Volatility spillover and volatility impulse response functions in crude oil, gold and exchange markets

Preliminary and uncompleted version

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Abstract

This paper investigates the existence of volatility transmission among oil, gold and exchange markets and quantifies the persistence and dynamic adjustment of volatility and co-volatility of these markets in response to a financial historical shock. To do so, we apply a VAR-BEKK, along with a volatility impulse response functions (VIRFs), developed by Hafner and Herwarts (2006), to the above markets using weekly data from 6 January 1995 to 4 January 2013. We find the evidence of meteor shower and head wave effects among the three markets. While there is a spillover transmission from oil and exchange markets to the gold market, the reverse is not true. In response to the 2008 financial shock, we observe a positive and large volatility and co-volatility in the three markets. However the impact of the shock on the oil and gold volatilities is more sizable compared to its impact on the exchange volatility. Our finding also shows that the oil market has a leading position in absorbing the financial market shock.

Key words: Volatility transmission, VIRF,Crude oil, Gold and Exchange rate,
JELClassification : C58,C15,G1

Introduction

Undoubtedly, new developments in information and trading technologies have increased the integration of international financial markets in the world. This in turn has generated interest in examining the volatility transmission of financial market across markets. Although, the idea that volatility in one market may spill over to another is not new, investigating the volatility transmission mechanism, measuring the amount of persistency of volatility spillover, dynamic causality and predictability of volatility from one market to another market, are interesting subjects much paid attention in recent years.

Recent turmoil in oil and gold markets has sparked renewed interest in studying the behavior of these strategic commodities and their interactions. Most of studies in general concentrated on the several channels that directly or indirectly link the two commodity markets. First, while Oil is the most traded and volatile commodity and has crucial role in world economy fluctuations, a sharp and permanent increase in oil prices can be accomplished by lower economic growth and hence lower share prices. Consequently investors look for gold as an alternative asset in order to reserve value and this in turn causes gold price hikes. Second, the other linkage originates from inflation. Higher oil prices lead to higher production and transportation cost and hence push general price level up. Since gold is a good, its price also rises. In addition, Gold is commonly known as a "safe haven" to avoid high risk in financial markets and thus one of risk management tools in hedging and diversifying commodity portfolios. In this regard, gold is a commodity to hedge against inflation and has the value-preserving ability (for example see, Ghosh et al (2004),worthington and Pahlavani (2007), Blose (2010), Wang et al (2011)). (see Jaffe (1989)) (Hooker (2002) and Hunt (2006)) . (Pindyck and Rotemberg (1990)) (Kolluri (1981), Chua and Woodward (1982)) . Third, since oil and gold prices are denominated in the dollar currency, the exchange rate is another source of volatility that may also co-drive both these commodities instantaneously. This notability justifies with two reasons: first, since oil prices are denominated in the dollar currency, a deteriorating dollar against the euro can push up oil prices. Second, the physical assets, particularly gold, have the ability to resist changes in the internal and external purchasing power of the domestic currency. In this regard, Investors move from dollar-denominated soft assets to dollar-denominated physical assets during expected inflation to preserve their purchasing power from expected decline in the value of money (see Jaffe, 1989). Sari et al, 2010). Forth, linkage between gold and oil markets is provided by Melvin and Sultan (1990). Observing that oil exporting countries keep gold in their international reserves and it has a significant share in their asset portfolios, they assert that rising oil prices increases oil revenues for oil exporting countries; demand for gold increases by oil exporters and as a result gold price goes up.

Apart from price and return time series co-movements analyses that have a majority in recent studies, the time series relationship among higher moments of the oil and gold and exchange rate markets also deserves an examination because volatility transmission among the three markets seems to be important and common way that explains the flow of information among the oil and gold and exchange markets. Indeed, volatility spillover is the process in which volatility in one market affects those of other markets (Ross 1989, Eun and Shim, 1989 and So, 2001 and Ewing and Malik, 2013).In this context, volatility transmission among the three markets are not only relevant in valuation, portfolio selection, and risk management, but also has an important role in designing optimal hedging strategies for futures and options. In this regard, option and future prices in the one market are influenced by the degree of persistent in volatility in the other markets generated by an unexpected shock that fall down in these markets. As pointed out in Pindyck 2004, if changes in volatility are very persistent, then they will lead to changes in the prices of options and other derivatives that are tied to the prices of these commodities. But if changes in volatility are highly transitory, they should have little or no impact on market variables or option values. On the other hand, since the futures and options are priced according to the distributional properties of the returns and volatilities in these markets, having ability for forecasting the distribution of volatility gives crucial information for option traders for option pricing and risk management activities.

