# Modeling Asymmetric Volatility In Oil Prices

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**ABSTRACT**

*Recent volatility in crude oil prices has affected economies around the world, especially the US economy, which is the largest consumer of oil. This paper focuses on how shocks to volatility of crude oil prices may affect future oil prices. The paper uses daily crude oil price data for the past 10 years to test and model the oil price volatility by fitting different variations of GARCH including a univariate asymmetric GARCH model to the series. Tests show high persistence and asymmetric behavior in oil price volatility, and reveal that negative and positive news have a different impact on oil price volatility. These results will help interested observers better understanding of the energy markets and has important consequences for the overall economy.*

**Keywords:** Volatility Persistence; Time Series; GARCH

## I. INTRODUCTION

Recent volatility in crude oil prices has affected economies around the world. The United States (US) has been affected more than any other country mainly because it is the largest consumer of oil. An analysis of the crude oil prices in the recent past clearly reflects that the volatility has been more significant now than ever before. These fluctuations have led researchers around the world to dig deeper into the causes and effects of these phenomena. Newspapers like the *Wall Street Journal* and journals like the *Economist* are frequently discussing changing oil prices and how these may impact the economy. It is important that we find major causes for this recent volatility in crude oil prices but what is even more important is how this volatility may affect future oil prices. Volatility of oil prices is an important variable for economies around the world, and large changes in oil price volatility have a tendency to affect other macroeconomic variables and can significantly affect the planning and growth of an economy.

This paper examines fluctuations in crude oil prices and how exogenous shocks (news) to these fluctuations may have a permanent effect on them and how they may be affected differently by good or bad news. The paper uses daily crude oil price data from the past decade to test the volatility of crude oil prices. Tests show high persistence and asymmetric behavior in oil price volatility indicating that positive and negative news have different impacts on future volatility of oil prices. This paper provides a better understanding of energy markets, especially the behavior of oil prices over time. The first section gives a brief introduction on the background and goals of this paper. The second section discusses some earlier research that supports some of the ideas and techniques employed in this paper. The third section describes the source of the data followed by the methodology used to obtain the results for this research. The fifth section discusses the empirical results displayed in tables and a graph. The paper concludes with some policy implications and final remarks.

## II. LITERATURE REVIEW

In the last few years, a large volume of literature has appeared mainly focused on volatility in financial markets, especially the volatility in equity or foreign exchange markets. Some of the research is done by, Engle et al. (1990), Engle and Susmel (1993), Bollerslev, Chou, and Kroner (1992), Brooks and Persand (2003), Malik, Ewing, and Payne (2005), Hassan and Malik (2007), and Ederington & Guan (2010.) Most of the literature suggests that Engle's (1982) autoregressive conditional heteroskedasticity (ARCH) model, which was later generalized by Bollerslev (1986) and became known as the GARCH model and its other variants, tend to work better when it comes to modeling high frequency time series data. Harris and Sollis (2003) and Engle (2002) have explained the usefulness and relationship between different ARCH and GARCH models in their research and suggest that GARCH models are most suitable for modeling volatility of time series data.

The volatility of oil prices has been discussed earlier by Claessens and Varangis (1994), Daniel (2001), Ewing, Malik, and Ozfidan (2002), Kohl (2002), and Hamilton (2003). Lee et al. (1995) show how volatility in oil prices can have a significant impact on the macroeconomy by examining the relationship between oil price volatility and real Gross National Product (GNP) and found that any change in oil prices have a greater effect on real GNP for economies where oil prices have shown stability over time. Ferderer (1996) has discussed the existence of a negative relationship between major macroeconomic variables and changes in oil price volatility due to exogenous shocks. Huang, Masulis, and Stoll (1996) show that any changes in oil price volatility impact stock prices of oil companies, however, the impact of this volatility on the broad based stock market is relatively insignificant. Fan et al. (2008) study the risk spillover between the West Texas Intermediate (WTI) and Brent crude oil spot markets using a variant of GARCH and find that the technique using the GARCH model proves more effective than historical simulation with ARMA forecasts (HSAF) model. Bekiros and Diks (2008) using the WTI daily spot and future prices of crude oil, find that the data for the period from 1999 to 2007 is more “turbulent” than the data for 1991 to 1999. Surprisingly however, not enough research has been done to test the asymmetric behavior of oil price volatility and so this paper tries to address this issue by first testing for persistence in shocks to volatility and then the asymmetric behavior of oil price volatility.

