# Oil Price Volatility, Global Financial Crisis and The Month-of-the-Year Effect

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**Abstract**

This paper investigates the month-of-the-year effect in the UK Brent crude oil market using the GARCH (1,5) and GJR-GARCH (1,5) models in the light of Asian financial crisis and the global financial crisis using daily data over the period, January 4, 1988 and May 27, 2009. The result shows the presence of the month-of-the-year effect in volatility but not in the return in the oil market. However, the pattern of significance of monthly effect in volatility is affected by the choice of model. The significant month-of-the-year effect on volatility may be in line with information availability theory

The result shows that the Asian financial crisis has an impact on the oil price return series while the global financial crisis has no impact on oil price returns. The Asian financial crisis and global financial crisis did not account for the sudden change in variance.

**Keywords:** Month-of-the-year effect, Volatility, Oil prices, Global Financial crisis, Volatility persistence, GARCH

**JEL**: F10, G14

## 1. Introduction

The monthly seasonality in returns has been well documented and tested for various stock markets and countries (Rozeff and Kinney, 1976; Gultekin and Gultekin, 1983; Keim, 1983; Reinganum, 1983). The month-of-the-year effect is present when returns in some months are higher than other months. This seasonal market anomaly, if present, refutes market efficiency. Studies on monthly seasonality, also called January effect or year end effect or "tax loss selling" hypothesis, argued that investors, in order to reduce their taxes, sell their stocks in December (which is the tax month) to book losses. The selling of stocks by various investors will put downward pressure on the prices. As soon as December ends market corrects and stock prices rise. The stocks will give higher return in January. Wachtel (1942) was the first to point out the seasonal effect in the US markets. Rozeff and Kinney (1976), Gultekin and Gultekin (1983), Keim (1983), Reinganum (1983) among others also provided evidence supporting January effect in the USA. Berges, McConnell, and Schlarbaum (1984) and Tinic, Barone-Adesi and West (1990) found seasonal effect in Canada. January effect has also been investigated for emerging markets (Nassir and Mohammad, 1987; Ho, 1999; Fountas and Segerdakis, 1999; Kumar and Singh, 2008). Apart from the stock market, seasonal effect has also been investigated for other commodity markets (Kumar and Singh, 2008) and the foreign exchange market with more focus on the day-of-the-week effect (McFarland et al., 1982; Hilliard and Tucker, 1992; Cornett et al., 1995; Aydogan and Booth, 2003; and Yamori and Mourdoukow, 2003). Little or no work has been done on monthly seasonality of the oil market.

Most studies on the seasonal effects concentrated more attention on seasonal pattern in mean return (see also Jaffe and Westerfield, 1985; Solnik and Bousquet, 1990; Baronet, 1990, among others). An investor should be concerned not only with variations in asset returns, but also the variances in returns. Engle (1993) argues that risk-averse investors should reduce their investments in assets with higher return volatilities. Engle (1982) introduced the autoregressive conditional heteroskedasticity (ARCH) to model volatility by relating the conditional variance of the disturbance term to the linear combination of the squared disturbances in the recent past. Bollerslev (1986) generalized the ARCH model by modeling the conditional variance to depend on its lagged values as well as squared lagged values of disturbance, which is called generalized autoregressive conditional heteroskedasticity (GARCH). Since the work of Engle (1982) and Bollerslev (1986), variants of the GARCH models have been developed. Some of the models include IGARCH originally proposed by Engle and Bollerslev (1986), GARCH-in-Mean (GARCH-M) model introduced by Engle, Lilien and Robins (1987),the standard deviation GARCH model introduced by Taylor (1986) and Schwert (1989), the EGARCH or Exponential GARCH model proposed by Nelson (1991), TARCH or Threshold ARCH and Threshold GARCH were introduced independently by Zakoïan (1994) and Glosten, Jaganathan, and Runkle (1993), the Power ARCH model generalised by Ding, Zhuanxin, C. W. J. Granger, and R. F. Engle (1993) among others.

If investors can identify a certain pattern in volatility, then it would be easier to make investment decisions based on both return and risk (Kiymaz and Berument, 2003). The understanding of seasonality in risk and returns is important to financial managers, financial analysts and investors especially in assisting them in developing an appropriate strategy in the context of the financial market. Thus, an investigation of the monthly seasonal effect in returns should also consider the monthly seasonal effect on volatility. Several studies have been done using the GARCH framework to investigate the seasonal effect. Berument and Kiymaz (2001) model seasonal effect using GARCH model. Their findings show that the seasonal effect is present in both volatility and return equations. Several studies have been done using the GARCH framework to investigate the seasonal effects (Berument and Kiymaz, 2001; Choudhry, 2000; Balaban, Bayar and Kan, 2001; Kiymaz and Berument, 2003; Yalcin and Yucel, 2006, Chandra, 2004; Apolinario, Santana, Sales and Caro, 2006 among others).Little or no work has been done on the month-of-the-year effect in the crude oil market using GARCH models. This paper attempts to fill this gap. The month-of-the-year effect in return contradicts the weak form of market efficiency, which states that asset prices are random and it is not possible to predict asset price and return movements using past price information. The understanding of the month-of-the-year effect in risk and returns is important to financial managers, financial analysts and investors to develop appropriate strategy in the context of any commodity or asset market.

The Asian Financial crisis of 1997 and the Global Financial crisis of 2008 could have affected oil price volatility. The Asian Financial Crisis which began in 1997 was a period of financial crisis that affected much of Asia raising fears of a worldwide economic meltdown due to financial contagion. The crisis started in Thailand on July 2, 1997 with the devaluation of Thai baht caused by the decision of the Thai government to float the baht, cutting its peg to the United States dollar, after being unsuccessful in an attempt to support it in the face of a severe financial overextension that was in part real estate driven. Prior to the crisis, Thailand economy was in the glimpse of collapse as it had acquired a burden of foreign debt. The crisis spread to other Southeast Asia countries (Philippine, Malaysian, Indonesian, Singapore, South Korea, Hong Kong and Taiwan) and Japan with their currencies slumping, stock markets collapsing and other asset prices declining, and a precipitous rise in private debt. The Asian crisis made international investors reluctant to lend to developing countries, leading to economic slowdowns in developing countries in many parts of the world. The economic slowdowns affected the demand for oil reducing the price of oil, to as low as $8 per barrel towards the end of 1998, causing a financial pinch in OPEC nations and other oil exporters. This reduction in oil revenue led to the 1998 Russian financial crisis, which in turn caused Long-Term Capital Management in the United States to collapse after losing $4.6 billion in 4 months (Lowenstein, 2000).

