Volatility Spillover between ICE WTI Crude Oil Futures and FTSE 100 Index Traded in UK

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Date of Submission: 05, September, 2011

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Abstract

This dissertation report investigates the presence of volatility spillover effect between ICE crude oil futures and FTSE 100 equity index using different bivariate extension of asymmetric EGARCH, GJR GARCH, and non-asymmetric scalar BEKK GARCH model under maximum likelihood estimation method. We have used daily return of crude oil futures and FTSE 100 index from 6th February, 2006 to 15th July 2011 traded in the same time zone, London. We use different values of ARCH (q) and GARCH (p) in the models and compare the model fit using different information criteria (Akaike, Schwarz, Shibata, and Hannan-Quinn). Information criteria reveal that ARMA(1,0) EGARCH(1,1) is the best fitted model out of all model specifications applied for FTSE 100 equity index whereas ARMA (1,0) scalar BEKK (1,1) is the best for ICE crude oil futures. A significant effect of historical volatility of squared return is found from almost all the model specifications on conditional variance of both the return series. We also find a significant bidirectional volatility spillover between crude oil market and equity market in UK.

1. Introduction

Petroleum is the major source of energy for driving the wheel of world economy. Petroleum prices have substantial direct and indirect impact on all sectors particularly production sector as well as household sector. Petroleum is used as direct or indirect input in almost all types of production, and increase in the price leads less consumption and lower productivity. Increase in petroleum price adversely affects agricultural production and thus increasing the price of all agricultural commodities. As a result there is an adverse impact of oil price shocks on aggregate price level of commodities and services affecting the macro economy as a whole. (More literature on this impact can be found on Mork (1994), Sadorsky (1999), Hamilton and Herrera (2004), Kilian (2008) etc.)

The fluctuations in crude oil price influence equity market by increasing the cost of input, transportation cost, cost of capital due to increase in inflation and thereby reducing earnings per share. In this paper we are to test how volatility or shocks in crude oil market effects the equity market or if there is any bidirectional movement in volatility between this two markets. We have collected daily price data of ICE WTI light sweet crude oil futures traded in London and FTSE 100 index. Intercontinental Exchange (ICE) became the centre for global petroleum trading after its acquisition of International Petroleum Exchange (IPE) in June 2001. The ICE West Texas Intermediate (WTI) light sweet crude oil futures contract launched on February 3 2006. This contract is cash settled against the prevailing market price for US light sweet crude. While Brent is a waterborne cargo market where crude oil arrives in discrete quantities over a short period of time, WTI is a mid-continent pipeline market where crude oil flows continuously at near-constant rates. Light, sweet crudes are preferred by refiners because of its low sulphur content and relatively high yields of high-value products such as gasoline, diesel fuel, heating oil, and jet fuel.

FTSE 100 is a portfolio of 100 most highly capitalized UK companies traded in London Stock Exchange and is considered as the most widely used indicator of UK stock market. Chang et. al. (2009) used discounted cash flows and equity pricing model to analyze the effect of oil price shocks on equity prices. The most affected sectors due to changes in crude oil price include the oil related industries like oil exploration, production and refining, the highly oil sensitive transportation industries like airlines, shipping, cargo industries and the highly oil based manufacturing industries like aluminium, steel, polymer etc (Hammoudeh et. al., 2002). The direction of the relationship between stock price and crude oil price depends on whether the stock of the company is a producer or a consumer of petroleum products. However, most companies in the world are direct or indirect consumer of petroleum and hence there is a negative effect of crude oil price shocks on the equity market as a whole (Chang et. al., 2009). Therefore in this paper we tried to see the impact of volatility spillover between crude oil market and equity market as a whole.

This paper examines volatility spillover between ICE WTI crude oil futures and FTSE 100 equity index traded in the same time zone using daily return data. We tried to see the volatility spillover effect between them using different EGARCH specifications, GJR-GARCH specifications and asymmetric Scalar BEKK specifications. The outcome of the study will be beneficial for financial portfolio analysts, financial hedgers, and all individual investors to understand the dynamics of financial market and invest wisely. This study should also help to understand the volatility dynamics for those who involved in volatility trading and investors who are risk averse.

2. Literature Review:

This paper is to investigate volatility spillover between crude oil market and equity market in the same time zone. Our objective is to test whether shocks in one market transmit to the other market using financial models and also to compare the output of different models. Volatility spillover is comovement of volatility between two markets; more specifically it is the economic phenomena of transmission of volatility in prices or returns from one market to other market. McAleer (2005) define volatility spillover as the risk of one asset depending dynamically on its own past risk and on the past risk of other assets.

Being the most influential commodity in the global economy, several researches have been devoted to analyze the dynamics of volatility in the crude oil market. Hamilton (1985) attributed oil shocks as exogenous events whereas it is influenced mostly by historical events such as Iraq invasion of Kuwait in 1990. Sadorsky (2006) compares and analyze different econometric models in forecasting volatility of crude oil futures prices. Cheong (2009) found volatility persistence in both European Brent and the WTI markets and a significant asymmetric effect in the European Brent market when comparing time varying volatility. Du et. al. (2009) used stochastic volatility model and Bayesian Markov Chain Monte Carlo methods to investigate the volatility spillover effects between crude oil and agricultural commodity market and found evidence of volatility spillover between these markets.

A large number of literatures are found on volatility spillover test and time varying correlations between financial and commodity markets but only a few of these spot lights on the relationship between crude oil and stock markets. Kaneko and Lee (1995) investigated the effect of changes in oil price on Japanese stock market returns and report that the effect is significant. Jones and Kaul (1996) found an opposite reaction of oil price shocks on the stock price of US, UK, Japan and Canadian stock market by analysing the effect of shocks on real cash flows using quarterly data. Huang et. al. (1996) found evidence of relationship between oil futures return and oil stock returns through estimating vector autoregressive model using daily data. Sadorsky (1999) investigates the effect of real oil price shocks on real stock returns by estimating and analyzing vector autoregressions using monthly data and conclude that positive shocks to oil prices decrease real stock returns. Ciner (2001) found significant non-linear relationship between real stock returns and crude oil futures price by performing a linear and non-linear causality tests. Papapetrou (2001) used impulse response functions to investigate the effect of oil price on stock price dynamics of Greece and conclude that an increase in oil price decrease real stock returns. Hammoudeh and Aleisa (2002) observed significant volatility spillover from crude oil market to stock market indices of oil exporting countries and their 2004 study reveals that Saudi Arabian stock market can be forecasted by crude oil futures price dynamics, being the stock market leader among Gulf Cooperating Council (GCC) countries. Maghyereh (2004) report no significant effect of oil price shocks on stock indices returns in 22 emerging economies whereas Basher and Sadorsky (2006) used a multifactor arbitrage pricing model and report significant effect of oil price volatility on returns from emerging stock markets. Kilian and Park (2007) also report the negative effect of oil price increase on stock price and abnormal shocks due to sudden increase in oil price is driven by precautionary demand for oil over artificial shortage of future oil supplies. Nandha and Faff (2007) reported a negative effect of oil price shocks on all global industry indices except oil, gas and mining. Sadorsky (2008) investigate the impact of oil price change on the stock price of different sized companies and reveals an asymmetric effect on medium sized companies whereas for small and large companies the effect is fairly symmetric. Bjørnland (2008) suggests a positive effect of oil price increase on stock returns in Norway where he shows that the effect eventually died out following an immediate increase in stock returns. Park and Ratti (2008) perform an analysis to estimate the effect of oil price shocks on the real stock returns of US and 13 European countries and find leverage effects on real stock return for US and Norway and oil price uncertainty have a significant effect on real stock returns in the same month. However Miller and Ratti (2009) show that international stock markets respond negatively to increases in the price of crude oil.

Agren (2006) perform volatility spillover test from crude oil market to equity market using BEKK model and showed strong evidence of volatility spillover in almost all major financial market in the world. However he didn't compare the output of the model with other asymmetric GARCH models to see whether there is any leverage effect exists affecting the conditional volatility of the market under investigation. Aloui and Jammazi (2009) use Markov switching EGARCH model to investigate the impact of crude oil price shocks on stock markets of France, UK and Japan and reveals that the net increase in oil price have a significant effect on the volatility of real returns and the probability of transition across regimes. In this paper we investigate the volatility spillover effect between crude oil futures return and FTSE 100 equity index return using asymmetric EGARCH and GJR GARCH specifications as well as non-asymmetric Scalar BEKK GARCH specifications.

3. Methodology

In order to analyze the transmission of volatility or volatility spillover effects between the crude oil market and equity market we have collected daily price data of FTSE 100 index to represent UK equity market and also collected daily price data on ICE WTI crude oil futures traded in the same time zone (London). We have converted the data into continuously compounded rate of return (Rt) by taking the first difference of the log prices i.e.

