

**Volatility Analysis on Precious Metals Returns and Oil Returns:  
An ICSS Approach**

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**Abstract**

This study examines volatility persistence on precious metals returns taking into account oil returns and the three world major stock equity index (Dow Jones Industrials, FTSE 100, and Nikkei 225) using daily data over the sample period January 1995- May 2008. We first determine when large changes in the volatility of each market returns occurs identifying major global events that would increase the volatility of these markets using the Iterated cumulative sums of squares (ICSS) algorithm to identify the break points or sudden changes in the variance of returns in each market using the standardized residuals obtained through the GARCH(1,1) mean equation. Our main results identify a clear relationship between precious metals returns and oil returns, while the interaction between precious metals and stock returns seems to be an independent one. In relation to volatility persistence, the results are showing clear evidence of high volatility persistence between these markets.

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## 1. Introduction

The objective of this paper is to examine the effects of oil returns on precious metals markets, including the major financial markets (US-Dow Jones Industrial, Japan-Nikkei 225, and UK-FTSE 100) as a proxy to identify the strength of volatility persistence among these markets.

Hamilton (1983), Gilbert and Mork (1984), concluded that increases in oil prices generates important effects in macro variables like Gross National Product (GNP). Hamilton (1983) concluded that increases in oil prices are responsible for declines in real GNP; therefore, if oil prices play an important role in the economy, it is reasonable to expect the existence of correlations between oil prices and stock prices, but what would be the relation of these variables with precious metals? The analysis of interlinkages between these variables is of high importance for investors, if our analysis does not find the existence of relationships between these variables this will imply that there are possibilities of diversification in between these markets.

Ross (1989) argued that volatility is a measure of information flow; the analysis can be view as an investigation of the extent to which the rate of information flow in correlated across markets. The increasing integration of major financial markets throughout the world has generated interest in studying the transmission of financial markets shocks across markets (Ewing et al., 2002). It is important for financial markets participants to understand the volatility transmission mechanism across time and sector in order to facilitate optimal portfolio decisions. Thus, it is natural to be concerned with how information, and therefore, volatility, may flow from one market to another. Since index futures and options are an important tool that financial market participants can use in order to hedge against portfolio risk, and because the volatility of the index is a key determinant of futures and options valuation, it is important to understand what affects index volatility in those markets (Ewing et al., 2002).

A number of techniques have been used to model volatility. The autoregressive conditional heteroskedasticity (ARCH) model developed by Engle (1982), and later generalized by Bollerslev (1986) is the most popular method used for analyzing high-frequency financial time series data. Multivariate generalized autoregressive conditional

heteroskedasticity (GARCH) models have been used to estimate the spillover effects and volatility among different markets. It has been concluded that higher levels of conditional volatility in the past are associated with higher conditional volatility in the current period, what is associated with a volatility persistence value that is normally very close to one. A persistence value close to one is indicative of an integrated GARCH (IGARCH) process. The estimates of volatility persistence for each return series provide information about the extent to which past shocks and volatility matter in the construction of forecast of future conditional variance. The greater is the persistence, the more weight that should be given to recent observations of volatility, in terms of explaining future behavior of the variance. The volatility of the series will return to its conditional variance faster than would be the case when there is greater persistence. An alternative way of interpreting volatility persistence is to compute the half-life of an innovation or shock to the series, which will provide the days that return series takes to lose half of its effect of the variance.

The current situation in energy markets is an area of great interest for researchers, in a moment where the oil prices are soaring, investors' eyes tend to divert to commodities markets, therefore, we consider of interest the analysis of interactions between stock returns, oil returns and precious metals returns. The behavior of oil prices has received special attention, as the oil market has undergone structural transformations that have placed oil prices on a new high path, where new large consumers like China and India are playing an important role in the current market behavior. The rise in oil prices and the increase in oil price volatility have resorted to a wide list of drivers included strong demand (mainly from outside OECD), lack of spare capacity in upstream oil, distributional bottlenecks, OPEC supply response, geopolitical and weather shocks and the increasing role of speculators and traders in price information (Fattouh, 2007). The level of volatility in financial markets influence the corporate sector's investment decisions and bank's willingness and ability to extend credit facilities (Panetta et al., 2006), therefore, is important to know what impact changes in the volatility level might have on financial stability. The current economic situation reminds us the Bretton Woods system and brings to our minds the following questions:

- a) Could be possible to be thinking about the importance of precious metals markets as a key variable that could be use by governments to help in maintaining financial stability?
- b) Precious metals are sources of increasing value, they are perceived as important and stable stores of value; why not use them to diversify portfolios?
- c) Have been enough research done analyzing the role of precious metals for the economy?

Because risk management practices have improved considerably during the past years, financial institutions are better equipped to mitigate adverse effects in volatility, financial factors affects volatility investor's risk tolerance, hedging strategies, structural changes in financial markets, etc. Financial derivatives for example have allowed market participant to price, unbundle and disperse risk throughout the financial system, therefore, the analysis of equity markets, precious metals markets and oil prices deserve particular attention, due to the fact that these markets could be used in order to diversify the investors' risk.

The graphical analysis of oil prices (figure 1) from January 1995 to May 2008 show how the crude oil prices are following a clear upward movement, being possible to identify the same behavior between the Brent and the WTI prices therefore, we decide to use the Crude oil Brent prices in our analysis. In relation to the Dow Jones Industrials, FTSE 100 and Nikkei 225 the graph for the last 13 years (figure 2) allow us to identify clearly the higher instability that exists in the main world equity markets. It is possible to appreciate pronounce downturns in the markets during the Asian Crisis (1997-1998), the terrorist attacks that affected the United States in September 11, 2001, the dot.com bubble or I.T bubble crisis covering roughly 1995 to 2001, the Internet Bubble bursting during 2002 and the Chinese Correction during 2007 that was the global stock market plunge of February 27, 2007. The equity indexes reflect the clear instability of the markets during this particular time period, with special attention to the Nikkei 225 that seems to be the most volatile index. The oil and stock market prices seems to be reacting in a negatively manner to these major market crisis, but if we pay attention to what is going on in the precious metals markets (figure 3) the results are not following the same pattern with what is happening in the oil and equity markets. Precious metal markets seem to reflect

an independent behavior, a clear upward trend is appreciated in gold and platinum and in a softer manner in silver prices after the Asian Crisis, situation that remains until nowadays.

We believe that stock markets are influenced by shocks in oil and precious metals markets, while precious metals markets are appreciated as more stable and secure assets, that will not be much affected by external shocks, therefore if we can identify an independent behavior of precious metals regarding to oil and equity markets during times of crisis, this would be a high valuable information for investors that would be able to design their investment strategies taking into account the use of precious metals in the composition of their portfolios.

