Volatility Transmission between Gold and Oil Futures under Structural Breaks

Bradley T. Ewing [a] and Farooq Malik [b]

Abstract:

This paper employs univariate and bivariate GARCH models to examine the volatility of gold and oil futures incorporating structural breaks using daily returns from July 1, 1993 to June 30, 2010. We find strong evidence of significant transmission of volatility between gold and oil returns when structural breaks in variance are accounted for in the model. We compute optimal portfolio weights and dynamic risk minimizing hedge ratios to highlight the significance of our empirical results. Our findings support the idea of cross-market hedging and sharing of common information by financial market participants.

JEL Classification: G1

Key Words: Volatility transmission, oil volatility, gold volatility, structural breaks, GARCH.

[a] Rawls Endowed Professor in Operations Management, Rawls College of Business, Texas Tech University, Lubbock, TX 79409-2101. Phone: 1-806-742-3939. E-mail: bradley.ewing@ttu.edu

[b] *Corresponding author.* Associate Professor of Finance, College of Business Sciences, Zayed University, P. O. Box 19282, Dubai, United Arab Emirates. Phone: 971-4-4021545. Fax: 971-4-4021010. Email: farooq.malik@zu.ac.ae

1. Introduction

Historically, economies have relied on oil for use in production, transportation and other energy related activities. Not surprisingly, oil related information such as production, prices, and futures are among the most widely watched of economic variables and indicators. Economic theories abound as to the role that oil plays in the performance of the overall economy and associated business cycles. Particular attention is often paid to the ways in which oil markets are tied to changes in consumer and producer prices. Interestingly, the role of gold prices is also often linked to output and prices. For example, gold is used in a number of productive capacities and has traditionally served as a hedge against inflation. It is therefore natural to expect that in asset pricing models the prices and/or volatilities of these two commodities could be linked. Moreover, while such a linkage or channel might exist, it is quite possible that the dynamics have changed over time particularly due to structural changes in the underlying economy or fundamentals that drive these two markets. Consequently, it is important to take into account the possible existence of sudden changes, or breaks, in the time series behaviors of these prices or their respective volatilities. This paper specifically examines the linkage that may exist between the volatilities in these assets prices allowing for sudden changes or regime shifts in variances. Knowledge about the accurate time series relationships between gold and oil markets will benefit financial market participants and policy makers alike.

A number of channels exist through which gold and oil markets could be linked together, the most obvious being inflation. Traditional macroeconomic models suggest higher oil prices place upward pressure on the overall price level particularly through greater production and transportation costs. A number of studies have confirmed the oil price – inflation link (e.g., Hunt, 2006; Hooker, 2002). Moreover, inflationary expectations may lead investors to purchase gold, a

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commodity, either to hedge against the expected decline in the value of money (see Jaffe, 1989) or to speculate on the associated increase in the price of gold.[1]

An alternative channel for establishing a relationship between gold and oil markets is provided by Melvin and Sultan (1990) who conclude that political unrest and oil price changes are significant determinants of volatility in gold prices. They reason that higher oil prices result in greater revenue streams for oil exporting countries. Consequently, since gold constitutes a significant share of their respective portfolios, this pushes up the demand for gold and leads to higher gold prices.

Additionally, Ross (1989) shows that volatility in asset returns depends upon the rate of information flow, suggesting that information from one market can be incorporated into the volatility generating process of the another market. Since the flow of information and the time used in processing that information varies across markets, one may expect different volatility patterns across markets. Similarly, Fleming, Kirby, and Ostdiek (1998) show that cross-market hedging and sharing of common information can transmit volatility across markets over time. Based on the above mentioned reasons, we would expect to find evidence of volatility transmission between the gold and oil markets.

The present paper studies the volatility dynamics of gold and crude oil futures using daily data from July 1, 1993 to June 30, 2010. We find significant structural breaks in volatility (i.e. volatility shifts) in both the gold and oil return series using modified iterated cumulative sums of squares (ICSS) algorithm. This is consistent with widespread evidence that variance in asset prices contain structural breaks (see Starica and Granger, 2005). We then introduce these structural breaks into univariate GARCH models to capture the true impact of news on volatility

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[1] Alan Greenspan has argued that gold is a "store of value measure which has shown a fairly consistent lead on inflation expectations and has been over the years a reasonably good indicator." (*Wall Street Journal*, Feb 28, 1994)

in each market and then into bivariate GARCH models to accurately estimate the volatility spillover dynamics across markets. We find strong evidence of significant transmission of volatility between gold and oil markets after structural breaks are incorporated into the model. We further show that some of these important dynamics would be overlooked if structural breaks are ignored in the model. Perhaps just as importantly, our results also indicate that volatility shifts have been more frequent over the recent global financial crisis and the great recession. Thus, recent economic and geo-political events have likely led to greater economic uncertainty, substantially affecting both gold and oil, and increasing the risk of investing in these markets.