The global financial crisis of 2008, an ongoing major financial crisis, could have affected stock volatility. The crisis which was triggered by the subprime mortgage crisis in the United States became prominently visible in September 2008 with the failure, merger, or conservatorship of several large United States-based financial firms exposed to packaged subprime loans and credit default swaps issued to insure these loans and their issuers. On September 7, 2008, the United States government took over two United States Government sponsored enterprises Fannie Mae (Federal National Mortgage Association) and Freddie Mac (Federal Home Loan Mortgage Corporation) into conservatorship run by the United States Federal Housing Finance Agency (Wallison and Calomiris, 2008; Labaton and Andrews, 2008). The two enterprises as at then owned or guaranteed about half of the U.S.'s $12 trillion mortgage market. This causes panic because almost every home mortgage lender and Wall Street bank relied on them to facilitate the mortgage market and investors worldwide owned $5.2 trillion of debt securities backed by them. Later in that month Lehman Brothers and several other financial institutions failed in the United States (Labaton, 2008). The crisis rapidly evolved into a global credit crisis, deflation and sharp reductions in shipping and commerce, resulting in a number of bank failures in Europe and sharp reductions in the value of equities (stock) and commodities worldwide. In the United States, 15 banks failed in 2008, while several others were rescued through government intervention or acquisitions by other banks (Letzing, 2008). The financial crisis created risks to the broader economy which made central banks around the world to cut interest rates and various governments implement economic stimulus packages to stimulate economic growth and inspire confidence in the financial markets. The financial crisis could have affected the uncertainty in the demand for oil, thus, causing uncertainty in the price of oil.

The purpose of this paper is to investigate the month-of-the-year effect in the Crude Oil market using GARCH (1, 5) and GJR-GARCH (1, 5) models in the light of Asian and the global financial crises. The rest of this paper is organised as follows: Section two discusses an overview of the Global oil market while chapter three discusses the literature review. Section four discusses methodology while the results are presented in Section five. Concluding remarks are presented in Section six.

## 2. Overview of the Global Oil Market

Prior to the establishment of OPEC, the United States and British oil companies provided the world with increasing quantities of cheap oil. The world price was about $1 per barrel, and during this time the United States was largely self-sufficient, with its imports limited by a quota. In 1960, as a way of curtailing unilateral cuts in oil prices by the big oil companies in the U.S and Britain, the governments of the major oil-exporting countries formed the Organization of Petroleum Exporting Countries, or OPEC. OPEC’s goal was to try to establish stability in the petroleum market by preventing further cuts in the price that the member countries - Iran, Iraq, Kuwait, Saudi Arabia, and Venezuela - received for oil. The OPEC countries succeeded in stabilizing the oil prices between $2.50 and $3 per barrel up till the early 70s. Apart from the four founding members of OPEC, other countries later joined OPEC. The membership of OPEC has fluctuated overtime. Indonesia withdrew from OPEC in January 2009, Angola joined OPEC in January 2007, Ecuador withdrew from OPEC in January 1993 and rejoined in November 2007, and Gabon withdrew from OPEC in July 1996. The current membership of OPEC include Algeria, Ecuador, Iran, Iraq, Kuwait, Libya, Nigeria, Qatar, Saudi Arabia, United Arab Emirates, and Venezuela. OPEC member countries agreed on a quota system to help coordinate its production policies, but attempts to stabilize prices within a price band relied on producers having to constrain supply to create a tight market, thus generating an economic disincentive to build stocks (UNCTAD, 2005). OPEC members benefit from higher short-term prices; however, a tight market generates volatility and reduces the market’s ability to respond to contingencies (UNCTAD, 2005). Furthermore, disagreements on production quotas and members' mistrust have added to uncertainty and fuelled volatility.

The displacement of coal as a primary source of energy and development of internal-combustion engine and the automobile led to increasing oil consumption throughout the world, especially in Europe and Japan, thus, causing an enormous expansion in the demand for oil products.

The era of cheap oil came to an end in 1973 when, as a result of the Arab-Israeli War, the Arab oil-producing countries cut back oil production and embargoed oil shipments to the United States and the Netherlands. This raised prices fourfold to $12 per barrel. The Arab nations' cut in production, totaling 5 million barrels, could not be matched by an increase in production from by countries (UNCTAD, 2005). This shortfall in production, which represented 7 per cent of world production outside the USSR and China, caused shock waves in the market especially to oil companies, consumers, oil traders, and some governments (UNCTAD, 2005). Furthermore, the Iranian revolution in 1979 which led to a reduction in Iran's output by 2.5 million barrels of oil per day forced up oil prices in 1979. The outbreak of war between Iran and Iraq in 1980 aggravated the situation in the world oil market. The war led to a loss in oil production of 2.7 million barrels per day on the Iraqi side and 600,000 barrels per day on the Iranian side. This force oil prices to increase to $35 per barrel (UNCTAD, 2005). The high oil prices contributed to a worldwide recession which gave energy conservation a push reducing oil demand and increasing supplies. There were significant increases in oil supplies from non-OPEC countries, such as those in the North Sea, Mexico, Brazil, Egypt, China, and India. This forced down the oil prices. Attempts by OPEC to stabilize prices during this period (after the Iran-Iraq war) were unsuccessful. The failure of OPEC to stabilize prices during this period has been attributed to members of OPEC producing beyond allotted quotas (UNCTAD, 2005). By 1986, Saudi Arabia had increased production from 2 million barrels per day to 5 million barrels per day. This made oil prices to crash below $10 per barrel in real terms (UNCTAD, 2005). Oil prices remain volatile despite various efforts by OPEC to stabilize prices. As at 1989, the Soviet Union increased its production to 11.42 million barrels per day, accounting for 19.2 percent of world production in that year. This led to further reduction in oil prices.

The invasion of Kuwait by Iraq leading to the Gulf War in 1990 caused prices to rise, but with the increasing world oil supply, oil prices fell again, maintaining a steady decline until 1994. The lower oil prices brightened the economies of United States and Asia, thus, boosting oil demand and prices rise again. The financial crisis in Asia in 1997 caused economies in the region to grind to a halt. Oil demand fell and the surplus oil production pushed down oil prices. Oil prices decreased to around $10 per barrel in late 1998. In 1999, there was a sudden increase in demand which along with production cutbacks by OPEC raises oil prices to about $30 per barrel in 2000 but they fell once again in 2001. However, since March 2002, oil prices have been on an upward trend climbing to record level reflecting especially the developments related with the war in Iraq and increasing speculative trading in oil futures on Futures exchanges. As at July 11, 2008, the crude oil prices per barrel of the UK Brent in US$ per barrel was $143.68. Figure 1 shows the trend in daily oil prices since 1988. From July 14, 2008, oil prices have been gradually falling possibly reflecting world economic recession. As at January 2, 2009, the crude oil prices per barrel of the UK Brent was \$42.68. However since January 9, 2009, oil prices have been fluctuating, rising to \$61.28 per barrel as at May 27, 2009.

