ISCTE Business School
University Institute of Lisbon

IMPACT OF FOSSIL-FUEL SUBSIDY REMOVAL TO THE INDONESIA STOCK MARKET

Bima Al Hussien

Dissertation submitted as partial requirement for the conferral of Master in Finance

Supervisor:

Prof. Dr. José Dias Curto, Associate Professor, ISCTE – IUL Business School,

Quantitative Methods Department

January 2016

ISCTE Business School
University Institute of Lisbon

IMPACT OF FOSSIL-FUEL SUBSIDY REMOVAL TO THE INDONESIA STOCK MARKET

Bima Al Hussien

Abstract

In 2015, government of Indonesia introduced new policy which remove the fossil fuel subsidy applying since the freedom of Indonesia. The Premium gasoline is now unsubsidized, and the Solar diesel is remove. Some previous studies found that there is positively relationship of oil price change to the stock market. However, as the literatures we have, there has not been study regarding to the effect of fossil-fuel price change caused by subsidy removal. Therefore, this new policy attracts us to find whether there is impact of new subsidy policy applied to Indonesia Stock Market, represented by using the data of Jakarta Composite Index (JKSE), since the fossil-fuel price changes dramatically

Because there is heteroskedasticity in the residual error in the natural regression model that we compute, we consider the GARCH model in order to deal with the problem. Besides, we also proceed the GJR and EGARCH to explain the asymmetry effect. We conclude that the subsidy removal do affect the Jakarta Composite Index (JKSE), yet the oil price return do not. Additionally, the subsidy removal (bad news for market participants) give more negative shock to conditional variance than subsidy existence (positive news). Then, taking into account the model selection using Akaike Information Criterion (AIC) and Schwarz's Bayesian Criterion (SBC), we found that, in this study, the GJR can explain better than GARCH and EGARCH.

Keywords: Subsidy removal; JKSE; regression; GARCH; GJR; EGARCH; AIC; SBC.

Acknowledgment

Prima facie, I am grateful to Allah S.W.T, The Most Beneficent and The Most Merciful.

Foremost, I would like to express my deepest appreciation to my supervisor, Prof. Dr. José Dias Curto for the continuous support of my dissertation, for his patience, motivation, enthusiasm, and insight. Also, I place on record, my sincere thanks to all professor in ISCTE Business School for the immense knowledge, and valuable guidance extended to me.

Last, but certainly not the least, I also take this opportunity to express gratitude to my parents for their unceasing support. This dissertation is dedicated to you all, especially for my Father in heaven. Your guiding hand will remain with me forever.

List of Content

List of Tables

List of Figures

1. INTRODUCTION

Capital market is linked to the change of environment, which is macroeconomic and microeconomic instruments. Many issue of macroeconomic such as change of interest rate, foreign exchange rate, inflation and economic policy determined by government affect the volatility of price and trading volume on capital market (Asri & Setiawan, 1998). One of sensitive economic policy in Indonesia is the subsidy from government to fossil-fuel price. Investor's reaction to this government's policy is very crucial, because their reaction determine the condition of economy. If they react negatively, then investment flow will decline within short term and even long term period. This will mitigate the economic growth of country. Then, it is also applied in the opposite way when they react positively or at least neutral. The negative impact to economy can be muffled.

Besides macroeconomic, the microeconomic also plays rule. The price change caused by subsidy policy affect cost of company's financial, such as company's operational expense and needs of higher salary from employees. The more expensive the living cost within the country, the higher needs of salary employees need.

When government of Indonesia, at June 22 2013, announced to increase the price of fossil fuel, there is change of Jakarta Composite Index (JKSE) price. JKSE closed at price 4,515 at one day before the announcement. After announcement, at June 24 2015, the JKSE is closed at price 4,429.46, which represents a 1.89% declining. Contrarily, when government decrease price of fossil fuel at January 15 2009, JKSE also change. Before the announcement, the price is closed at 1,329.49, but after announcement, the general level of stock prices increase to 1,363.88, which represents a 2.59% increasing. This has not been analyzed statistically, but this shows different reaction to announcement of fossil fuel price.

Reforming fossil-fuel subsidies has become a pro and contra conflict in policy challenge due to its effect directly and indirectly to many factor in the country.

The size of fossil-fuel subsidies in Indonesia has fluctuated considerably over time, reflecting changes in international oil price, the exchange rate and subsidy policy in terms of political regime. As there are various kind of fossil fuels, Government of Indonesia compensated only fossil fuels that is mainly used for common people transportation, such as car, motorcycle, and boat. Fossil-fuels compensated by Government of Indonesia are gasoline, diesel and kerosene. Indonesia introduced subsidies in for social considerations to make available a “basic need” at a price affordable to the poor (Moururugane, 2010).

Indonesia subsidy policy has focused on consumer subsidies in the form of under-pricing of energy, through producer subsidies in the form of tax expenditure also exist (Morgan, 2007). Central Government of Indonesia compensated the revenue loss which is provided to the state-owned energy company, PT. Pertamina. It is determined administratively and is a function of the inputs used in the production process. The government announced cost of subsidy annually in the Annual State Fiscal Plan, whose plan should be approved by the parliament. It is based on calculation by Downstream Oil and Natural Gas Regulatory Body, BPH Migas, which estimates the quantity of fuels to be subsidized and the international market price for the coming year.

The subsidy is paid to PT Pertamina that received the payment at the end of every three months. This payment reimbursed it for the below-market products it has sold during this time (Beaton & Lontoh, 2010).