Volatility in gold and oil prices is not only an important factor in derivative valuation and hedging decisions but also has significant consequences for broader financial markets as well as the overall economy. Volatility in oil prices directly impacts both consumer behavior and financial markets and thus affects the performance of the overall economy. Traditionally, gold is used as a hedge, and is often considered a useful indicator of future inflation, while gold also constitutes an important asset in a standard portfolio. Changes in the volatility of gold and oil prices can also affect the risk exposure of their producers and consumers potentially altering their respective investments in gold and oil. Asset volatility also determines the value of commodity-based contingent claims. Thus, correctly estimating volatility dynamics in gold and oil prices is important for building accurate pricing models, forecasting future price volatility and has implications for understanding broader financial markets and the overall economy.

2. Literature Review

Oil price volatility is an important input in modern macroeconometric models, financial market risk assessment calculations such as Value at Risk (VaR), and option pricing formulas for

futures contracts. Haigh and Holt (2002) analyze the crude oil contracts for their effectiveness in reducing price volatility for an energy trader. They find that modeling the time-variation in hedge ratios via multivariate GARCH methodology, which takes into account volatility spillovers between markets, results in significant reductions in uncertainty. Guo and Kliesen (2005) show that a volatility measure constructed using daily crude oil futures prices has a significant negative effect on future gross domestic product (GDP) growth. Malik and Hammoudeh (2007) use a multivariate GARCH model to find significant volatility and shock transmission among US equity, Gulf equity and global crude oil markets.

In a recent study, Driesprong, Jacobsen and Maat (2008) examine data from both developed and emerging markets to show statistically and economically significant predictability of stock returns when incorporating oil price changes in their model. Geman and Kharoubi (2008) examine the diversification effect from including crude oil futures into a portfolio of stocks and find that the desirable negative correlation effect is more pronounced in the distant maturity oil futures. Ewing and Malik (2010) using univariate GARCH models report that, contrary to previous findings, oil shocks have a strong initial impact on volatility but dissipate very quickly. They argue that understanding this behavior of volatility in oil prices is important for derivative valuation and hedging decisions. Wu, Guan and Myers (2011) using a volatility spillover model find evidence of significant spillovers from crude oil prices to corn futures prices and show that these spillover effects are time-varying. Based on this strong volatility link, they propose a new cross-hedging strategy for managing corn price risk using oil futures.

The literature examining gold market prices has also covered a number of different research areas. Cai, Cheung and Wong (2001) find that prices of gold futures have time varying volatility and that US announcements concerning GDP and inflation have a strong impact on

gold return volatility. Capie, Mills, and Wood (2005), using weekly data for a span of 30 years, find that gold has served as a hedge against fluctuations in the foreign exchange value of the dollar. Conover et al. (2009) present recent evidence on the benefits of adding gold to a U.S. equity portfolio. They report that adding a 25% gold allocation substantially improves performance of a portfolio and that gold provides a good hedge against the negative effects of inflationary pressures. Batten and Lucey (2010) investigate the volatility of gold futures using intraday data from January 1999 to December 2005 with GARCH methodology and find significant variation in volatility across the trading day. Baur and McDermott (2010) examine the role of gold in the global financial system using data from 1979 to 2009. They show that gold is both a hedge (not positively correlated with the stock market on average) and a safe harbor (not positively correlated with the stock market in a market crash) for major European stock markets and the US. They argue that gold may act as a stabilizing force for the financial system by reducing losses in the face of extreme negative market shocks and find that gold was a strong haven for most developed markets during the peak of the recent financial crisis.

Although numerous studies examine gold and oil individually, only a handful of studies examine them together, taking into account the potential for an economic link between the two markets. One such seminal work was by Melvin and Sultan (1990) who estimate the risk premium in gold prices with GARCH parameterization. They conclude that South African political unrest and changes in oil prices are significant determinants of variance in gold spot prices. Their work helped pioneer the incorporation of quantitative measures of political unrest in econometric models of asset price determination. In a more recent study, Hammoudeh and Yuan (2008) use univariate GARCH models to investigate the volatility properties of gold, silver, and copper. They find that monetary policy and oil shocks have a significant impact on gold prices.

