significant for copper only, which implied that investment in gold and silver could be good in anticipation of bad times. In addition, past oil shock does not impact all three metals similarly, whereas monetary policy has a significant effect on precious metals but not on copper if the treasury bill rate is used as a monetary policy variable. Another study by Du (2012) had estimated the volatility of gold price, silver, and platinum using daily spot prices for the period of 1996-2011. The main result showed that the EGARCH model had outperformed the standard GARCH model in forecasting the volatility. Tang (2010) modeled the conditional volatility of aluminum and copper in daily and weekly spot price returns, and the main findings revealed that the regime-switching models with GARCH had outperformed the standard GARCH models in predicting the degree of volatility.

A recent study by Arouri et al. (2015) used several multivariate GARCH models to investigate the effect of the volatility of gold price returns on Chinese stock market returns. The result showed that the estimation using the VAR-GARCH model was the best performing model to determine the hedging ratio and suggested that investment in gold could be considered to increase the effectiveness of portfolio diversification by the addition of gold. Behmiri and Manera (2015) investigated the role of outliers and oil price shocks in the volatility of ten metals by using GARCH and Glosten, Jagannathan and Runkle-GARCH (GJR-GARCH) models. The findings showed removal of outliers improved the GARCH performance in estimating volatility. In terms of leverage effect, copper has the existence of leverage effect and no leverage effect for nickel and palladium. Sinha and Mathur (2013) examined the volatility of five base metals in the return series by using GARCH models. The result indicated that there was a presence of persistence in metal price volatility. The findings also implied that volatility of the equity market had influences on weekly price volatility of future contract of aluminum, lead, and zinc while did not influence on copper and nickel.

There are pieces of literature that have examined the relationship between metal prices and explanatory variables in the long run or short run. For example, Zhang and Wei (2010) analyzed the relationship between gold and crude oil prices. The results found the influence of crude oil price movement was higher than the gold price movement on economic growth and both prices had no significant nonlinear Granger causality to each other. Yusupov and Duan (2010) explored the long-run relationships between seven base metals, gold, and oil using daily spot prices that had covered the period 1995-2010 using the Johansen cointegration and VEC Granger causality approach. The findings showed the existence of several cointegrating relationships among the base metals, gold, and crude oil, however, did not prove any cointegration to each other in which helped the benefit from diversification between asset. In addition, aluminum and copper had appeared significant to Granger-cause other commodities. Bildirici and Turkmen (2015) explored the relationship between oil, gold, silver and copper returns in Turkey using nonlinear ARDL and augmented nonlinear Granger causality approach. The results concluded that there was the existence of a long-run relationship between oil return and the return of gold and silver, and the movement of world oil return had a significant impact on gold return in the short run.

Some study for example Celik (2016) had examined the relationship between dollar exchange rate, gold price and grape production in Turkey during the period 1950-2015 using an ARDL approach. The results revealed that the existence of a long-run relationship among variables and found that the negative relationship between the grape production and dollar exchange rate, whereas a positive relationship between the grape production and gold price. Le and Chang (2011) employed the ARDL bounds testing approach to investigate the relationships between two global significant commodities (oil and gold) and the financial variables (interest rates, exchange rates, and stock prices) in Japan's perspectives. The results showed the gold price had a significant impact on the interest rate and yen in the long-run and short-run and suggested that the investors included gold in their portfolio investment.

Thus, based on this background, this study contributes and fills the literature gap in certain aspects. First, since there is comprehensive study on the determinants of volatility in equity and commodity markets (for example, Brunetti & Gilbert, 1995; Fernandez, 2008; Gilbert, 2006; Kroner et al., 1993; Pindyck, 2004), however, there is a limited evidence in explaining the determinants of volatility for a single precious metals. Therefore, understanding the main factors that reflect the volatility of precious market are important in managing risk and return of portfolio investment. Second, this study utilizes a more recent data set using the GARCH approach in constructing the volatility for all variables, and then estimate the determinants of the volatility for three precious metal using ARDL method.

METHOD

Volatility modeling is an important aspect for market participants in managing their portfolio risk and return. Variance or standard deviation is often used as the risk measure in commodities market behavior. Thus, this section will summarize the volatility model in order to construct the conditional variance, and then discuss the ARDL model in analyzing the effects of world oil price and US factors volatility upon the volatility of each precious metal (gold, silver, and copper).

