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Volatility persistence and returns spillovers between oil and gold prices: Analysis before and after the global financial crisis

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ABSTRACT

This paper investigated volatility persistence and returns spillovers between oil and gold markets using daily historical data from 1986 to 2015 partitioned into periods before the global crisis and after the crisis. The log-returns, absolute and squared log-returns series of these asset prices were used as proxy variables to investigate volatility persistence using the fractional persistence approach. The Constant Conditional Correlation (CCC) modelling framework was applied to investigate the spillover effects between the asset returns. The volatility in the gold market was found to be less than that at the oil market before and after the crisis periods. The returns spillover effect was bidirectional before the crisis period, while it was unidirectional from gold to oil market after the crisis. The fact that there was no returns spillover running from oil to gold after the crisis suggested a measure of optimum allocation weights and hedge ratio. The results obtained are of practical implications for portfolio managers and decision managers in these two ways: gold market should be used as a hedge against oil price inflationary shocks; and the volatility at the oil market can be used to determine the behaviour of gold market.

1. Introduction

Recently, there has been a great increase in the literature on gold market dynamics. This is due to the recent global financial crisis that plunged the United States, the United Kingdom and other world economies into recession which forced investors to diversify their investment into gold. Also, the global demand for gold has increased as a result of the lesson learnt by investors (Apergis and Eleftheriou, 2016). There is equally a dynamic relationship between gold and oil prices, and this was more evident during the 2008–2009 crisis. Besides, modelling co-volatilities at oil and gold markets is important for international investors and portfolio managers since it helps to forecast the volatility evolution of the prices of those assets and implement the optimal portfolio and hedging strategies via the computation of spillovers between the markets.

Gold and oil are the most actively traded commodities in the world. Gold is noted as a store of wealth during periods of economic and political instability (Aggarwal and Lucey, 2007) and as a volatile monetary asset commodity (Batten et al., 2010; Lucey et al., 2013). The main importance of oil comes from the industrial perspective and the daily global consumption is about 90 million barrels[1]. For production process, it is a vital input of production and its price is driven by demand and supply shocks (Lombardi and Van Robays, 2011). For centuries, gold has been considered a leader in the precious metals market. It is an investment which is commonly referred to as a “safe haven” in high-risk financial markets. The price is less susceptible to exchange rate fluctuations, unlike oil prices, which depend significantly on the appreciation/depreciation of US dollars (Baur and McDermott, 2010).

Stock and oil price shocks have been found to greatly affect most of the world's economies. This has led to individuals and government agencies having to revert to investment in gold, since

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[1] See 2012 US Energy Information Administration Daily world oil consumption in millions of barrels.

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it is a durable commodity that does not lose value. Changes in oil price particularly have economic impact and these often raise serious concerns among policy makers around the world, as a result of its negative effect on net oil importing economies. Therefore, investors have shifted towards keeping gold as another source to invest instead of oil and stocks. One of the most obvious channels through which gold and oil markets could be linked together is through inflationary shocks (Hooker, 2002; Hunt, 2006). From the theory of macroeconomics, higher oil price often places upward pressure on the overall price level, particularly in the area of greater production and transportation costs. Then, inflationary expectations may lead investors to see gold as an alternative to oil, in order to hedge against the expected decline in the value of the investment on oil (Jaffe, 1989). Melvin and Sultan (1990) assert that political unrest and oil price changes are significant determinants of volatility in gold prices. Once there is high oil price at the market, the oil exporting countries generate more revenue. Since gold constitutes higher share of their respective portfolios, the demand for gold is pushed up and the price of gold at the market is pushed up. Ross (1989) claims that asset returns exert volatility which depends on the rate of information flow and this information can be incorporated into the volatility-generating process of another market. Different volatility patterns are expected since the information flow and the processing time vary across market. Fleming et al. (1998) argue that cross-market volatility can be employed to transmit information and cross-market hedging across markets over time.

Understanding the complex relationship between oil and gold, and/or with the rest of the economy is more important. This can be viewed in terms of prices (values at their levels) or looking at the variance and co-volatility, that is the anticipated volatility and shock spillovers between the returns of two financial asset prices. The uncertainties in shocks between a pair of these asset prices may be more prevalent, and understanding their possible implications will be of interest to both investors and policy makers (Salisu and Oloko, 2015). Therefore, stakeholders in these financial markets are usually concerned with the relationships among these prices, particularly the returns and shocks spillovers among them. The analysis of the spillover effects among asset prices provides useful information on how the fluctuations among returns, at mean and variance equations levels, will affect the economic activities and portfolios maximisation by the government and investors. Also, with the current bearish behaviour of oil price at the international markets, it is of interest to study the relationship between oil price and gold prices. We were motivated to look at this gap owing to the fact that oil prices affect gold prices both at price and variance series levels (Gil-Alana and Yaya, 2014).