**3. Literature Review**

The market anomalies, which are proofs of market inefficiencies, have well documented in the finance literature. Market anomalies show the existence of predictable behavior in stock returns may lead to profitable trading strategies, and in turn, abnormal returns. The market anomalies that have attracted the attention of researchers are broadly known as calendar or seasonal effects. The most popular seasonal effects studied are the day of the week effect and the month-of-the-year or January effect.

The month-of-the-year effect is present when returns in some months are higher than other months. . In the USA and some other countries, December is the year-end month and also the tax month. It is argued that investors will sell shares that have lost values in December in order to reduce their taxes. The sale by various investors will put a downward pressure on the share prices and thus lowers stock returns. As soon as the tax month (December) ends, investors start buying shares in January and share prices will start rising. This will make stock returns to be high in the month of January. This tax-loss selling hypothesis has been found to be consistent with the 'year-end' effect and the 'January effect' in stock returns by various studies (Kumar and Singh, 2008; Bepari and Mollik, 2009). Wachtel (1942) was the first to point out the seasonal effect in the US stock markets. Some other studies in the USA supporting this effect include Rozeff and Kinney (1976), Keim (1983) and Reinganum (1983). Rozeff and Kinney (1976) found that stock returns in January to be larger than in other months. Keim (1983) found that small firm returns were significantly higher than large firm returns during the month of January. Reinganum (1983), however, found that the tax-loss-selling hypothesis could not explain the entire seasonality effect.

Seasonal effect has been found in other developed countries apart from United States. Gultekin and Gultekin (1983) examined data of 17 industrial countries with different tax laws and confirmed the January effect. Berges, McConnell, and Schlarbaum (1984) and Tinic, Barone-Adesi and West (1990) found seasonal effect in Canada. Boudreaux (1995) found the presence of the month-end effect in markets in Denmark, Germany and Norway. The seasonal effect in stock returns has also been found in UK (Lewis, 1989), Australia (Officer, 1975; Brown, Keim, Kleidon and Marsh, 1983) and Japan (Aggarwal, Rao and Hiraki, 1990). Raj and Thurston (1994) investigated the January and April effects in the New Zealand stock market and found no significant effect. Nassir and Mohammad (1987) investigated the January effect in Malaysia and found the average January returns to be significantly positive and higher than in other months. Ho (1999) found that six out of eight emerging Asian Pacific stock Markets exhibit significantly higher daily returns in January than in other months. Other studies include Fountas and Segerdakis (1999), Pandey (2002), Lazar et al. (2005), and Bepari and Mollik (2009).

Apart from the stock market, the seasonal effect has also been investigated for other financial markets such as the foreign exchange market. McFarland et al. (1982), Hilliard and Tucker (1992), Cornett et al. (1995), Aydogan and Booth (2003) and Yamori and Kurihara (2004) investigated the day-of-the-week effect for the foreign exchange market. Yamori and Kurihara (2004) investigated the day-of-the-week effect for 29 foreign exchange markets in the 1980s and found the presence of the day-of-the-week effect. They also stated that the day-of-the-week effect disappeared for almost all 29 countries in the 1990s. Little or no work has been done on the day-of-the-week effect of the oil market.

Most of the studies on the seasonal effect discussed so far have focused attention on seasonal pattern in mean return. An investor should be concerned not only with variations in asset returns, but also the variances in returns. Engle (1993) argues that risk-averse investors should reduce their investments in assets with higher return volatilities. Engle (1982) introduced the autoregressive conditional heteroskedasticity (ARCH) model which was later generalized (GARCH) by Bollerslev (1986). The GARCH (p, q) model has p ARCH terms and q GARCH terms and is given as :

$$\sigma_t^2 = \omega + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 \tag{1}$$

where, $\sigma^2$ is conditional variance of $\varepsilon_t$ and $\omega > 0$, $\alpha \geq 0$ , $\beta \geq 0$ . Equation (1) shows that the conditional variance is explained by past shocks or volatility (ARCH term) and past variances (the GARCH term). Equation (2) will be stationary if the persistent of volatility shocks, $\sum_{i=1}^{p}\alpha_i + \sum_{j=1}^{q}\beta_j$ is lesser than 1 and in the case it comes much closer to 1, volatility shocks will be much more persistent.

The work of Engle (1982) and Bollerslev (1986) has led to the development of various models to model financial market volatility. Some of the models include IGARCH originally proposed by Engle and Bollerslev (1986), GARCH-in-Mean (GARCH-M) model introduced by Engle, Lilien and Robins (1987),the standard deviation GARCH model introduced by Taylor (1986) and Schwert (1989), the EGARCH or Exponential GARCH model proposed by Nelson (1991), TARCH or Threshold ARCH and Threshold GARCH were introduced independently by Zakoïan (1994) and Glosten, Jaganathan, and Runkle (1993), the Power ARCH model generalised by Ding,. Zhuanxin, C. W. J. Granger, and R. F. Engle (1993) among others.

Kiymaz and Berument (2003) argued that It is important to know whether there are variations in volatility of asset returns by the day-of-the-week and whether a high (low) return is associated with a correspondingly high (low) volatility for a given day. If investors can identify a certain pattern in volatility, then it would be easier to make investment decisions based on both return and risk (Kiymaz and Berument, 2003). Thus, an investigation of the seasonal effect in returns should also consider the seasonal effects on volatility. Several studies have been done using the GARCH framework to investigate the seasonal effect. Berument and Kiymaz (2001) model the seasonal effect using GARCH model. Their findings show that the day of the week effect is present in both volatility and return equations. Maghyereh (2003) using the standard GARCH, exponential GARCH (EGARCH) and the GJR models examined the seasonality of monthly stock returns as well as January effect in the Amman Stock Exchange (ASE) of Jordan. He found no evidence of monthly seasonality as well as January effect in the ASE returns.