With these in mind, we focus on uncovering the interdependencies in volatility transmission among the oil, gold and exchange rate markets. (Highlighting the contribution of the paper) In this vein, we aim to answer the following questions: first, what is the pattern of volatility spillover among the markets? Second, how a shock to one market does influence the dynamic adjustment of volatility to the other markets. Third, how amount of these transmissions effects is persistence? And finally, whether having a forecast of volatility distributions in the three markets does help investors in managing risk activities or not?. To do so, we apply a VAR-BEKK, proposed by Engle and Korner (1995), along with a volatility impulse response function (VIRFs), developed by Hafner and Herwarts (2006), to the oil, gold, and Dollar-Euro returns using weekly data from 6 January 1995 to 4 January 2013. Using VAR-BEKK formulation enables us to reveal the transmission of volatility in the within and across the three markets. The existence of volatility transmission across the markets in the financial literature is called “meteor showers” denoting information flows from one market to another (see Engle 1990). Using this approach also enables us to investigate the existence of any “heat waves” indicating that the volatility in one market is more persistent (see Engle 1990). Applying VIRF to the three time series returns allows us to track precisely how a shock to one market influences the dynamic adjustment of volatility in the other markets. In this regard, we analyze the effects of a historical shock, financial crisis of 2008, followed by a creation of empirical distribution of random shocks, on the volatility and co-volatility of the three markets.

The VIRF approach also allows us to calculate the distribution of volatility impulse-response of the markets by using a non-parametric method and hence forecast the distribution at any desired time horizon. As pointed earlier, forecasting the distribution of volatility gives convenient time information on risk management to participant investors in these three markets.

The rest of the paper is organized as follows. Section 2 provides the brief econometrics methodology of volatility Impulse response functions. Section 3 discusses the data, their dynamic interdependencies among returns and volatilities series. Section 4 outlines the estimation and empirical results. Finally, the last section provides the concluding remarks.

1. Econometric methodology

Multivariate GARCH (MGARCH) models are common to estimate volatility spillovers among different markets. In this study, we employ a tri-variate VAR-BEKK in order to study interdependencies in the first and second moments.

1.1. Interdependencies in returns and volatilities

In order to explore the dynamics of dependencies and spillovers in returns, we employ a tri-variate VAR as follows

$$\boldsymbol{r}_t = \boldsymbol{\mu} + \Gamma_1 \boldsymbol{r}_{t-1} + \Gamma_2 \boldsymbol{r}_{t-2} + \boldsymbol{\varepsilon}_t,\ \ \boldsymbol{\varepsilon}_t | \Omega_{t-1} \sim (\mathbf{0}, \boldsymbol{H}_t) \quad (1)$$

where $\boldsymbol{r}_t = [r_t^o, r_t^g, r_t^e]'$ is a 3×1 vector of return series for oil, gold, and USD/EUR exchange rate at time t respectively; $\boldsymbol{\mu}$ is a 3×1 vector of constants and specifies the unconditional mean; and Γ_1, Γ_2 are 3×3 matrices of coefficients. $\boldsymbol{\varepsilon}_t$ is a vector of residuals and defined as $\boldsymbol{\varepsilon}_t = \boldsymbol{H}_t^{1/2}\boldsymbol{z}_t$, where $\boldsymbol{z}_t$ denotes an i.i.d. random vector of dimension 3 with independent components, mean zero and identity covariance matrix. The market information available at time $t-1$ denoted as Ω_{t-1}. $\boldsymbol{H}_t$ is the symmetric matrix of conditional variances and covariances. Equation (1) is a general VAR model for the mean equation with two lags. We adopt two lags in our model to remove all autocorrelations and cross-correlations. We don't use more than two lags in order to reach convergence and avoid more estimation of parameters.

As the previous VAR model requires that we specify its conditional variance covariance matrix H_t, we utilize a BEKK (1, 1) proposed by Engle and Kroner (1995) with the following representation in order to model the volatility matrix

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

Where C is an 3×3 upper triangular parameter matrix and A and B are 3×3 parameter matrices. Matrix A measures the extent to which conditional variances are correlated with past squared unexpected returns and consequently the effects of shocks on volatility. At the same time, matrix B depicts the extent to which current level of conditional variance-covariance matrix is related to past conditional variance-covariance matrices. BEKK (1, 1) representation assures that H_t is a positive definite symmetric matrix. We consider student's t distribution for the conditional distribution of $\boldsymbol{\varepsilon}_t$ since data distributions are non-normal.

1.2. Volatility Impulse Response Functions (VIRFs)

We employ Hafner and Herwartz's (2006) methodology for the above estimated model to evaluate the dynamic impact of a historical shock on volatilities. VIRF approach is similar to Koop et al (1996) which regard a shock as being generated from the data generating process. VIRFs enable us to visually track the impacts of a specific historical shock and volatility spillovers between markets.

VEC model of the BEKK model in Eq. (2) proposed by Bollerslev et al (1998) as

$$vech(H_t) = vech(C) + R \times vech(\varepsilon_{t-1}\varepsilon_{t-1}') + F \times vech(H_{t-1}) \quad (3)$$

where $vech(\cdot)$ denote the operator that stacks the lower fraction of a 3×3 matrix into a $N^* = N(N+1)/2$ dimensional vector. R and F are $(N^*)^2$ parameter matrices, whereas $vech(C)$ contains N^* constant coefficients.