$FTSE(Rt)=100*Ln(FTSE_t / FTSE_{t-1})$

$ICE (Rt) = 100*Ln(ICE_t / ICE_{t-1})$

The sample daily data from 6th February, 2006 to 15th July, 2011 is collected from Bloomberg database which yields 1374 observations. Initially we perform descriptive statistics analysis on the price series and return series of the data. The normality test on the data has been carried out by calculating Skewness, kurtosis and Jarque-Bera coefficient. The Augmented Dickey Fuller (ADF) test of unit roots is used to test stationarity of the variables to ensure that outcome of the analysis is not spurious (Dickey and Fuller, 1981). The test of unit root has been carried out considering the presence of both intercept and trend using up to lag length 2. If the variables are non-stationary then we carry out Johansen approach for cointegration test.

We used different type of graphical analysis on the variables for visual inspection of the data properties. We plot daily returns from ICE crude oil futures and FTSE 100 index to see volatility pattern and if there is any co-movement exist. We observe the distribution of the variables by plotting unconditional density function for the return series. We also plot autocorrelogram of the squared return series to observe any ARCH effects on the data. The autocorrelation functions including Portmanteau statistics of the squared return series has been calculated to test for autocorrelated volatilities and volatility clustering.

We use ARCH-GARCH models developed by Engle (1982) to capture the distinguishing feature of financial time series where period of extreme volatility is followed by period of low volatility. The asymmetry effect or leverage effect, where bad news or unexpected drop likely to increase volatility more than good news or unexpected increase of the same magnitude, can not be captured by simple GARCH (p, q) model. Therefore to capture the leverage effect in the daily return series from crude oil market and stock market we use bivariate version of the univariate Exponential Generalised Autoregressive Conditional Heteroscedasticity (EGARCH) model developed by Nelson (1991) as an extension of the Bollerslev's (1986) GARCH model. The bivariate version of EGARCH used in our analysis is developed by Braun et. al. (1995), Kroners and Ng (1996, 1998), Henry and Sharma (1999) and Engle and Cho (1999). We then compare the outcome from bivariate EGARCH with GJR GARCH developed by Zakoian (1990) and Glosten, Jagannathan and Runkle

(1993). We also compare the outcome with multivariate non-asymmetric Scalar BEKK GARCH model (due to Baba et. al., 1990). All specifications of bivariate EGARCH and GJR GARCH are used under maximum likelihood estimation method whereas Scalar BEKK GARCH is used under maxSQP estimation method. The maximum likelihood method uses the quasi-Newton method of Broyden, Fletcher, Goldfarb and Shanno (BFGS). This function is the well-known MaxBFGS function provided by Oxmetrics. Maximum likelihood estimation is better than Ordinary Least Squares (OLS) estimation based on Greene (2000) where the former leads the estimated parameters to converge to their population counterparts at a faster rate. MaxSQP function implements a sequential quadratic programming technique to maximize a non-linear function subject to non-linear constraints, similar to Algorithm 18.7 presented in Nocedal and Wright (1999). MaxSQP function is particularly useful to impose the stationarity and/or positivity constraints like $\alpha_1 \geq 0$ in the ARCH(1).

In this report we use following conditional mean equation and conditional variance equation using same values of ARCH (q) and GARCH (p) in all EGARCH, GJR GARCH and Scalar BEKK GARCH models to investigate and compare volatility spillover outcome between crude oil market and equity market and to test whether any of these effects are asymmetric.

The conditional mean equation:

$$\text{FTSE}_t = \omega_1 + \psi_1 \text{FTSE\^{}2}_{t-1} + \varepsilon_t$$

$$\text{ICE}_t = \omega_3 + \psi_2 \text{ICE\^{}2}_{t-1} + \varepsilon_t$$

Here,

ω_1 and ω_3 = Constant terms in the conditional mean equation

ε_t is the error term with $\varepsilon_t \sim N(0,1)$

The conditional variance equation:

$$\sigma^2{}_{FTSE_t} = \omega_2 + \sum_{i=1}^{3} \delta_i \sigma^2{}_{FTSE^2{}_{t-i}} + \sum_{j=1}^{3} \varphi_j \sigma^2{}_{ICE^2{}_{t-j}} + \sum_{i=1}^{q} \alpha_i \varepsilon^2{}_{FTSE_{t-i}} + \sum_{j=1}^{p} \beta_j \sigma^2{}_{FTSE_{t-j}}$$

$$\sigma^2{}_{ICE_t} = \omega_4 + \sum_{i=1}^{3} \delta_i \sigma^2{}_{ICE^2{}_{t-i}} + \sum_{j=1}^{3} \varphi_j \sigma^2{}_{FTSE^2{}_{t-j}} + \sum_{i=1}^{q} \alpha_i \varepsilon^2{}_{ICE_{t-i}} + \sum_{j=1}^{p} \beta_j \sigma^2{}_{ICE_{t-j}}$$

Here in the conditional mean equation and conditional variance equation we use return series of FTSE 100 index and ICE WTI crude oil futures. The coefficients δ_i in the conditional variance equation indicates the effects of historical volatility of squared return whereas the coefficients φ_j show the effects of volatility spillover. We use squared return series of FTSE 100 index and ICE crude oil futures as explanatory variables in the GARCH models.

The conditional mean equation and conditional variance equation used in EGARCH (p, q) model for the equity market (FTSE 100) is in the following:

$$\text{FTSE}_t = \omega_1 + \psi_1 \text{FTSE\^{}2}_{t-1} + \varepsilon_t$$

$$\ln(\sigma^2{}_{FTSE_t}) = \omega_2 + \sum_{i=1}^{3} \delta_i \ln(\sigma^2{}_{FTSE^2{}_{t-i}}) + \sum_{j=1}^{3} \varphi_j \ln(\sigma^2{}_{ICE^2{}_{t-j}})$$

$$+ \left[1 - \beta(L)\right]^{-1} \left[1 + \alpha(L)\right] f(\varepsilon_{t-1} / \sigma_{FTSE_{t-1}})$$

Where, $f(\varepsilon_{t-1} / \sigma_{FTSE_{t-1}}) = \theta_1 \varepsilon_{t-1} + \theta_2 (\left|\varepsilon_{t-1} / \sigma_{FTSE_{t-1}}\right| - E\left|\varepsilon_{t-1} / \sigma_{FTSE_{t-1}}\right|)$

The conditional mean equation and conditional variance equation used in EGARCH (p, q) model for the crude oil market (ICE WTI crude oil futures) is in the following:

$$\mathrm{ICE}_t = \omega_3 + \psi_2 \mathrm{ICE}\text{^}2_{t-1} + \varepsilon_t$$

$$\ln(\sigma^2{}_{ICE_t}) = \omega_4 + \sum_{i=1}^{3} \delta_i \ln(\sigma^2{}_{ICE^2{}_{t-i}}) + \sum_{j=1}^{3} \varphi_j \ln(\sigma^2{}_{FTSE^2{}_{t-j}})$$

$$+ \left[1 - \beta(L)\right]^{-1} \left[1 + \alpha(L)\right] f(\varepsilon_{t-1} / \sigma_{ICE_{t-1}})$$

Where, $f(\varepsilon_{t-1} / \sigma_{ICE_{t-1}}) = \theta_1 \varepsilon_{t-1} + \theta_2 (\left|\varepsilon_{t-1} / \sigma_{ICE_{t-1}}\right| - E\left|\varepsilon_{t-1} / \sigma_{ICE_{t-1}}\right|)$

Here, α(L) and β(L) are q^{th} and p^{th} order polynomial lag operator such that,

$\alpha(L) = \alpha_1 L + \alpha_2 L^2 + \ldots\ldots\ldots\ldots.. + \alpha_q L^q$

$\beta(L) = \beta_1 L + \beta_2 L^2 + \ldots\ldots\ldots\ldots.. + \beta_p L^p$

In an EGARCH model we use the natural log of the conditional variance as the dependent variable and hence is always positive and do not require parameter restrictions to impose non-negativity. The function $f(\varepsilon_{t-1} / \sigma_{FTSE_{t-1}})$ in the EGARCH model allows for the asymmetry effect. In particular the term multiplied by the parameter θ_1 allows the sign of the errors to affect the conditional variance while the term multiplied by θ_2 allows for magnitude effect or separate size effect. If there is an asymmetry effect then $\theta_1 < 0$ but if $\theta_1 = 0$ there is no asymmetry effect.