Since 2015, Indonesia, under Joko Widodo’s regime, announces removal of subsidies on Premium gasoline and introduces fixed subsidy on Solar diesel (Global Subsidies Initiative, 2015). This is a game changer for Indonesia, because the subsidy removal is never known beforehand. Its implication is that the Premium gasoline prices reflect market levels, reducing the financial burden on the state (Ali, 2010). The government of Indonesia also announces a new pricing mechanism for fossil-fuel. Premium gasoline is to be sold at market prices, but the distribution costs to remote areas will continue to be subsidized. This, in some circumstances, distinguish fossil fuel price for Java Island, and Non-Java Island. As an information, Java Island is the most populous in Indonesia. Solar diesel will be sold at IDR 1,000 below the market price (Global Subsidies Initiative, 2015). However, even though there is no subsidy given now, the price of fossil fuel is still determined by government. Government will anounce the price change every two to four weeks.

This susbsidy removal is followed by many contra because government conduct the policy when the world's crude oil price decline significantly. Since the subsidy removal is sort of an extreme change, many Indonesian people, especially small and medium enterprise people tend to adjust their price suddenly to cover the expense cost. This increase the primary needs price, and increase the cost of living.

Although the subsidy removal always be the sensitive issue and unhappy news for people and businesses, the government needs to do that sooner or later. Subsidy removal may be one of policy government do to unlever the budget for national expenses and shift it to more productive sector, such as infrastructure, education, agribusiness, military defence, natural disaster, and other sectors that can produce persistant development in a country.

Surely, the real impact of subsidy removal policy will be felt by many sector, especially economic instrument. One of signal of economic activities in a country is its stock market. Therefore, we will study the effect of new subsidy removal policy in Indonesia to Indonesia Stock Market, represented by its index, which is Jakarta Composite Index.

The objective of this study is to look for the research finding of how the subsidy removal affect the Indonesia stock market's condition, *cet. par*. The finding is not to judge the policy made by the government of Indonesia, but to look how the stock market has been affected by the subsidy removal. The findings will be beneficial for academicians, investors and business person, and government. Academically, the findings hopefully will attract more researches in subsidy policy's impact. Besides, the findings will also give investor and business person signal when the subsidy that affect business changes. The last but not least, the findings will provide more consideration for government in establishing the subsidy policy.

This thesis will be divided into sections. Next section, Literature Review, will tell about previous related study to this research and some theory used in this thesis. The third section is Methodology which will discuss about data used and statistical method used in this research. The fourth session will analyze the result from the method discussed in third section. The last but not least is Conclusion, which wrap the result and discussion of this dissertation.

2. LITERATURE REVIEW

In this section, we briefly revises what has been about certain topic related to impact of fossil-fuel subsidy, fossil-fuel price, and crude oil price to the stock market.

Research about impact of fossil-fuel subsidy to the stock market is limited. Most of the researches focused on the price of fossil fuel or of crude oil using quantitative method. This is primarily because fossil-fuel subsidies policy are rarely used in many country over the world.

1. Market Efficiency

Stepping back, Kendall and Hill (1953), reveals in his research that there is no cycle of price change regularly from observed. In other word, there has been stock movement, that does not follow particular pattern, or we know it as random walk. Stock prices change every day without affected by stock price from one day before. If stock prices do follow random walk pattern, then investor cannot use past price change to predict future price change, so that it cannot be used to get abnormal return. Those stock price fluctuation indicates market efficiency where in perfectly efficient market, all information will be reflected in stock price.

There are some research defining efficient capital market. Human (1998) defines efficient capital market as market which its securities has reflected all relevant information. The sooner information reflect the security price, the more efficient the capital market is. Therefore, Investor hardly catch the abnormal return consistently by doing trading transaction in stock exchange. Meanwhile, Jones (2007) defines efficient capital market as a market where its security price reflects all information regarding to its assets. This concept state that investor will absorb all information about asset in determining price, in order to make decision in long position or short position. All of those information are information about past condition, current condition and all action that has been announced but will still happen in future such as stock split. Besides, investor also consider the opinion in market. If they believe that there will be declining of interest rate, then price will reflect this believe before the interest rate truly decline.

1.1. Form of market efficiency

Key in assessing market efficiency is information, since there is no perfectly efficient or inefficient market, and then the degree of market efficiency is questioned. According to Fama(1991), the 1970 review divides work on market efficiency into three categories based on used information. Those three levels are Strong Form, Semi Strong Form, and Weak Form.

a. Weak-form

Weak-form test is one of most traditional form used to assess security prices determined in a weak form market, historical data should already be reflected in current prices and should be no value in predicting future price changes. Moreover according to Fama(1991), it covers the more general area of tests for return predictability, which also includes the burgeoning work on forecasting returns with variables like dividend yields and interest rates. Therefore, we can call a market as weak-form if price information in the past does not worth in determining price change in the future.

b. Semi-strong Form

More comprehensive level of market efficiency involves not only market data, but also all publicly known and available data. Foster (1986) describes number of announcement that may influence the securities price as follows: earning-related announcement, forecast announcement, dividend announcement, financing announcement, government-related announcement, investment announcement, legal announcement, market-production-sales announcement, management-Board of Director announcement, merger-acquisition announcement, securities industries announcement, and other announcements.

Semi-strong form is tested by how fast stock price will change and adjust with the existence of announcement of new information. Lag happens in adjusting stock price to certain announcement, and investor can use the lags, so that they will get abnormal return. Therefore, we call this capital market as semi-strong form. This means, investor cannot get abnormal return by using information that is publicly known.

c. Strong Form

In strong form efficient market, securities current price fully reflect publicized information, and information that can be obtainable from fundamental analysis of corporation and economy (non-public information). Therefore, no Investor should be able to obtain abnormal return by using public and available or non-public information. The strong form cover both weak and semi-strong form and represents the highest level of market efficiency.