Narayan, Narayan and Zheng (2010) examine the long-run relationship between prices of gold and oil futures of different maturities and report evidence of co-integration. They conclude that investors use the gold market as a hedge against inflation, and the oil market can be used to predict gold prices and vice versa. Sari, Hammoudeh and Soytas (2010) examine spot prices of gold and oil using the autoregressive distributed lag approach and find strong feedbacks in the short-run but a weak relationship in the long-run. The present paper fills a void in the existing literature by explicitly studying the volatility and shock transmission mechanism between gold and oil returns using recent daily data. Furthermore, our research allows for the possibility of structural breaks in volatility, a point that is particularly important given the evidence on political unrest/regime changes, geo-political events, financial and economic crises, that may mask or alter the inter-market relationships.

3. Empirical Methodology

This section documents how we detect structural breaks in variance. We also describe our univariate and bivariate GARCH models and discuss how we incorporate structural breaks into our models to illustrate the change in volatility dynamics.

3.1. Detecting structural breaks

A structural break in the unconditional variance will result in a structural break in the GARCH process (see Hillebrand, 2005). Inclan and Tiao (1994) provide a cumulative sums of squares (*IT*) statistic to test the null hypothesis of a constant unconditional variance against the alternative of a break in the unconditional variance. Their method is designed for iid processes, and Andreou and Ghysels (2002) and Sanso, Arrago and Carrionet (2004) show that the statistic is significantly oversized when used on a dependent process like GARCH. Fortunately, a

nonparametric adjustment can be made to the *IT* statistic which makes it appropriate for a dependent process like GARCH (Lee and Park, 2001; Sanso, Arrago and Carrionet, 2004).

Inclan and Tiao (1994) propose an iterated cumulative sums of squares (ICSS) algorithm which is based on the *IT* statistic for testing multiple breaks in the unconditional variance. Their algorithm can be applied to the modified *IT* statistic with the nonparametric adjustment to avoid the problems that occur when the standard *IT* statistic is applied to a dependent process. In the present paper, we apply the ICSS algorithm to the modified *IT* statistic for detecting structural breaks in the unconditional variance which is referred in the literature as the "modified ICSS algorithm." We use the usual 5% significance level to test for multiple breaks in the unconditional variance of return series.[2]

3.2. Univariate GARCH Model

We use the benchmark GARCH (1,1) model given as:

$$R_t = \mu + \rho R_{t-1} + \varepsilon_t \tag{1}$$

$$h_t = \omega + \alpha \varepsilon_{t-1}^2 + \beta h_{t-1} \tag{2}$$

where R_t represents the corresponding gold or oil return series and ε_t is normally distributed with a zero mean. h_t represents the conditional variance and depends upon the mean volatility level (ω), the news from previous period (ε_{t-1}^2), and the conditional variance from the previous period (h_{t-1}). The sum of α and β measures the volatility persistence for a given shock and most studies using high frequency financial time series data find this sum to be close to one, indicating that shocks are highly persistent. The Q-statistic detected significant autocorrelation in the gold and oil return series and thus an AR(1) specification was used in Equation 1. The modified ICSS

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[2] Interested readers are referred to Rapach and Strauss (2008) who provide a detailed description as they use this exact methodology to detect structural break points in the unconditional variance of exchange rates.

algorithm is applied to the residual series (ε_t) obtained from Equation 1 to detect break points in the variance.

3.3. Bivariate GARCH Model

Here we use the same mean equation as the univariate model but use the popular BEKK parameterization given by Engle and Kroner (1995) for the bivariate GARCH (1,1) model which is given as :

$$H_{t+1} = C'C + B'H_tB + A'\varepsilon_t\varepsilon_t'A \tag{3}$$

note that for our bivariate case C is a 2×2 lower triangular matrix with three parameters and B is a 2×2 square matrix of parameters which represents the extent to which current levels of conditional variances are related to past conditional variances. A is a 2×2 square matrix of parameters and measures how conditional variances are correlated with past squared errors. The elements of A capture the effects of shocks on volatility (conditional variance). For our bivariate case, the total number of estimated parameters is eleven.

Expanding the conditional variance for each equation in the bivariate GARCH (1,1) model gives:

$$h_{11,t+1} = c_{11}^2 + b_{11}^2 h_{11,t} + 2b_{11}b_{21}h_{12,t} + b_{21}^2 h_{22,t} + a_{11}^2 \varepsilon_{1,t}^2 + 2a_{11}a_{21}\varepsilon_{1,t}\varepsilon_{2,t} + a_{21}^2 \varepsilon_{2,t}^2 \tag{4}$$

$$h_{22,t+1} = c_{12}^2 + c_{22}^2 + b_{12}^2 h_{11,t} + 2b_{12}b_{22}h_{12,t} + b_{22}^2 h_{22,t} + a_{12}^2 \varepsilon_{1,t}^2 + 2a_{12}a_{22}\varepsilon_{1,t}\varepsilon_{2,t} + a_{22}^2 \varepsilon_{2,t}^2 \tag{5}$$

Equations (4) and (5) reveal how shocks and volatility are transmitted across the two series over time.[3] We use quasi-maximum likelihood estimation and the robust standard errors are calculated by the method given by Bollerslev and Wooldridge (1992).