The VIRF is defined by Hafner and Herwartz (2006) as the expectation of volatility conditional on an initial shock and history, subtracted by the baseline expectation that only conditions on history, which can be shown as:

$$V_t(z_0) = E[vech(H_t)|\Omega_{t-1}, z_0] - E[vech(H_t)|\Omega_{t-1}] \quad (4)$$

in which z_0 is an initial specific shock hitting the system at time 0, estimated from $\boldsymbol{z}_t = \boldsymbol{H}_t^{-1/2}\,\boldsymbol{\varepsilon}_t$, Ω_{t-1} is the observed history up to time t−1, and $V_t(z_0)$ is the $N^* = N(N+1)/2$ vector of the impact of the identical and independent shock components of z0 on the t-step ahead conditional variance–covariance matrix components. For a BEKK (1, 1) model with the number of dimension equal to 3, there will be 6 components in the vech representation model of Eq. (4). Therefore, the first, fourth and sixth elements of $V_t(z_0)$ (denoted as $v_{1,t}, v_{4,t}$ and $v_{6,t}$ respectively (represent the reaction of the conditional variance of the first, second and third variable respectively to the shock, z0, that occurred t periods ago.

Applied to a BEKK (1, 1) and then the vech representation, the one-step ahead VIRF is obtained as:

$$V_1(z_0) = R \times \left(vech\left(H_0^{\frac{1}{2}} z_0 z_0' H_0^{\frac{1}{2}} \right) - vech(H_0) \right) = R D_N^{+} \left(H_0^{1/2} \otimes H_0^{1/2} \right) D_N vech(z_0 z_0' - I_N) \quad (5)$$

in which H_0 is the conditional variance–covariance matrix at initial time 0, D_N denotes the duplication matrix defined by the property $vech(Z) = D_N vech(Z)$ for any symmetric $(N \times N)$ matrix Z, D_N^+ denotes the Moore-Penrose inverse of matrix Z, I_N is the identity matrix, $\otimes$ is the Kronecker Tensor product and R is identical to that specified in Eq. (3). And for any $t \geq 2$, the VIRF is:

$$V_t(z_0) = (R+F)^{t-1} R D_N^{+} \left(H_0^{\frac{1}{2}} \otimes H_0^{\frac{1}{2}} \right) D_N vech(z_0 z_0' - I_N) = (R+F) \times V_{t-1}(z_0) \quad (6)$$

Eq. (6) shows that Hafner and Herwartz (2006) VIRF has the following distinctive properties in comparison with the traditional Choleski decomposition impulse response function analysis of the conditional mean in linear systems:

1. The VIRF is a symmetric function of the shock, as opposed to an odd function in the traditional analysis, which can be shown by the feature of $V_t(z_0) = V_t(-z_0)$.
2. The VIRF is not a homogeneous function of any degree, in contrast to the traditional linear analysis.
3. The VIRF depends on the history through the volatility state H_0 at the time when the initial shock occurs. In contrast, the traditional impulse response functions do not depend on the history of the process.
4. The decay or persistence of shocks is measured by the moving average matrices $\Phi_t = (R+F)^{t-1} R$, which is analogous to the traditional analysis.

2. Data

We employ weekly return series consisting of a total of 519 return samples transformed from daily prices of gold, oil, and USD/EUR exchange rate over the period 31 January 2003 to 4 January 2013. Raw data of daily prices (5-days per week) is converted to weekly return series in two steps. First, weekly prices are calculated by averaging five days a week. At the next step, all weekly prices are converted into a weekly return series, i.e. $r_t^i = \ln\left(P_t^i / P_{t-1}^i\right)$, for $T = 1,2,\ldots,T$, in which r_t^i is the returns for market i at time t, P_t^i is the current price, and P_{t-1}^i is the previous week's price. Gold price, quoted in US dollar per troy ounce, were downloaded from the website of the World Gold Council (http://www.gold.org). Daily crude oil price were obtained for the West Texas Intermediate (WTI) benchmark from NYMEX and it is expressed in US dollar per barrel. WTI crude oil price is a primary representative for determining the international crude oil benchmark price. The exchange rate, obtained from http://www.fxtop.com, is the value of the US dollar to one euro and a rise (fall) in exchange rate means depreciation (appreciation) of US dollar in this study. Weekly prices are shown in logarithmic format in fig. 1.