The GJR GARCH model used in this paper was developed by Zakoian (1990) and Glosten, Jagannathan, and Runkle (1993). The conditional mean and variance equation used in the GJR GARCH model for FTSE 100 index and ICE WTI crude oil futures in this paper are:

$$\text{FTSE}_t = \omega_1 + \psi_1 \text{FTSE\^{}2}_{t-1} + \varepsilon t$$

$$\sigma^2{}_{FTSE_t} = \omega_2 + \sum_{i=1}^{3} \delta_i \sigma^2{}_{FTSE^2{}_{t-i}} + \sum_{j=1}^{3} \varphi_j \sigma^2{}_{ICE^2{}_{t-j}} + \sum_{i=1}^{q} \alpha_i \varepsilon^2{}_{FTSE_{t-i}}$$

$$+ \sum_{j=1}^{p} \beta_j \sigma^2{}_{FTSE_{t-j}} + \gamma \varepsilon^2_{FTSE_{t-1}} d_{t-1}$$

$$\text{ICE}_t = \omega_3 + \psi_2 \text{ICE\^{}2}_{t-1} + \varepsilon t$$

$$\sigma^2{}_{ICE_t} = \omega_4 + \sum_{i=1}^{3} \delta_i \sigma^2{}_{ICE^2{}_{t-i}} + \sum_{j=1}^{3} \varphi_j \sigma^2{}_{FTSE^2{}_{t-j}} + \sum_{i=1}^{q} \alpha_i \varepsilon^2{}_{ICE_{t-i}}$$

$$+ \sum_{j=1}^{p} \beta_j \sigma^2{}_{ICE_{t-j}} + \gamma \varepsilon^2_{ICE_{t-1}} d_{t-1}$$

Based on G@RCH program, $d_{t-1} = 1$ if $\varepsilon_{t-1} < 0$ and $d_{t-1} = 0$ otherwise. If the estimated value of $\gamma > 0$ then we can conclude that the asymmetry effect or leverage effect is present and bad news ($\varepsilon_{t-1} < 0$) or negative shocks increases volatility more than the good news ($\varepsilon_{t-1} > 0$).

BEKK GARCH model is a restricted version of the VEC model and is derived by Baba, Engle, Kraft and Kroner (BEKK) (1990) and later it is defined in Engle and Kroner (1995). The BEEK GARCH model is better than DCC and VECH in the sense that it allows conditional covariance matrix (H_t) to be positive definite. The standard form of the model is:

$$H_t = CC' + \sum_{i=1}^{q} \sum_{k=1}^{K} A'_{ki} \varepsilon_{t-i} \varepsilon'_{t-i} A_{ki} + \sum_{j=1}^{p} \sum_{k=1}^{K} B'_{kj} H_{t-j} B_{kj}$$

Here, A_{ki} , B_{kj} , and C are (N x N) parameter matrix and C is of lower triangle. If p=q=1 then the BEKK GARCH (1,1) model can be represented as follows:

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

If there are n= 3 variables in the model then the number of parameters to be estimated is n (5n +1)/2 i.e. we will have to estimate 24 parameters in the model. To reduce this number we can impose the restrictions that A and B matrix are equal to scalar times the identity matrix- i.e. Scalar BEKK GARCH.

After running different GARCH models we use misspecification tests, and graphical analysis to observe the adequacy of the models. We use different information criteria (Akaike, Schwarz, Shibata, Hannan-Quinn) to compare the fit of competing models where our objective is to minimize the criteria value.

4. Empirical Analysis

4.1 Preliminary Data Analysis:

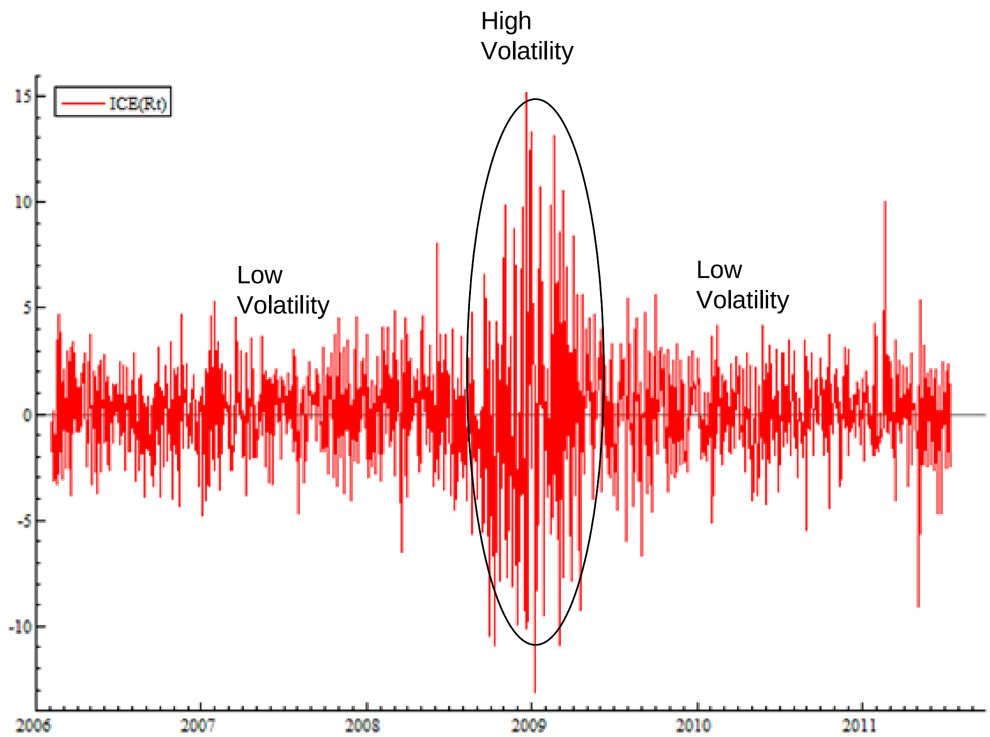
The summery statistics in Table 4.11 shows that the average returns from both crude oil (ICE) and stock (FTSE) is positive where the daily return from ICE WTI crude oil future is higher than equity FTSE 100 index. The standard deviation figures show that daily return from crude oil is more volatile than equity market for the sample period. The skewness and kurtosis coefficient shows non-normality for both daily returns from ICE and FTSE for the sample period. The kurtosis coefficients are very high for both daily returns from ICE and FTSE indicating leptokurtic distribution as is common for returns from financial time series. A normal distribution or Gaussian distribution has skewness coefficient equals to 0 and kurtosis coefficient equals to 3 and hence is not possible to make the assumption of Gaussianity for the distribution of the concerned variables. The Jarque-Bera coefficient for normality is also very high for both the return series rejecting the null hypothesis of normal distribution.

We also perform Augmented Dickey Fuller (ADF) Test at lag 2 with intercept and time trend to check the stationarity of the variables with null hypothesis $H_0 \sim I(1)$ against $H_1 \sim I(0)$. The 1% critical value for the ADF test is -3.96104 and the statistics indicates that the both daily price series for ICE WTI crude oil futures and FTSE 100 index are not stationary i.e. they have unit root. However the daily return series for ICE and FTSE are stationary indicating cointegrated relationship i.e. we can predict a long run relationship between daily returns from ICE crude oil futures and FTSE 100 index. Thus it is not necessary to apply the Johansen's cointegration test.

Table 4.11: Descriptive Statistics

Variables	Mean	SD	Skewness	Kurtosis	JB	ADF
ICE	78.351	20.697	0.70852	3.597	135.37	-1.61779
FTSE	5578.1	725.47	-0.82238	2.88936	155.57	-1.60934
ICE(Rt)	0.028677	2.6353	0.10028	7.3515	1086.4	-22.4071
FTSE(Rt)	0.0011773	1.4352	-0.088611	10.14	2920.4	-24.4524

The graphical representation in Figure 4.11 and Figure 4.12 indicate that the return from ICE and FTSE both display volatility clustering as periods of low volatility combine with periods of high volatility. This is a clear sign of presence of ARCH effect in the series. We can also plot the autocorrelation function against the lag to get a first visual impression of the magnitude of the autocorrelation problem of the error terms.