## III. METHODOLOGY

ARCH and GARCH models are the most popular methods used for modeling volatility of high-frequency time series data.[1] A common reason for the use of ARCH and GARCH models for time series is that volatility in high-frequency time-series data is time-varying i.e. time periods of high volatility have a tendency to cluster. Many authors have utilized the ARCH and GARCH models to capture this phenomenon since these models usually provide a better fit in comparison to a constant variance model.[2] Since this paper uses a high-frequency time series data, the use of the GARCH model and its variations is appropriate. The paper employs three different variations of the GARCH model. The first two models used in this paper test the persistence of shocks to volatility. The third model tests for asymmetric behavior of volatility. The paper employs a univariate GARCH model and a GARCH-M (GARCH in mean) model which explain how shocks to volatility may be highly persistent in the future.

Non-linear GARCH models were introduced to capture the effect of good and bad news separately. So, the third model used in this paper, known as the Exponential GARCH (EGARCH) model which is non-linear GARCH model is used to test the asymmetric behavior of volatility i.e. the possibility that good and bad news may have a different impact on oil price volatility. Our GARCH models are given as follows:

### III-A: GARCH (1,1) model

The GARCH (1,1) can be written as:

$$Y_t = \mu + \varepsilon_t, \quad \varepsilon_t \mid I_{t-1} \sim N(0,h_t) \tag{1}$$

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

Equation 1 is the mean equation and equation 2 is the conditional variance equation from the univariate GARCH model. The term (1,1) in GARCH (1,1) is a reference to the presence of a first-order autoregressive GARCH term and a first-order moving ARCH term. $Y_t$ is the volatility of the time series and $h_t$ is the forecast variance in time period t based upon time period t-1. $\varepsilon_t$ is the residual term and N is the conditional normal density

[1] Please refer to Engle (2002) for a detailed survey.
[2] See Klaassen 2002

with a zero mean and $h_t$ variance. $I_{t-1}$ is the information set available at time t-1. In equation 2, ω is the mean, $h_{t-1}$ is the conditional variance from the previous period and $\varepsilon_{t-1}^2$ is the news from the previous period. The α is the ARCH term in the variance equation which captures information about volatility observed in the last period and β is the GARCH term which gives the last period forecasted variance. Engle and Bollerslev (1986) indicated that the sum of the coefficients α and β in equation (2) shows the persistence of volatility for a shock (news). As this value gets closer to 1, the shocks to volatility will be more persistent meaning the conditional variance will take a long time to converge to its steady state. When this value equals 1 it entails an *integrated* GARCH (IGARCH) process which means that any news will have a permanent effect on the variance of a series. The results of this paper are expected to show the sum of α and β to be close to 1 meaning that shocks to volatility are highly persistent. This implies that the study of asymmetric effects of news on crude oil prices becomes rather more important. An AR (1) (autoregressive process of order one) specification for mean equation is used since the series shows significant autocorrelation as detected by the Ljung-Box Q-statistic.