The remainder of the paper is organized as follow. In section 2 we present the main literature analyzing this issue. Section 3 describes the data and methodology that is used to detect changes in variance where the ICSS algorithm and GARCH model are discussed. Section 4 reports the main results and Section 5 concludes the analysis.

## **2. Literature Review**

Huan, Masulis and Stoll (1996) examined the relationship of oil futures returns to stock returns during the 1980's using a vector autoregressive (VAR) approach to study the lead-lag relationship between oil futures returns and stock returns while controlling for interest rate effects, seasonality's and other effects. Their conclusions were that oil futures returns are not correlated with stock market returns. Despite the frequently cited importance of oil for the economy, the authors found little evidence of such a link. In fact, the lack of correlation suggest that oil futures, like other futures contracts also appear to have little correlation with stocks, what is a good vehicle for diversifying stock portfolios.

Aggarwal, Inclan and Leal (1999) examined what kind of events caused shifts in the volatility of emerging stock markets, using an iterated cumulative sum squares (ICSS) algorithm to identify the points of shocks/sudden changes in the variance of returns in each market and how the long shift lasts. They identified that the October 1987 crash was the only global event during the period 1985-1995 that caused a significant jump in the

volatility of several emerging stock markets. They examined ten of the largest emerging markets in Asia and Latin America. Their findings shown that the high volatility in emerging markets is marked by several shifts, the large changes in volatility seems to be related to important country-specific political, social and economic events. The number of change in variance varies from country to country and they also depend on the data frequency, more change points are found with daily returns than with weekly or monthly returns.

Ewing, Malik and Ozfidan (2002) analyzed how volatility in the oil and natural gas sectors changes over time and across markets, examining the bivariate and univariate time-series properties of oil and natural gas index returns. They analyzed daily closing values for the period from 01/04/1996 to 29/10/1999, and they found that volatility (conditional variance) in oil returns is directly affected by its own volatility, and by the volatility in the natural gas returns. Thus, they found significant direct and indirect transmissions of volatility in oil returns from the natural gas sector to the oil sector, but they did not find that volatility in oil returns was affected by shocks originated in either the oil sector or gas sector. Also, they found absence of an indirect effect of shock in the natural gas sector on the oil sector. The behavior of natural gas return volatility differs from that of oil.

Al-Eisa, Al-Nsour, and Hammoudeh (2003) provided an institutional analysis of the financial valuations for the individual Gulf Cooperation Council (GCC) markets (Oman, Kuwait, Bahrain, Saudi Arabia and UAE). They examined whether any long-run relationship exist among these markets, using cointegration techniques and investigating the transmission of changes and volatility in oil prices, as represented by NYMEX oil futures prices, to the individual GCC stock markets, using the vector error correction models and the GARCH models. They analyzed daily data for the GCC stock indices and the oil prices that cover the period 15/02/1994 to 25/12/2001. They found that the five GCC markets are strongly cointegrated what means that they have many long-run relationships and are co-moved over time. Oil price volatility spillover is significant in all the GCC markets, this volatility moves these markets in the same direction with the oil volatility at NYMEX, which mean that if the oil prices become more volatile in NYMEX, the share prices in GCC markets felt this volatility.

Fernández (2004) examined the presence of structural breaks in volatility using two alternative approaches, the iterative cumulative sum of squares (ICSS) algorithm and wavelet analysis, looking at the effect of the outbreak of the Asian crisis and the terrorist attacks on September 11, 2001, on emerging Asia and Latin America, she also analyzed North America and European's stock markets. Her results shown that the number of shift detected by the two methods was substantially reduced when filtering out the data for conditional heteroskedasticity and serial correlation. In particular, for the filtered stock data, the ICSS algorithm did not find any volatility shifts over 1997-2002, whereas wavelet analysis found evidence of volatility breakpoints at some given scales of the data and only for 1997-1998.

Zhang et al (2005) investigated the Shanghai stock exchange and analyzed how regulations affect volatility, applying CUSUM type test on the SSE Composite Return Index as well as Markow-Swithching ARCH model. Their found that there was at least one break within the last decades and volatility of returns has a significant reduction after the break. Their results shown a main structural break that happened at mid 1997 which was consistent with the fact that some critical regulation improvement appears during that year.

Agren (2006) studied volatility spillovers from oil prices to stock markets within an asymmetric BEKK model, using weekly data on the aggregate stock markets of Japan, Norway, Sweden, the UK and the US. He found strong evidence of volatility spillover for all stock markets with the exception of the Swedish one, where only weak evidence was found.

Wang and Moore (2007) analyzed sudden changes in volatility in the stock markets of new European Union members (Poland, The Czech Republic, Hungary, Slovakia and Slovenia), using weekly data over the sample period 1994-2006. Their used the iterative cumulative sum squares (ICSS) algorithm and they found that sudden shifts are largely explained by domestic, economic and financial factors, which are more likely to be the major causes behind the shifts being consistent with Aggarwal et al. (1999).

The analysis of the literature shows that oil shocks and stock markets have received much attention, but there is a lack of evidence regarding to the interaction of these markets with precious metal markets. Our objective is to analyze volatility taking into

account the ICSS algorithm to detect jumps in volatility using a GARCH (1,1), we intend to identify sudden changes in variance which will be used to correct the GARCH model. Therefore, we will be able to do a comparison between the results without taking into account the jumps and also, what happened after the model is corrected for it.

### 3. Data and Methodology

#### 3.1 Data

Our analysis focuses on the period 1 January 1995 to 25 April 2008. The data set consists of daily closing values for the stock market indices for the major markets: US (Dow Jones Industrials), UK (FTSE-100) and Japan (Nikkei 225). In the case of the precious metals data, we took the US\$/Troy ounce for gold, the London Free Market Platinum price in US\$/Troy ounce, and the Zurich silver price in US\$/kilogram, and finally we will use the oil prices taking into account the Crude Oil Brent. All our data series are from DataStream International, giving a total of 3480 observations for each series. Following Kanas (2000) we use continuously compounded stock returns; we also applied the same procedure to work out the precious metals returns, calculated as the first difference of the natural log. That is, S= Stock Prices;  $S_t = \ln(P_t^s) - \ln(P_{t-1}^s)$ ; and PM= Precious Metals Prices;  $PM_t = \ln(P_t^{PM}) - \ln(P_{t-1}^{PM})$ ;  $OR_t^{OR} = \ln(P_t^{OR}) - \ln(P_{t-1}^{OR})$

#### 3.2 Methodology

##### 3.2.1 ICSS Algorithm

Inclan and Tiao (1994) designed the Iterative cumulative Sums of Squares (ICSS) algorithm. This algorithm allows for detecting multiple break points in variance in time series. However, the literature has shown that the ICSS algorithms tend to overstate the number of actual breaks in variance (Fernández, 2004). Bacmann and Dubois (2002) pointed out that the behavior of the ICSS algorithm is questionable under the presence of conditional heteroskedasticity. They have shown that this problem can be solved by

filtering the return series by a GARCH (1,1) model, and applying the ICSS algorithm to the standardized residuals. The present analysis will test for volatility shifts before and after filtering the data for conditional heteroskedascity and serial correlation for comparison purposes.