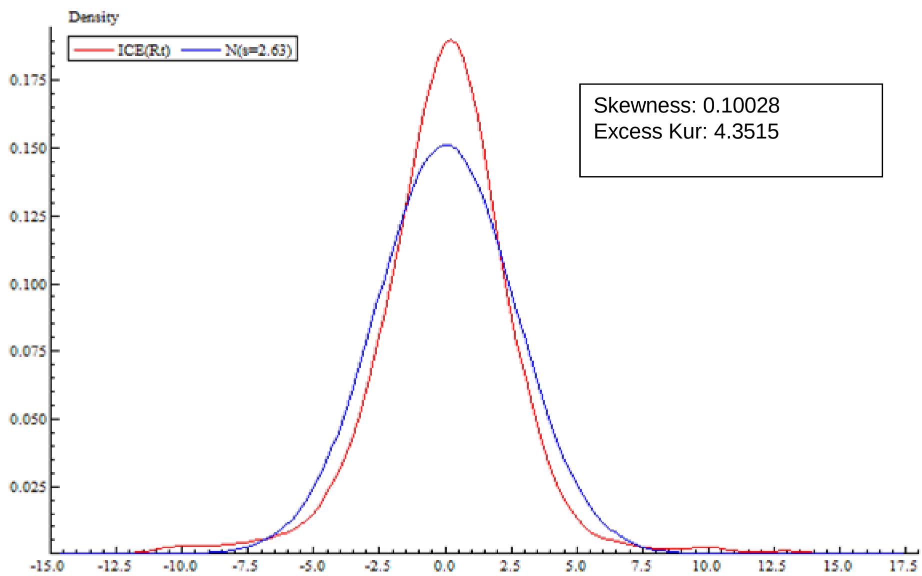
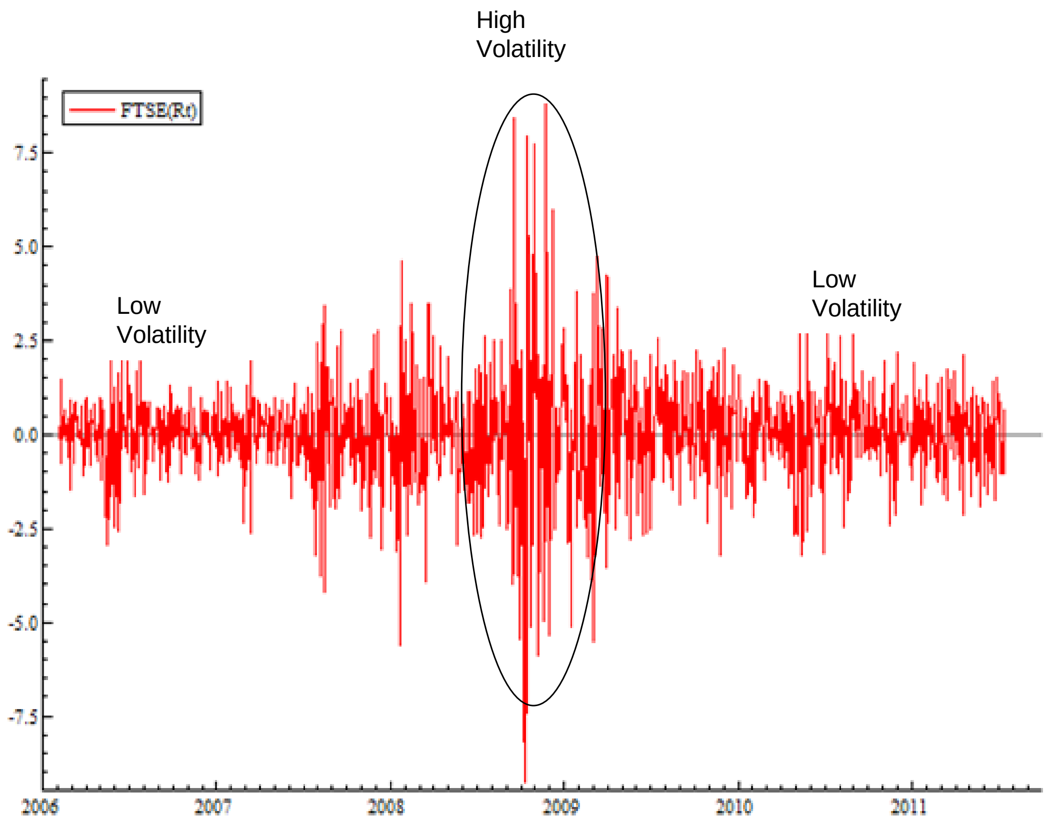


Figure 4.11: Daily returns (%) of ICE WTI crude oil futures and Unconditional Density Estimation



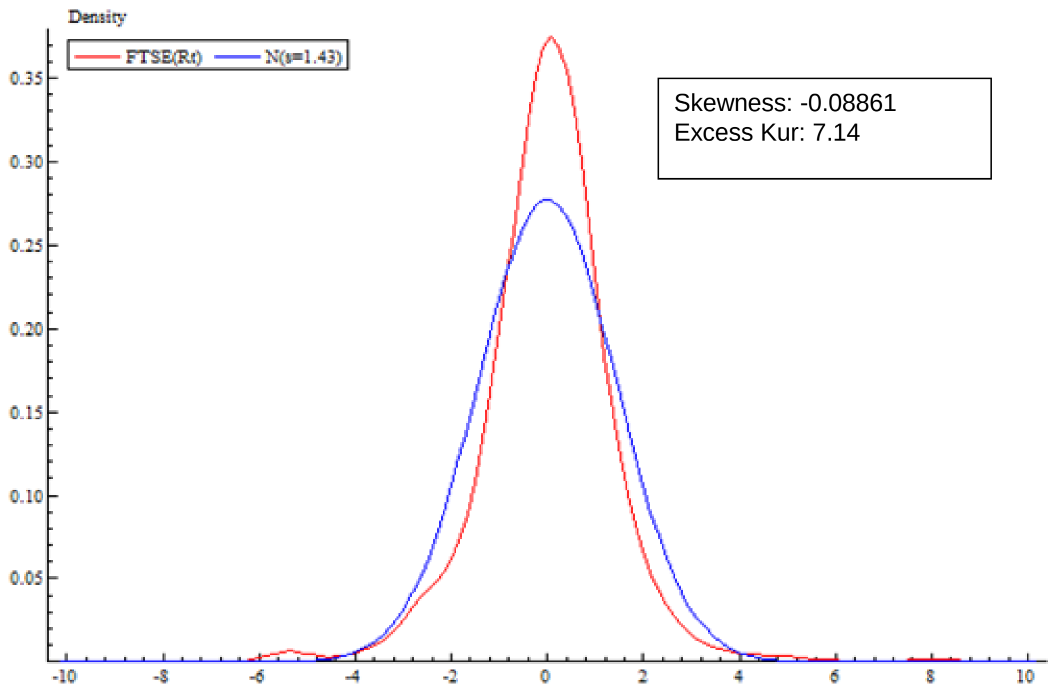
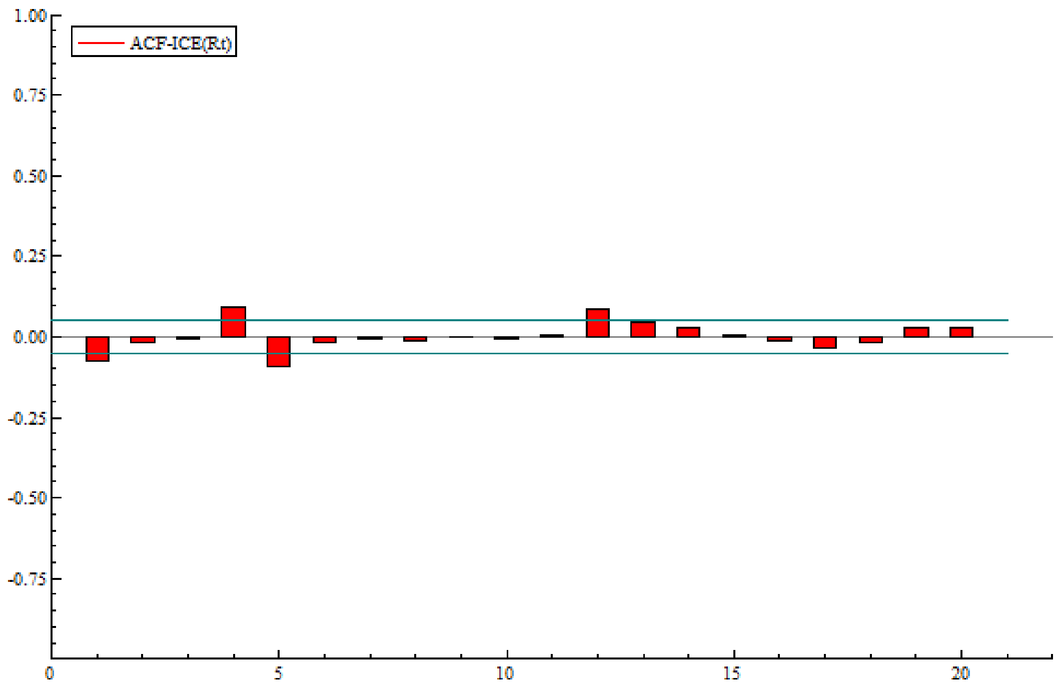


Figure 4.12: Daily returns (%) of FTSE 100 index and Unconditional Density Estimation

The Figure 4.13 suggests that the daily return series of the ICE and FTSE is a short memory process (in the level) and an AR(4) term might be needed in the conditional mean equation. We have previously seen from Figure 4.1 that the daily returns from ICE and FTSE exhibits volatility clustering where periods of low volatility mingle with periods of high volatility. In addition to this inspection, we can plot the autocorrelogram of the squared (or absolute) returns to highlight the presence of ARCH effects in the data. Figure 4.4 suggests that squared returns are strongly autocorrelated, exhibiting volatility clustering.