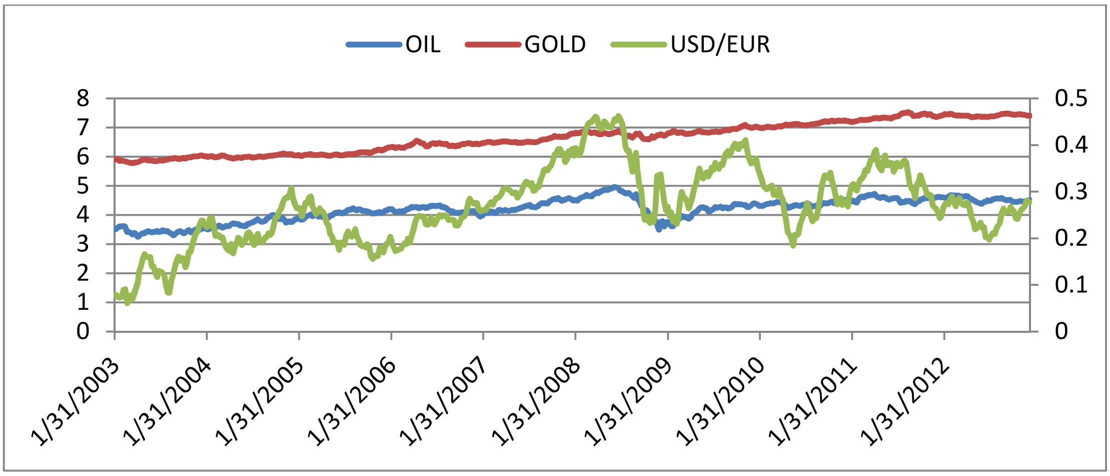
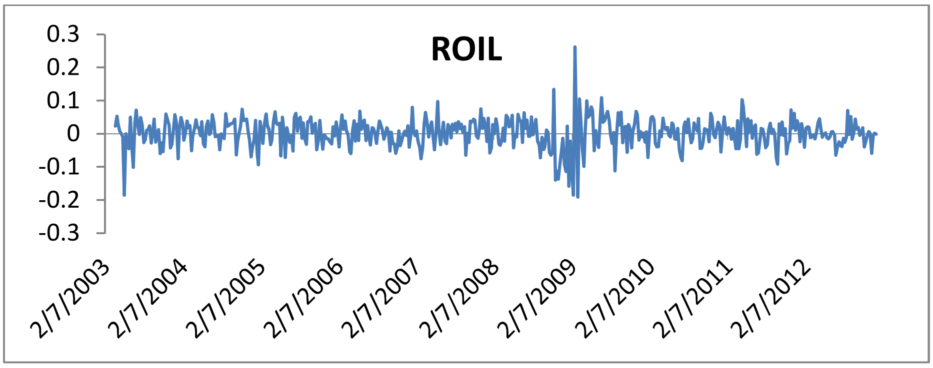


Fig. 1. Logarithmic weekly price of Oil, Gold, and Exchange rate

Descriptive statistics of the series are reported in Table 1. Oil has the highest volatility according to the minimum and maximum values of returns and comparing standard deviation of return series. The statistics relating to skewness, kurtosis, and J-B all reveal that none of these series is normal. Given the data characteristics, we adopt t-distribution for our analysis. Fig. 2 represents return series.

Table 1. Descriptive statistics

	ROIL	RER	RGOLD
Mean	0.001965	0.000384	0.002904
Median	0.005725	0.000577	0.004694
Maximum	0.261982	0.068819	0.087530
Minimum	-0.191006	-0.046249	-0.090478
Std. Dev.	0.043770	0.012135	0.022213
Skewness	-0.386474	-0.012997	-0.413008
Kurtosis	7.167606	5.011286	4.768425
Jarque-Bera	387.7745	87.32504	82.22449
Probability	0.00000	0.000000	0.000000
Sum Sq. Dev.	0.990467	0.076131	0.255092



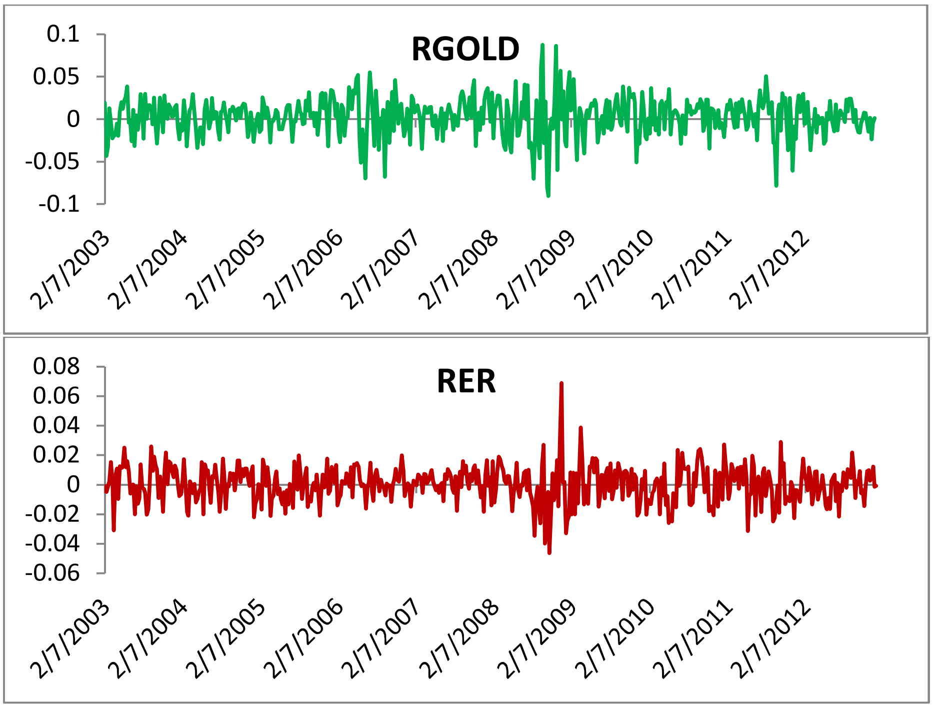


Fig. 2. Weekly returns of Oil, Gold, and Exchange rate

We employ the augmented Dickey and Fuller (1979) (ADF), Philips and Perron (1988) (PP), and Kwiatkowski et al. (1992) (Kwiatkowski, Philips, Schmidt, and Shin- KPSS) tests to find the order of integration for all three variables. Results are reported in Table 2. The ADF and PP tests reject the null hypothesis of unit root for all the return series and KPSS test for stationary shows that the return series are I(0) series.