The ICSS algorithm assumes that the time series of interest has a stationary unconditional variance over an initial time period until a sudden break takes place. The unconditional variance is then stationary until the next sudden change occurs. This process repeats through time, giving a time series observations with a number of  $m$  breakpoints in the unconditional variance in  $n$  observations. To estimate the number of changes and the point of time of variance shifts accumulative sum of squared residuals is used,

$$C_k = \sum_{t=1}^k \varepsilon_t^2 \quad (1)$$

Where  $k = 1, \dots, T$ , and  $\{\varepsilon_t\}$  is a series uncorrelated random variables with zero mean and unconditional variance  $\sigma_t^2$ . The variance in each interval is denoted by  $\sigma_j^2$ ,  $j = 0, 1, \dots, NT$ , where  $NT$  is the total number of variance changes in  $T$  observations. By letting  $1 < \kappa_1 < \kappa_2 < \dots < \kappa_{N_T} < T$  the set of breakpoints, the variance then is defined as,

$$\begin{aligned} \sigma_t^2 &= \sigma_0^2 & 1 < t < \kappa_1 \\ &= \sigma_1^2 & \kappa_1 < t < \kappa_2 \\ &\dots \\ &= \sigma_{N_T}^2 & \kappa_{N_T} < t < T \end{aligned} \quad (2)$$

The statistic DK is defined as follows,

$$D_k = \frac{C_k}{C_T} - \frac{k}{T} \quad \text{with } D_0 = D_T = 0. \quad (3)$$

Where CT is the sum of the squared residuals from the whole sample period. If there are no changes in variance over the whole sample period  $D_k$  oscillate around zero, otherwise, if there are one or more shifts in variance,  $D_k$  will departure from zero. The critical values, which define the upper and lower limits for the drifts under the null hypothesis of stationary variance, determine the significant change in variance of the series. If the maximum of the absolute value of the statistic  $D_k$  is greater than the critical value, the null hypotheses of no sudden changes is rejected. Let  $k^*$  be the value of  $k$  at which  $\max_k |D_k|$  is attained, and if  $\max_k = \sqrt{(T/2)^* |D_k|}$  exceeds the critical values, then  $k^*$  is taken as an estimate of the change point. The term  $\sqrt{(T/2)}$  is used to standardize the distribution. The critical value of 1.358 is the 95<sup>th</sup> percentile of the asymptotic distribution of  $\max_k = \sqrt{(T/2)^* |D_k|}$ . Therefore, upper and lower boundaries can be set at  $\pm 1.358$  in the  $D_k$  plot.

The ICSS is an iterative approach because the process must be repeated over subsamples to identify multiple change points. For example, if a point change is observed at  $\tau T$ , then, this point is used to partition the sample into two subsample, to  $\tau T$  and  $(\tau T+1)-T$ . The CSS is then estimated over both subsamples to identify additional point changes. The process is repeated until no new change points are identified.

### 3.2.2 The GARCH model

Once the change points in variance have been identified the GARCH model is estimated without and with sudden changes in variance. The standard GARCH (1,1) model is defined for the case without sudden changes as follow,

$$Y_t = \mu + \delta_1 X_{t-1} + e_t, \text{ where } e_t | I_{t-1} \sim N(0, h_t) \text{ and } h_t \text{ is given by the variance equation (4)}$$

$$h_t = \omega + \alpha e_{t-1} + \beta h_{t-1} \quad (5)$$

The GARCH(1,1) model with sudden changes and taken into account our variables is as follow,

$$Y_t = \mu + \delta_1 X_{t-1} + \delta_2 Z_{t-1} + e_t \quad (6)$$

$$h_t = \omega + \alpha e_{t-1} + \beta h_{t-1} \quad (7)$$

where:

Y<sub>t</sub> = Precious Metals Returns (Gold, Silver and Platinum)

X<sub>t</sub> = Stock Markets Returns (Dow Jones Industrials, FTSE 100 and Nikkei 225)

Z<sub>t</sub> = Crude Oil Brent.

$e_t | I_{t-1} \sim N(0, h_t)$  and  $h_t$  is given by the variance equation

$$h_t = \omega + d_1 D_1 + \dots + d_n D_n + \alpha e_{t-1} + \beta h_{t-1} \quad (8)$$

where D<sub>1</sub>...D<sub>n</sub> are the dummy variables: 1 for each point of sudden change of variance onwards and 0 for otherwise. Given the modified GARCH model, this incorporates the regime shifts detected by the ICSS algorithms, the persistence of volatility, i.e.  $\alpha + \beta$  is predicted to be smaller than that found by the conventional GARCH model. The GARCH (1,1) model would be adapted to our analysis, taking into account precious metals returns vs. stock market returns, and precious metals returns vs. oil returns. Therefore, the mean equation will be adjusted as follow,

$$PM_y = c_0 + \sum_{i=1}^m \alpha_i SMx_{t-i} + \sum_{i=1}^n \lambda_i OR_{t-i} + \varepsilon_{yt} \quad (9)$$

$$h_{yt} = \beta_0 + d_1 D_1 + \dots + d_n D_T + \sum_{i=1}^a \beta_1 h_{yt-1} + \sum_{i=1}^b \kappa_1 \mu_{yt-1}^2 \quad (10)$$

We use continuously compounded stock returns; we also applied the same procedure to work out the precious metals returns and oil prices returns, calculated as the first difference of the natural log. That is, S= Stock Prices;  $S_t = \ln(P_t^s) - \ln(P_{t-1}^s)$ , and PM= Precious Metals Prices;  $PM_t = \ln(P_t^{PM}) - \ln(P_{t-1}^{PM})$ .  $OR_t^{OR} = \ln(P_t^{OR}) - \ln(P_{t-1}^{OR})$

Where PM<sub>y</sub> = Gold, Silver, Platinum.

SM = Dow Jones Industrials, FTSE 100, Nikkei 225.

OR = Crude Oil Brent.