This paper considered the persistence of volatility and returns spillover effects between the prices of oil and gold. The analysis was carried out for periods before and after the global financial crises. The fractional persistence approach and univariate volatility modelling were applied in measuring volatility persistence in the returns and conditional volatility series, respectively. The Constant Conditional Correlation (CCC) multivariate GARCH framework was used to study the spillovers/transmission of returns between the asset returns series.

The paper is structured as follows: Section 2, which comes immediately after this introduction, reviews the time series methodology applied in the paper, which includes the fractional persistence and multivariate GARCH modelling approaches. Section 4 presents the data, empirical analysis and the results. In Section 4, we infer from the results obtained in Section 5 the management of gold prices in the presence of oil risk; this is investigated using estimates of optimum portfolio weight and hedge ratio. Section 6 renders the concluding remarks and policy implications.

2. Review of relevant literature

Historical time series of international gold price has a close relationship with that of oil price, and different statistical tools have been employed to investigate this relationship (Aruga and Managi, 2011; Zhang and Wei, 2010; Chan et al., 2011). Lamoureux and Lastrapes (1990) aver that standard GARCH models tend to overestimate the underlying volatility persistence when a break is not allowed in the long time series. Bampinas and Panagiotidis (2015) examined the causal relationship between crude oil and gold prices during pre-crisis and post global crisis periods and found, for the pre-crisis period, that causality was linear and only runs from oil to gold, while, at the post global crisis period, the causality was nonlinear and bi-directional. Fernandez (2010) applied Geweke and Porter-Hudak's (GPH) semi-parametric method and periodogram regression-based method of fractional integration and found anti-persistence measure of gold returns. Chkili (2015) applied the bivariate Fractionally Integration GARCH (FIGARCH) model to investigate the dynamic relationship between the mean and variance time series of gold and oil prices. The results indicated the significant dynamic time varying correlation between the two markets and gold seemed to be less persistent.

There is the need to study the market surge between the two asset prices in terms of volatility using the variants of bivariate Generalised Autoregressive Conditional Heteroscedasticity (GARCH), with its univariate version proposed in Bollerslev (1986). This is the Multivariate GARCH (MGARCH) model with constant or dynamic conditional correlation and covariance matrices, such as the full parameterised BEKK model (Baba et al., 1989), the CCC or Dynamic Conditional correlations (DCC) model. These models are flexible and efficient in studying the time-varying correlations and returns spillover effects between two asset prices, which is not possible in the case of univariate GARCH modelling frameworks[2].

Choi and Hammoudeh (2010) applied the DCC model to study the time volatility and correlations in the returns of Brent oil, copper, gold and silver and the S&P500 index. They found increasing significant correlations among all the commodities since the 2013 Iraq war but decreasing volatility correlations into S&P500 index. Kiohos and Sariannidis (2010) explored, in the short run, the effects of oil and financial markets on the gold market. They used a GJR-GARCH model in testing the relationships between them using daily data from January 1, 1999 to August 31, 2009. Their findings showed that the oil market had positive influences on the gold market, and indicated volatility persistence in the gold market.

Singh et al. (2011) analysed the time-varying volatility in crude oil, heating oil, and natural gas futures market. They incorporated changes in important macroeconomic variables and major political and wealth-related events into the conditional variance equations. Their results showed that, among the macro variables considered, the spread between the 10-year and 2-year Treasury Constant Maturity rate had a positive relationship with the volatility of all commodities. Ciner et al. (2013) investigated return relations among stocks, bonds, gold, oil and exchange rates, taking data from the US and the UK. Their results showed significant relationship between oil and gold, whereas weak relationship was found in the case of gold with both UK and US exchange rates. Owing to this fact, gold was placed as a safe-haven commodity against exchange rate shocks, while it was not placed as a safe-haven commodity against oil price shocks.