Table 2: Unit root tests for crude oil, gold and exchange returnes

		ADF	PP	KPSS
Returns				
Intercept	ROIL	-11.16312***	-19.51685***	0.064678
	RGOLD	-18.41313***	-18.02213***	0.056865
	RER	-17.62007***	-17.60812***	0.127793
Intercept and trend				
	ROIL	-11.15566***	-19.50607***	0.034926
	RGOLD	-18.39559***	-17.99963***	0.056449
	RER	-17.63962***	-17.61503***	0.029448

3. Estimation and empirical results

We estimate equation 1, 2 jointly by maximum likelihood estimator assuming a conditional t student in disturbances. The model converges after 132 iterations and the final criterion was 0.0000019. The results of the full model shown by equations (1) and (2) are reported in table 3. In addition the diagnostic tests are also presented in Panel B and panel C of Table 3.

Table 3. The VAR-BEKK(2,1) model

Conditional mean equation

$$\boldsymbol{r}_t = \boldsymbol{\mu} + \Gamma_1 \boldsymbol{r}_{t-1} + \Gamma_2 \boldsymbol{r}_{t-2} + \boldsymbol{\varepsilon}_t$$

$$\boldsymbol{\mu} = \begin{bmatrix} 0.00362110 \\ (0.00160468) \\ \\ 0.00268365 \\ (0.00081281) \\ \\ 0.00058347 \\ (0.00047361) \end{bmatrix}, \quad \Gamma_1 = \begin{bmatrix} 0.22353893 & -0.03690973 & -0.02280136 \\ (0.04575792) & (0.08540464) & (0.16087266) \\ \\ -0.00535645 & 0.26740682 & -0.14245626 \\ (0.02019318) & (0.04609391) & (0.07611900) \\ \\ 0.00611142 & 0.05878610 & 0.19522495 \\ (0.01221526) & (0.02355786) & (0.04428602) \end{bmatrix}, \quad \Gamma_2 = \begin{bmatrix} -0.09961834 & -0.14137319 & 0.21212821 \\ (0.04620453) & (0.08695175) & (0.16410947) \\ \\ -0.01771548 & -0.07538420 & -0.00165452 \\ (0.02017260) & (0.04405854) & (0.07778724) \\ \\ -0.00094829 & -0.05087134 & 0.04457112 \\ (0.01234011) & (0.02380780) & (0.04690062) \end{bmatrix}$$

Panel B: Multivariate Q(40)= 373.07841 Significance Level as Chi-Squared(360)= 0.30629

Ljung-Box Q(40)	55.	40	39
p-value	(.051)	(.45)	(.48)
Jarque–Bera test	48	.87	10
P-value	(0.0)	(0.6)	(0.0)

Conditional variance-covariance structure

$$H_t = C'C + A'\varepsilon_{t-1}\varepsilon'_{t-1}A + B'H_{t-1}B$$

$$C = \begin{bmatrix} -0.00684633 & 0.00022040 & 0.00218140 \\ (0.00467140) & (0.00247395) & (0.00169401) \\ \\ 0 & 0.00284735 & -0.00045933 \\ & (0.00170920) & (0.00279675) \\ \\ 0 & 0 & 0.00000068 \\ & & (0.00459536) \end{bmatrix}, \quad A = \begin{bmatrix} 0.21722014 & 0.06317798 & 0.06165239 \\ (0.05512082) & (0.02647104) & (0.01382576) \\ \\ -0.04334961 & 0.34543488 & -0.00161071 \\ (0.10137065) & (0.05220617) & (0.03129849) \\ \\ -0.76396171 & -0.27329898 & 0.06234953 \\ (0.17837249) & (0.08667949) & (0.05304532) \end{bmatrix}, \quad B = \begin{bmatrix} 0.79020650 & -0.07027795 & -0.08027964 \\ (0.03546986) & (0.02150769) & (0.01122209) \\ \\ 0.03642883 & 0.94626150 & 0.03379347 \\ (0.06958834) & (0.02591323) & (0.01939319) \\ \\ 1.03770391 & 0.06726391 & 0.97894339 \\ (0.12328536) & (0.06356023) & (0.03736531) \end{bmatrix}$$

- Panel C:
- No GARCH $H_0: a_{ij} = b_{ij} = 0\ (for\ i, j = 1{,}2{,}3)$ [0.0000]
- Diagonal GARCH $H_0: a_{ij} = b_{ij} = 0\ (for\ i, j = 1{,}2{,}3\ \&\ i \neq j)$ [0.0000]
- Eigen values from BEKK-t student:
- 0.9651 0.94343 0.87+ 0.17i 0.87-0.17i 0.71+0.43i 0.71- 0.43i
- Log Likelihood 3985.1195
- the estimated degree of freedom of the Student distribution: 15
- p-value (0.0)

Note: Standard errors displayed as (.).