## 4. Empirical Results

### 4.1 Descriptive Statistics

The descriptive statistics of precious metals returns (results are given in table 1) show a common trend. The three markets present positive and small mean values. The standard deviation indicates that the gold market is the less volatility with a coefficient of 0.89%, the silver returns are the most volatile with a coefficient of 1.73% and finally platinum show 1.36% standard deviation. In the case of stock returns the situation is slightly different; our results show that the mean values for the Dow Jones, FTSE 100 are positive and small being consistent with the results that we got for the precious metals returns, while the results for the Nikkei 225 are showing a negative mean. The analysis of the stock returns volatility shows that overall the Nikkei 225 is the most volatile stock returns series, with a daily standard deviation 1.39%, regarding to the Dow Jones the standard deviation is the 1.03% and in the case of the FTSE 100 1.07%. The analysis of oil returns represented by the Brent returns show a small positive mean values, the volatility analysis show that the oil returns are the most volatile market in relation to stock returns and precious metals returns, showing a coefficient of 2.24%. The skewness and kurtosis coefficients indicate that stock returns, precious metals returns and oil returns are leptokurtic and negatively skew regarding to the normal distribution, which Caporale *et al.* (2002) note is a common finding for stock returns. The Jarque-Bera test also rejects the hypothesis that stock returns, precious metals returns and oil returns are normally distributed in all the cases.

### 4.2 Unit Roots Tests

The results from the ADF tests are given in table 2. The values of the test statistics indicate that we can reject the null hypothesis of the existence of a unit root in levels for all variables during all periods indicating that all series are  $I(0)$ .<sup>3</sup> Given that all

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<sup>3</sup> The LMF test results indicated that the ADF tests were free from serial correlation; for brevity we do not show the test results here.

variables are integrated of the same order, (i.e.  $I(0)$ ), we proceed directly to perform our volatility analysis using GARCH (1,1) modeling.

#### 4.3. ICSS Break Points

The ICSS algorithm results are presented in tables 3 to 5. First we decide to run the algorithm using the original series to work out the number of break points, as can be seen in table 3 and table 4, the number of sudden changes in volatility is quite high, being the main problem the non existence of common break points between the sudden changes in volatility for the different indices, what is a major problem in order to introduce all the break points in the variance equation. Another problem is the number of observations that should be consider as a breakpoint, if we consider appropriate to eliminate an important number of observations of the data set this action could be generating by its own a break point, due to the fact that there will be an important gap between the observation that generated the jump and the last observation included in the sample were is consider that the volatility shock disappeared. In order to solve this problem we decided to implemented the GARCH(1,1) using the mean equation for each of the precious metals under analysis (equation 9), the results are presented in table 5 and in figures 4 to 12. It is possible to appreciate how the numbers of sudden changes in volatility have been reduced for each of the precious metals equation and also, how we solve the problem of getting different number and days on volatility jumps.

#### 4.4 Volatility Results

The analyses of the coefficients for the volatility persistence are presented in tables 6 to 8. The parameter conditions constraints are:  $\beta_0 \geq 0$ ,  $1 \geq \beta_1 \geq 0$ ,  $1 \geq \kappa_1 \geq 0$  ( $\beta_1 + \kappa_1 \leq 1$ ). These constraints are applied to the parameters to enforce stationarity and a positive conditional variance. Volatility persistence will be measured through the sum of the following coefficients for each equation ( $\beta_1 + \kappa_1 \leq 1$ ). The GARCH(1,1) results are obtained through two main regressions:

- a) First of all we run a normal GARCH(1,1), represented by equation (6) or (9) which will give us the variance output represented by equation (7).
- b) Then we run a GARCH(1,1) represented by equation (6) or (9), but in this case the variance will be adjusted to the breakpoints found by the ICSS algorithm in order to compare the volatility persistence results, the variance output is represented by equation (10).

Regarding the returns-generating process (the results are presented through tables 6 to 8) we can draw the following conclusions.

#### *4.4.1 Gold Analysis*

The analysis of the GARCH(1,1) model for the Gold equation (table 6) show a significant negative relation between gold returns and the Dow Jones returns, a positive significant coefficient in the case of Gold-FTSE 100, while the coefficient is insignificant regarding to the Nikkei 225. The results for the GARCH(1,1) with dummies show an insignificant relationship between the Gold returns and the three stock markets returns. The results also show that there is a significant positive relationship between the gold market returns and the Brent returns, both the GARCH(1,1) and the GARCH(1,1) with dummies show a positive significant relation between precious metal returns and oil returns, with all the coefficients being significant at 1% and 5% significant level. This situation reflects that, in general when the oil markets are appreciating there is a trend of increasing returns for the gold market.

Examining the variance estimates we can appreciate that for both models the GARCH parameter for volatility persistence is moving between 0.75 as the lowest value to 0.95 as the highest. With regard to volatility persistence the sum of the GARCH coefficients is close to 1 implying extreme persistence in volatility for both GARCH models, the GARCH(1,1) and the GARCH(1,1) with dummies.

#### *4.4.2 Silver Analysis*

The analysis of the GARCH(1,1) model for the Silver equation (table 7) show an insignificant relation between silver returns and the Dow Jones returns, while a positive significant coefficient is found in the case of Silver-FTSE 100, and Silver-Nikkei 225. These results are confirmed by the output obtained from the GARCH(1,1) with dummies which also show an insignificant relationship between Silver returns and the Dow Jones returns and a significant relationship between Silver returns and the FTSE 100 and the Nikkei 225. The results also show that there is a significant positive relationship between the silver market returns and the Brent returns, both the GARCH(1,1) and the GARCH(1,1) with dummies show an positive significant relation between the silver precious metal returns and oil returns, with all the coefficients being significant at 1% and 5% significant level. This situation reflects that, in general when the oil markets are appreciating there is a trend of increasing returns for the silver market, result that is consistent with the findings for the gold market.

Examining the variance estimates we can appreciate that for both models the GARCH parameters for volatility persistence are positive and significant with all the coefficients moving between 0.82 as the lowest value to 0.94 as the highest.

#### *4.4.3 Platinum Analysis*

The analysis of the GARCH(1,1) model for the Platinum equation (table 8) show a significant positive relation between platinum returns and the Dow Jones returns and the Nikkei 225, an insignificant coefficient in the case of Platinum-FTSE 100. The results for the GARCH(1,1) with dummies are consistent with the results from the GARCH(1,1). Our findings also show that there is a significant positive relationship between the platinum market returns and the Brent returns, both the GARCH(1,1) and the GARCH(1,1) with dummies show an positive significant relation between precious metal returns and oil returns, with all the coefficients being significant at 1% and 5% significant level. This situation reflects that, in general when the oil markets are appreciating there is a trend of increasing returns for the platinum market.

Examining the variance estimates we can appreciate that for both models The GARCH parameter for volatility persistence is moving between 0.85 as the lowest value to 0.86 as the highest.

With regard to volatility persistence the coefficients for each of the equations are significant, with the characteristic of a reduction in the magnitude of the GARCH coefficients for the GARCH with dummies. Regarding to the sum of the GARCH coefficients is close to 1 in all the cases implying extreme persistence in volatility for both GARCH models, the GARCH(1,1) and the GARCH(1,1) with dummies, results that we believe are influenced by the volatility persistence that characterised equity markets. Overall our results are showing that the GARCH with dummies tend to correct the level of volatility persistence as is possible to appreciate in the reduction of the coefficients magnitude. The results also show weak evidence regarding to the influence of stock returns in precious metals returns, while the oil market seems to have a direct effect in the precious metals markets.