Ewing and Malik (2013) considered daily samples between July 1993 and June 2010 for multivariate GARCH models in order to

[2] See Baba et al. (1989), Bollerslev (1990), Engle (2002), Engle and Ng (1993), Engle and Kroner (1995), Kroner and Ng (1998) and Tse and Tsui (2002).

examine the volatility transmission between gold and oil futures, incorporating structural breaks. They found strong evidence of significant volatility transmission between gold and oil price returns in the presence of structural breaks. Mensi et al. (2013) applied VAR-GARCH to investigate the returns and volatility transmission between the S&P500 and commodity price indices for energy, food, gold and beverages for the period 2000- 2011.They found significant volatility transmission between the S&P500 and commodity markets. The results further revealed highest correlation between the S&P500 index and gold prices, and between the S&P500 index and WTI oil price. Shams and Zarshenas (2014) found evidence of co-movements in gold, oil prices and exchange rates based on copular functions and applications of GARCH models.

3. Methodology

3.1. Long memory process and fractional persistence technique

Granger and Joyeux (1980) and Hosking (1981) define long memory process[3] for both time and frequency domain approaches. The time domain uses a stationary time series process X_t with an autocovariance function

$$\gamma(k) = Cov(X_t, X_{t+k}) = E(X_t, X_{t+k}) \tag{1}$$

at lag k that is independent of t, then long memory exists if,

$$\gamma(k) \sim c_\gamma k^{2d-1}, \quad \text{as } k \to \infty \tag{2}$$

for $0 < d < 0.5$, where d is the memory (differencing) parameter or the fractional difference parameter. The constant c_γ is positive finite, $0 < c_\gamma < \infty$. Therefore, as the number of lags increases to infinity, the dependence between events apart diminishes very slowly in an hyperbolic decay. Short-range dependence is characterised instead by quickly decaying correlations at an exponential rate to zero as in Autoregressive Moving Average (ARMA) and Markov processes. The asymptotic behaviour in definition (2) means that the autocovariances are not summable, that is,

$$\lim_{n\to\infty} \sum_{k=-\infty}^{\infty} \gamma(k) = \infty \tag{3}$$

In the frequency domain, long memory process is then defined as:

$$f(\lambda) \sim c_f |\lambda|^{-2d}, \quad as\ \lambda \to 0 \tag{4}$$

implying that the spectral density will be unbounded at low frequencies. For example, at $\lambda = 0$, there is a blow-up of the spectral density $f(\lambda)$ at the origin and this implies having a pole at frequency zero, that is,

$$f(0) = \frac{1}{2\pi} \sum_{k=-\infty}^{\infty} \gamma(k) = \infty \tag{5}$$

Different estimation methods for estimating and testing the fractional persistence parameter have been proposed in the literature. These are classified as non-parametric, semi-parametric and parametric methods. In this paper, both semi-parametric and parametric methods were employed. Two semi-parametric methods were first applied in estimating the differencing parameters. These were the log-periodogram regression and the local Whittle estimation, also known as the Gaussian semi-parametric estimation methods. Initially, the log-periodogram method was proposed in Geweke and Porter-Hudak (1983), but a refined version of the estimator is given in Robinson (1995a).[4] The method defines the spectral ordinates $\lambda_1, \lambda_2, \dots, \lambda_m$ from the periodogram of X_t that is $I_X(\lambda_k)$, and $k = 1, 2, \dots, m$, where m, a bandwidth which increases slowly with n. The log-periodogram regression is then given as:

$$\log\left[I_X(\lambda_k)\right] = a + b\log(\lambda_k) + v_k \tag{6}$$

where v_k is assumed to be i.i.d. Then, the differencing parameter is estimated from the least square estimator $\hat{b}$ as:

$$\hat{d} = -\frac{1}{2}\hat{b} \tag{7}$$

This estimator is asymptotically normal and correspond to the theoretical standard error $\pi(2\pi m)^{-1/2}$. The Gaussian semi-parametric estimation is based on local Whittle estimator of Kunsch (1987), which is further developed in Robinson (1995b). In the frequency domain, the authors defined,

$$I(\lambda_k) \sim e^{f(\lambda_k)^{-1}} \tag{8}$$

with $\theta = (C, d)$ and at zero frequency,

$$L(C, d) = \sum_{k=1}^{m}\left[\log C - 2d\log(\lambda_k) + \frac{I(\lambda_k)}{C\lambda_k^{-2d}}\right] \tag{9}$$

By minimisation, we obtain the Gaussian semi-parametric estimator as,:

$$\hat{d} = \arg\min\left(\log\left\{m^{-1}\sum_{k=1}^{m}\left[\frac{I(\lambda_k)}{\lambda_k^{-2d}}\right]\right\} - 2dm^{-1}\sum_{k=1}^{m}\log(\lambda_k)\right) \tag{10}$$