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[3] The coefficient terms in equations (4) and (5) are a non-linear function of the estimated elements from equation (3). Following Ewing and Malik (2005), a first-order Taylor expansion around the mean is used to calculate the standard errors for these coefficient terms.

3.4. GARCH Models with Structural Breaks

Lamoureux and Lastrapes (1990) show that standard GARCH models overestimate the underlying volatility persistence and structural breaks should be incorporated into a GARCH model to get reliable parameter estimates. We augment our univariate GARCH model with structural breaks as:

$$R_t = \mu + \rho R_{t-1} + \varepsilon_t \tag{6}$$

$$h_t = \omega + d_1 D_1 + ... + d_n D_n + \alpha \varepsilon_{t-1}^2 + \beta h_{t-1} \tag{7}$$

where, following Lamoureux and Lastrapes (1990), and Aggarwal, Inclan, and Leal (1999), $D_1..., D_n$, are the set of dummy variables taking a value of one from each point of structural break in variance onwards and zero elsewhere.[4]

For our bivariate GARCH model, we follow Ewing and Malik (2005) and introduce a set of dummy variables to the model given in (3) such that:

$$H_{t+1} = C'C + B'H_t B + A'\varepsilon_t \varepsilon_t 'A + \sum_{i=1}^{n} D_i 'X_i 'X_i D_i \tag{8}$$

where D_i is a 2×2 square diagonal matrix of parameters and X_i is a 1×2 row vector of volatility break variables, and n is the number of break points found in variance. First (second) element in X_i row vector represents the dummy for first (second) series. If the first series undergoes a volatility break at time t, then the first element will take a value of zero before time t and a value of one from time t onwards.

4. Data

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[4] Lamoureux and Lastrapes (1990) note that standard errors can have a potential bias because "dummy variables do not satisfy the conditions necessary for the estimators to have the usual asymptotic properties". Following their approach of bootstrapping, we found the bias to be trivial and did not change our results reported in the paper. We also conducted Monte Carlo Simulations which conclude that adding dummy variables for volatility breaks results in correct parameter estimates. Detailed results of bootstrapping and simulations are available on request.

We use daily futures data for gold and crude oil from July 1, 1993 to June 30, 2010. Price for gold futures is for the nearest expiration contract on COMEX and the data was obtained from Bloomberg. Price for the crude oil futures is for the nearest expiration contract on NYMEX and the data was obtained from the U.S. Department of Energy.

Consistent with earlier research, returns are used as both series in level form possess a unit root. Table 1 gives descriptive statistics for both return series and shows excess kurtosis (i.e. fat tails). The correlation between both the return series in our sample is 0.20. A plot of gold and oil returns is shown in Figure 1 and Figure 2, respectively.

5. Empirical Results

The modified ICSS algorithm identifies nine structural break points for the gold series and seven break points for the oil series (see Table 2) and the corresponding volatility regimes (with bands at ±3 standard deviations) are shown in Figures 1 and 2. Not surprisingly, we note that shifts in variance are more prevalent during the period of the recent financial crisis. Also there appears to be some common variance shifts across both series as major events trigger a variance change in different markets simultaneously. For example, in early September 2008 the two series experienced a sudden increase in volatility simultaneously due to turmoil in financial markets. Political, economic, social or environmental events may coincide with these break points. However, markets may anticipate some events in advance or may take some extra time to respond to other events. Thus we do not expect breaks points reported here to precisely coincide with actual real world events. In this paper, we do not attempt to identify the causes of the break

points but instead focus on how these empirically detected break points affect volatility dynamics.[5]

Results obtained from estimation of our baseline univariate GARCH model are provided in Table 3. We found all parameters to be highly significant with a volatility persistence of 0.99 for the gold series and a volatility persistence of 0.98 for the oil series, if structural breaks are ignored. This high level of volatility persistence is consistent with earlier studies using high frequency data. We then incorporate the detected structural breaks into our univariate GARCH model by including a set of dummy variables in the variance equation. As can be seen from Table 3, the volatility persistence drops substantially for both gold and oil markets after accounting for structural breaks. The estimated half-life of shocks changes dramatically from about 69 days to about 5 days for gold and from 34 days to 3 days for oil. This implies that after accounting for breaks a shock is expected to lose half of its original impact in few days. Another interesting finding is that the ARCH coefficient, which measures the initial impact of news on volatility, has increased for both series after accounting for breaks although the overall volatility persistence has decreased.[6] This is consistent with what seems to be the general consensus among market participants that markets react relatively strongly to incoming news but absorb it fairly quickly. This is in line with the seminal work of Poterba and Summers (1986) who argue that shocks are generally short lived and is also consistent with Schwert (1989) who notes that increases in volatility around the October 1987 stock market crash returned to much lower levels after a very short period of time.