We first focus on evaluation of meteor shower and head wave effects among the mentioned three market. These are considered by testing on the form of the conditional covariance of A and B matrices and the persistence of estimated system captured by the eigenvalues of sum of A and B matrices. The null hypotheses of off-diagonality and the eigenvalues A and B matrices are reported in the lower panel of Table 3. The hypotheses of conditional homoscedasticity (no GARCH) and diagonality of A and B matrices(diagonal GARCH) statistically reject at the one percent level. The rejection of these hypotheses confirm the existence of Metero shower effect since this effect indicates the evidence of increased interdependence among the markets. The existence of Heats wave (persistency) effect can be understood from the eigenvalues of $A \otimes A + B \otimes B$ reported in the end of table 3. While all eigenvalues are less that unity in modulus, indicating the system in second moment are stationary, some eigenvalues are near to unity suggesting that there is a high level persistency in volatility transmission cross the three markets. The results of estimated A and B matrices also provide a good statistical description of the conditional mean and conditional variance-covariance processes characterizing oil, gold, and exchange markets. First, The significance of a_{12} and b_{12} suggests that there is a spillover from oil to gold in the second moment, confirming the theories behind their relationship. For example, this result support the evidence that gold as an asset can reserve value against high and sharp increase in oil prices. On the other hand, the significance of a_{13} and b_{13} shows spillover effect from oil to exchange market. This result was also predictable. Second, there is no significant spillover from gold to oil and exchange markets. This result suggests that the gold market is more affected by the oil and exchange market. Investors and speculators use gold as a hedge or safe haven in their portfolio, so changes in oil prices and exchange rates can be a stimulus for changes in gold price. Although we showed the spillover from oil to gold, we have not analyzed the spillover transmission from exchange rate to gold. And the last hypothesis concerns on the effect of exchange rate volatility on oil and gold markets. According to the results, there is a volatility transmission from exchange market to oil and gold market. This is a valuable result since this verifies the evidence that USD/EUR exchange rate affects the oil and gold prices since they are denominated in US dollar. These properties can be further apprehended through Fig. 2 and 3 in which we plot the time-variations of conditional variance and covariance estimated over the whole period for the oil, gold and exchange markets under investigation. Fig. 3 indicates that all markets show signs of volatility clustering and their volatilities, particularly, the volatility of oil and gold markets, have considerably increased during and the aftermath of the 2008 Financial Crisis. The oil market is more volatile and has the highest value of conditional variance in comparing to the other market over the whole period. More interestingly, the gold market has become more volatile after 2005. As we can see from Fig. 4 the conditional correlation of Gold and oil markets is more volatile and has the highest value in comparing to the other conditional correlation, particularly after 2005. These results may be interpreted with the general views that pointed out earlier. First, financial markets interdependency: cross-market hedging and sharing of common information can transmit volatility across markets over time, second, gold is commonly known as “safe haven”: gold is one of risk management tools in hedging and diversifying commodity portfolios. And finally: oil price-inflation link: an increase in oil prices via inflation channels increase gold prices.

Although our results may support the existence of volatility transmission among the three markets so far, those not clearly identify the dynamic adjustment and magnitude of spillover effects across the markets. In next section, using VIRF analysis we more precisely concentrate on the dynamic volatility transmission and magnitude of a shock from one market to the others markets.