Volatility Models

GARCH Model. GARCH model was introduced by Bollerslev (1986) which included the lagged of conditional variance terms to forecast the variance equation. The general GARCH (p, q) model can be written as follows:

$$h_t = \gamma_0 + \delta_1 h_{t-1} + \lambda_1 \mu_{t-1}^2 \tag{1}$$

In equation [1], the value of variance scaling parameter (h_t) now depends on both the past value of the shocks, which are captured by the lagged squared residual terms (μ_{t-1}^2) and on the past value of itself, which is captured by lagged h_t terms (Y_t).

GARCH-M Model. GARCH-M model or GARCH in mean allows the conditional mean (Y_t) to depend on its own conditional variance (h_t). Therefore, the GARCH-M (p,q) model has the following form:

$$Y_t = \beta_0 + \beta' X_t + \theta h_t + \mu_t \quad (2)$$

$$h_t = \gamma_0 + \sum_{i=1}^{p} \delta_i h_{t-1} + \sum_{j=1}^{q} \gamma_1 \mu_{t-1}^2 \quad (3)$$

EGARCH Model. Nelson (1991) proposed the exponential GARCH or EGARCH model to capture the asymmetric response of returns with the following specification of the variance equation:

$$\log h_t = \gamma + \sum_{j=1}^{p} \zeta_j \left| \frac{\mu_{t-j}}{\sqrt{h_{t-j}}} \right| + \sum_{j=1}^{q} \varepsilon_j \frac{\mu_{t-j}}{\sqrt{h_{t-j}}} + \sum_{i=1}^{p} \delta_i \log(h_{t-i}) \quad (4)$$

Where γ , ζ_j , ε_j and δ_i are parameters to be estimated. The left-hand side is the log of the variance series. This makes the leverage effect exponential instead of quadratic, and therefore the estimate of the conditional variance is guaranteed to be non-negative. The EGARCH model allows for the testing of asymmetries as well as the TGARCH model. To test for asymmetries the parameters of importance are the ε_j. If $\varepsilon_1 = \varepsilon_2 = \varepsilon_3 \ldots\ldots=0$, then the model is symmetric. When $\varepsilon_j < 0$, then positive shocks (good news) generate less volatility than negative shocks (bad news).

EGARCH-M Model. EGARCH-M model is known as Nelson's EGARCH model in which includes standard deviation into the mean equation. This model has extra capabilities to determine the risk premium from the study variables.

TGARCH Model. A major restriction of the ARCH and GARCH specifications is that both models are assumed that shocks are symmetric. Thus, the threshold ARCH (TARCH) model by Zakoian (1994) and threshold GARCH (TGARCH) by Glosten et al. (1993) are developed to capture asymmetries in terms of negative and positive shocks. To do that, it simply adds into the variance equation a multiplication dummy variable to check whether there is a statistically significant difference when shocks are negative. Thus, the specification of the conditional variance equation for TGARCH (1,1) is written as follows:

$$h_t = \gamma_0 + \gamma \mu_{t-1}^2 + \varphi \mu_{t-1}^2 d_{t-1} + \delta h_{t-1} \quad (5)$$

Where, d_t takes the value of 1 for $\mu_t < 0$, and 0 otherwise. So, 'good news' and 'bad news' have a different impact. Goods news has an impact γ , while bad news had an impact φ . If φ >0, we conclude that there is asymmetry, while if φ =0 the news impact is symmetric.

Autoregressive Distributed Lag (ARDL) Model

In modeling the relationship between the volatility of returns for individual precious metal upon the volatility of world oil prices and US factors, this study used an ARDL method as proposed by Pesaran et al. (2001). The advantage of the ARDL model is this technique can examine the cointegration (long-run co-movement) between variables whether the time series variables are stationary at I(0), or purely I(1), or mixtures of I(0) and I(1) for particular variables. This technique is also applicable to the short sample period.