Robinson (1995b) notes that this estimator is consistent for $d \in (-0.5, 0.5)$. Although the log-periodogram regression approach is widely applied, its consistency at nonstationary range, $d \geq 0.5$, is far less than that of the Gaussian semi-parametric approach.[5]

3.2. Multivariate volatility modelling

Following Bollerslev (1990), we define a bivariate CCC-MGARCH model specification involving two asset returns, A and B, for both conditional mean and variance equations thus:

$$r_t = \Phi + \Theta r_{t-1} + \varepsilon_t, \quad \varepsilon_t = D_t z_t \tag{11}$$

where $r_t = (r_t^A, r_t^B)'$ with r_t^A and r_t^B being the returns on asset price A and B at time t, respectively; Θ is a (2×2) matrix of coefficients of the form $\Theta = \begin{pmatrix}\theta_{11} & \theta_{12}\\ \theta_{21} & \theta_{22}\end{pmatrix}$; Φ is a (2×1) vector of constant terms of the form $r_t = (\phi^A, \phi^B)'$; $\varepsilon_t = (\varepsilon_t^A, \varepsilon_t^B)'$ with ε_t^A and ε_t^B being the error terms from the mean equations of the two asset markets, A and B, respectively; $z_t = (z_t^A, z_t^B)'$ is a (2×1) vector of independently and identically distributed errors[6]; and

[3] Long memory is often used interchangeably as long-range dependence, strong dependence or persistence. This is a special case of fractional dependence $-0.5 < d < 0.5$; hence long memory is a subset of this range.

[4] The version of the GPH estimator by Robinson (1995a) is implemented in statistical packages for computing fractional dependence parameters.

[5] Extensions of the log-periodogram and Gaussian semiparametric methods can be found in Velasco (1999a, 2000) for the log-periodogram estimate, and in Velasco (1999b), Velasco and Robinson (2000), Phillips and Shimotsu (2004, 2005), Abadir et al. (2007) and others for the Gaussian semiparametric method.

[6] Note, z_t can follow normal, Student t or Generalised Error distributions, and we assumed normal distribution in this work.

$D_t = diag\left(\sqrt{h_t^A}, \sqrt{h_t^B}\right)$ with h_t^A and h_t^B being the conditional variances of r_t^A and r_t^B, respectively. The parameters θ_{12} and θ_{21} in the matrix Θ then measures the return spillover effects from asset price B to asset price A, and asset price A to asset price B, respectively.

The variance equation is specified as:

$$H_t = D_t' z_t z_t' D_t = D_t' R D_t = \sqrt{h_t^A} \rho_{A,B} \sqrt{h_t^B} \quad (12)$$

where D_t is as defined earlier in the mean specification with h_t^A and h_t^B defined as any univariate GARCH(1,1) variant,

$$h_t^i = \omega^i + \alpha^i \varepsilon_{t-1}^2 + \beta^i h_{t-1}^i \quad (i = A, B) \quad (13)$$

where $\omega > 0$, $\alpha \geq 0$ and $\beta \geq 0$ are the parameters in the model, conditioned in order to realise stationary and mean reverting conditional volatility of the shocks in the return series. Since the shock reverts itself to a more stable state, we obtain the persistence of volatility for each conditional variance series and half-life thus:

$$\text{Persistence} = \alpha + \beta \quad (14)$$

$$\text{Half–life} = \ln(0.5)/\ln(\alpha + \beta) \quad (15)$$

The smaller the persistence, the smaller the market volatility and half-life gives the period of time the persistence of volatility is halved.

In modelling CCC-MGARCH specification, apart from the preliminary exploratory data analysis, tests for serial correlation and ARCH effects, the CCC specifications tests are necessary. These are tests for asymmetry and CC tests. The asymmetry test is the sign and size bias test of Engle and Ng (1993) that set the null hypothesis of symmetric model specification against the alternative of asymmetric specification. In a case where asymmetry is present, we consider the Glosten, Jaganathan and Runkle (GJR-GARCH) specification of Glosten et al. (1993):

$$h_t^i = \omega^i + \alpha^i \varepsilon_{t-1}^2 + \beta^i h_{t-1}^i + \gamma^i I_t^i \varepsilon_{t-1}^2 \quad (i = A, B) \quad (16)$$

where $I_t^i = 1$ if $\varepsilon_{t-1}^i < 0$ and $I_t^i = 0$, otherwise. If γ^i is positive and statistically significant, it implies that negative shocks increase the volatility of the series more than positive shocks of the same magnitude.