Figure 3: The Estimated Conditional Variance

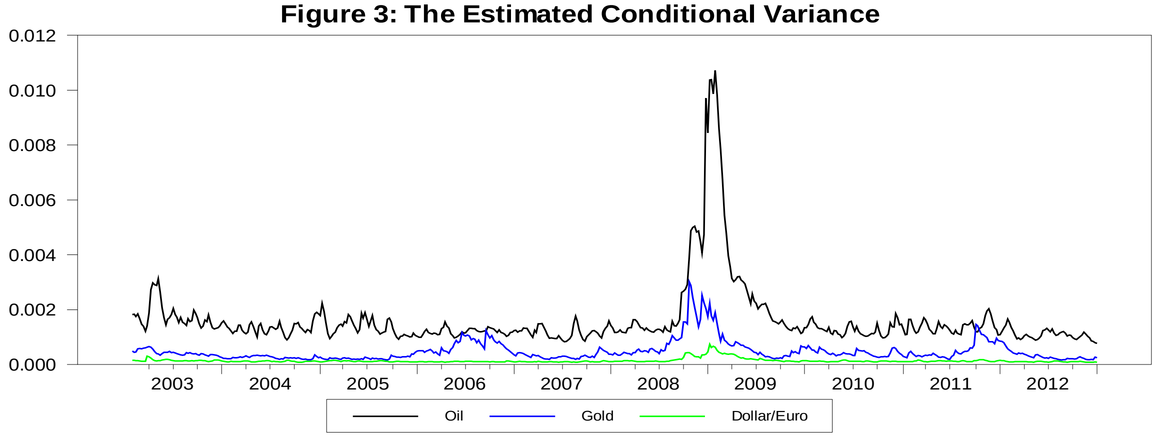
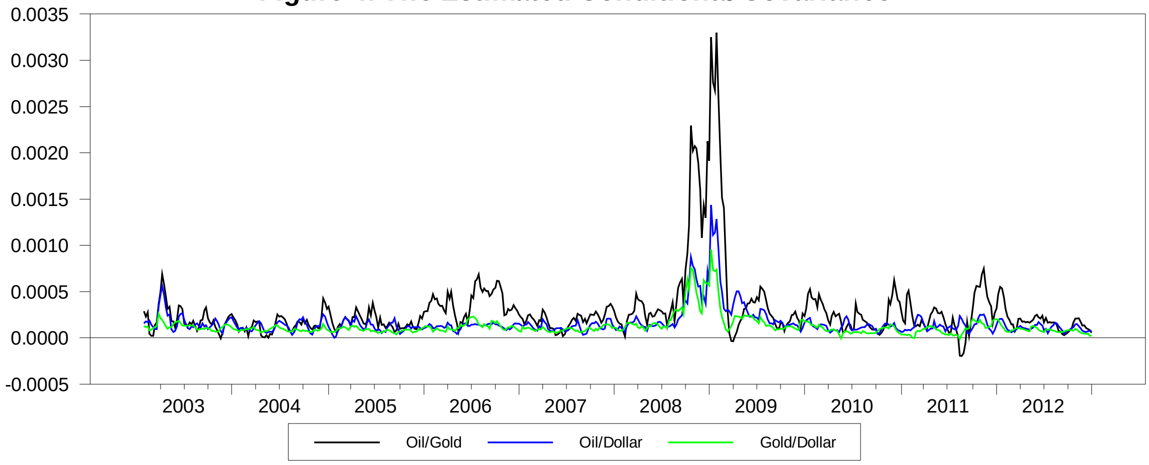


Figure 4: The Estimated Conditional Covariance



4. Volatility Impulse Response Analysis

In this section we undertake a more in-depth analysis of volatility transmission among the three oil, gold and exchange markets. We, more precisely, concentrate on the dynamic volatility transmission and magnitude of a shock from one market to the others markets. This can be examined by the volatility Impulse response Function explained in section 2.2. To do so, we focus on some informative historical shocks token place within our sample period. We consider the 2008 financial crisis as a historical shock and investigate the dynamic persistence and magnitude of shock on the volatility of three markets. Considering the 2008 financial crisis as a historical shock seems to be a convenient historical shock to our purpose in the study since this crisis is not only consistent in the financial markets but also it reflected in the commodity derivatives market. Although, there is negative correlation between the financial market and commodity markets, during the financial turmoil,l commodity markets attract more attention to the investors to hedge against the financial risk. Thus, the major effect of global financial turbulence has shown in the commodity markets especially on two commodities, oil and gold futures markets. The destructive potential of crisis, originated initially from the bankruptcy of the Lehman Brothers in USA on September 15, 2008. To estimate the initial historical shock $\boldsymbol{z}_t = \boldsymbol{H}_t^{-1/2}\ \boldsymbol{\varepsilon}_t$, we set t=15/9/2008 and consider the estimated residuals and the Vectorized conditional covariance matrix as $\widehat{\varepsilon_t} = (-.05, .06, .02)'$ and $vech(\widehat{\Sigma}_t) = (..16, .6, .9, .2, .3, .2)' \times 10^{-3}$,respectively. Having this initial shock and equations (5) and (6) we can derive the volatility impulse responses of the shock on the three markets.

Figs. 5 and 6 depict the volatility impulse response of conditional variance and conditional covariance of the markets to the financial crisis shock. According to Fig. 5 the shock has large and positive impact of the expected of conditional variances and co-variances. However, the magnitude of the impact is not the same for all markets. The impact of the shock on the oil and gold volatilities is more sizable compared to its impact on exchange volatility. The volatility in oil market immediately increases about 600% following Financial Crisis. Interestingly volatility of Gold market sluggishly starts its increase and reaches its maximum peak (about 300%) at 6 to 7 weeks. Similar Pattern can be seen in exchange market in response to the shock, however with relatively smaller in magnitude. This finding may reflect that the oil market has a leading role in absorbing news from the financial market. In this regard, gold and perhaps other commodity markets follow the oil market behavior in responding to the identified market shock.

The responses of conditional co-variances of markets are presented in Fig. 6. The conditional covariance of oil and gold markets starts its increase after 5 weeks. The finding again confirms that volatility transmission across markets is usually attributed to news and cross-market hedging which contemporaneously and dynamically changes expectations across markets. The conditional covariance of exchange rate and gold markets in response to the shock gradually increases and reaches its maximum point at 6 weeks. This result support this fact that the exchange rate is another source of volatility that may interconnects with the gold market. As pointed out earlier, during the 2008 Financial crisis, a sharp deterioration of dollar against euro stimulates investors to move from dollar-denominated soft assets to dollar-denominated physical assets to preserve their purchasing power from the expected decline in the value of dollars.