By Fama (1991), Semi-strong form and strong form test is named to Event Study.

2. Event Study

In economic and finance, there is always question of how to assess impact of an event to corporates value. We can assess by arranging event study to look into impact of event toward corporates value. Event study measures relationship between an event affecting securities and the return of those securities (Kritzman, 1994). Damodaran (1996) correspondendly states that the information can be market-wide such as macroeconomic announcement, or firm specific such as earnings or dividend announcement.

According to Jones (2007), event study is defined as an empirical analysis of security price behavior surrounding a particular event, meaning that a company's security returns are examined to determine the impact of a particular event of security price. In accordance to Jones (2007) and MacKinlay (1997) state that event study is an observation to look stock movement in capital market, in order to know whether the abnormal return exist caused by particular specific event. The main purpose conduction event study is to assess the abnormal return happened from stock.

Based on Jones (2007) and MacKinlay (1997), we can conclude that event study is feasible to be applied in assessing the capital market reaction, using stock price movement approach, toward an event, and is also able to examine the efficient market hypothesis in semi-strong form.

Taking into account the efficient market hypothesis, where an ideal market prices fully reflect available information, the subsidy policy by government of Indonesia is the one of available information exist. When the subsidy is removed, the stock market might react instantaneously. Therefore, the finding of this study should also support the efficient market hypothesis.

3. Previous Studies

Cooke, Hague, Cockburn, Lahga, and Tiberti (2014) study the impact of subsidy in Ghana by using a simulation of impact of subsidy reforms on household welfare and simulation of scenario for mitigating the impact through scaling up cash transfers to poorest households. They found that the removal of fuel subsidies, causing an increase in prices, results in negative impact on household welfare. Similarly in Gabon, the reform of fuel subsidies are strongly biased the toward higher-income household. The top 10 percent of the income distribution benefits from one-third of the total subsidy, while the bottom 30 percent benefits only 13 percent of subsidy (Said & Leigh, 2006).

Meanwhile in China, we see the conflicts emerging between energy subsidy, energy demand and climate change considerations. Hence, (Lin & Jiang , 2011) study the impacts of energy subsidy reforms and their finding, using Computable General Equilibrium (ECG) model, show that energy subsidy removal will result in a significant fall in energy demand and emissions, but will have the negative impact on macroeconomic variables. In spite of the bad impact to the macroeconomic, (Jiang & Tan, 2013) in their research finding conclude that the energy subsidy will have significant impact on energy-intensive industry, and consequently push up the general price level in small variation.

Specifically in Indonesia, (Dartanto, 2013), by applying CGE-microsimulation, found that removing 25% of fuel subsidies will increase the incidence of poverty by 0.259 percentage points, *ceteris paribus*.

As the price of fossil-fuel is reflected by the price of global oil price which sometimes change dramatically, researches about the impact of global oil price shocks such as Zhang and Chen (2011) shows that there are jumps varying in time in China’s stock market, and that China’s stock returns are correlated only with expected volatilities in global oil prices. Zhang and Chen in their research used ARMA-GARCH model to examine whether the fluctuations of oil price can explain the volatility behavior for stock returns, and ARJI (-ht)-EGARCH model as modified model which postulates that a time-varying conditional jump follows an ARMA process in heteroscedasticity condition.

Besides, Fayyad and Daly (2010) also concluded that oil prices shock do affect GCC markets and advanced market of UK and USA in varying degrees. They used mainly Vector Auto Regressive (VAR) approach to forecast systems of interrelated time series and to analyze the dynamic impact of random disturbances on the system of variables using data of UK's stock market and USA's stock market. By using VAR with GARCH (VAR-GARCH) in mean model, Caporale, Ali, and Spagnolo (2015) suggest that oil price volatility affects stock return positively during periods characterized by demand-side shocks. However, in contrast, the impact of oil price uncertainty is insignificant during periods with precautionary demand shocks. In addition, the study of Antonakakis, Chatziantonion, and Filis (2014) reveals that oil price shocks as a cause of economic policy uncertainty give negative responds to aggregate demand oil price shock. Moreover, Kang and Ratti (2013) use structural VAR as method to find the relation between oil price shocks and influence stock market return. In their finding, they state that in US, an unanticipated increase in policy uncertainty has a significant negative effect on real stock returns. The direct effect of oil shock on real stock return are improved by respond of endogenous policy uncertainty.

Further about fossil-fuel subsidized price, Prabowo (2009) conducts research about the effect of the decrease of subsidized-fuel price announcement on Indonesian stock Market. The observation include ten industrial sector indexes as a whole from two event studies, so he can find which sector has the biggest impact to the announcement of subsidy. The research using statistical test and find that the announcement gives positive cumulative abnormal return during event windows, and agriculture is the most affected sector among ten sector observed.

Regarding to the volatility, volatility is clasified by three measures which are conditional, realized and implied volatility. Supply-side shocks and oil specific demand shock do not affect volatility, while oil price changes due to aggregate demand shocks lead to a declining in stock market volatility (Degiannakis, Filis, and Kizys, 2014). The conditional volatility which is the conditional variance of daily log-returns process is estimated by APARCH model. Then, to examine the effects of three oil price shocks on stock market volatility, they use VAR framework.

Barunik, Kocenda, and Vacha (2015) note that the volatility spillovers across the petroleum markets by using two approaches which are volatility index and together with realized semivariances, they reveals overall volatility spillovers due to negative returns materialize to a greater degree than volatility spillovers due to positive returns.