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[5] One should be cautious when looking at news reports for events surrounding these break points as there is a natural bias in media to always cite reasons for sudden market volatility even in cases where the market is adjusting to some previous news. A direction for future research could be to conduct event studies on the break points reported here to isolate their causes perhaps using intra-daily data.

[6] As a robustness check, we also estimated an asymmetric GARCH model and a GARCH-in-Mean model, and found that our results reported in this paper were unchanged. Detailed results are not reported but are available on request.

The log likelihood increased after accounting for structural breaks for both gold and oil series indicating that the models with structural breaks give a better fit. The significance of structural breaks is further supported by the likelihood ratio statistic (LR). The likelihood ratio statistic is calculated as LR = 2[L(Θ_1)-L(Θ_0)] where L(Θ_1) and L(Θ_0) are the maximum log likelihood values obtained from the GARCH models with and without structural breaks, respectively. This statistic is asymptotically χ^2 distributed with degrees of freedom equal to the number of restrictions from the more general model (with breaks) to the more parsimonious model (without breaks). We reject the null of no change even at the 1% significance level for both gold and oil models.[7]

While our intention is to model the volatility and shock transmission between gold and oil return series allowing for structural breaks, it is helpful to first examine the baseline case of the bivariate GARCH model without structural breaks which is reported in Table 4. Consistent with our univariate GARCH models, we find that both gold and oil volatility is significantly affected by news and volatility in its own market. However, it is interesting to find that volatility in either gold or oil markets is not directly affected by the news and volatility from the other market (Note that in the first (second) equation the coefficients for h_{22} (h_{11}) and ε_2^2 (ε_1^2) is statistically insignificant). However, we do find that volatility in oil market indirectly affects the volatility in gold market (Note that the coefficients for h_{12} is statistically significant in the first equation) while both news and volatility in gold market indirectly affects the oil market (Note that the coefficients for both h_{12} and $\varepsilon_1 \varepsilon_2$ is statistically significant in the second equation).

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[7] Another way to test model specification is to look at the statistical significance of the dummy variables. In our case, all 16 (9+7) dummy variables (except one) were significant at the conventional level (not shown) underscoring that the models with structural breaks are more appropriate than the models ignoring the breaks.

The results for the bivariate GARCH model after incorporating structural breaks are presented in Table 5. We still find that both the gold and oil volatility is affected significantly by news and volatility in its own market and similar indirect affects across markets exist. However, what is interesting is that we find that volatility in gold and oil markets is now *directly* affected by the volatility from the other market (Note that in the first (second) equation the coefficient for h_{22} (h_{11}) is statistically significant). The coefficients which capture the direct volatility transmission across markets are not only statistically significant but these coefficients are larger than before. We also note that own volatility impact in each market is smaller in size, consistent with our univariate GARCH results (see smaller coefficient for h_{22} (h_{11}) in equation 2 (1).[8] As explained in the introduction section, volatility transmission across markets is usually attributed to cross-market hedging and changes in common information which simultaneously changes expectations across markets as suggested by Fleming, Kirby, and Ostdiek (1998). Thus our results could be interpreted as an outcome of cross-market hedging undertaken by financial market participants within these markets.

The standard full battery of diagnostics was done on the residuals from all models reported. All diagnostic tests revealed no problems implying that the mean and variance equations were specified properly. This is an interesting finding which means that unless the researcher specifically tests for the possibility of structural breaks in variance, the structural breaks will be incorrectly ignored.

6. Some Economic Implications of the Findings

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[8] For multivariate GARCH models, the overall volatility persistence is calculated by summing all the ARCH and GARCH terms. We do not calculate and report the volatility persistence as some of the coefficients are insignificant and thus interpretation of volatility persistence by summation is not meaningful.

Our results have important economic implications because decisions regarding asset pricing, risk management and portfolio allocation require accurate estimation of conditional volatility. In order to understand the importance of conditional volatility regarding the above financial decisions, we follow the applications outlined by Kroner and Ng (1998).