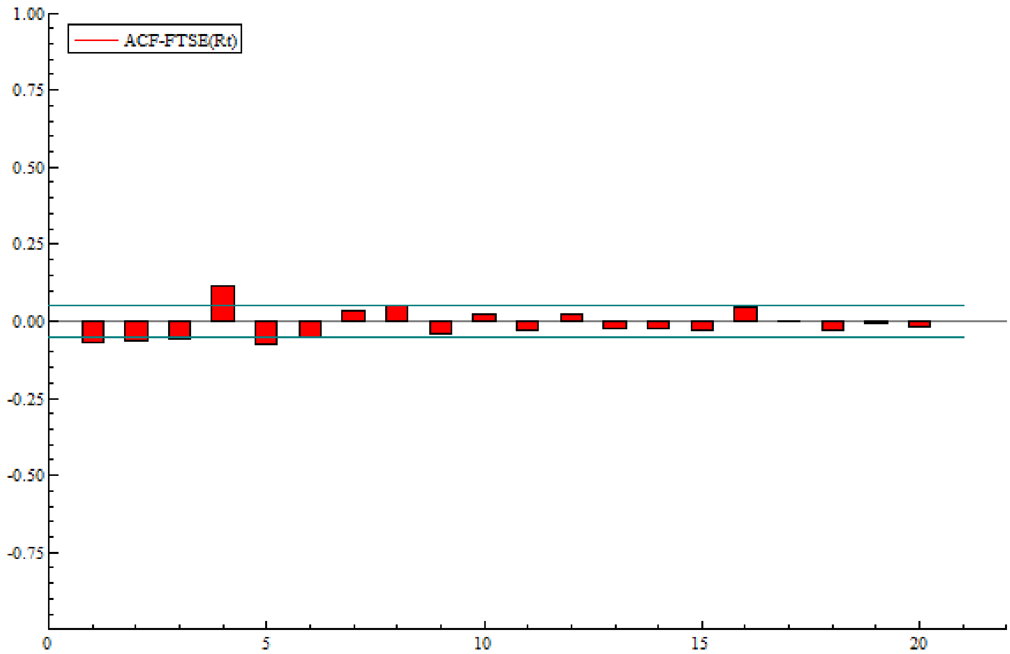


Figure 4.13: Autocorrelogram on daily returns (in %) of ICE crude oil futures and FTSE100 index.

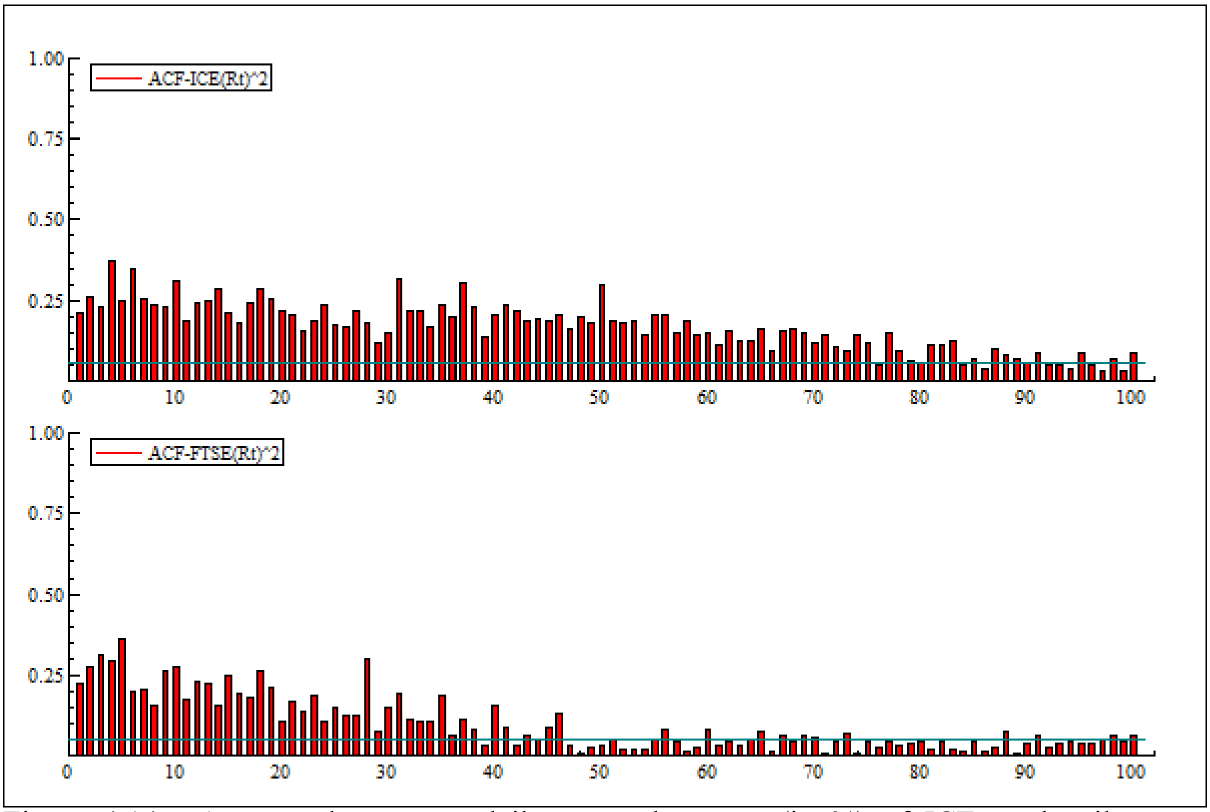


Figure 4.14: Autocorrelogram on daily squared returns (in %) of ICE crude oil futures and FTSE100 index.

Table 4.12 shows autocorrelations functions of squared returns for ICE crude oil futures and FTSE 100 index. We can see that both the squared return series are strongly autocorrelated with statistically significant portmanteau statistic calculated for 5 lags and 1374 observations. Therefore the significant dependence in squared residuals is indicative of autocorrelated volatilities and establishes our initial finding about volatility clustering.

Table 4.12: Autocorrelation functions of squared daily returns for both ICE and FTSE time series.

Variables	ρ(lag1)	ρ(lag2)	ρ(lag3)	ρ(lag4)	ρ(lag5)	Portmanteau statistics
ICE(Rt)^2	0.21292	0.26332	0.22820	0.37189	0.24905	505.564
FTSE(Rt)^2	0.22528	0.27387	0.31376	0.29100	0.36409	608.041

4.2 **Analysis of Model Outputs:**

The maximum likelihood estimates of the parameters under EGARCH models, GJR model and Scalar BEKK GARCH models are presented in table 4.21 and 4.22. Table 4.21 presents volatility spillover coefficients from ICE crude oil futures to FTSE 100 index where the dependent variable in conditional mean and conditional variance equation is daily return from FTSE 100 index. We perform 3 different EGARCH specifications to test the volatility spillover.