#### *4.5 Standardized Residual*

The diagnostic tests on the standardised residuals for both GARCH models<sup>4</sup> indicates that in the case of the Jarque-Bera test we reject the hypothesis that the residuals are normally distributed in all the cases, hence justifying the use of the Bollerslev-Woolridge robust *t*-statistics. The Ljung-Box statistics for all metals equations indicate that there are no residual linear or non linear dependencies in most of the cases. Finally to check the validity of the assumption of constant correlation adopted in the estimation of the models (Kanas, 2000), the LB statistics for the cross products of the standardised residuals from the precious metals returns equation are calculated and these statistics indicated that the assumption of constant correlation over time can be accepted in almost all the cases. These exceptions are normally corrected after increasing or decreasing the number of lags in the test.

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<sup>4</sup> The results are not shown for brevity, being available upon request.

The ARCH-LM residual test results show that overall the variance equation for the GARCH model is correctly specified, as we reject the null hypothesis of remaining ARCH effects in the equation in almost all the cases. This problem is corrected after increasing or decreasing the number of lags using on the estimation. The test results show that the variance equation is correctly specified as well for the GARCH dummy model, as we reject the null hypothesis in almost all the cases.

## **5. Conclusions**

In this study we have used the Inclan and Tiao (1994) iterated cumulative sums of squares (ICSS) algorithm to identify the sudden shifts in volatility in precious metals markets (Gold, Platinum and Silver), three major stock markets (Dow Jones Industrials, FTSE 100, and Nikkei 225) and one oil price (Crude Oil Brent). In our analysis we first implemented the ICSS algorithm to identify sudden changes in variance using each series individually, our results shown a great number of breakpoints and inconsistency among each of the series under analysis in relation to finding common points that allow us to find out the relevant dummy variables that should be included in the GARCH model to analyze volatility persistence. Therefore, and in order to avoid the overestimation of breakpoints detected by the ICSS algorithm we decided to use the GARCH(1,1) model to obtain the standardized residuals, which would be use to estimate the relevant volatility jumps that would be identified as the main dummy variables to analyze the relationship between precious metals returns, stock returns, and oil returns.

We first used the normal GARCH(1,1) model and afterwards we also used the ICSS-GARCH extended model which incorporates the volatility breakpoints identified by the ICSS algorithm. Our main results show that there is a significant positive relationship between precious metals market returns and the Brent returns, both the GARCH(1,1) and the GARCH(1,1) with dummies show a positive significant relation between precious metal returns and oil returns, with all the coefficients being significant at 1% and 5% significant level. This situation reflects that, in general when the oil markets are appreciating there is a trend of increasing returns for the gold market. In relation to the equity markets most of the coefficients appears to be insignificant meaning that shocks in

equity markets do not tend to generate major effects in precious metals markets. We also found that all the coefficients for the ICSS model are statistically significant; with the characteristic that volatility persistence coefficient tends to reduce its value after including the dummy variables that correct the results for sudden shifts in conditional volatility.

Our results are of importance to investors due to the fact that stock markets are influenced by shocks in oil and precious metals markets, while precious metals markets are appreciated as more stable and secure assets, therefore the independent behavior of precious metals regarding to oil and equity markets during times of crisis, and the constant upward trend that these markets are facing represent high valuable information for investors that would be able to design their investment strategies taking into account the use of precious metals in the composition of their portfolios. Our initial results are presenting evidence of the important implication of the new role that precious metals markets could develop for investors thus we consider that this is a topic worthy of future research. We would suggest the use of EGARCH modeling and also to take into account different frequency on the data analysis (weekly and monthly) that will provide more evidence in understanding precious metals markets real importance.