First let us compute the optimal fully invested portfolio holdings subject to a no-shorting constraint. Portfolio managers encounter this problem when deriving their optimal portfolio holdings. Assuming that expected returns are zero, the risk minimizing portfolio weight is given as:

$$w_t = \frac{h_{22t} - h_{12t}}{h_{11t} - 2h_{12t} + h_{22t}}$$

assuming a mean-variance utility function, the optimal portfolio holding of the gold portfolio is given as w_t if $0 \leq w_t \leq 1$, 1 if $w_t > 1$ and 0 if $w_t < 0$. The optimal holding of the oil portfolio is $1 - w_t$. We found that the model that ignores structural breaks gives an average optimal weight of 0.854 while the model that incorporates structural breaks gives an average of 0.911. This example shows how our bivariate GARCH results could be used by financial market participants for making optimal portfolio allocation decisions and shows that the choice of the model matters in terms of optimal portfolio selection.

As another example, let us consider the problem of estimating the dynamic risk minimizing hedge ratio using both specifications of our bivariate GARCH model. Kroner and Sultan (1993) show that to minimize the risk of a portfolio an investor should short $\$\beta$ of the oil portfolio that is $1 long in the gold portfolio, where the 'risk minimizing hedge ratio' β is given as:

$$\beta_t = \frac{h_{12,t}}{h_{22,t}}$$

where $h_{12,t}$ is the conditional covariance between the gold and oil returns, and $h_{22,t}$ is the conditional variance of the oil returns. We found that the average estimated value of risk minimizing hedge ratio for our bivariate GARCH model without structural breaks is 0.032 compared to 0.067 for the model that accounts for structural breaks. For example, when holding a long position for $1000 in the gold portfolio, investors will short $32 using the model without structural breaks and $67 for the model with structural breaks. Clearly, the choice of the model affects the estimated hedge ratio and ignoring structural breaks will lead to wrong hedging decisions.

7. Summary and Concluding Remarks

This paper employs univariate and bivariate GARCH models to examine volatility dynamics of gold and oil futures taking into account the role played by structural breaks in variance. We detect the time periods of structural breaks in volatility of gold and oil returns endogenously using the modified iterated cumulated sums of squares (ICSS) algorithm using daily data from July 1, 1993 to June 30, 2010. We find strong evidence of direct significant transmission of volatility between the gold and oil markets. However, if we ignore structural breaks in variance, then we only find weak indirect effect between these two important markets. This paper makes a timely and essential contribution by studying the volatility dynamics of gold and oil markets. [9]

Understanding the behavior of volatility in gold and oil prices is not only important for derivative valuation and hedging decisions but also has significant consequences for broader financial markets and the overall economy. Since many different financial assets are traded based

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[9] The recent volatility in the gold and oil markets triggered CME Group Inc. (the largest futures exchange) on Oct 18, 2010 to introduce trading in the gold and oil futures contracts based on volatility indexes to "give global market participants tradable tools to express their opinions on the direction of the volatility of the markets."

on gold and oil, it is important for financial market participants to understand the volatility transmission mechanism over time and across these series in order to make proper decisions. We compute optimal portfolio weights and dynamic risk minimizing hedge ratios to highlight the significance of our empirical results. Our findings support the idea of cross-market hedging and sharing of common information by investors.

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Table 1
Descriptive Statistics

	Gold returns	Oil returns
Mean	0.0002	0.0003
Standard deviation	0.0105	0.0244
Skewness	0.1762	-0.1101
Maximum	0.0883	0.1640
Minimum	-0.0755	-0.1654
Kurtosis	10.1304	7.0677
Jarque-Bera	9040 (0.00)	2943 (0.00)
Q(16)	45.57(0.00)	37.93 (0.00)

Notes: The sample of daily returns covers from July 1, 1993 to June 30, 2010. The number of usable observations is 4257. Q(16) is the Ljung-Box statistic for serial correlation. Jarque-Bera statistic is used to test whether or not the series resembles normal distribution. Actual probability values in parentheses. The correlation between returns of gold and oil is 0.20.

Table 2
Structural Breaks in Volatility

Series	Break Points	Time Period	Standard Deviation
Gold Return	9	July 1, 1993- September 21, 1993	0.0137
		September 22, 1993- June 23, 1994	0.0073
		June 24, 1994- April 7, 1996	0.0045
		April 8, 1996- December 26, 1996	0.0030
		December 27, 1996- November 13, 2005	0.0093
		November 14, 2005- February 28, 2007	0.0146
		March 1, 2007- November 7, 2007	0.0091
		November 8, 2007- September 7, 2008	0.0149
		September 8, 2008- March 22, 2009	0.0245
		March 23, 2009- June 30, 2010	0.0108
Oil Return	7	July 1, 1993- August 25, 1994	0.0196
		August 26, 1994- January 8, 1996	0.0130
		January 9, 1996- July 12, 2005	0.0245
		July 13, 2005- October 18, 2007	0.0183
		October 19, 2007- September 10, 2008	0.0226
		September 11, 2008- April 22, 2009	0.0571
		April 23, 2009- September 28, 2009	0.0245
		September 29, 2009- June 30, 2010	0.0186

Notes: Time periods detected by modified ICSS algorithm. Sample period is from July 1, 1993 to June 30, 2010.