Regarding to the previous studies about asymetric impact on stock market, there are some researches found its evidence. When there are momentous fluctuations in oil prices, asymmetric unexpected changes in oil prices will negatively affect S&P500 returns (Lee and Chiou, 2010). They used the Markove regime-switching model to monitor oil price volatility, and the ARMA GARCH model to analyze the expected, unexpected, and negatively unexpected changes in spot or futures into consideration withing the stock return. Moreover, they use ARJI model to understand the jump intensity, that follows an ARMA process and incorporates the generalized GARCH effect of return series. In addition, the asymmetric effect is also examined by using quantile regression approach (Lee and Zeng, 2011) which found that oil price shock do affect real stock return mostly under extreme perform of stock market. The use of quantile regression approach is to distinguish the effects of oil price shocks due to that the negative response of stock prices to oil prices shock is only vound when oil prices rises.

Bangun (2008), using T-Paired sample method and Kolmogorov-Smirnove test find the asymetric effect of fuel price announcement. The market only reacted at the time of fuel price increase, however when the price secended the market did not react to the issue. When fossil fuel price increase, the affected sector are property, basic industry, finance, manufacturing, miscellaneous industry, and trade and service, while agriculture, consumer goods, infrastructure, and mining are not affected. On the other hand, when the announcement of fossil fuel price state the price decline, the affected sector is only Infrastructure, while others are not affected. Align with research of Bangun(2008), Abadi (2012) determine the effect of oil price changes on sector indices return in Indonesian Stock Market. He use purposive sampling method with non-parametric test with Spearman rank correlation coefficient. He concluded that the sector affected the most by fossil-fuel price are agriculture, mining, and trade and service.

Speaking of the impact of oil price, we need to use the proper model in order to be able to capture the relationship of oil price and its impact. Pourshahabi, Sattari, and Shirazi (2012) use the EGARCH to capture stochastic variation and asymmetries in oil prices and found that coefficient of real oil price and income variables are significant and of expected sign. Further, Chen, and Kuan (2002) in their paper noted that EGARCH model may capture detected time irreversibility in US Stock Index return series may be attriuted volatility asymmetry and that such asymmetry. Next, EGARCH also has been compared to ARIMA and GARCH model in forecasting the international cotton price series primarily due to its ability to capture asymmetric volatility pattern (Lama, Jha, Paul, and Gurung, 2015). They conclude that EGARCH model outperformed the ARIMA and the GARCH model. Likewise, EGARCH still outperforms in testing policy action on exchange rate meand and volatility, as studied by Goyal, and Arora (2012). Result of the research of Imarhiagbe (2015) show that the oil price volatility has positive impact on volatility of external. This can be done by using GARCH and EGARCH.

Examining the asymmetry in conditional variance, Peters (2001) found that GJR and APARCH give better forecast than EGARCH, and asymmetric GARCH in conditional variance can be used when making the noticeable improvements.

Bentes, Menezes, and Ferreira (2013) examine the conditional volatility of NIKKEI 225, S&P 500 and STOXX 50 returns focusing on the asymmetric property of those markets. Their finding show that the conditional variance is an asymmetric function of past residuals and since the impact of shocks take longer time to dissipate in the United States, they conclude that S&P500 market exhibits less market efficiency than NIKKEI 225, and STOXX50.

Based on the original EGARCH, EGARCH seems to have several modified and developed model thoroughly documented in some literature, such as a Multiple-Sign-Volume Sensitive Regime EGARCH Model (MSV-EGARCH). MSV-EGARCH is able to correctly fit GARCH-type dynamics of series under study and dominates competing standard asymmetric models (Curto, and Tomaz, 2009). Comparing the EGARCH to SV models, Shimada, Tsukuda, and Miyakoshi (2009) study the US market that exert asymmetric influence on the conditional mean and volatility of Japanes market using retruns on stock price indices and show that EGARCH and SV models lead to similar results for the spillover effects. Then, Shi and Kobayashi (2008) consider to test for jumps for the subsamples of S7P500 and found that it is consistent for

EGARCH and EGARCH-t. This study strengthen the usage of EGARCH model is the proper model for asymetries.

However contrary to ARCH, GARCH, EGARCH, or other ARCH family, Barragan, Ramos, and Veiga (2013) test changes in correlation between stock and oil markets based on estimated wavelet correlations. This method does not need adjustment for heteroskedasticity biasses on correlation coefficent. Barraga, Ramos, and Veiga (2013), in their result, acquire the weak correlation between stock markets after oil shock. Still, according to Chiarella, Kang, Niktopoulos, and To (2013), there is negative relation in crude oil future markets, especially over periods of high volatility principally driven by market-wide shocks. Additionally, Shaeffer, et. al. (2012) analyse the impact on market value of chosen group of oil companies in Dow Jones Sustainability Index (DJSI) to evaluate variation in three indicators: beta of chosen companies, sensitivity of their stock prices related to variation in oil crude price, and the volatility of their stock prices. Finding in their research stated that betas of only two of the companies declined due to participation in DJSI, and there was no change in volatility with oil prices for any of the companies.

Using combination of Least Square Support Vector Machine (LSSVM) with GARCH, EGARCH, and GJR, Ou and Wang (2010) reveal in their research that EGARCH-LSSVM is unable to defeat EGARCH in term of R squared, yet for the formed GARCH and GJR, LSSVM is better. Noticeably, the GARCH, GJR, and especially EGARCH are well-proved to be the approaching model to forecast leverage effect volatility of stock markets.