Table 4.21: Volatility Spillover coefficients from ICE crude Oil Futures to FTSE 100 Index

Variables	EGARCH Models			GJR GARCH	Scalar BEKK GARCH Models		
	ARMA (1,0) EGARCH (1,1)	ARMA (1,0) EGARCH (0,1)	ARMA (1,0) EGARCH (0,2)	ARMA (1,0) GJR GARCH (0,2)	ARMA(1,0) S-BEKK GARCH(1,1)	ARMA(1,0) S-BEKK GARCH(0,1)	ARMA(1,0) S-BEKK GARCH(0,2)
Conditional Mean Equation ~ ARMA (1,0)							
Constant	0.0054 (0.07886)	0.036803 (0.04111)	0.032690 (0.01994)	0.04747 (0.0346)	0.046153 (0.03244)	0.049713 (0.02942)*	0.065893 (0.02872)**
F^2 $_{(t-1)}$	0.009233 (0.01179)	-0.001748 (0.0116)	-0.000891 (0.00295)	0.003865 (0.0128)	0.004534 (0.01142)	0.002714 (0.01022)	0.003591 (0.00964)
AR (1)	-0.043545 (0.0217)**	-0.048578 (0.0309)	-0.045628 (0.0104)***	-0.045856 (0.02296)**	-0.049113 (0.02917)*	-0.051168 (0.02862)*	-0.05196 (0.0283)*
Conditional Variance Equation							
Constant	0.15297 (0.50917)	0.122807 (0.0787)	0.126777 (0.0788)	0.540324 (0.07137)***	0.167058 (0.0472)***	0.778176 (0.04934)***	0.76945 (0.05093)***
FTSE^2 $_{(t-1)}$	-0.020368 (0.007)***	-0.001465 (0.00871)	0.000005 (0.0087)	0.177598 (0.50929)	-0.000002 (0.000001)*	0.000002 (0.000002)	-0.000004 (0.000002)
FTSE^2 $_{(t-2)}$	-0.01016 (0.0085)	0.031419 (0.0188)*	0.0321 (0.0182)*	-0.26891 (0.0452)***	-0.127669 (0.25277)	0.472908 (0.0677)***	0.000002 (0.0000008)**
FTSE^2 $_{(t-3)}$	0.012066 (0.0079)	0.049784 (0.0139)***	0.044591 (0.0130)***	0.224461 (0.0555)***	0.230618 (0.0982)**	0.497295 (0.0635)***	0.49145 (0.06364)***
ICE^2 $_{(t-1)}$	0.001883 (0.00288)*	0.006489 (0.00282)**	0.006807 (0.0028)**	0.011652 (0.00807)	0.052196 (0.0204)**	0.124991 (0.0358)***	0.122454 (0.03651)***
ICE^2 $_{(t-2)}$	0.002002 (0.00326)*	0.010783 (0.0041)***	0.010438 (0.0042)**	0.019792 (0.01123)*	0.000001 (0.00005)	0.146431 (0.0402)***	0.142863 (0.03997)***
ICE^2 $_{(t-3)}$	0.003710 (0.00309)	0.002373 (0.0036)	0.002298 (0.0036)	0.013531 (0.01121)	-0.000000 (0.0000004)	0.019551 (0.26047)	0.03806 (0.14428)
ARCH α_1	0.000319 (0.29037)	0.813837 (0.2887)***	0.825473 (0.3005)***	-0.187171 (0.50657)	0.269728 (0.0931)***	0.36341 (0.0649)***	0.363162 (0.0644)***
ARCH α_2			0.304675 (0.33242)	0.378714 (0.07763)***			0.497103 (0.0696)***
GARCH β_1	0.977592 (0.0107)***				0.915256 (0.0221)***		
GJR γ_1				0.259997 (0.0771)***			
GJR γ_2				0.269567 (0.11951)**			
EGARCH θ_1	-0.146193 (0.0385)***	-0.183601 (0.054)***	-0.180696 (0.0517)***				
EGARCH θ_2	0.131943 (0.0345)***	0.145515 (0.0982)	0.125240 (0.0995)				
Information Crieteria (to be minimized)							
Akaike	3.083758	3.228627	3.229114	3.190854	3.131829	3.205141	3.204284
Schwarz	3.141245	3.282282	3.286601	3.248341	3.181651	3.25113	3.254106
Shibata	3.083519	3.228418	3.228875	3.190615	3.131648	3.204987	3.204104
Hannan - Quinn	3.105279	3.248713	3.250634	3.212374	3.150479	3.222357	3.222935

Figures in the parenthesis () are standard errors, * statistically significant at 10% level,
** statistically significant at 5% level, *** statistically significant at 1% level
ARMA(1,0)-GJR GARCH(1,1) and ARMA(1,0)-GJR GARCH(0,1) result non convergence

Table 4.22: Volatility Spillover coefficients from FTSE 100 Index to ICE crude Oil Futures

Variables	EGARCH Models			Scalar BEKK GARCH Models		
	ARMA (1,0) EGARCH (1,1)	ARMA (1,0) EGARCH (0,1)	ARMA (1,0) EGARCH (0,2)	ARMA(1,0) S-BEKK GARCH(1,1)	ARMA(1,0) S-BEKK GARCH(0,1)	ARMA(1,0) S-BEKK GARCH(0,2)
Conditional Mean Equation ~ ARMA (1,0)						
Constant	0.07602 (0.0599)	0.062201 (0.06746)	0.03469 (0.20262)	0.072696 (0.059258)	0.0814 (0.062137)	0.084993 (0.061829)
ICE^2 $_{(t-1)}$	0.002686 (0.0054)	0.003891 (0.00549)	0.006805 (0.03512)	0.005382 (0.0066435)	0.00428 (0.006365)	0.00452 (0.0064323)
AR (1)	-0.034121 (0.0274)	-0.02596 (0.0312)	-0.029903 (0.28921)	-0.04057 (0.02848)	-0.026189 (0.029583)	-0.028976 (0.029019)
Conditional Variance Equation						
Constant	1.564995 (0.2498)***	1.349427 (0.0669)***	1.295813 (0.0893)***	0.223063 (0.06427)***	1.617501 (0.09206)***	1.618828 (0.09218)***
ICE^2 $_{(t-1)}$	-0.006196 (0.0024)**	0.010683 (0.0055)*	0.015038 (0.0055)***	-0.000001 (0.0000005)	-0.000006 (0.0000038)	-0.000001 (0.00000076)
ICE^2 $_{(t-2)}$	0.001278 (0.00298)	0.016507 (0.0036)***	0.01462 (0.0066)**	0.000002 (0.0000014)	0.436711 (0.05927)***	-0.000002 (0.0000043)
ICE^2 $_{(t-3)}$	-0.001885 (0.0021)	0.009978 (0.0028)***	0.014003 (0.005)***	-0.000000 (0.0000004)	0.327013 (0.06054)***	0.326414 (0.06224)***
FTSE^2 $_{(t-1)}$	0.001431 (0.0057)	0.013519 (0.008)*	0.012301 (0.0084)	0.169285 (0.03937)***	0.471981 (0.12041)***	0.471526 (0.12080)***
FTSE^2 $_{(t-2)}$	-0.001112 (0.0075)	0.013632 (0.01198)	0.014749 (0.01542)	-0.000001 (0.0000009)	0.416301 (0.18181)**	0.413871 (0.18338)**
FTSE^2 $_{(t-3)}$	-0.005101 (0.0068)	0.020631 (0.01132)*	0.019552 (0.0105)*	0.000002 (0.000011)	0.438833 (0.14938)***	0.432697 (0.14985)***
ARCH α_1	-0.472689 (0.1424)***	0.128979 (0.28503)	0.06657 (0.45073)	0.202394 (0.03455)***	0.366959 (0.06703)***	0.365121 (0.06694)***
ARCH α_2			0.791518 (0.4611)*			0.441519 (0.05944)***
GARCH β_1	0.986628 (0.006)***			0.96973 (0.00888)***		
GJR γ_1						
GJR γ_2						
EGARCH θ_1	-0.136997 (0.0349)***	-0.200086 (0.0513)***	-0.188293 (0.0648)***			
EGARCH θ_2	0.219923 (0.0499)***	-0.047619 (0.12561)	-0.182863 (0.1002)**			
Information Crieteria (to be minimized)						
Akaike	4.449352	4.530902	4.526428	4.448667	4.514958	4.516166
Schwarz	4.506839	4.584557	4.583915	4.498489	4.560948	4.565988
Shibata	4.449112	4.530694	4.526189	4.448487	4.514804	4.515986
Hannan - Quinn	4.470872	4.550988	4.547948	4.467318	4.532174	4.534817

Figures in the parenthesis () are standard errors, * statistically significant at 10% level,
** statistically significant at 5% level, *** statistically significant at 1% level
GJR GARCH models found non convergent for the same parameters

Results for Dependent variable FTSE 100

The ARMA (1, 0) EGARCH (1, 1) model shows that historical volatility of squared returns at lag 1 has significant effect on conditional variance of the dependent variable FTSE at 1% level. There is significant volatility spillover effect at 10% level from squared return of ICE crude oil futures to returns from FTSE 100 index at lag 1 and lag 2. There is also highly significant GARCH effect found at 1% level indicating high persistence of the conditional variance of the return from FTSE 100. The estimated value of θ_1 is negative and highly significant indicating significant asymmetry effect i.e. bad news has more impact on conditional variance than the good news. The estimated value of θ_2 is also found highly significant indicating strong separate size effect or news effect on the conditional variance of the dependent variable FTSE 100.