The ARDL technique has three steps. First, we used the Bound testing approach in investigating the co-movement (cointegration) between variables using ARDL (p, q, r, s, t) model as follows:

$$\Delta VOLM_t + \beta_4 VSP500_{t-1} + \beta_5 VUS10Y_{t-1} + \sum_{i=1}^{p} \lambda_1 \Delta VOLM_{t-i} + \sum_{i=0}^{q} \lambda_2 \Delta VOIL_{t-i} + \sum_{i=0}^{r} \lambda_3 \Delta VDXY_{t-i} + \sum_{i=0}^{s} \lambda_4 \Delta VSP500_{t-i} + \sum_{i=0}^{t} \lambda_5 \Delta VUS10Y_{t-i} + \varepsilon_t \quad (6)$$

In equation (6), VOLM is the individual volatility of precious metal (gold, silver, and copper), VOIL is volatility of oil price, VDXY is the volatility of the US Dollar Index, VSP500 is the volatility of Standard & Poor 500 Index, and VUS10Y is the volatility of 10 years of the United States government bond. The model in equation (6) is estimated separately for each volatility of precious metal (gold, silver, copper). The selection of the optimal lag orders of the ARDL models was based on the lowest value of the Schwarz criterion (SC).

To test whether cointegration is established or not, the computed Wald test (joint test or F test) from equation (6) need to compare with the critical value (normally for case III) as proposed by Pesaran et al. (2001). If the estimated F-statistics fall above the upper bound of the critical values, then the null hypothesis of no cointegration is rejected. Likewise, if the estimated F statistics are falling below lower bound then the null hypothesis cannot be rejected. If the estimated value falls inside the critical value band, the result is inclusive. The hypothesis to test the existence of cointegration or not is as follows:

$$H_0 : \beta_1 = \beta_2 = \beta_3 = \beta_4 = \beta_5 = 0 \quad (7)$$

$$H_A : \beta_1 \neq \beta_2 \neq \beta_3 \neq \beta_4 \neq \beta_5 \neq 0 \quad (8)$$

If the F-statistics is above the upper bound critical value, the null hypothesis (H_0) will be rejected and indicates the existence of cointegration. If the F-statistics fall below the lower bound critical value indicates no cointegration exists while F-statistics fall between the upper and lower bound critical value then it is inconclusive among variables.

The second step, once the cointegration is confirmed, the long-run relationship between the volatility of metal and the volatility of world oil price and US factors can be estimated using long-run ARDL (p, q, r, s, t) as follows:

$$VOLM_t = \beta_0 + \sum_{i=1}^{p} \beta_1 VOLM_{t-i} + \sum_{i=0}^{q} \beta_2 VOIL_{t-i} + \sum_{i=0}^{r} \beta_3 VDXY_{t-i} + \sum_{i=0}^{s} \beta_4 VSP500_{t-i} + \sum_{i=0}^{t} \beta_5 VUS10Y_{t-i} + \varepsilon_t \quad (9)$$

The long-run model in equation (9) is important in generating the error correction term, in which the error correction from the long-run model is used to estimate the short model. Thus, the ARDL specification of the short-run dynamics can be derived by constructing an error correction model

(ECM) of the following form:

$$\Delta VOLM_t = \beta_0 + \sum_{i=1}^{p} \beta_1 \Delta VOLM_{t-i} + \sum_{i=0}^{q} \beta_2 \Delta VOIL_{t-i} + \sum_{i=0}^{r} \beta_3 \Delta VDXY_{t-i} + \sum_{i=0}^{s} \beta_4 \Delta VSP500_{t-i} + \sum_{i=0}^{t} \beta_5 \Delta VUS10Y_{t-i} + \varphi ECT_{t-1} + \varepsilon_t \qquad (10)$$

In equation (10), the parameter φ should fall between $-1 < \varphi < 0$, and it measured the speed of adjustment of the target variables during the short-run period to back to the long-run equilibrium after the shock.

Data

The data set were daily closing prices of gold, silver, copper, world oil price, US dollar index, S&P 500 and US 10 years bond yield, which contained 1 839 observations respectively. The data covered from 4 January 2010 to 28 April 2017. All data were collected from Datastream. World oil price (in US dollar per barrel) is reflected West Texas Intermediate (WTI) in which is used as a benchmark for crude oil pricing and traded on the New York Mercantile Exchange. Gold and silver prices are measured in US dollar per troy ounce, while the copper price is measured in US dollar per lbs. These three metals prices are traded in Chicago COMEX division of the New York Mercantile Exchange. US dollar index (DXY) is representing the strength of the US dollar against the basket of world major currencies including Euro, Japanese yen, British pound, Canadian dollar, Swiss franc, and Swedish krona. S&P 500 index is a stock market index representing 500 large United States companies in terms of market capitalizations that traded in the New York Stock Exchange (NYSE) and NASDAQ. US government 10 years bond yield is traded under the supervision of the US Department of Treasury.