Apart from the stock markets, monthly seasonal effect has also been investigated for commodity markets using GARCH framework. Kumar and Singh (2008) employed GARCH-in-mean model to study the volatility, risk premium and seasonality in risk-return relation of the Indian stock and commodity markets. They found risk-return relationship to be positive though insignificant for Nifty and Soybean whereas significant positive relationship is found in the case of Gold. They also found Seasonality in risk and return. Some other studies on the seasonal effect using different variations of the GARCH model include Miralles and Miralles (2000), Choudhry (2000), Amigo and Rodríguez (2001), Balaban, Bayar and Kan (2001), Kiymaz and Berument (2003), Yalcin and Yucel (2006), Chandra (2004), Apolinario, Santana, Sales and Caro (2006) among others. Little or no work has been done on the monthly seasonal effect in the crude oil market using GARCH models. This paper attempts to fill this gap.

## 4. Methodology

### *4.1 The Data*

The time series data used in this analysis consists of the daily crude oil prices of UK Brent spot price from January 4, 1988 to May 27, 2009 downloaded from the website of the Energy Information Administration. All the prices are in dollars per barrel. The return on oil price is defined as:

$$R_t = \log\left(\frac{OP_t}{OP_{t-1}}\right) \tag{2}$$

where $OP_t$ mean price of crude oil (UK Brent) at day t and $OP_{t-1}$ represent price of crude oil (UK Brent) at day t-1.

The $R_t$ of Equation (2) will be used in investigating the volatility of the oil market over the period, January 2, 1988 to May 27, 2009.

The Asian Financial crisis of 1997 and the Global Financial crisis of 2008 could have affected oil price volatility. In this study, July 2, 1997 is taken as the date of commencement of the Asian financial crisis while December 31, 2008 is taken as the end of Asian financial crisis.. To account for Asian financial crisis (ASF) in this paper, a dummy variable is set equal to 0 for the period before July 2, 1997 and after December 31, 1998; and 1 thereafter.

The global financial crisis could have affected the uncertainty in the demand for oil, thus, causing uncertainty in the price of oil. In this study, September 7, 2008 is taken as the date of commencement of the global financial crisis. To account for global financial crisis (GFC) in this paper, a dummy variable is set equal to 0 for the period before September 7, 2008 and 1 thereafter.

*4.2 Properties of the Data*

Table 1 reports the preliminary statistics (evidence) for the oil price return series for the entire study period as well as the return for each month of the year. The average return for the entire study period is 0.0002. The standard deviation of the return is 0.0242, and skewness is -0.6872. The kurtosis is 17.763 which is much larger than 3, the kurtosis for a normal distribution. The Jarque-Berra normality test rejects the normality of returns at the 5 percent level. The negative skewness is an indication of a non-symmetric series. Figure 2 clearly show that the distribution of the stock return series show a strong departure from normality.

When the return of each month is analyzed in Table 1, the findings indicate that December has a mean return of 0.08 percent, while January has a mean return of -0.15 percent. The signs of the returns are inconsistent with the results of Rozeff and Kinney (1976), Keim (1983), Reinganum (1983) among others. The lowest return of -0.26 percent is observed for October while the highest return of 0.15 percent is observed for March. The lowest standard deviation of 0.0192 is observed for July while the highest standard deviation of 0.0346 is observed for January. March, April, June, July, August and November have positive skewness while all other months have negative skewness. However, the impact of the negative skewness appears to be predominant as the overall skewness is negative

The kurtosis for each month is larger than 3, the kurtosis for a normal distribution. The Jarque-Bera normality test rejects the hypothesis of normality for the each month of the year.

The Ljung-Box test Q statistics as reported in Table 2 are all significant at the 5% for all reported lags confirming the presence of autocorrelation in the stock return series. The Ljung-Box test $Q^2$ statistics for are all significant at the 5% for all reported lags confirming the presence of heteroscedasticity in the oil price return series.

Table 3 shows the results of unit root test for the oil price return series. The Augmented Dickey-Fuller test and Phillips-Perron test statistics for the oil price return series are less than their critical values at the 1%, 5% and 10% level. This shows that the oil price return series has no unit root. Thus, there is no need to difference the data.

In summary, the analysis of the oil price return indicates that the empirical distribution of returns in the oil market is non-normal, with very thick tails. The leptokurtosis reflects the fact that the market is characterised by very frequent medium or large changes. These changes occur with greater frequency than what is predicted by the normal distribution. The empirical distribution confirms the presence of a non-constant variance or volatility clustering.

*4.3 Models used in this Study*

This study will attempt to model the volatility of daily oil price return using the GARCH (1, 5) and GJR-GARCH (1, 5) models in the light of Asian financial crisis and the global financial crisis. Different models including EGARCH model were initially tested in the study. The GARCH (1, 5) and GJR-GARCH (1, 5) models were chosen on the basis of maximum log-likelihood or minimum Akaike information Criterion. The GARCH (1,5) model will first be applied in investigating the volatility and month-of-the-year effect of the oil price return series. Then, the GARCH (1,5) model and the and GJR-GARCH (1, 5) model will be augmented to account for sudden change in variance in the volatility equation.

Thus, the mean and variance equations of the GARCH (1,5) model are given as :

$$R_t = b_0 + eR_{t-1} + \sum_{j=1}^{11} b_j \delta_{jt} + g_1 ASF + g_2 GFC + \varepsilon_t \qquad \varepsilon_t / \phi_{t-1} \sim N(0, \sigma_t^2, v_t) \tag{3}$$

$$\sigma_t^2 = h_0 + \alpha \varepsilon_{t-1}^2 + \sum_{j=1}^{5} \beta_j \sigma_{t-j}^2 \tag{4}$$

Where $R_t$ represents the return on oil price in day t. $\delta_{jt}$ represents month of the year j in day t. $\delta_{1t}, \delta_{2t}, \delta_{3t}, \delta_{4t}\ \delta_{5t}, \delta_{6t}, \delta_{7t}, \delta_{8t}, \delta_{9t}, \delta_{10t}$ and $\delta_{11t}$ represent January, February, March, April, May, June, July, August, September, October and November respectively.. In this study, δjt are dummy variables such that $\delta_{jt}$ =1 if day t is January and zero otherwise; $\delta_{2t}$ =1 if day t is February and zero otherwise and so forth. The coefficients $b_1$ to $b_{11}$ are the mean returns for January through November respectively and $\varepsilon_t$ is the stochastic term. December dummy variable is excluded to avoid dummy variable trap. The intercept term $b_0$ indicates mean return for the month of December and coefficients $b_1 \ldots b_{11}$ represent the average differences in return between December and each other month. These coefficients should be equal to zero if the return for each month is the same and if there is no seasonal effect. $g_1$ and $g_2$ represent the impact of ASF and GFC on oil price return series respectively. ε is an error term assumed to follow a conditional student t distribution with v degrees of freedom. $\sigma_t^2$ is the conditional variance of $\varepsilon_t$

Thus, $b_1 \ldots b_{11}$ represent size and direction of the effect of each month-of-the-year on oil price return. In other words, $b_1$, $b_2$, $b_3$, $b_4$, $b_5$, $b_6$, $b_7$, $b_8$, $b_9$, $b_{10}$ and $b_{11}$ represent January effect, February effect, March effect, April effect, May effect, June effect, July effect, August effect, September effect, October effect and November effect respectively on oil price returns.