### III-B: GARCH-in-Mean (1,1) model

This variation of GARCH is important because it determines the relationship between expected risk and expected returns associated with crude oil prices. An explanatory variable that captures risk is desirable to model expected returns in financial markets. Some function of the variance can be added to the conditional mean equation Eq. (1) as an additional regressor to model time varying risk premium. This model in which the conditional variance is added to the mean equation given by Engle et al. (1987) is known as the GARCH-in-Mean model and is given as:

$$Y_t = \mu + \gamma h_t + \varepsilon_t \tag{3}$$

The term γ in equation 3 is the estimated coefficient for expected risk and it measures the risk return trade-off. A significant value of γ implies that expected returns in the future are significantly related to the expected risk of the investment where the significance of the value is given by the p-value, shown in parentheses. A p-value of 0.05 or less is considered significant at the 5% level. In this model the p-value is expected to be significant which would imply that expected returns have a significant relationship with expected risk.

### III-C: EGARCH (1,1) model

For most time series it is typical that downward movements lead to higher volatility compared to upward movements of similar magnitude. The concept can be explained in terms of the asymmetric impact of bad news versus good news. One of the variants of the GARCH models is the exponential GARCH (EGARCH) model which was proposed by Nelson (1991). According to Engle and Ng (1993) the EGARCH model lets positive return shocks (good news) to have a different impact on volatility than negative return shocks (bad news.) In this model the forecasts of the conditional variance are guaranteed to be nonnegative[3]. The conditional variance is given as:

$$\text{Log}(\sigma_t^2) = \omega + \beta\log(\sigma_{t-1}^2) + \alpha(\varepsilon_{t-1}/\sigma_{t-1}) + \delta(\varepsilon_{t-1}/\sigma_{t-1}) \tag{4}$$

The parameter δ in this model measures the asymmetry so when δ = 0 good news and bad news of the same magnitude have the same effect on volatility. The impact is asymmetric when δ does not equal zero. The impact of good news is measured by the sum of α and δ whereas the impact of bad news is calculated by the difference between α and δ. Therefore, given α is positive, a negative value of δ will show that the effect of bad news exceeds the effect of good news on the return series.

## IV. DATA

The data consists of daily observations of West Texas Intermediate (WTI) crude oil spot prices with a total

[3] The Threshold ARCH (TARCH) model was not used in this paper since it does not guarantee nonnegative forecasts of the conditional variances.

 

of 2506 usable observations based upon a period from May 1, 2000 to April 30, 2010[4]. The data were obtained from the Energy Information Administration (EIA). The selection and range of these data is important in terms of the major events that have taken place during this time. Some of these events include the terrorist attacks in New York in 2001, the hurricanes Rita and Katrina in 2005 and the recent supply fears in 2008 that led to a huge increase in price of oil followed by a decline to record low levels and then eventually becoming stabilized.

**Table 1**
**Descriptive Statistics for Return Series**

| | |
|---|---|
| **Mean** | 0.000480 |
| **Median** | 0.001303 |
| **Maximum** | 0.164137 |
| **Minimum** | -0.170918 |
| **Std. Dev.** | 0.026853 |
| **Skewness** | -0.254411 |
| **Kurtosis** | 7.345756 |
| | |
| **Jarque-Bera** | 1999.01<br>(0.00) |
| | |
| **Sum** | 1.203237 |
| **Sum Sq. Dev.** | 1.806280 |
| **Q(16)** | 650.76<br>(0.00) |
| | |
| **Observations** | 2506 |

Notes: The above statistics are for daily crude oil returns. 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 are in parentheses**.**

**Table 2**
**Unit Root Tests**

| | |
|---|---|
| **ADF** | 0.0000 |
| **Lags** | 15 |
| **PP** | 0.0001 |
| **Bandwidth** | 38 |

Notes: The lag length of the Augmented Dickey-Fuller (ADF) test was automatically selected through the Schwarz information criterion and the bandwidth for the Phillips-Perron (PP) was set using the Bartlett Kernel.