3. DATA AND METHODOLOGY

This section describes the main features of time series data deployed for this thesis. Besides, the data applied in statistic will get a binary treatment, in order to make it more manageable. Further, this section also refer to hypotheses and statistical method used in model.

1. Data

We will test the impact of fossil-fuel subsidy removal to Indonesia stock market based on the fossil-fuel price before the new subsidy removal policy applied.

The selected data of fossil-fuel prices are taken from combination source of Ministry of Energy and Mineral Resources of Republic Indonesia and PT. Pertamina Corporation since 2008 until June 2015.

In addition, the time series is the daily data including the changes in fossil-fuel price announced by government of Indonesia. To provide better data either there is subsidy or not, there is additional dummy data served in binary. The required data will be obtained from Yahoo! Finance and source of Ministry of Energy and Mineral Resources of Republic Indonesia.

1.1. Variable Analysis

Firstly, we start to analyze each of variables which are the stock price, and oil price. In economics and finance, Even though it is widely known that the stock price (price level) is not stationary, in order to confirm it, we do the Unit Root Test by using Augmented Dickey-Fuller (ADF) and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests, where we will use the asymptotic critical value for 5%.

If the stock price is not stationary, which exactly is similar to what we have expected before, then we take the first difference of the log of price (log return) as below.

$$R = \log(P_t) - \log(p_{t-1}) \qquad (1)$$

Where the log return (R) is the log of price today ($log(P_t)$) minus the log of price one day before ($log(P_{t-1})$). After taking the log return, we apply the ADF test and KPSS test again. In this test, we expect that it will be stationary.

Besides the stock price, we also do the ADF test and KPSS tests to the oil price, which is also the price level. If it is not stationary, we then take the first difference as below.

$$Ro = \log(Po_t) - \log(Po_{t-1}) \tag{2}$$

Where *Ro* is oil price return in which log of current oil price ($\log(Po_t)$) minus with the log of oil price the day before ($\log(Po_{t-1})$). Next, we check it again by applying the ADF test and KPSS test in order to confirm the stationarity. Besides, we also compute the correlogram of residuals and correlogram of residuals squared. If we cannot reject null in correlogram of residuals, then we can conclude that the residuals are white noise meaning that the model can capture most of the linear relations in the series. In terms of the correlogram of residuals squared, if we reject the null for correlation, then it lead us to conclusion of non-conditional heterokedsaticity.

Secondly, we also should compute the descriptive statistic measures by computing mean of stock price and log return, mean of oil price, standard deviation, skewness, and kurtosis. Also, we include the Jarque Bera test.

1.2. Descriptive statistic measure

In term of skewness and kurtosis, they are used to test the distribution, whether it is a normal distribution. Regression assumes that dependent variables have normal distributions. Non-normal distribution of variables, which might be a leptokurtic, highly skewed right, or variables with substantial outliers, can distort the relationships result and the significance test. Therefore, it is substantial to test the data distribution. Skewness is the data distribution's shape either it is symmetric or is skewed to one side. If the peak of data is at left and the longer tail is at right, then the distribution is skewed right or positive skew. Vice versa, if the peak of data is at right and the longer tail is at left, then the distribution is skewed left or negative skew. However, if the peak of data is exactly in the middle and both tails are the similar left and right, then it is the normal distribution (zero skewness). Regarding to term of kurtosis, which also is used together with skewness to conclude about the distribution. It is mesokurtic, when the center of data distribution has sharpest peak, and the coefficient of kurtosis will be similar to three. If it will be higher than three (the common situation in finance), the distribution is leptokurtic.

According to (Cramer, 1997), by using significance level of 5% and two-tailed test, if test statistic of skewness is between -2 and +2, it might be symmetric. Then, if it is lower than -2, it is very likely negative skew, while if it is higher than +2, it is likely positive skew. For kurtosis, if test statistic of Kurtosis is between -2 and +2, it might be positive, negative or zero, but we surely know it is a mesokurtic. If it is lower than -2, it is platykurtic and if it is higher, it is a leptokurtic which the kurtosis value measured by the respective coefficient is higher than three.

Last thing to do after check for skewness and kurtosis is to use Jarque-Bera test, which is a test statistic for testing whether the series is normally distributed. The test static of Jarque-Bera is based on the skewness and kurtosis measures. Under the null hypothesis of a normal distribution, the Jarque-Bera statistic is distributed as $\chi 2$ with 2 degrees of freedom. In Eviews, we see the probability that Jarque-Bera statistic exceeds the observed value under null indicates that a small probability value which is lower than 5%, leads to the rejection of null hypothesis of a normal distribution.

Last but not least for descriptive statistic measurement, we analyze the correlation by using correlation in Eviews. This test is used to check about linear relationship between variables. The correlation coefficient can be positive or negative number. For example, a -0.5 means that there is negative relationship in which the two series run in the opposite way.

2. Hypotheses

As stated in the introduction, this dissertation aims to analyze the effect of fossil-fuel subsidy policy to the Indonesia stock market by comparing the old subsidy policy with the new subsidy policy, *ceteris paribus*, introduced in the early of 2015.

Hypothesis 1: There is impact of oil price change to the return of Indonesia stock market

This hypothesis expect the result to explain how the change of oil price affect the return of Jakarta Composite Index. There has been many literatures explain that there is relation between the oil price change to the stock market, however this hypothesis include the effect of subsidy and subsidy removal which also be the hypothesis below.

Hypothesis 2: There is impact of subsidy removal to the return of Indonesia Stock Market

This explains whether there is different effect of return when the subsidy still exist and when the subsidy is removed.