The lag length of the oil price returns used in accounting for autocorrelation of returns has been chosen on the basis of Akaike information Criterion.

To account for the impact of the month-of-the-year effect on volatility and shift in variance as a result of the Asian financial crisis and the global financial crisis, the GARCH model of Equations (3) and (4) is re-estimated with the mean Equation (3) while the variance equation is augmented as follows:

$$\sigma_t^2 = h_0 + \alpha\varepsilon_{t-1}^2 + \sum_{j=1}^{5}\beta_j\sigma_{t-j}^2 + \Theta_1 ASF + \Theta_2 GFC + \sum_{j=1}^{11} h_j\delta_{jt} \tag{5}$$

$h_1 \ldots h_{11}$ represent size and direction of the effect of each month-of-the-year on oil price return. In other words, $h_1$, $h_2$, $h_3$, $h_4$, $h_5$, $h_6$, $h_7$, $h_8$, $h_9$, $h_{10}$ and $h_{11}$ represent January effect, February effect, March effect, April effect, May effect, June effect, July effect, August effect, September effect, October effect and November effect respectively on oil price return series. $\Theta_1$ and $\Theta_2$ represent the impact of ASF and GFC on oil price volatility respectively.

To allow for possible asymmetric and leverage effects, the GJR-GARCH (1,5) model is augmented to account for the shift in variance as a result of the Asian financial crisis and global financial crisis. The mean equation is the same as in Equation (3) while the variance equation is given as:

$$\sigma_t^2 = h_0 + \alpha\varepsilon_{t-1}^2 + \sum_{j=1}^{5}\beta_j\sigma_{t-j}^2 + \gamma\varepsilon_{t-1}^2 I_{t-1}^- + \Theta_1 ASF + \Theta_2 GFC + \sum_{j=1}^{11} h_j\delta_{jt} \tag{6}$$

The volatility parameters to be estimated include $h_0$, $\alpha$, $\beta$ and $\gamma$. As the oil price return series show a strong departure from normality, all the models will be estimated with student t as the conditional distribution for errors. The estimation will be done in such a way as to achieve convergence.

## 5. The Results

The results of estimating the GARCH models as stated in Section 4.3 for the GARCH (1,5) model, augmented GARCH (1,5) model and the augmented GJR-GARCH (1,5) models are presented in Table 3. In the mean equation, e (coefficient of lag of oil price returns) is significant in the GARCH (1,5) model and the two augmented models confirming the correctness of adding the variable to correct for autocorrelation in the oil price return series. The coefficient $g_1$ representing coefficients of the Asian financial crisis is statistically significant at the 5% level in the GARCH (1,5) model and the two augmented models. However, $g_2$ representing coefficient of the global financial crisis is statistically insignificant at the 5% level in the GARCH (1,5) model and the two augmented models. This implies that the Asian financial crisis has an impact on the oil price return series while the global financial crisis has no impact on oil price returns.

The coefficients $b_1$, $b_2$, $b_3$, $b_4$, $b_5$, $b_6$, $b_7$, $b_8$, $b_9$, $b_{10}$ and $b_{11}$ representing January effect, February effect, March effect, April effect, May effect, June effect, July effect, August effect, September effect, October effect and November effect respectively on oil price return s are statistically insignificant at the 5% level in the GARCH (1,5) model and the two augmented models. This appears to show that monthly seasonal effect is absent the oil price return series.

The variance equation in Table 5 shows that the $\alpha$ coefficients are positive and statistically significant at the 5% level in the GARCH (1,5) model and the augmented models. This confirms that the ARCH effects are very pronounced implying the presence of volatility clustering in the GARCH (1,5) model and the augmented models.

Table 5 shows that the $\beta$ coefficients (the GARCH parameters) are statistically significant in the GARCH (1,5) model and the two augmented models. The sum of the $\alpha$ and $\beta$ coefficients in the in the GARCH (1,5) model and the augmented GARCH (1,5) model are 0.9914 and 0.9886 respectively. This appears to show that there is high persistence in volatility as the sum of $\alpha$ and $\beta$ are very close to 1. However, as a result of the Asian financial crisis and the global financial crisis, the volatility persistence is slightly lower in the augmented GARCH (1,5) model. In the augmented GJR-GARCH model, the sum of $\alpha$, $\beta$ and $\gamma/2$ is 0.9880. This also confirmed the high volatility persistence in the oil market. The Asian financial crisis and the global financial crisis could have accounted for the slight change in variance.

The augmented GARCH and GJR-GARCH models, where the Asian financial crisis and global financial crisis variables are added to variance equation indicates that $\Theta_1$ and $\Theta_2$ representing coefficients of the Asian financial crisis and global financial crisis respectively are all statistically insignificant at the 5% level. This implies that the Asian financial crisis and global financial crisis have no impact on volatility equation. This appears to indicate that the Asian financial crisis and global financial crisis did not account for the sudden change in variance.

Table 5 shows that the coefficients of $\gamma$, the asymmetry and leverage effects, are negative and statistically insignificant at the 5% level in the augmented GJR-GARCH (1,5) model. This shows that the asymmetry and leverage effects are rejected in the augmented GARCH (1,5) model for the crude oil market.

The coefficients $h_{11}$ representing November effect in volatility is statistically significant at the 5% level in the volatility equation of the augmented GARCH (1,5) model. However, in the augmented GJR-GARCH (1,5) model, $h_3$ and $h_{11}$ representing March effect and November effect are statistically significant in the volatility equation. This implies that the presence of seasonal effect in the oil price volatility in Nigeria. The result is affected by the choice of model.