Table 3
Estimation Results for Univariate GARCH Models

Panel A: Gold

Model	ω	α	β	α+β	Half life (days)	Log likelihood
Breaks Ignored	1.3E-07 (0.03)	0.03 (0.00)	0.96 (0.00)	0.99	68.96	13960.91
Breaks accounted for	2.5E-05 (0.11)	0.04 (0.04)	0.83 (0.00)	0.87	4.97	14046.14

Panel B: Oil

Model	ω	α	β	α+β	Half life (days)	Log likelihood
Breaks Ignored	6.8E-06 (0.00)	0.05 (0.00)	0.93 (0.00)	0.98	34.30	10125.11
Breaks accounted for	7.3E-05 (0.00)	0.06 (0.00)	0.74 (0.00)	0.80	3.10	10169.84

Notes: P-values in parenthesis are based on robust standard errors calculated from the method given by Bollerslev and Wooldridge (1992). α+β measures the volatility persistence. Half life gives the point estimate of half-life (j) in days given as $(\alpha+\beta)^j = \frac{1}{2}$. Estimated variance equation without structural breaks for GARCH model is $h_t = \omega + \alpha \varepsilon_{t-1}^2 + \beta h_{t-1}$.

Table 4
Results of Bivariate GARCH model ignoring Structural Breaks

Gold conditional variance equation:

$$h_{11,t+1} = 1.17 \times 10^{-7} + 0.965\,h_{11,t} + 0.004h_{12,t} + 4.69 \times 10^{-6}h_{22,t} + 0.034\varepsilon_{1,t}^2 - 0.002\varepsilon_{1,t}\varepsilon_{2,t} + 6.16 \times 10^{-5}\varepsilon_{2,t}^2$$

$$\quad(1.53)\qquad(155.68)\qquad(2.10)\qquad\quad(1.04)\qquad\qquad(5.26)\qquad(-1.69)\qquad\qquad(0.90)$$

Oil conditional variance equation:

$$h_{22,t+1} = 6.12 \times 10^{-6} + 3.30 \times 10^{-4}h_{11,t} + 0.035h_{12,t} + 0.940h_{22,t} + 0.006\varepsilon_{1,t}^2 - 0.033\varepsilon_{1,t}\varepsilon_{2,t} + 0.047\varepsilon_{2,t}^2$$

$$\quad(2.64)\qquad\qquad(1.71)\qquad\qquad(3.46)\qquad(80.23)\qquad(1.57)\qquad(-2.75)\qquad(4.82)$$

Notes: h_{11} is the conditional variance for the gold return series and h_{22} is the conditional variance for the oil return series. Directly below the estimated coefficients (in parentheses) are the corresponding t-values. The mean equations included a constant term and a lagged return term. Results for the mean equations are not reported for the sake of brevity but are available upon request.

Table 5
Results of Bivariate GARCH model incorporating Structural Breaks

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Gold conditional variance equation:

$$h_{11,t+1} = 1.52 \times 10^{-7} + 0.895 h_{11,t} + 0.110 h_{12,t} + 0.003 h_{22,t} + 0.025 \varepsilon_{1,t}^2 - 0.001 \varepsilon_{1,t} \varepsilon_{2,t} + 1.03 \times 10^{-5} \varepsilon_{2,t}^2$$

   (1.72)   (70.83)   (14.90)   (7.21)   (2.90)   (-1.12)   (0.56)

Oil conditional variance equation:

$$h_{22,t+1} = 6.93 \times 10^{-6} + 1.35 h_{11,t} - 2.16 h_{12,t} + 0.860 h_{22,t} + 0.009 \varepsilon_{1,t}^2 - 0.042 \varepsilon_{1,t} \varepsilon_{2,t} + 0.047 \varepsilon_{2,t}^2$$