The CCC test of Engle and Sheppard (2001) allows one to make a choice between CCC and Dynamic Conditional Correlation (DCC) model of Engle (2002). The DCC model allows for dynamic correlation, that is, R_t (in (2)), hence we re-write,

$$H_t = D_t R_t D_t \quad (17)$$

then,

$$R = D_t^{-1} H_t D_t^{-1} = \left\{ diag\left(\sqrt{h_t^A}, \sqrt{h_t^B}\right) \right\}^{-1} H_t \left\{ diag\left(\sqrt{h_t^A}, \sqrt{h_t^B}\right) \right\}^{-1} \quad (18)$$

and, $H_t = (1 - \pi_1 - \pi_2) H_0 + \pi_1 \varepsilon_{t-1} \varepsilon_{t-1}' + \pi_2 H_{t-1}$, where π_1 and π_2 are the parameters to deal with the effects of previous shocks and previous dynamic conditional correlations on the current dynamic conditional correlation, and these scalar parameters are non-negative, and H_0 is the unconditional variance computed as:

$$H_0 = \omega / (1 - \alpha - \beta) \quad (19)$$

By imposing the restriction $\pi_1 = \pi_2 = 0$, H_t in (20) reduces to a constant, H_0.

3.2.1. Estimation approach

Given a sample of N observations, the parameters of thee bivariate CCC and VARMA-MGARCH model are estimated by maximising the log-likelihood function:

$$L(\Theta) = \sum_{t=1}^{N} l_t(\Theta) = -N \ln(2\pi) - \frac{1}{2} \sum_{t=1}^{N} \ln\left|H_t(\theta)\right| - \frac{1}{2} \sum_{t=1}^{N} \varepsilon'_t(\theta) H_t^{-1} \varepsilon_t(\theta) \quad (20)$$

where θ is the parameter vector of the model. The log-likelihood function is maximised by Berndt et al. (1974) algorithm and parameter vector, θ estimated via quasi maximum likelihood estimation.

4. Data, empirical analysis and discussion

The data considered in this paper were the daily time series of gold and crude oil close prices, given in US dollars per troy ounce and US dollars per barrel, respectively. The gold prices were the set prices at London Bullion Market Association (LBMA), while crude oil prices were the prices at the West Texas Intermediate (WTI) market. Both series were retrieved from Federal Reserve Bank of St. Louis online database at www.stlouisfed.org. The LBMA and WTI markets were considered since these are well known international markets for the pricing of the two asset prices. Data spanning between 2 January 1986 and 8 September, 2015 were obtained.

Plots of gold and oil prices are given in Fig. 1. Abreak date corresponding to the onset of global financial crisis on the oil price was observed. This date was around February 2008 based on our data, and this partitioned the graph into panels A and B, corresponding to pre- and post-global financial crisis. Steady fluctuations in the gold prices before the global crisis were observed, whereas these prices fluctuated quite more after the crisis. Differences in the fluctuations in prices of oil before and after the crisis were not observed.

These fluctuations are the volatilities in prices experienced over time, and these are better observed in the log-returns series. Investors and stakeholders are interested in market stability than actual prices. Fig. 2 presents the plots of the returns for the two asset prices. By placing the two plots on the same time series scales, as observed on the left for gold returns and on the right side for oil returns, less turbulence was found for gold returns, implying lesser volatility across the time points. When panels C

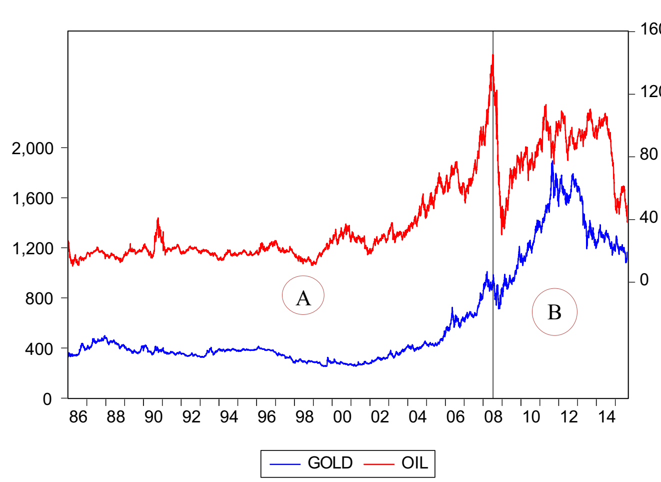

Fig. 1. Plots of daily gold and oil prices.