The estimated coefficients of the degree of freedom, *v* are significant at the 5-percent level in the GARCH (1, 5) model and the augmented models implying the appropriateness of student t distribution. The wald test for the mean equation (based on the null hypothesis of $b_1=b_2=b_3=b_4=b_5=b_6=b_7=b_8=b_9=b_{10}=b_{11}$) shows that F-statistic and Chi-square are statistically insignificant in the mean equation in the OLS, GARCH model and the augmented models. However, the wald test for the variance equation (based on the null hypothesis of $h_1=h_2=h_3=h_4=h_5=h_6=h_7=h_8=h_9=h_{10}=h_{11}$) in the augmented models shows that F-statistic and Chi-square are statistically significant in the variance equation. This appears to imply that the presence of month-of-the-year effect in oil price volatility but not in the oil price return series.

Diagnostic checks

Table 5 shows the results of the diagnostic checks on the estimated GARCH models for the GARCH (1,5) model and the two augmented models. Table 5 shows that the Ljung-Box Q-test statistics of the standardized residuals for the remaining serial correlation in the mean equation shows that autocorrelation of standardized residuals are statistically insignificant at the 5% level for the GARCH (1,5) model and the two augmented models confirming the absence of serial correlation in the standardized residuals. This shows that the mean equations are well specified. The Ljung-Box $Q^2$-statistics of the squared standardized residuals in Table 5 are all insignificant at the 5% level for the GARCH (1,5) model and the two augmented models. The ARCH-LM test statistics in Table 5 for the GARCH (1,5) model and the two augmented models further showed that the standardized residuals did not exhibit additional ARCH effect. This shows that the variance equations are well specified in for the GARCH (1,5) model and the two augmented models. The Jarque-Bera statistics still shows that the standardized residuals are not normally distributed. In sum, all the models are adequate for forecasting purposes.

A comparison of the augmented GARCH (1,5) model and the augmented GJR-GARCH (1, 5) model shows that GJR-GARCH (1,5) slightly ranked better in terms of the of maximum log-likelihood, lowest Akaike information, Schwarz and Hannan-Quinn criteria. Thus, the GJR-GARCH (1,5) model is a preferable model for the daily oil price return series.

## 6. Conclusion

This paper investigated the month-of-the-year effect in the crude oil market using the GARCH (1,5) and GJR-GARCH (1,5) models in the light of Asian financial crisis and the global financial crisis. Volatility persistence and asymmetric properties are investigated for the oil market. It is found that the oil market appears to show high persistence in volatility and clustering properties. The results from the asymmetry model rejected the hypothesis of leverage effect. The GJR-GARCH model is found to be the best model.

The result shows that the Asian financial crisis has an impact on the oil price return series while the global financial crisis has no impact on oil price returns. The Asian financial crisis and global financial crisis did not account for the sudden change in variance.

The result shows the presence of the month-of-the-year effect in volatility but not in return for the crude oil market. However, the pattern of significance of monthly effect in volatility is affected by the choice of model. The significant day-of-the-week effect on volatility may be in line with information availability theory (Choudry, 2000).

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Table 1. Summary Statistics of the Raw Oil price Return Series over the period, January 4, 1988 – May 27, 2009

| | Mean | Median | Max. | Min. | Std. | Skewness | Kurtosis | Jarque-Bera | | N |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | | Statistic | Probability | |
| Jan | 0.0007 | 0.0007 | 0.1813 | -0.3612 | 0.0346 | -2.0306 | 32.1094 | 16449.2100 | (0.0000)* | 457 |
| Feb | -0.0001 | 0.0000 | 0.0799 | -0.1108 | 0.0214 | -0.2521 | 6.1081 | 181.7643 | (0.0003)* | 440 |
| Mar | 0.0015 | 0.0015 | 0.1626 | -0.0900 | 0.0249 | 0.5181 | 7.8586 | 497.7063 | (0.0000)* | 484 |
| Apr | 0.0013 | 0.0011 | 0.1028 | -0.0710 | 0.0223 | 0.1255 | 4.5601 | 46.1959 | (0.0000)* | 444 |
| May | 0.0005 | 0.0000 | 0.0571 | -0.0636 | 0.0195 | -0.1730 | 3.3158 | 4.2255 | (0.0000)* | 462 |
| Jun | 0.0003 | 0.0000 | 0.0820 | -0.0760 | 0.0200 | 0.2173 | 4.5040 | 45.9569 | (0.0000)* | 450 |
| Jul | 0.0010 | 0.0011 | 0.0704 | -0.0804 | 0.0192 | 0.0965 | 4.6219 | 50.5801 | (0.0003)* | 455 |
| Aug | 0.0014 | 0.0015 | 0.1227 | -0.1351 | 0.0219 | 0.1748 | 9.9798 | 938.1269 | (0.0000)* | 461 |
| Sep | 0.0009 | 0.0000 | 0.0979 | -0.1989 | 0.0248 | -1.0973 | 13.6169 | 2189.0710 | (0.0000)* | 447 |
| Oct | -0.0026 | -0.0010 | 0.0889 | -0.1902 | 0.0263 | -1.0855 | 10.0399 | 1047.0330 | (0.0003)* | 463 |
| Nov | -0.0008 | 0.0000 | 0.1285 | -0.1288 | 0.0253 | 0.1373 | 8.5026 | 567.8819 | (0.0000)* | 449 |
| Dec | -0.0015 | -0.0003 | 0.1274 | -0.1683 | 0.0267 | -0.4095 | 9.2986 | 717.7780 | (0.0000)* | 427 |
| All | 0.0002 | 0.0001 | 0.1813 | -0.3612 | 0.0242 | -0.6872 | 17.7630 | 49820.3000 | (0.0000)* | 5439 |

Notes: p values are in parentheses. * indicates significance at the 5% level. Max denotes maximum. Min. denotes minimum. SD denotes Standard deviation. N denotes number of observations.