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## 7. Appendix

Figure 1: Crude Brent Oil & Crude Oil – WTI Spot Cushing

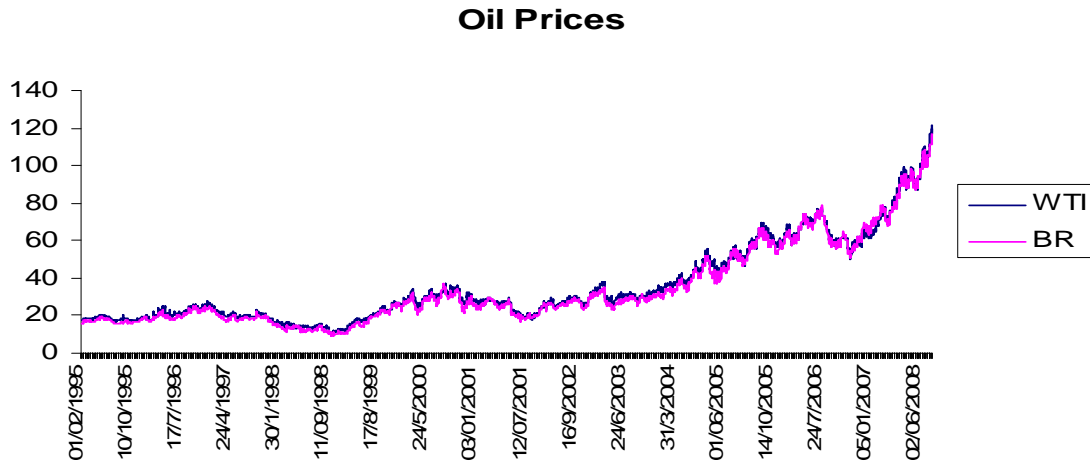


Figure 2: Dow Jones, FTSE-100 & Nikkei 225

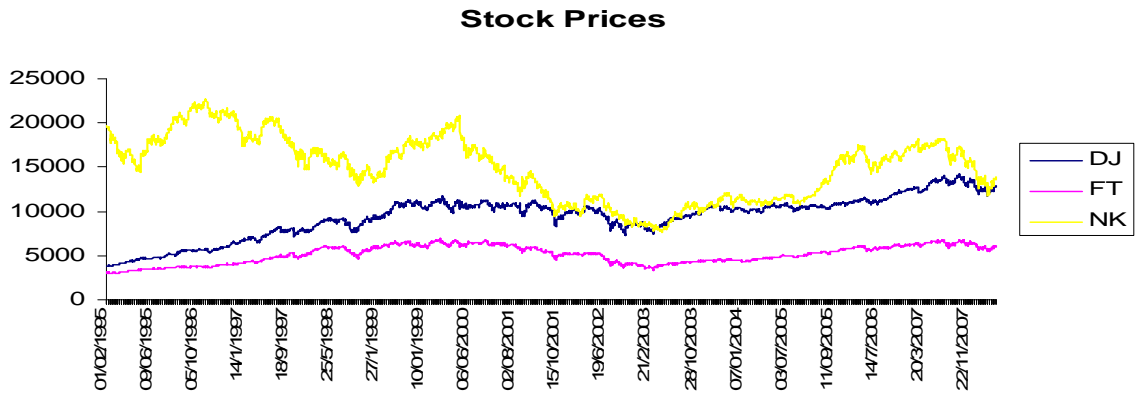
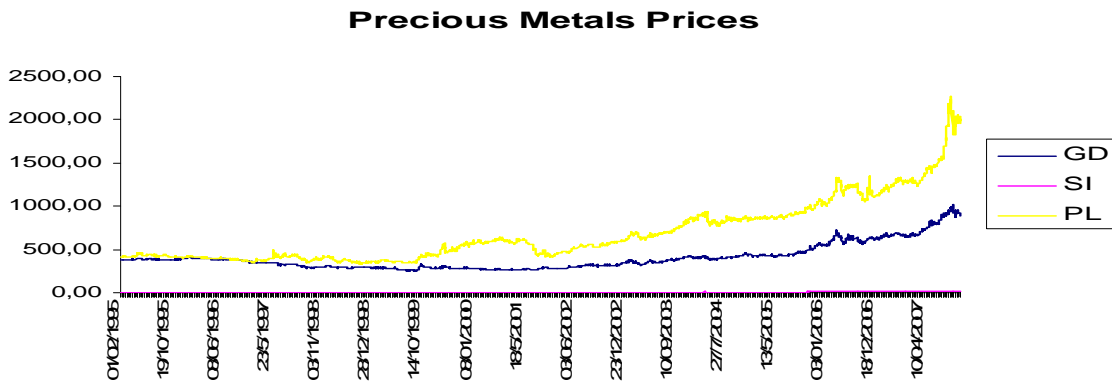


Figure 3: Gold, Silver and Platinum



*Table 1: Descriptive Statistics*

	<b>GOLD</b>	<b>SILVER</b>	<b>PLATINUM</b>	<b>DOW</b>	<b>FTSE</b>	<b>NIKKEI</b>	<b>BRENT</b>
Mean	0.000243	0.000356	0.000445	0.000349	0.000198	-0.000101	0.000570
Std. Dev.	0.008931	0.017309	0.013689	0.010342	0.010788	0.013954	0.022474
Skewness	-0.105000	-0.534531	-0.627836	-0.247420	-0.198963	-0.084421	-0.113218
Kurtosis	10.204	1.073	1.785	7.452	6.113	5.161	6.172
Jarque-Bera	7519	8837	32155	2905	1426	680	1464

*Table 2: Unit Roots*

	<b>GOLD</b>	<b>SILVER</b>	<b>PLATINUM</b>	<b>DOW</b>	<b>FTSE</b>	<b>NIKKEI</b>	<b>BRENT</b>
ADF	-58.18*	-13.04*	-13.13*	-43.14*	-14.71*	-43.77*	-21.87*

\*1% significance level.

*Table 3: Precious Metals Break Points\**

Gold Series	Silver Series	Platinum Series
May 9, 1995	March 29, 1995	March 27, 1995
December 29, 1995	May 9, 1995	May 9, 1995
March 1, 1996	October 2, 1995	March 4, 1996
December 31, 1996	December 2, 1996	February 11, 1997
March 4, 1997	December 8, 1997	May 28, 1997
May 16, 1997	December 16, 1997	August 24, 1998
July 2, 1997	May 29, 1998	September 21, 1998
October 9, 1998	March 15, 1999	December 10, 1998
September 17, 1999	September 27, 1999	December 18, 1998
October 5, 1999	September 30, 1999	January 22, 1999
December 8, 1999	June 21, 2000	January 27, 1999
February 2, 2000	January 1, 2001	September 23, 1999
February 8, 2000	May 14, 2001	November 18, 1999
July 19, 2000	August 14, 2002	January 26, 2000
January 26, 2001	July 14, 2003	February 29, 2000
March 13, 2001	January 2, 2004	August 7, 2000
May 17, 2001	April 12, 2004	July 13, 2001
September 7, 2001	May 10, 2004	October 16, 2001
September 18, 2001	March 8, 2005	June 3, 2001
January 31, 2002	December 5, 2005	April 9, 2004
August 8, 2002	April 14, 2006	May 17, 2004
January 31, 2003	June 14, 2006	December 7, 2004
July 22, 2004	October 3, 2006	October 28, 2005
December 5, 2005	February 25, 2008	May 5, 2006
May 5, 2006	March 19, 2008	June 19, 2006
October 3, 2006		October 30, 2006
November 1, 2007		November 16, 2006
March 3, 2008		November 21, 2006
March 17, 2008		March 14, 2007
		September 26, 2007
		November 15, 2007
		January 22, 2008

\*Break points calculated using the ICSS algorithm for each of the series. The ICSS algorithm for the individual series overestimate the number of points where sudden changes in volatility occur.

*Table 4: Stock and Oil Markets Break Points*

<b>Stock and Oil Markets Break Points*</b>			
Dow Jones Industrials	FTSE 100	Nikkei 225	Crude Oil Brent
December 14, 1995	May 28, 1995	October 2, 1995	July 3, 1995
January 8, 1996	July 31, 1998	December 3, 1996	December 29, 1995
November 29, 1996	September 10, 1998	January 30, 1997	December 13, 1996
October 14, 1997	January 21, 1999	October 20, 1997	January 22, 1998
March 7, 2002	December 31, 1999	January 15, 1998	March 16, 1999
October 18, 2002	February 6, 2000	August 25, 1998	March 3, 2000
January 4, 2003	November 9, 2000	November 3, 1998	February 13, 2001
May 13, 2003	April 9, 2001	February 27, 2001	September 12, 2001
May 17, 2005	September 21, 2001	April 17, 2001	January 16, 2002
June 7, 2007	December 7, 2001	March 19, 2002	November 29, 2004
	June 10, 2002	December 16, 2002	January 12, 2005
	October 16, 2002	December 8, 2004	May 13, 2005
	January 23, 2003	April 12, 2005	
	April 7, 2003	November 29, 2005	
	July 11, 2003	August 15, 2006	
	August 13, 2003	July 25, 2007	
	April 28, 2006	January 14, 2008	
	June 14, 2006		
	February 23, 2007		
	March 14, 2007		
	July 16, 2007		

\*Break points calculated using the ICSS algorithm for each of the series. The ICSS algorithm for the individual series overestimate the number of points where sudden changes in volatility occur, same situation was found in the case of the precious metals indices. Another problem is that each series are presenting a different number of break points that happened at different days during the period of analysis, therefore and in order to get a common number of break points we decide to use the standardized residuals of the GARCH(1,1) (equation 9) that will allow us to get the appropriate number of break points to improve our variance equation (equation 10).