In the ARMA (1, 0) EGARCH (0,1) specification we have considered no GARCH effect i.e. we have omitted considering the effect of conditional variance of lagged return on the conditional variance of the return of dependent variable. This is consistent, since in the model, instead of considering conditional variance of lagged return (GARCH) in the conditional variance equation, we are considering conditional variance of lagged squared returns as explanatory variable in the conditional variance equation. The result shows that there is significant effect of historical volatility at lag 2 and lag 3 on the conditional variance today. The conditional variance of lagged squared returns from FTSE 100 at lag 3 has significant effect at 1% level on the conditional variance of return from FTSE 100 today. The similar effect is observed from lag 2 of squared returns at 10% significance level. We find significant volatility spillover effect at lag 1 and lag 2 of squared returns from ICE crude oil futures to

FTSE 100 at 5% and 1% level respectively and as usual a highly significant leverage effect is found with negative coefficient. An almost similar result is found from ARMA (1, 0) EGARCH (0, 2) specification.

On the basis of all the information criteria computed (Akaike, Schwarz, Shibata and Hannan-Quinn) for all EGARCH specifications; the ARMA (1, 0) EGARCH (1, 1) is the best fitted model.

We can see from the conditional variance graph in Figure 4.21 obtained from AR(1) EGARCH (1,1) that the spikes around the end of 2008 and the beginning of 2009 is due to the worldwide financial market crash in 2008-2009.

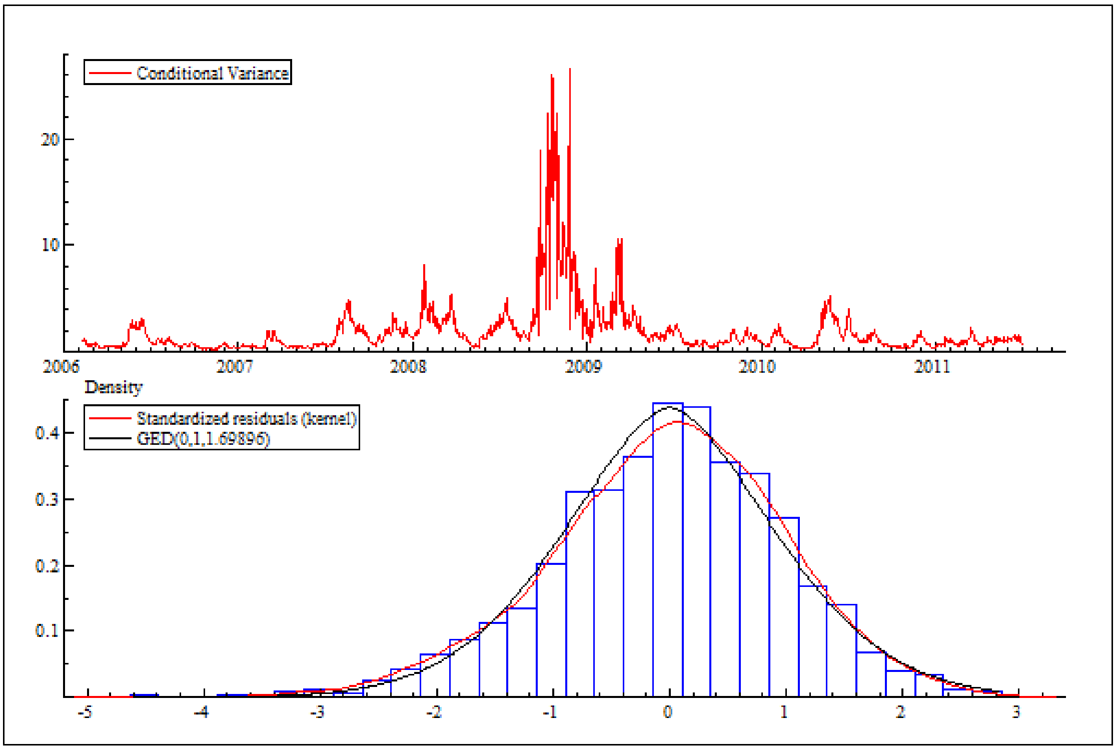


Figure 4.21 plots the conditional variance of the return series for FTSE 100 as well as the histogram of the standardized residuals obtained from the ARMA (1, 0) EGARCH (1, 1) model.

We perform three different GJR GARCH specifications using same sequence of ARCH (q) and GARCH (p) values as we used in EGARCH models, however AR (1)-GJR GARCH (1,1) and AR(1)-GJR GARCH (0,1) resulted non-convergence. The result from AR (1) GJR GARCH (0,2) indicates a significant effect of historical volatility of squared return at lag 2 and lag 3 on today's volatility of return. We also found significant volatility spillover effect from squared return of ICE crude oil futures to FTSE 100 at lag 2. The gamma 1 (γ_1) and gamma 2 (γ_2) coefficients are positive and highly significant indicating existence of highly significant leverage effect where past negative shocks have more impact on volatility than the past positive shocks of equal magnitude.

We also perform non-asymmetric GARCH model like Scalar BEKK GARCH following same sequence of ARCH and GARCH specifications as we followed before.

The results from AR (1) Scalar BEKK (1, 1) shows similar volatility effects as we observed from other models. It indicates a significant effect of historical volatility of squared return at lag 1 and lag 3 as well as highly significant GARCH effects on the conditional variance of daily returns from FTSE 100. A significant volatility spillover effect is observed from squared return of ICE crude oil futures at lag 1 and at 5% significance level.

The output from AR (1) S-BEKK GARCH (0, 1) indicates a highly significant (at 1% level) effect of historical volatility of squared return at lag 2 and lag 3 as well as volatility spillover effect from squared return of ICE crude oil futures both at lag 1 and lag 2 on the conditional variance of FTSE 100. The output from AR (1) S-BEKK

GARCH (0, 2) also shows similar volatility effects on the conditional variance of the dependent variable FTSE 100.

We can compare the model fit based on information criteria computed for all the models (EGARCH, GJR-GARCH, Scalar BEKK GARCH) and conclude that the ARMA (1, 0)- EGARCH (1, 1) is the best fitted model among all the competing models performed.

Results for Dependent variable ICE WTI crude oil futures

The ARMA (1, 0) EGARCH (1, 1) model shows that historical volatility of squared returns at lag 1 has a significant effect on conditional variance of the dependent variable ICE at 5% level. There is no significant volatility spillover effect found from squared return of FTSE 100 to returns from ICE crude oil futures. However there is highly significant GARCH effect found at 1% level indicating high persistence of the conditional variance of the return from ICE crude oil futures. The estimated value of θ_1 is negative and highly significant indicating significant asymmetry effect i.e. bad news has more impact on conditional variance than the good news. The estimated value of θ_2 is also found highly significant indicating strong separate size effect or news effect on the conditional variance of the dependent variable ICE crude oil return.

In the ARMA (1, 0) EGARCH (0,1) specification we have considered no GARCH effect i.e. we have omitted considering the effect of conditional variance of lagged return on the conditional variance of the return of dependent variable. This is consistent, since in the model, instead of considering conditional variance of lagged return (GARCH) in the conditional variance equation, we are considering conditional variance of lagged squared returns as explanatory variable in the conditional variance equation. The result shows that there is significant effect of historical volatility on the conditional variance today. The conditional variance of lagged squared returns from ICE crude oil futures at lag 2 and 3 has significant effect at 1% level on the conditional variance of return from ICE today. The similar effect is observed from lag 1 of squared returns at 10% significance level. We found significant volatility spillover effect at lag 1 and lag 3 of squared returns from FTSE 100 to ICE crude oil futures at 10% level and as usual a highly significant leverage effect is found with negative coefficient. An almost similar result is found from ARMA (1, 0) EGARCH (0, 2) specification.

On the basis of all the information criteria computed (Akaike, Schwarz, Shibata and Hannan-Quinn) for all EGARCH specifications; the ARMA (1, 0) EGARCH (1, 1) is found as the best fitted model.

We can see from the conditional variance graph in Figure 4.21 obtained from AR(1) EGARCH (1,1) that the spikes around the end of 2008 and the beginning of 2009 is due to the worldwide financial market crash in 2008-2009.