Hypothesis 3: There is news asymmetric impact on conditional volatility of Indonesia stock market.

Different with hypothesis above, using the binary dummy variable, this explain whether there is different effect of return before subsidy removal and after subsidy removal applied. The binary data of 1 represents the subsidy removal, and the binary data of 0 represents the subsidy existed. Especially for hypothesis 3, the hypothesis is able to be explained appropriately with the asymmetric model, GJR and EGARCH.

3. GARCH-TYPE MODELS

As also explained in literature review section, specifically in previous studies subchapter, we use the GARCH-type family model which is the most suitable model used in volatility model (Hansen & Lunde, 2001) to prove those three hypotheses above. We will present the data processed by Eviews.

Dacoronga, Gencay, Muller, Olsen and Pictel (2001) see volatility into three categories: Realized volatility, Implied Volatility, and Model Volatility. Realized volatility is also called historical volatility, determined by past observation. Implied volatility is a volatility forecast computed from market prices of derivatives such as options based on a model such as lognormal random walk (Majmudar and Banerjee, 2004). Majmudar and Banerjee also define Model volatility as a virtual variable in theoretical model such as GARCH (Generalized Autoregressive Conditional Heteroskedasticity) and stochastic volatility. Since we are focusing on GARCH model in this thesis, we mainly discuss the last category.

By using the logartihm return, S_t is the price of one specific asset at time t

$$yt = \ln\left(\frac{Pt}{Pt-1}\right) \qquad (3)$$

Then, F_t represent all of available information at time t-1, and $_t \sim$ N (0,1). When we consider a volatilty to be constant, the return at time t will be seen as:

$$y_t = E(Y_t \,|\, F_{t-1}) + w_t = \mu_{t|t-1} + \sigma\mathcal{E}_t,\ wt \sim N(0, \sigma^2) \tag{4}$$

As researched by Fama (1965), there is a volatility clustering effect in this formula, meaning that we have to assume because the volatility change through time and for the consequence, the variance should be heterokedasticity. So, we have to assume that σ^2 is a stochastic process and the conditional variance is $\sigma^2_{t\,|\,t-1}$

Then, Engle (1982) solve this problem by introducing an ARCH (Autoregressive Conditional Heterskedasticity) model. A linear regression model with ARCH is usually represented by:

$$yt = x_t\beta + u_t \tag{5}$$

$$u_t = \sigma_t \in_t , \tag{6}$$

$$\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + \alpha_1 u_{t-2}^2 + \ldots + \alpha_1 u_{t-q}^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i u_{t-i}^2 \tag{7}$$

$\alpha_0 > 0$ and $\alpha_i > 0$ ($i = 1,2,\ldots,q$), β is a vector of parameters that its value is commonly unknown, and $E(y_t) = x_t\beta$ is combination of exogenous and lagged exogenous variables included in information set ϕ_{t-1} (conditional mean).Where in original ARCH, we assume that ϵ_t follows a normal distribution : $\epsilon_t \sim N(0;1)$. But recently, it is considered to use alternative distribution such as Student's t and stable Paretian non Gaussian distributions. The conditional variance of u_t can change in time and it is a linear function of past realizations of the process (Engle, 1982). ARCH has advantage of being easy to use, because of its easiness of formulation and estimation, and also the impact of volatility clustering.

ARCH introduced in Engle (1982) allows the conditional variance to change over time as a function of past errors so it leaves the unconditional variance constant. But on the other hand, ARCH has problem, which is unable to allow past conditional variances in current conditional variance equation. It is only u_{t-i}^2 affects the current volatility, which may be unrealistic because the future may respond differently to good or bad news ($u_t > 0$ or $u_t < 0$). Another problem is that the long lag is needed to deal with the long memory of the processes.

Improving the ARCH, Bollerslev (1986) cover the ARCH's problem by introducing Generalized ARCH (GARCH) model. GARCH is proposed to allow for much more flexible lag structure. GARCH can be compared to the ARMA in time series traditional analysis. Engle and Bollerslev (1986) note that low order GARCH model can have similar properties to high order ARCH model without the problems of estimating many parameters subject to non-negativity constraints. GARCH model appears to be a natural and simple generalization of the ARCH model, and empirical evidence suggest that it fits as well or even better than ARCH model with linearly decreasing weights with coarsely the similar mean lag. Linear regression model with GARCH effect of order p and q: GARCH (p,q) is represented by:

$$yt = x_t\beta + u_t \tag{8}$$

$$u_t = \sigma_t \in_t , \tag{9}$$

$$\alpha_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i u_{t-i}^2 \; + \sum_{i=1}^{p} \delta \sigma_{t-i}^2 \tag{10}$$

The restriction $\alpha_0 > 0$, $\alpha_i \geq 0$ for I = 1,2, …,q and $\delta_j \geq 0$ for j = 1,2, …, p are considered to ensure that conditional variance is non-negative. The last equation shows the effect of GARCH. The $\sum_{i=1}^{q} \alpha_i + \sum_{i=1}^{p} \delta_j < 1$ is to ensure a covariance stationary process. The process is weakly stationary and the second moment of unconditional distribution are finite. When $\sum_{i=1}^{q} \alpha_i + \sum_{i=1}^{p} \delta_j = 1$, the model is integrated in variance which is named by Engle and Bollerslev(1986) as Integrated GARCH.

GARCH model has benefit for being more flexible than ARCH model when parametrizing the conditional variance. The GARCH model does not only captures thick tailed returns, but also the volatility clustering effect.

One of the main issue of GARCH model is about its symmetry, which sign of past shocks does not affect future volatility or we can say that GARCH models impose a symmetric response of volatility to both positive and negative shocks. This is so since the variance specifically in this model is a function of size of past realizations of squared erros.