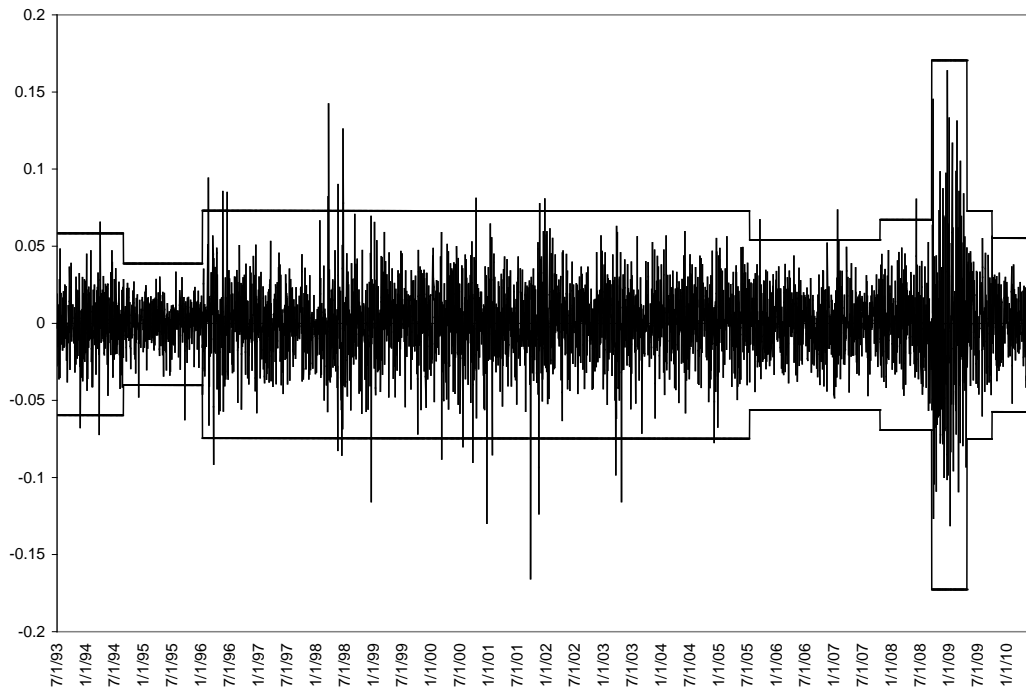   (50.09)   (9.85)   (-19.53)   (59.77)   (1.23)   (-1.99)   (3.80)

Notes: h_{11} is the conditional variance for the gold return series and h_{22} is the conditional variance for the oil return series. Directly below the estimated coefficients (in parentheses) are the corresponding t-values. The mean equations included a constant term and a lagged return term. Results for the mean equations are not reported for the sake of brevity but are available upon request.

Figure 1: Daily Gold Returns
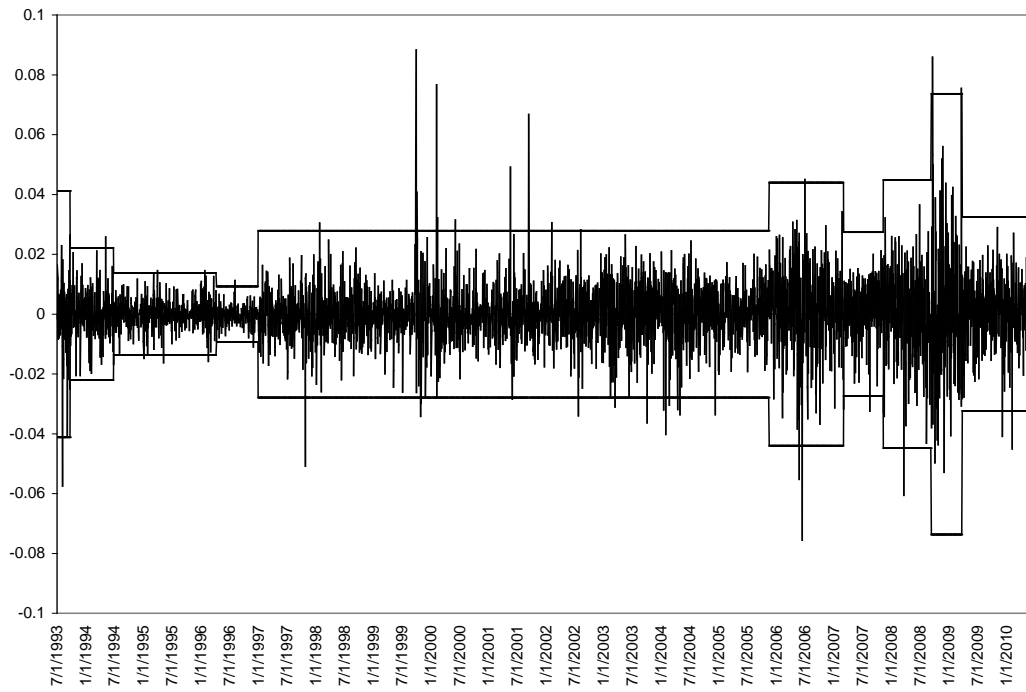
Note: Bands at ±3 standard deviations, change points estimated using modified ICSS algorithm.

Figure 2: Daily Oil Returns

Note: Bands at ±3 standard deviations, change points estimated using modified ICSS algorithm.