Table 2. Autocorrelation of the Oil price return Series over the period, January 4, 1988 – May 27, 2009

| | Lags | | | |
|---|---|---|---|---|
| | 1 | 6 | 12 | 20 |
| Ljung-Box Q Statistics | 5.0236 | 22.6170 | 26.9890 | 61.5610 |
| | (0.0250)* | (0.0010)* | (0.0080)* | (0.0000)* |
| Ljung-Box $Q^2$ Statistics | 61.7580 | 516.0800 | 569.9800 | 633.9300 |
| | (0.0000)* | (0.0000)* | (0.0000)* | (0.0000)* |

Notes: p values are in parentheses. * indicates significance at the 5% level

Table 3. Unit Root Test of the Oil Price Return Series over the period, January 4, 1988 – May 27, 2009

| | Statistic | Critical Values | | |
|---|---|---|---|---|
| | | 1% level | 5% level | 10% level |
| Augmented Dickey-Fuller test | -71.5108 | -2.5654 | -1.9409 | -1.6167 |
| Philips-Perron test | -71.5010 | -2.5654 | -1.9409 | -1.6167 |

Table 4. Parameter Estimates of the GARCH Models January 2, 1988 – May 27, 2009

| | | **GARCH (1,5)** | | **AUGMENTED GARCH (1,5)** | | **AUGMENTED GJR-GARCH (1,5)** | |
|---|---|---|---|---|---|---|---|
| | | Coef. | Prob. | Coef. | Prob. | Coef. | Prob. |
| **Mean Equation** | | | | | | | |
| $b_0$ | | 0.0002 | (0.7948) | 0.0001 | (0.8914) | 0.0001 | (0.9167) |
| $e_1$ | | 0.0431 | (0.0004)* | 0.0417 | (0.0006)* | 0.0415 | (0.0006)* |
| $g_1$ | | -0.0023 | (0.0265)* | -0.0023 | (0.0520)* | -0.0023 | (0.0472)* |
| $g_2$ | | -0.0037 | (0.1504) | -0.0040 | (0.1514) | -0.0039 | (0.1552) |
| $b_1$ | | 0.0006 | (0.6373) | 0.0007 | (0.5861) | 0.0007 | (0.6060) |
| $b_2$ | | 0.0003 | (0.7930) | 0.0005 | (0.6961) | 0.0005 | (0.7036) |
| $b_3$ | | 0.0014 | (0.2525) | 0.0014 | (0.2788) | 0.0014 | (0.2767) |
| $b_4$ | | 0.0014 | (0.2686) | 0.0015 | (0.2563) | 0.0015 | (0.2598) |
| $b_5$ | | 0.0004 | (0.7676) | 0.0004 | (0.7677) | 0.0004 | (0.7623) |
| $b_6$ | | -0.0001 | (0.9425) | -0.0000 | (0.9950) | -0.0000 | (0.9950) |
| $b_7$ | | 0.0009 | (0.4690) | 0.0009 | (0.4591) | 0.0010 | (0.4518) |
| $b_8$ | | 0.0003 | (0.7861) | 0.0004 | (0.7551) | 0.0004 | (0.7473) |
| $b_9$ | | 0.0013 | (0.2521) | 0.0014 | (0.2633) | 0.0015 | (0.2439) |
| $b_{10}$ | | -0.0012 | (0.3180) | -0.0011 | (0.3775) | -0.0011 | (0.3742) |
| $b_{11}$ | | -0.0002 | (0.8478) | -0.0001 | (0.9241) | -0.0001 | (0.9256) |
| **Variance Equation** | | | | | | | |
| $h_0$ | | 0.0000 | (0.0001)* | 0.0000 | (0.0167)* | 0.0000 | (0.0135)* |
| $\alpha$ | | 0.0611 | (0.0000)* | 0.0602 | (0.0000)* | 0.0552 | (0.0000)* |
| $\beta_1$ | | 0.9763 | (0.0000)* | 0.9551 | (0.0000)* | 0.9514 | (0.0000)* |
| $\beta_2$ | | 0.1383 | (0.0076)* | 0.129 | (0.0213)* | 0.1261 | (0.0208)* |
| $\beta_3$ | | 0.1995 | (0.0007)* | 0.2099 | (0.0009)* | 0.208 | (0.0007)* |
| $\beta_4$ | | -0.9997 | (0.0000)* | -0.9753 | (0.0000)* | -0.9675 | (0.0000)* |
| $\beta_5$ | | 0.6159 | (0.0000)* | 0.6097 | (0.0000)* | 0.6081 | (0.0000)* |
| $\gamma$ | | | | | | 0.0134 | (0.1977) |
| $\Theta_1$ | | | | 0.0000 | (0.1013) | 0.0000 | (0.0841) |
| $\Theta_2$ | | | | 0.0000 | (0.3028) | 0.0000 | (0.3315) |
| $\Theta_3$ | | | | -0.0000 | (0.2407) | -0.0000 | (0.2241) |
| $h_1$ | | | | -0.0000 | (0.0865) | -0.0000 | (0.0828) |
| $h_2$ | | | | 0.0000 | (0.4676) | 0.0000 | (0.4651) |
| $h_3$ | | | | -0.0000 | (0.0514) | -0.0000 | (0.0455)* |
| $h_4$ | | | | -0.0000 | (0.1338) | -0.0000 | (0.1225) |
| $h_5$ | | | | -0.0000 | (0.8695) | -0.0000 | (0.8383) |
| $h_6$ | | | | -0.0000 | (0.1128) | -0.0000 | (0.1096) |
| $h_7$ | | | | -0.0000 | (0.0981) | -0.0000 | (0.0890) |
| $h_8$ | | | | -0.0000 | (0.5557) | -0.0000 | (0.5291) |
| $h_9$ | | | | -0.0000 | (0.1915) | -0.0000 | (0.1788) |
| $h_{10}$ | | | | -0.0000 | (0.5556) | -0.0000 | (0.4996) |
| $h_{11}$ | | | | -0.0012 | (0.0000)* | -0.0011 | (0.0000)* |
| $\nu$ | | 5.9980 | (0.0000)* | 6.1705 | (0.0000)* | 6.2141 | (0.0000)* |
| Persistence | | 0.9914 | | 0.9886 | | 0.9880 | |
| LL | | 13372.2 | | 13381.7 | | 13382.4 | |
| AIC | | -4.9096 | | -4.9083 | | -4.9082 | |
| SC | | -4.8817 | | -4.8646 | | -4.8633 | |
| HQC | | -4.8999 | | -4.8931 | | -4.8925 | |
| **Wald Test** | | | | | | | |
| Mean Equation | F | 0.9454 | (0.4897) | 0.9209 | (0.5125) | 0.9416 | (0.4933) |
| | $\chi^2$ | 9.4542 | (0.4896) | 9.2090 | (0.5124) | 9.4156 | (0.4932) |
| Variance Equation | F | | | 1.0760 | (0.3767) | 1.0905 | (0.3652) |
| | $\chi^2$ | | | 10.7600 | (0.3765) | 10.9054 | (0.3649) |

Notes: p-values are in parentheses. * indicates significant at the 5% level.