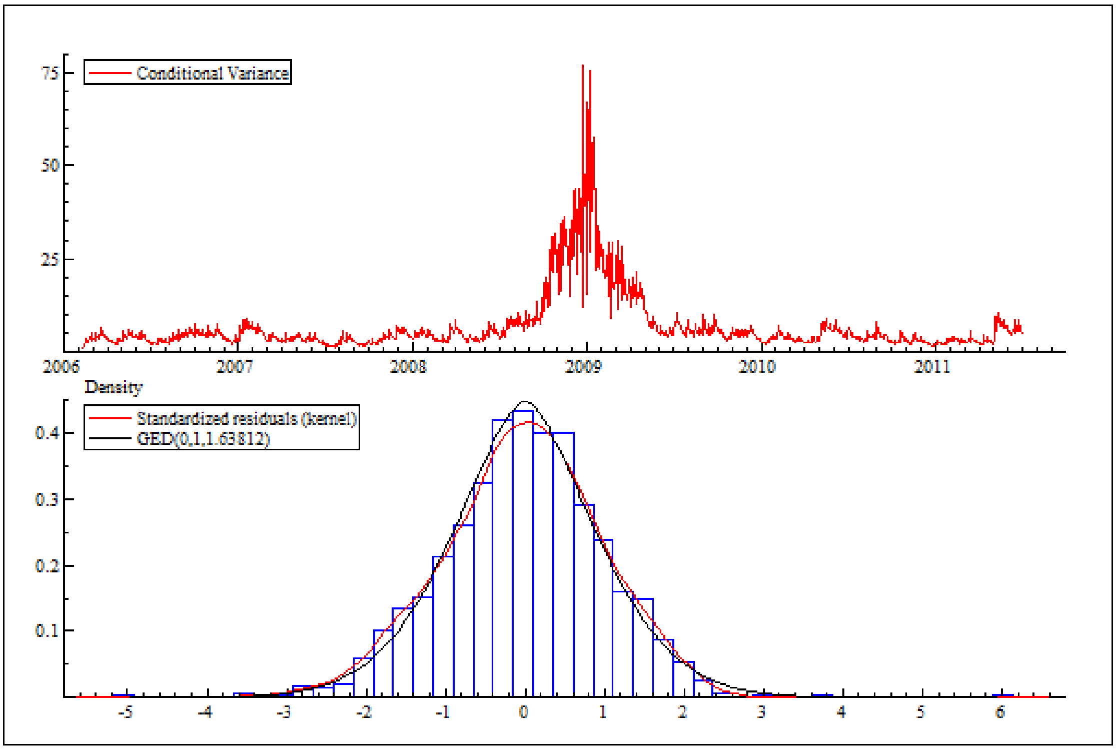


Figure 4.22 plots the conditional variance of the return series for ICE crude oil futures as well as the histogram of the standardized residuals obtained from the ARMA (1, 0) EGARCH (1, 1) model.

We perform three different GJR GARCH specifications using same sequence of ARCH (q) and GARCH (p) values as we used in EGARCH models, however all specifications resulted non-convergence. We also perform non-asymmetric GARCH model like Scalar BEKK GARCH following same sequence of ARCH and GARCH specifications as we followed before.

The results from AR (1) Scalar BEKK (1, 1) indicates insignificant effect of historical volatility of squared return but highly significant GARCH effects on the conditional variance of daily returns from ICE crude oil futures. A highly significant volatility spillover effect at lag 1 is observed from squared return of FTSE 100 at 1% significance level.

The output from AR (1) S-BEKK GARCH (0, 1) indicates a highly significant (at 1% level) effect of historical volatility of squared return at lag 2 and lag 3 as well as highly significant volatility spillover effect from squared return of FTSE 100 on the conditional variance of ICE crude oil futures. The output from AR (1) S-BEKK GARCH (0, 2) also shows similar volatility effects on the conditional variance of the dependent variable ICE.

We can evaluate the model fit based on information criteria computed for all the models (EGARCH and Scalar BEKK GARCH) and conclude that the ARMA (1, 0)-Scalar BEKK GARCH (1, 1) is the best fitted model among all the competing models performed for the dependent variable ICE crude oil futures. In figure 4.23 we can see the conditional variance derived from this model for ICE crude oil futures exhibiting high level of volatility during the period of 2008-2009 due to global financial market crisis.

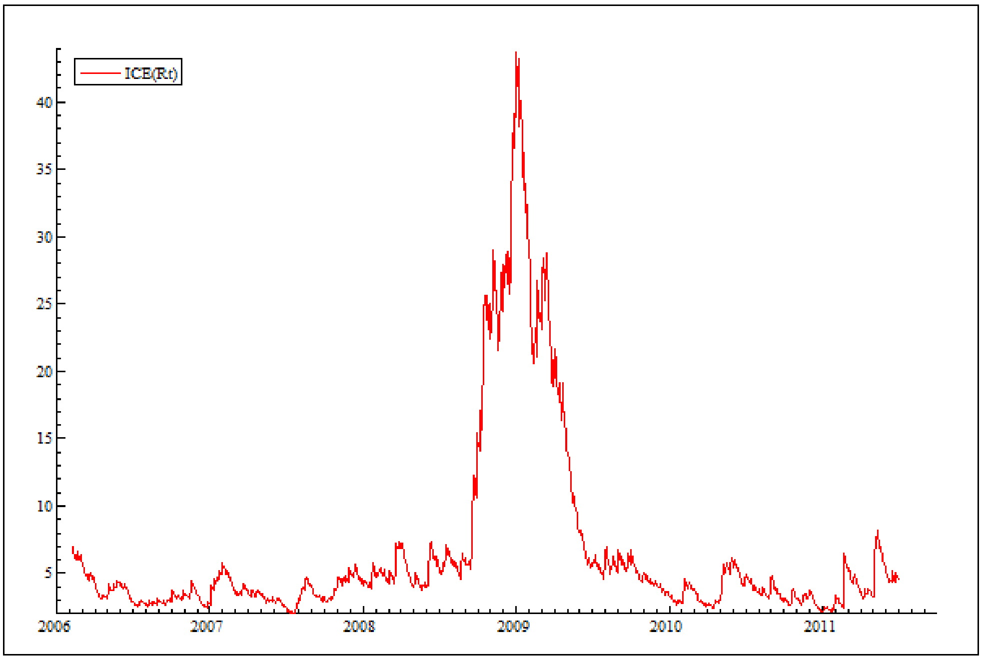


Figure 4.23 plots the conditional variance of the return series for ICE crude oil futures obtained from the ARMA (1, 0) Scalar BEKK GARCH (1, 1) model.

5. Conclusions

We tried to investigate the existence of volatility spillover effects between crude oil market and equity market using daily return data of ICE WTI crude oil futures and FTSE 100 equity index traded in the same time zone. We used a total 1374 observations to perform the empirical analysis. The standard deviation figures in the descriptive statistics analysis reveals that return from crude oil is more volatile than the equity market and the distribution of the sample data is non-normal and lepto-kurtic as is usual for financial time series. The ADF test for stationarity at lag 2 with intercept and trend indicates cointegrated relationship between the daily return from ICE crude oil futures and FTSE 100 equity index. The graphical analysis reveals the sign of ARCH effect where period of low volatility come together with high volatility. A significant volatility clustering is also observed by plotting the autocorrelogram of the squared returns.

We use different bivariate extensions of asymmetric EGARCH, GJR GARCH, and non-asymmetric scalar BEKK GARCH using different values of ARCH (q) and GARCH (p) values under maximum likelihood estimation method. A significant effect of historical volatility of squared return is found from almost all the model specifications on conditional variance of both the return series.

We use different information criteria (Akaike, Schwarz, Shibata, Hannan-Quinn) to compare the model fit between all specifications. Based on all the information criteria the ARMA (1,0) EGARCH (1,1) model is the best fitted model among all the EGARCH specifications used and reveals no significant volatility spillover from FTSE 100 to ICE crude oil futures. However a significant volatility spillover is found from ICE crude oil futures to FTSE 100 equity index at both lag 1 and lag 2 at 1%

significant level. The estimated value of θ_1 is found negative and highly significant for both the series indicating significant asymmetry effect in both crude oil and equity market. However the estimated value of θ_2 is found highly significant in the ARMA (1,0) EGARCH (1,1) specification indicating strong separate size effect or news effect on the conditional variance of crude oil futures and equity.

The best fitted model among all the scalar BEKK speficications is the ARMA (1,0) scalar BEKK (1,1) for both the series based on all information criteria. This model reveals volatility spillover from crude oil to equity at 5% level at lag 1, whereas a highly significant (at 1% level) volatility spillover is found from equity to crude oil return.

Information criteria also reveal that ARMA(1,0) EGARCH(1,1) is the best fitted model out of all model specifications applied for FTSE 100 equity index whereas ARMA (1,0) scalar BEKK (1,1) is the best for ICE crude oil futures. Therefore we can conclude from our analysis that there is bidirectional volatility spillover between crude oil market and equity market in UK.

However the limitation of this study is we didn't consider the jump diffusion effect of oil price dynamics in our spillover analysis, where based on Askari and Krichene (2008) oil price dynamics exhibit random variation, high volatility, and jump. I intend to capture the random variation effect and jump diffusion effect of oil price movement in my future spillover analysis between crude oil market and equity market, using SVMJ (Stochastic Volatility Merton Jump) model.

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