Thus, Black (1976) starting his view that volatility themselves are not constant found evidence of so-called “Leverage Effect” as a term of the asymmetric effect. A bad news outcomes higher volatility than a positive news.

Glosten, Jagannathan, and Runkle (1993) suggested the method to deal with the leverage effect called GJR, the abbreviation of their names. In their paper, they reveals that positive unanticipated returns appear to result in downward revision of the conditional volatility while negative unanticipated returns result in an upward revision of conditional volatility.

GJR formula mimics GARCH by using a dummy variable that makes it possible to analyze the impact of negative news. The dummy variable takes value one whenever the past shock is negative:

$$\sigma^2_{t\mid t-1} = \alpha_1 + (\lambda_1 + \gamma I_{\varepsilon_{t-1}} < 0)\varepsilon^2_{t-1} + \beta_1 \sigma^2_{t-1} \tag{11}$$

A positive and statistically significant estimate for γ indicates a negative asymmetric volatility response to positive and negative shocks. GJR model seems to be the better prediction of volatility forecast for out-of-sample based on Harvey-Newbold encompassing test than FCGARCH and EGARCH (Matias, 2012). Also, based on Diebold-Mariano test, the GJR together with FCGARCH can reveal to best predict both realized and implied volatility (IV) (Salgado, 2011).

Besides GJR, there is also a model to solve asymmetric effect named EGARCH. The EGARCH model was constructed in a way that a negative shock leads to a higher conditional variance in the subsequent period than a positive shock would (Nelson, 1991). As well as the GJR, EGARCH also features an asymmetry coefficient (γ) that allow the leverage effect to be considered. Therefore, in other words, EGARCH will tell how each of good news or bad news affect the dependant variable. However, unlike the GARCH, the logartihmic transofmation of the conditional variance implies that no restriction on parameteres are required to ensure that $\sigma_t > 0$

$$\ln \sigma^2_t = \omega + \sum_{i=1}^{q} \alpha_i \frac{|u_{t-i}|}{\sigma_{t-i}} + \sum_{i=1}^{q} \gamma_i \frac{u_{t-i}}{\sigma_{t-i}} + \sum_{i=1}^{p} \beta_i \ln \sigma^2_{t-i} \tag{12}$$

In this study, EGARCH hypotethically will estimate how bad news, which can be due to subsidy removal, have impact to Jakarta Composite Index. Garcia (2012) concluded in her dissertation that EGARCH is the most accurate volatitlity predicot for asymmetric model, beating GJR in CAC40, FTSE100, and NIKKEI 225.

Therefore, based on those previous studies, assuming the errors are conditional heteroskedastic, we use the General Autoregressive Conditional Heteroskedasticity (GARCH) type to deal with the conditional variance.

4. Methodology

In order to be able to test our three hypotheses above, we proceed the regression of conditional mean equation using the formula below in which we assume that the errors are conditional homokedasticity.

$$R = c + \beta_2 \times Dummy + \beta_3 \times Ro + \varepsilon \tag{13}$$

Where R is as a dependent represents the log return. Then both subsidy, which is represented by Dummy, and oil price return, which is represented by Ro, are as independent variable.

However, and contrary to OLS assumptions, we assume that the errors are conditional heterokedasticity. We use GARCH type models as explained before to deal with the conditional variance.

Afterward, we proceed with the regression above, but by considering the GARCH, the GJR, and the EGARCH models for conditional volatility of the errors as stated on Literature Review Section.

Considering GARCH-type model, we still need to run the ARCH LM test to detect the conditional heteroskedasticity, which is usually called as ARCH effect. The null hypothesis on ARCH LM test is that there is no ARCH effect in the series. If the p-value is larger than 0.05, we cannot reject the null hypothesis meaning that the series is not affected by ARCH effect which is proper for the model.

Then, in order to check if there is an asymmetric effect in the conditional variance, we estimate the GJR model by setting the threshold to 1 in Eviews. We also compute the ARCH LM test. If the estimate for the parameter of RESID(-1)^2*(RESID(-1)<0) is statistically significant, we conclude that there is an asymmetric effect in the volatility. Thus, we can interpret that the bad news has a larger impact on volatility compared to the good news.

In order to compare with the GJR model, we also use EGARCH as another asymmetric model. Having regressed by considering EGARCH model, we still compute the ARCH LM test in EGARCH, in order to check the ARCH effect on regression residuals.

Since we use two method for dealing with asymmetric effect, which are GJR and EGARCH, we compare both of them based on information criterion in order to know which one seems statistically more appropriate to explain the conditional volatility of the series. We consider the information criteria using Akaike Information Criterion and Schwarz's Bayesian Criterion. The smaller the value of information criterion, the better the model works to explain the regression.

4. RESULTS AND DISCUSSIONS

In this section, we focused on analyzing the research by interpreting the statistical model. Beforehand, we need to analyze data for each variable, so that the data is appropriate to be analyzed in the regression model.

1. Data Analysis

First of all, we conduct the data analysis for every variable. The first data variable analyzed is the price which is taken from the adjusted closing price of Jakarta Composite Index. Generally speaking, the price level in time series is non-stationary, although we still confirm it by looking the graph and testing the unit root test using ADF and KPSS. It is important to check the stationary because a stationarized series is relatively easy to predict.