**Table 3**

| | | | | |
|---|---|---|---|---|
| **GARCH (1,1)** | | | | |
| $\alpha$ | $\beta$ | $\alpha + \beta$ | $TR^2$ | Q(16) |
| 0.07<br>(0.00) | 0.91<br>(0.00) | 0.98 | 0.03<br>(0.18) | 12.70<br>(0.69) |
| **GARCH-in-Mean (1,1)** | | | | |
| $\alpha$ | $\beta$ | $\gamma$ | $TR^2$ | Q(16) |
| 0.07<br>(0.00) | 0.91<br>(0.00) | -1.06<br>(0.49) | 0.03<br>(0.19) | 13.13<br>(0.66) |
| **EGARCH (1,1)** | | | | |
| $\alpha$ | $\delta$ | $\alpha + \delta$ | $TR^2$ | Q(16) |
| 0.14<br>(0.00) | -0.04<br>(0.04) | 0.10 | 0.03<br>(0.13) | 12.68<br>(0.70) |

Notes: The sum of $\alpha$ and $\beta$ is close to 1 showing shocks to volatility of crude oil prices are highly persistent. $TR^2$ refers to the ARCH LM test for a null of no ARCH in the residuals. The Ljung-Box Q-statistics are given in the last column with 16 lags and tested for a null hypothesis of no autocorrelation.

[4] The number of observations of the data is in conformity with earlier research using similar techniques.

 

Table 1 displays the descriptive statistics of the oil price returns, showing some evidence of skewness and kurtosis. As for a normally distributed random variable the skewness is zero and kurtosis is three therefore our series is negatively skewed with fat tails. The probability values of the Jarque-Bera (1980) test statistic imply that our variable is non-normally distributed. Table 1 also shows the significant p-values for the Ljung-Box Q-statistic suggesting that autocorrelation exists in the residuals.

Table 2 shows the results of the unit root tests. These results are based upon the Augmented Dickey-Fuller (1979) and the Phillips-Perron (1988) tests and the significant p-values mean that we reject the null hypothesis of no unit root in the return series.

## V. EMPIRICAL RESULTS

The results of the tests are given in Table 3 where the first portion of the table describes the results for the GARCH (1,1) model. It can be seen that the sum of the ARCH and GARCH terms given by $\alpha$ and $\beta$ respectively is 0.98 which is very close to 1. This indicates the shocks to volatility are highly persistent and the effects of these shocks will sustain in future periods for a long period of time. These results are consistent with the expectations which were discussed in the earlier section.

The second part of Table 3 shows the results for the GARCH-in-mean (1,1) model. Once again the sum of $\alpha$ and $\beta$ indicates high persistence of shocks to volatility. It is also important to note that the value of the coefficient $\gamma$ is not significant. This is given by the p-value of 0.49 in parentheses given in the middle section of Table 3 which suggests that the expected returns are not significantly related to the expected risk. This is in contrast to the expectations discussed earlier in the methodology section however; these results are still important and imply that the expected risk and return relationship for the time series data used in this paper is not significant.

The results of the Exponential GARCH model are given in the third and last part of Table 3. These results show a $\delta$ value of -0.04 along with a p-value of 0.04 (given in parentheses.) The p-value is less than 0.05 meaning that the results are statistically significant. As discussed earlier, the negative value of $\delta$ suggests that the effect of bad news is significantly greater than the effect of good news on crude oil returns for the sample used in this paper[5]. These results are consistent with the expectations from this research.