*Table 5: GARCH(1,1) Residuals Break Points\**

<b>Gold-Dow Jones Ind.-Brent</b>	<b>Gold-FTSE 100-Brent</b>	<b>Gold-Nikkei 225-Brent</b>
March 28, 1995 (obs.63)	March 28, 1995 (obs.63)	March 28, 1995 (obs.63)
March 29, 1995 (obs.64)	March 29, 1995 (obs.64)	March 29, 1995 (obs.64)
December 30, 1995 (obs.522)	August 15, 1995 (obs.163)	December 30, 1995 (obs.522)
May 28, 2001(obs.1672)	November 2, 1995 (obs.220)	May 28, 2001 (obs.1672)
September 5, 2001(obs.1744)	February 29,1996 (obs.305)	September 5, 2001 (obs.1744)
September 12, 2001(obs.1749)	July 31, 1996 (obs.414)	September 10, 2001 (obs.1747)
	December 12, 1996 (obs.522)	
<b>Silver-Dow Jones Ind.-Brent</b>	<b>Silver-FTSE 100-Brent</b>	<b>Silver-Nikkei 225-Brent</b>
September 29, 1999 (obs.1239)	September 29, 1999 (obs.1239)	September 29, 1999 (obs.1239)
May 7, 2001 (obs.1657)	July 5, 2001 (obs.1657)	May 7, 2001 (obs.1657)
July 7, 2003 (obs.2222)	July 4, 2003 (obs.2221)	July 7, 2003 (obs.222)
<b>Platinum-Dow Jones Ind.-Brent</b>	<b>Platinum-FTSE 100-Brent</b>	<b>Platinum-Nikkei 225-Brent</b>
May 31, 1996 (obs.371)	May 31, 1996 (obs.371)	May 31, 1996 (obs.371)
February 10, 1997 (obs.552)	February 10, 1997 (obs.552)	February 10, 1997 (obs.552)
August 27, 2002 (obs.1998)	August 27, 2002 (obs.1998)	August 27, 2002 (obs.1998)

\*The ICSS algorithm using the GARCH(1,1) standardized residuals have the advantage of reducing the number of Points where sudden changes in volatility occurs and also have the quality of providing a common break point for our mean equation, allowing us to reduce the number of dummy variables that should be introduce in the GARCH(1,1) variance equation..