All data set except US ten years government bond are transformed into return series using the following formula:

$$R_t = \left[\frac{P_t}{P_{t-1}} - 1 \right] x100 \qquad (11)$$

where P_t is the daily price at time t, and P_{t-1} is the previous price.

RESULTS AND DISCUSSION

Results of Volatility Model

Table 1 reports the estimation results of the volatility model for all variables. As can be seen from Table 1, for the gold returns volatility modeling, AR(1)-EGARCH (2, 2) is the most robust model among GARCH family models based on the lowest AIC value. The coefficients of α_1, α_2 and β_2 are statistically significant at 1% significant level in which proves that volatility from the previous records has a significant impact on current uncertainty. For the estimation of silver returns volatility, AR (1)-TGARCH (2, 1) outperforms other GARCH family models based on the lowest AIC value. The coefficients of α_1, α_2 and β_2 are statistically significant at 1% significant level in which indicates that the volatility from the previous records has a significant impact on current uncertainty. For copper returns volatility estimation results, AR (1)-TGARCH (1, 1) had the lowest AIC value shows the best estimation model among GARCH family models. The coefficients of α_1 and β_1 are statistically significant at 5% and 1% respectively in which indicates that volatility from the previous records has a significant impact on current uncertainty.

The ARCH-LM test statistics under the GARCH estimation found do not exhibit an additional ARCH effect remaining in the residual of gold, silver and copper returns series. This shows that the variance equation in GARCH models' is well specified for the three metals. For serial correlation detection test, Ljung-Box Q-statistics found no serial correlation problem based on any lag order in the residual of gold, silver and copper returns. Lastly, all GARCH family models exhibit not normally distributed for all three metals data distribution as rejects the null hypothesis of normality at a 1% significance level based on Jarque-Bera statistics.

The next step after GARCH estimation is to extract the conditional variance for all variables as volatility series is investigating the relationship among the variables using the ARDL approach. The selection of volatility series for all explanatory variables (world oil price, US dollar index, S&P 500 and US 10 years bond yield) are also based on the lowest value of the Akaike Information Criterion (AIC) among GARCH family models. The estimation results found that EGARCH-M (2, 2) is the best to represent the model for volatility series of world oil returns and the US dollar Index. Whereas, EGARCH-M (2, 1) is the best model to representing the volatility of the S&P 500 return, while TGARCH (1, 1) is the best model to representing the volatility of the US 10 years bond yield. However, the full results of the volatility tests for world oil price and US factors (US dollar index, S&P 500 and US 10 years bond yield) are not reported here in order to save the space. The full results are available upon request.

Table 1

Selected GARCH estimation results

	Gold Returns				
Coefficients	AR(1)-GARCH(2,1)	AR(1)-GARCH-M (2,1)	AR(1)-EGARCH (2,2) *	AR(1)-EGARCH-M (2,2)	AR(1)-TGARCH (2,1)
Mean					
μ	0.0001	0.0004	0.0001	0.0004	0.0001
AR(1)	-0.0191	-0.0193	-0.0178	-0.01779	-0.019609
λ		-0.0283		-0.02764	
Variance					
ω	1.58E-06***	1.58E-06***	-0.71058***	-0.7076***	1.55E-06***
γ			-0.0507***	-0.05066***	-0.00193
α (1)	0.0720***	0.0719***	0.1125***	0.1127***	0.07414***
α (2)	-0.0443***	-0.0441***	0.1049***	0.1054***	-0.0455***
β (1)	0.95851***	0.9585***	-0.0077	-0.0071	0.9589***
β (2)			0.947212***	0.947054***	
α+β	0.9863	0.9862	1.157	1.1580	0.9876