Fig.5: Conditional Variance Impulses Response(crisis 2008 Sep 15)

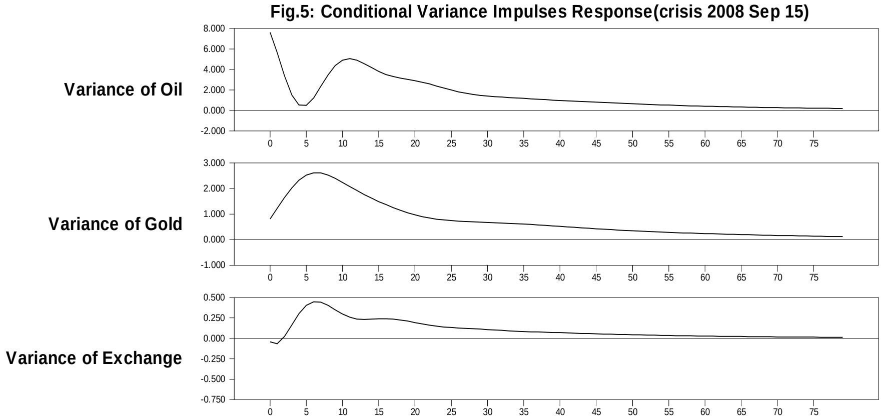
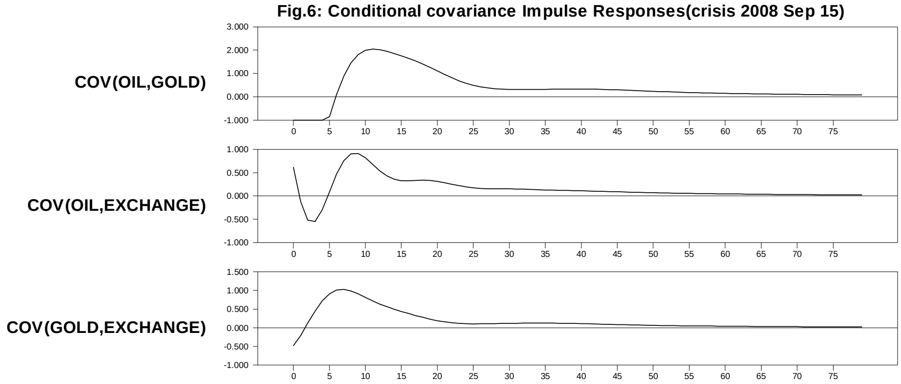


Fig.6: Conditional covariance Impulse Responses(crisis 2008 Sep 15)



4.1. Simulated VIRF distributions

Having demonstrated the impacts of historical events on expected conditional volatility, we now estimate hypothetical random shocks and their associated volatility impulse responses to uncover the volatility impact of possible future shocks. We fit the VIRF distribution, followed by the crisis, within the sample period.

I am writing this subsection.

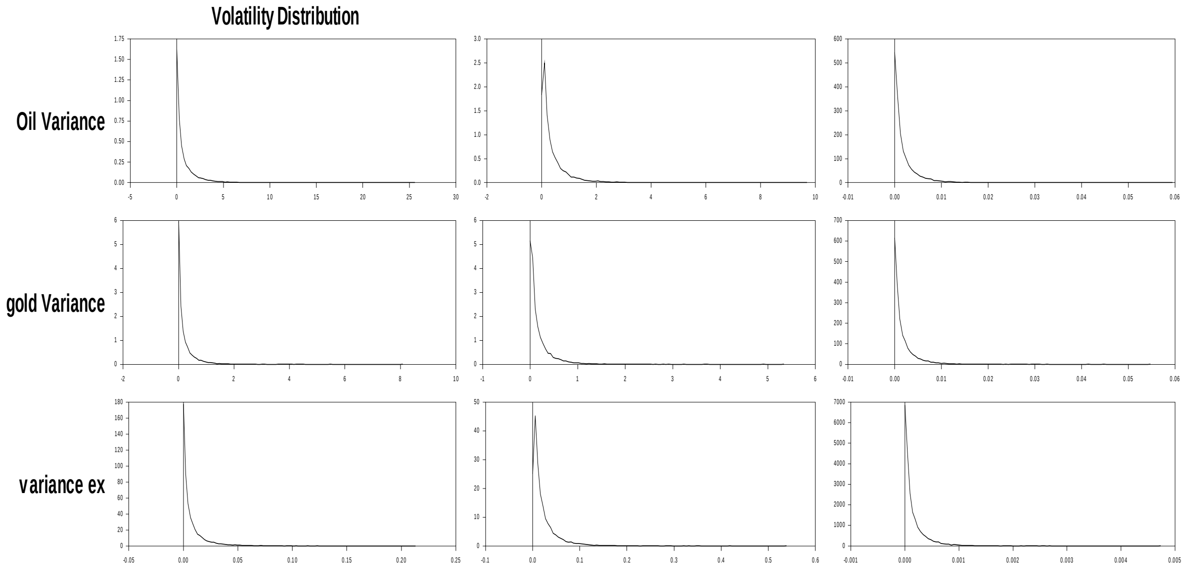


Figure 1

5. Conclusion

I am writing this section.

References