Figure 4: GARCH (1,1) Gold- Dow Jones Industrials-Brent

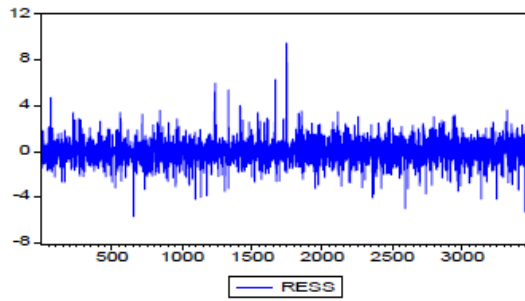


Figure 5: GARCH (1,1) Gold- FTSE 100-Brent

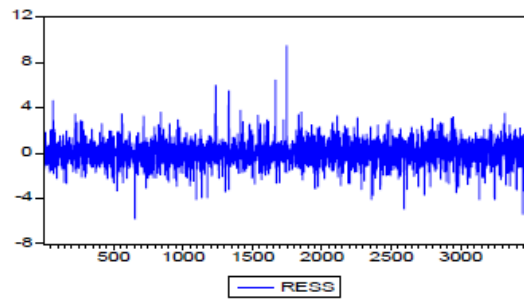


Figure 6: GARCH (1,1) Gold- Nikkei 225-Brent

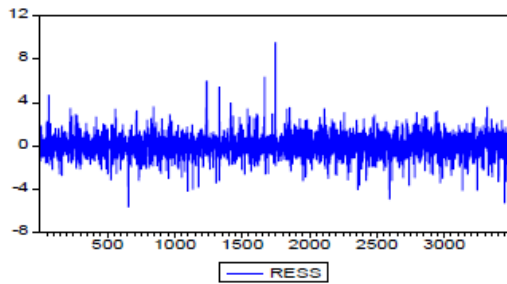


Figure 7: GARCH (1,1) Silver- Dow Jones Industrials-Brent

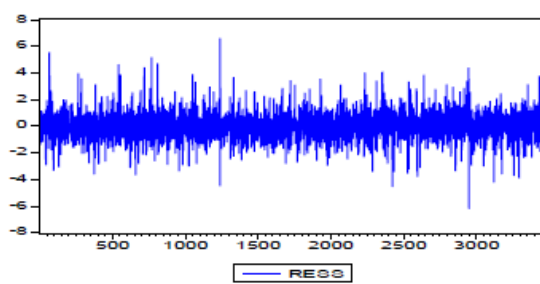


Figure 8: GARCH (1,1) Silver- FTSE 100-Brent

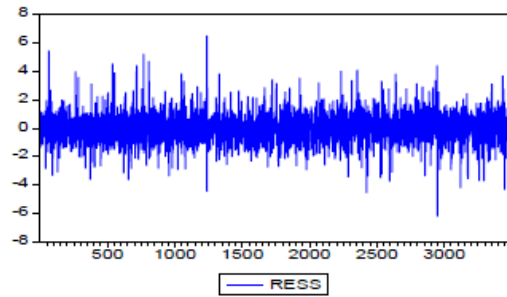


Figure 9: GARCH (1,1) Silver-Nikkei 225-Brent

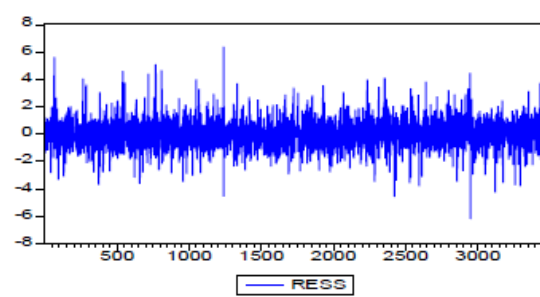


Figure 10: GARCH (1,1) Platinum- Dow Jones-Brent

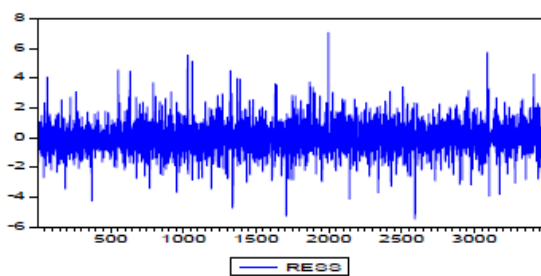


Figure 11: GARCH (1,1) Platinum-FTSE 100-Brent

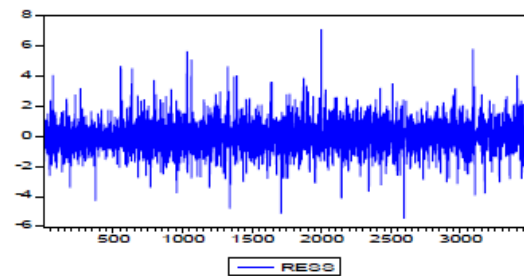
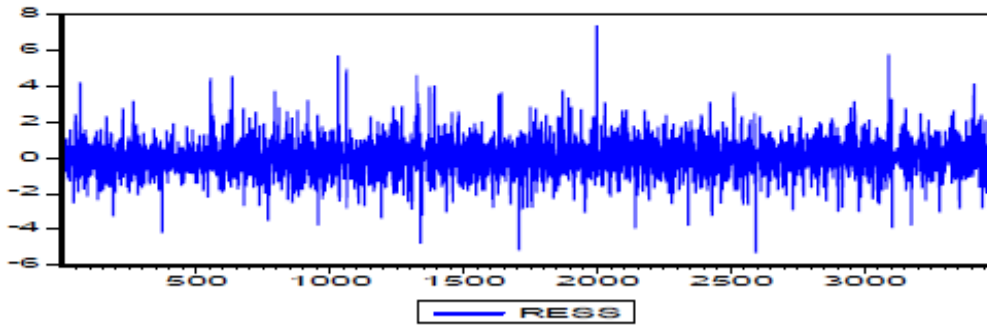


Figure 12: GARCH (1,1) Platinum-Nikkei 225-Brent



## GARCH(1,1) Results

Table 6: Gold Analysis

	Gold-Dow Jones Industrials-Brent		Gold-FTSE 100-Brent		Gold-Nikkei 225-Brent	
	<i>GARCH (1,1)</i>	GARCH(1,1) with dummies	<i>GARCH (1,1)</i>	GARCH(1,1) with dummies	<i>GARCH (1,1)</i>	GARCH(1,1) with dummies
$\omega$	0.0000 (0.789)	0.0000 (0.665)	-0.0001 (0.550)	0.0001 (0.682)	-0.0001 (0.643)	-0.0001 (0.275)
$\alpha$	-0.0349** (0.015)	-0.0042 (0.762)	0.0351* (0.009)	-0.0083 (0.688)	0.0115 (0.213)	0.0062 (0.480)
$\lambda$	0.0209* (0.000)	0.0149** (0.011)	0.0146** (0.012)	0.0287* (0.001)	0.0145** (0.013)	0.0229* (0.000)
$\beta_0$	0.0000** (0.018)	0.0000** (0.011)	0.0000** (0.021)	0.0000* (0.000)	0.0000** (0.011)	0.0000* (0.000)
$\beta_1$	0.0505* (0.000)	0.0535* (0.000)	0.0515* (0.000)	0.1746* (0.000)	0.0527* (0.000)	0.1284* (0.000)
$\kappa_1$	0.9510* (0.000)	0.9483* (0.000)	0.9504* (0.000)	0.7582* (0.000)	0.9491* (0.000)	0.8567* (0.000)
$\beta_1 + \kappa_1$	1.00	1.00	1.00	0.932	1.00	0.984

\*1% significance level, \*\*5% significance level and \*\*\*10% significance level.  $\beta_1$  is the coefficient for previous shocks and  $\kappa_1$  is the coefficient for persistence.

Table 7: Silver Analysis

	Silver-Dow Jones Industrials-Brent		Silver-FTSE 100-Brent		Silver-Nikkei 225-Brent	
	<i>GARCH (1,1)</i>	GARCH(1,1) with dummies	<i>GARCH (1,1)</i>	GARCH(1,1) with dummies	<i>GARCH (1,1)</i>	GARCH(1,1) with dummies
$\omega$	0.0000 (0.885)	0.0000 (0.910)	0.0000 (0.905)	0.0000 (0.926)	0.0000 (0.941)	0.0004 (0.194)
$\alpha$	0.0135 (0.539)	0.0074 (0.728)	0.0542** (0.011)	0.0427** (0.043)	0.0570* (0.000)	0.0661* (0.000)
$\lambda$	0.0333* (0.000)	0.0317* (0.001)	0.0323* (0.001)	0.0340* (0.000)	0.0300* (0.002)	0.0635* (0.000)
$\beta_0$	0.0000* (0.001)	0.0000* (0.008)	0.0000* (0.002)	0.0002 (0.314)	0.0000* (0.002)	0.0000* (0.000)
$\beta_1$	0.0579* (0.000)	0.0562* (0.000)	0.0572* (0.000)	0.0836* (0.000)	0.0580* (0.000)	0.1386* (0.000)
$\kappa_1$	0.9393* (0.000)	0.9414* (0.000)	0.9404* (0.000)	0.9093* (0.000)	0.9394* (0.000)	0.8245* (0.000)
$\beta_1 + \kappa_1$	0.996	0.997	0.997	0.992	0.997	0.962

\*1% significance level, \*\*5% significance level and \*\*\*10% significance level.  $\beta_1$  is the coefficient for previous shocks and  $\kappa_1$  is the coefficient for persistence.

Table 8: Platinum Analysis

	Platinum-Dow Jones Industrials-Brent		Platinum-Silver-FTSE 100-Brent		Platinum-Silver-Nikkei 225-Brent	
	<i>GARCH (1,1)</i>	GARCH(1,1) with dummies	<i>GARCH (1,1)</i>	GARCH(1,1) with dummies	<i>GARCH (1,1)</i>	GARCH(1,1) with dummies
$c_0$	0.0002 (0.187)	0.0002 (0.263)	0.0003 (0.147)	0.0002 (0.215)	0.0003 (0.114)	0.0002 (0.175)
$\Lambda$	0.0540* (0.005)	0.0423** (0.019)	0.0279 (0.208)	0.0175 (0.414)	0.0447* (0.004)	0.0403* (0.004)
$\Lambda$	0.0294* (0.000)	0.0296* (0.000)	0.0279* (0.000)	0.0288* (0.000)	0.0272* (0.001)	0.0245* (0.004)
$\beta_0$	0.0000* (0.000)	0.0000* (0.000)	0.0000* (0.000)	0.0000* (0.000)	0.0000* (0.000)	0.0000* (0.000)
$\beta_1$	0.1312* (0.000)	0.1392* (0.000)	0.1307* (0.000)	0.1374* (0.000)	0.1310* (0.000)	0.1337* (0.000)
$\kappa_1$	0.8609* (0.000)	0.8574* (0.000)	0.8608* (0.000)	0.8593* (0.000)	0.8607* (0.000)	0.8620* (0.000)
$\beta_1 + \kappa_1$	0.991	0.996	0.990	0.996	0.991	0.995

\*1% significance level, \*\*5% significance level and \*\*\*10% significance level.  $\beta_1$  is the coefficient for previous shocks and  $\kappa_1$  is the coefficient for persistence.