Table 1 *(Continued)*

	Gold Returns				
Coefficients	AR(1)-GARCH(2,1)	AR(1)-GARCH-M (2,1)	AR(1)-EGARCH (2,2) *	AR(1)-EGARCH-M (2,2)	AR(1)-TGARCH (2,1)
Log Likelihood	5764.31	5764.33	5773.12	5773.15	5764.34
AIC	-6.2693	-6.2682	-6.2767	-6.2756	-6.2682
SIC	-6.2512	-6.2472	-6.2527	-6.2486	-6.2472
ARCH LM	1.5747	1.5645	2.1396	2.0579	1.6257
Q(6)	1.0126	0.9899	1.2775	1.2219	1.0006
Q(12)	5.0275	4.9956	6.0636	6.037	4.94
Q^2(6)	4.7914	4.7623	3.8258	3.744	4.8628
Q^2(12)	6.7462	6.6789	6.8206	6.7101	6.7419
J Bera	1036.35***	1031.62***	762.76***	757.05***	1037.83***

	Silver Returns				
Coefficients	AR(1)-GARCH(2,1)	AR(1)-GARCH-M (2,1)	AR(1)-EGARCH (2,1)	AR(1)-EGARCH-M (2,1)	AR(1)-TGARCH (2,1) *
Mean					
μ	-0.0001	0.0004	0.00006	-0.0005	0.00003
AR(1)	-0.090222***	-0.090308***	-0.082121***	-0.0829***	-0.090256***
λ		-0.02502		0.030062	
Variance					
ω	3.5E-06***	3.52E-06***	-0.2109***	-0.2095***	3.61E-06***
γ			0.0053	0.0054	-0.0162**
α (1)	0.1707***	0.1709***	0.3213***	0.3209***	0.1807***
α (2)	-0.1460***	-0.1464***	-0.2259***	-0.2251***	-0.1443***
β (1)	0.9669***	0.9669***	0.9819***	0.9822***	0.9639***
β (2)					
α+β	0.9916	0.9916	1.0773	1.0779	1.0003
Log Likelihood	4609.69	4609.71	4609.01	4609.05	4611.41
AIC	-5.0122	-5.0111	-5.0104	-5.0093	-5.0129
SIC	-4.9942	-4.9901	-4.9894	-4.9853	-4.9919
ARCH LM	1.3567	1.3037	1.9435	2.0292	1.4337
Q(6)	2.3649	2.3802	2.5573	2.5103	2.3184
Q(12)	12.512	12.494	12.605	12.585	11.979

Table 1 *(Continued)*

Coefficients	Silver Returns AR(1)-GARCH(2,1)	AR(1)-GARCH-M (2,1)	AR(1)-EGARCH (2,1)	AR(1)-EGARCH-M (2,1)	AR(1)-TGARCH (2,1) *
Q^2(6)	3.5963	3.5137	3.8258	4.6435	3.9369
Q^2(12)	6.1	6.0017	6.8206	7.1615	6.4415
J Bera	560.18***	557.53***	623.97***	627.49***	584.71***

	Copper Returns				
Coefficients	AR(1)-GARCH(2,2)	AR(1)-GARCH-M (2,2)	AR(1)-EGARCH (2,2)	AR(1)-EGARCH-M (2,2)	AR(1)-TGARCH (1,1) *
Mean					
μ	-0.000117	-0.0025*	-0.00032	-0.00291**	-0.00034
AR(1)	-0.019086	-0.02063	-0.01399	-0.0122	-0.02021
λ		0.186509*		0.198474**	
Variance					
ω	5.88E-08	4.45E-08	-0.48274***	-0.53987***	3.15E-06***
γ			-0.07987***	-0.07939***	0.056659***
α (1)	0.059572***	0.060299***	0.041012	0.041241	0.015644**
α (2)	-0.058423***	-0.05944***	0.158234***	0.158705***	
β (1)	1.872599***	1.880946***	0.25388**	0.243578*	0.94018***
β (2)	-0.874085***	-0.88206***	0.707582***	0.711335***	
α+β	0.999663	0.999743	1.160708	1.154859	0.955824
Log Likelihood	5275.165	5276.464	5282.728	5284.355	5283.364
AIC	-5.735617	-5.73594	-5.74276	-5.74345	-5.74563
SIC	-5.714599	-5.71192	-5.71874	-5.71642	-5.72762
ARCH LM	1.055871	0.915333	1.679471	1.845715	0.977346
Q(6)	4.1098	4.1438	3.8746	4.1704	4.3383
Q(12)	12.902	12.994	13.94	15.688	13.557
Q^2(6)	5.4201	5.5006	10.404	9.7648	6.0677
Q^2(12)	10.187	9.9527	14.003	13.288	9.7732
J Bera	74.69193***	74.29221***	64.6805***	66.57781***	58.09735***