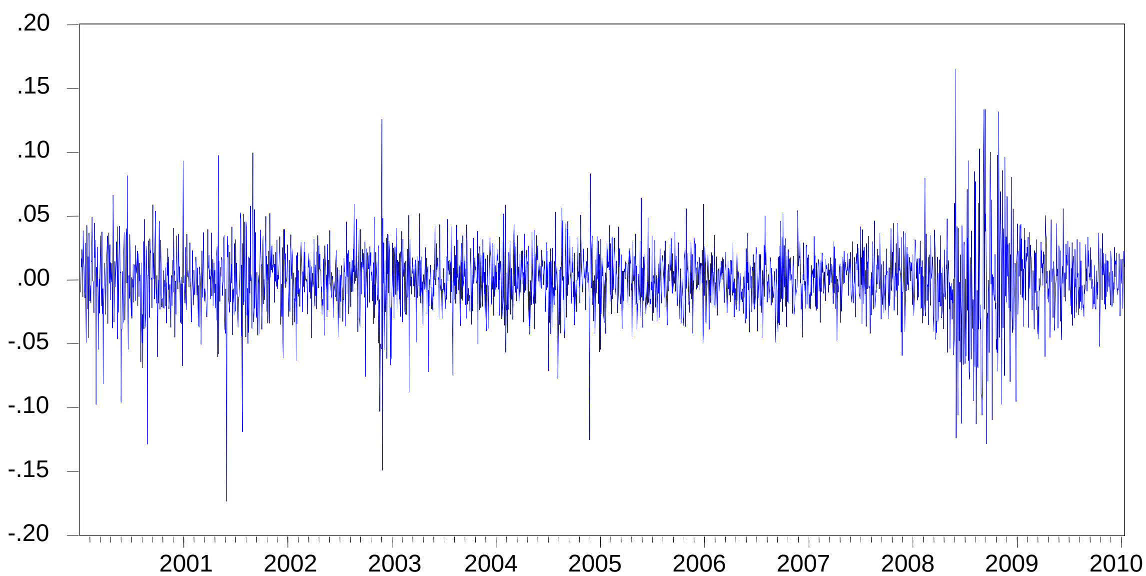


**Figure 1: Daily Return Volatility**

[5] A larger sample size is also tested and it appears that the effect of good news is not significantly different from the effect of bad news as we go further into the past suggesting that bad news has really been more significant in the last decade or so.

The return volatility for crude oil prices is shown in Figure 1. Please note that the graph shows volatility clustering i.e. time periods of high volatility tend to bunch together. This is especially true for the years 2001-02 and then 2008-09 when supply fears led to high volatility in prices. Also, it is interesting to see that the volatility changes significantly during the periods where there is bad news e.g. the terrorist attacks in September of 2001 and the hurricanes Rita and Katrina in 2005 which damaged oil refineries in the gulf coast and oil prices were significantly affected by these natural disasters. The other major change in variance appears at a more recent time shown by a more volatile period towards the end when the supply fears for oil led to high speculation and an enormous increase in crude oil prices. Just two years ago, these oil prices had gone up to $147 per barrel in the international market. These are just some of the examples of how bad news may significantly affect the volatility of oil prices.

## VI. CONCLUDING REMARKS

The main focus of this paper is to attempt to find the asymmetric effects of news on volatility of crude oil prices. The paper employs the popular GARCH model and its variants to fit daily crude oil spot prices for the past 10 years. It is evident from the results that not only shocks to volatility are highly persistent but they also show significant asymmetric behavior indicating that bad (negative) news seems to have a more significant impact on oil prices than good (positive) news of the same magnitude. The research also suggests that the asymmetric behavior in oil price volatility is more significant during the past decade but as the study is extended further into the past, the asymmetric behavior seems less significant. This implies that news has had a significant (and asymmetric) impact on oil prices within the recent past and hence a more careful approach should be adopted when making forecasts about the volatility of crude oil prices. The results are useful for oil futures traders who need to perceive the effects of news on return volatilities before executing their trading strategies and for investors who would like to effectively price, speculate, and hedge in the oil market. These results are also important for policy makers since the impact of natural catastrophes and political or financial crises seems far deeper than any good news. The forecast of oil price volatility and other outstanding issues have been left for future studies.

## AUTHOR INFORMATION

**Dr. S. Aun Hassan** earned a Ph.D. in Financial Economics from Texas Tech University in Lubbock, TX in 2005. He is currently working as an assistant professor at Colorado State University Pueblo and joined this institution in Fall 2009. Previously, he worked as assistant professor at Morningside College in Sioux City, IA from 2006 to 2009. Dr. Hassan has published research papers in the *Journal of Economics and Finance* and the *Quarterly Review of Economics and Finance.*

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**NOTES**