LL, AIC, SC, HQC and N are the maximum log-likelihood, Akaike information Criterion, Schwarz Criterion, Hannan-Quinn criterion and Number of observations respectively

Table 5. Autocorrelation of Standardized Residuals, Autocorrelation of Squared Standardized Residuals and ARCH LM test of Order 4 for the GARCH Models over the period January 4, 1988 – May 27, 2009

| | GARCH (1,5) | AUGMENTED GARCH (1,5) | AUGMENTED GJR-GARCH (1,5) |
|---|---|---|---|
| **Ljung-Box Q Statistics** | | | |
| Q(1) | 0.1896 | 0.2485 | 0.2536 |
| | (0.6630) | (0.6180) | (0.6150) |
| Q(6) | 8.9605 | 8.7772 | 8.8426 |
| | (0.5360) | (0.5530) | (0.5470) |
| Q(12) | 22.4700 | 21.6360 | 21.4670 |
| | (0.0960) | (0.1180) | (0.1230) |
| Q(20) | 26.8790 | 25.6320 | 25.3330 |
| | (0.1390) | (0.1780) | (0.1890) |
| **Ljung-Box $Q^2$ Statistics** | | | |
| $Q^2(1)$ | 0.1090 | 0.0463 | 0.0318 |
| | (0.7410) | (0.8300) | (0.8590) |
| $Q^2(6)$ | 17.5740 | 18.4230 | 18.1870 |
| | (0.0630) | (0.0480) | (0.0520) |
| $Q^2(12)$ | 22.3300 | 23.6750 | 23.3330 |
| | (0.0990) | (0.0710) | (0.0770) |
| $Q^2(20)$ | 23.0760 | 24.3220 | 23.8420 |
| | (0.2850) | (0.2290) | (0.2490) |
| **ARCH-LM TEST** | | | |
| ARCH-LM (1) | 0.1089 | 0.0463 | 0.0317 |
| | (0.7414) | (0.8297) | (0.8586) |
| ARCH-LM (5) | 1.7280 | 1.8003 | 1.7827 |
| | (0.0687) | (0.0552) | (0.0582) |
| ARCH-LM (10) | 1.4630 | 1.5375 | 1.5238 |
| | (0.1097) | (0.0833) | (0.0877) |
| ARCH-LM (20) | 1.1180 | 1.1683 | 1.1535 |
| | (0.3218) | (0.2717) | (0.2858) |
| **Jarque-Berra** | 967.9594 | 882.8008 | 861.1792 |
| | (0.0000)* | (0.0000)* | (0.0000)* |

Note: p values are in parentheses

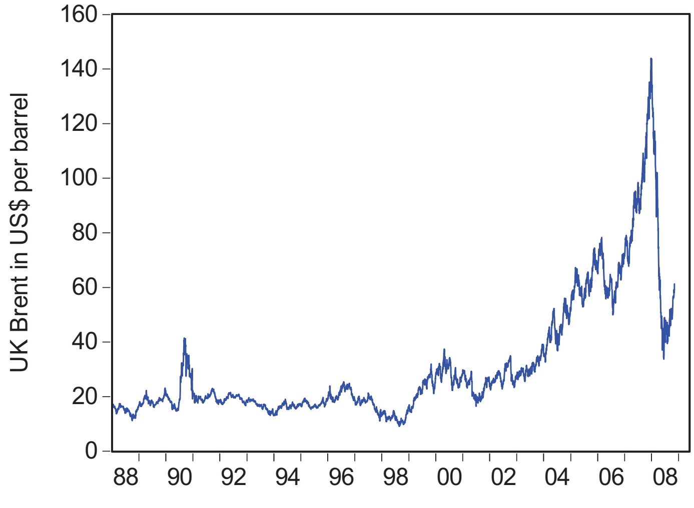


Figure 1. Trends in Daily Crude Oil Prices (UK Brent) in US$ per Barrel over the period, January 4, 1988 – May 27, 2009

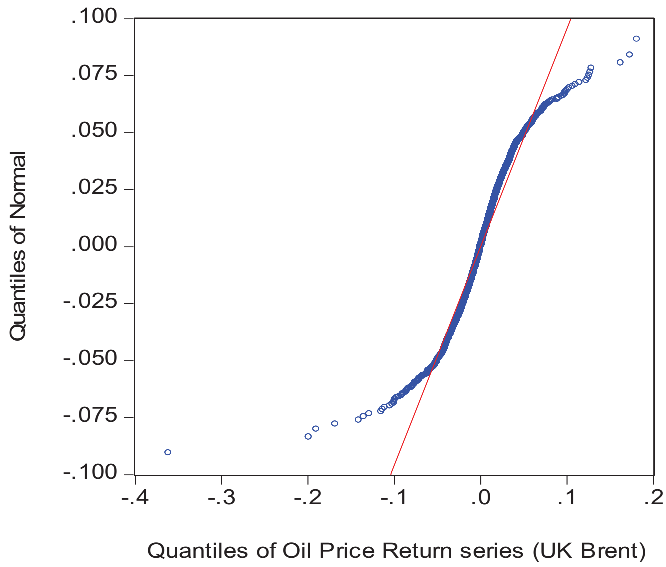


Figure 2. Quantile-Quantile Plot of Oil priceReturn Return Series over the period, January 4, 1988 – May 27, 2009

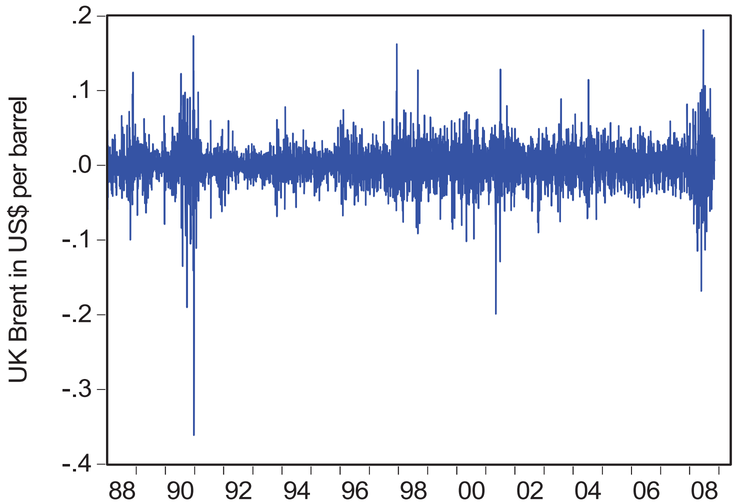


Figure 3. Log-differenced of daily price of crude oil (US$ per barrel)