Note: *, **, *** denotes 10%, 5%, 1% significance level respectively

ARDL Estimation Results

Table 2 reports the estimation result of the ARDL model using bound testing for each metal equation. The selection of optimal lag order for each ARDL model for gold, silver, and copper volatility series is determined by the minimum value of the Schwarz criterion. As can be seen from Table 2, the computed F-statistic is higher than the upper value of critical bound at the 1% significance level for all metals. This indicates that there is a cointegrating relationship (or long-run co-movement) among explanatory variables (the volatility of world oil price and US factors) upon the volatility of returns for gold, silver, and copper.

Table 3 summarizes the estimation results of the long-run elasticities for each metal market volatility. As can be seen from Table 3, the volatility of world oil price is negatively and statistically significant in influencing the volatility of silver at a 5% significant level, whereas the volatility of world oil price is not statistically significant to influence the volatility of gold and copper. The volatility of the US dollar index is positively and statistically significant in influencing the volatility of silver and copper at a 1% significant level, whereas no significant impact on the volatility of gold. Specifically, 1% increase in the volatility of US dollar index lead to increase the volatility of silver by 9.03%, and for copper by 5.77%, in which indicates that the volatility of silver and copper price are very sensitive to the movement of US dollar. The volatility of the S&P 500 is positively and statistically significant to affect the volatility of gold and copper at a 5% significant level. In other words, a 1% increase in the volatility of the S&P 500 lead to an increase in the volatility of gold by 0.23%, and 0.83% for copper. The volatility of US 10 years bond yield has a positive and significant relationship with the volatility of gold and silver at 10 % and 1% significant level respectively, while no significant impact on the volatility of copper. Based on the result it shows that a 1% increase of the volatility of the US 10

Table 2
Bound test results

Model	Maximum Lag	Lag Order (a,b,c,d,e)	F Statistic
Gold	4	(4,0,1,0,2)	7.7896***
Silver	4	(4,2,0,0,2)	27.9214***
Copper	4	(2,1,1,1,0)	8.9661***
Critical Values For F Statistic		Lower Bound, I0	Upper Bound, I1
	10%	2.45	3.52
k=4	5%	2.86	4.01
	1%	3.74	5.06

Note: *, **, *** denotes 10%, 5%, 1% significance level respectively

Table 3
Long-run elasticities results

	Coefficients		
Variables	Gold (4,0,1,0,2)	Silver (4,2,0,0,2)	Copper (2,1,1,1,0)
Oil	0.0053	-0.1176**	-0.0369
US Dollar Index	-0.2553	9.0272***	5.7657***
SP500	0.2338**	0.2256	0.8271***
US 10Y Bond Yield	0.0512*	0.1819***	0.0046
C	0.00007***	0.0001***	0.000005***

Note: *, **, *** denotes 10%, 5%, 1% significance level respectively

years bond yield leads to an increase in the volatility of gold by 0.05%, and silver by 0.18%.

Table 4 summarized the estimation results of the short-run ARDL model for each metal market volatility. As can be seen from the table, in the short run, the volatility of world oil price, US dollar index, US 10 years bond, and S&P500 are positively and statistically significant in influencing the volatility of gold at least at 10% significant level. In the short run, the volatility of the US dollar index plays a major role in which a 1% increase in its volatility leads to an increase in the volatility of gold price by 1.27%. For the volatility of silver, only the volatility of world oil price and US 10 years bond yield are statistically significant, whereas the volatility of the US dollar index and S&P500 are not significant. In contrast, the volatility of copper is only significantly influenced by the volatility of S&P500.

The lag optimum of the short-run model is identified using the minimum value of the Schwarz criterion. Thus, the coefficient in Table 4 is representing the sum of the coefficient for all explanatory variables. In terms of error correction, the coefficients of the ECT for the volatility of gold, silver, and copper are -0.05, -0.32 and -0.03

Table 4
Short-run model results

	Independent Variables				
	Short Run				
Dependent Variable	Oil	US Dollar Index	SP500	US 10 Years Bond Yield	ECT(-1)
Gold	0.0074**	1.2698***	0.0225*	0.0502***	-0.0511***
Silver	0.1314***	6.1008	0.2499	0.3472***	-0.3225***
Copper	0.0091	0.5212	0.0347*	-0.0037	-0.0341***

Note: *, **, *** denotes 10%, 5%, 1% significance level respectively. The significant level is determined using the Wald statistic (joint restriction).

respectively and statistically significant at 1% significance level. This indicates that about 5%, 32% and 3% of the disequilibrium for gold, silver, and copper respectively are adjusted on the next day to meet the long-run equilibrium of the metal volatility.

Discussion

Since the sum of the two estimated ARCH and GARCH coefficients ($\alpha_1+\alpha_2+\beta_1+\beta_2$) is more than one for gold return series, this finding indicates that the conditional variance is exponentially increasing over time. The negative coefficient of γ (leverage effect) is statistically significant at a 1% confidence level indicates that negative shocks imply a higher next period conditional variance than positive shocks and leverage effect exist in gold returns series.

For the silver return series, the sum of the two estimated ARCH and GARCH coefficients ($\alpha_1+\alpha_2+\beta_1$) is closer to one in which indicates that conditional variance is persistent. The negative coefficient of γ (leverage effect) is statistically significant at a 5% level in which shows that the negative shocks imply a higher next period conditional variance than positive shocks and leverage effect exist in silver returns series. The same findings are found for copper return series in which shows that the two estimated ARCH and GARCH coefficients ($\alpha_1+\beta_1$) are closer to one indicates that conditional variance is persistent. The negative coefficient of γ (leverage effect) is statistically significant at a 1% significant level indicates that negative shocks imply a higher next period conditional variance than positive shocks and leverage effect exist in copper returns series.

The main results from Bound tests revealed that there was a long-run co-movement (cointegration) among all explanatory variables (the volatility of world oil price and US factors) upon the volatility of returns for gold, silver, and copper. This findings signal that all explanatory variables are moving together towards the long equilibrium of the volatility of return series for all precious metals, and therefore the investor can use this information to manage their risk and return of their investment portfolio in the precious metals. The investor also needs to observe the volatility of world oil price and US factors accordingly before making their investment decision in the potential precious metal.

SUMMARY AND CONCLUSIONS

The focal point of this paper is to model the volatility of returns for three precious metals by focusing on the role of world oil price and US factors volatility. The volatility model is estimated using the GARCH model in constructing the conditional variance, and then the ARDL model is used in modeling the determinants of volatility for the three precious metals.

The new findings of this study can be summarized into three aspects. First, there is a long-run co-movement (cointegration) between the volatility of all precious metal (gold, silver, and copper) on its determinants (volatility of world oil price and US factors). Second, in the long run, the effects of world oil price and US factors volatility upon the volatility of precious metals are differed according to the type of metal, and the volatility of the US dollar plays a major rule in influencing the volatility of silver and copper. Third, in the short run, the volatility of gold is statistically significantly influenced by the volatility of all explanatory variables, whereas the volatility of silver has only significantly influenced by the volatility of world oil prices and US government bonds. In addition, the volatility of copper only significantly influenced by the volatility of the US stock market.

However, there are some differences in this empirical study as compared with the previous study. For example, Batten et al. (2010) found that macroeconomic determinants (business cycle, monetary environment, and financial market sentiment) played a different role in the price volatilities of four precious metal (gold, silver, platinum, and palladium price). Gold volatility is shown to be explained by monetary variables, but this is not true for silver. Overall, there is limited evidence that the same macroeconomic factors are jointly influenced by the volatility process of the four precious metals. Another studied by Soytas et al. (2009) in Turkey argued that the movement of world oil prices had no predictive power of precious metal prices (gold and silver). Thus, these findings suggest that domestic gold is also considered a safe haven in Turkey during the devaluation of the Turkish lira.

The policy implications of this study can be summarised as follows. First, for the investors and market participants in the metal market, understanding the nature of volatility and its determinants are important in managing the risk and return of their investment portfolio, and also acts as a hedging instrument against the uncertainties of other financial assets and inflation. Second, for the central bankers, by understanding the nature of volatility and its determinant, this will help the monetary authority to intervene in the world metal market in stabilizing their international reserve and currency. For example, the central bank may also use gold to stabilize currency value during the high volatility of national currency due to speculative activities. Third, for the manufacturer especially silver and copper business-related companies, understanding the volatility and its determinant may help them to manage their inventory strategies for business activities.

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