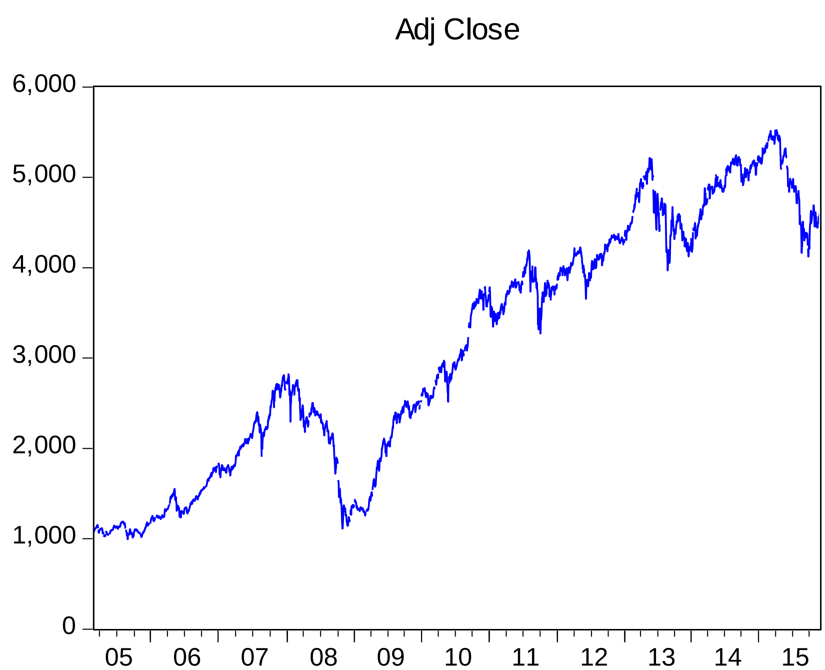


Figure 1. Price of adjusted close of Jakarta Composite Index 2005 - 2015

As seen on figure 1, we can see that the price move inconstantly meaning that the series might be a non-stationary. Surely, we cannot absolutely conclude that the series is stationary by just looking the graph. Therefore, we need to do the computation to confirm this using the unit root test.

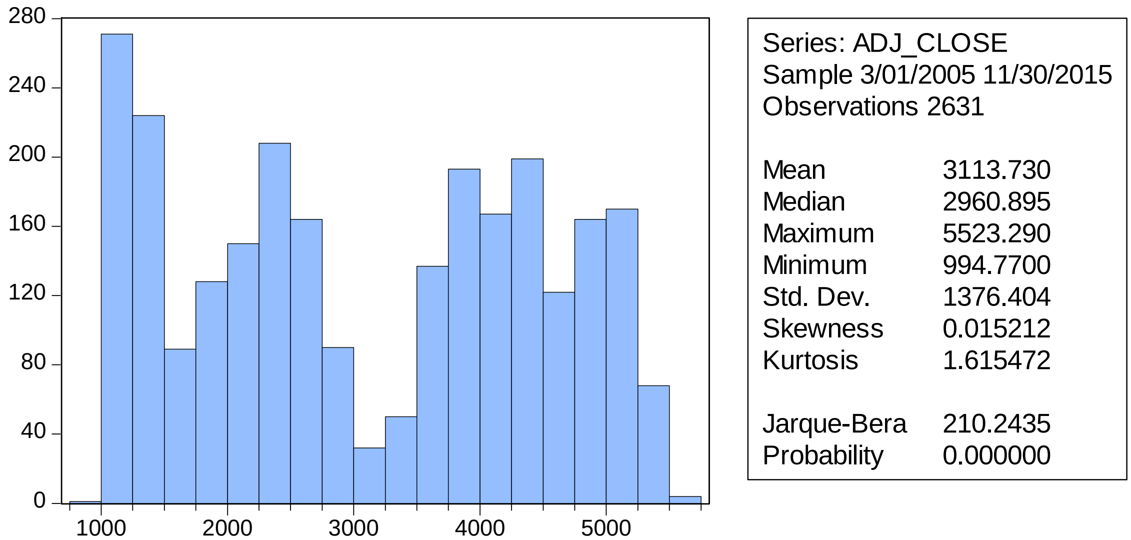


Figure 2 Data distribution of price of Jakarta Composite Index 2005-2015

Regarding to the descriptive statistic measure, we see that the skewness is near 0, then we also can say that the distribution is more or less symmetrical. For the kurtosis, the value is 1.6 which is around to be mesokurtic, but still cannot be said as a leptokurtic. By considering the skewness and kurtosis, the estimates are not very distant from those of the normal distribution. To confirm this, we use the Jarque-Bera test. The Jarque-Bera test value is 210.2435 with the associate probability of 0. This is statistically significant, so we reject the null hypothesis of a normal distribution meaning that even though the data distribution is almost symmetry, the data is still not normally distributed yet.

Table 1. Probability value of the unit root test

	Stock Price	**Log return**	**Fuel price**	**Return fuel price**
ADF	0.5954	0.0000	0.2621	0.0000
KPSS	0.289323	0.059829	0.671531	0.057172

Moreover, to check the stationarity, we use the unit root test in Eviews by applying the test of ADF and KPSS. We also include the Trend and Intercept in test equation, and use the automatic selection of Newey-West Bandwidth. As shown in table 1, the p-value associate to the ADF test statistic is 0.5954, which is larger than 0.05 (the significance level used by default), so that we cannot reject the null hypothesis of no unit root in the series. Based on this, we can conclude that the series is not stationary.

Then, in order to confirm this, we also apply the KPSS as also seen in table 1. In KPSS, we compare the KPSS test value with the asymptotic critical values. The result show that the test value of KPSS, 0.2893, is larger than asymptotic critical values of 5%, 0.146. Hence, we reject the null hypothesis of stationarity, which leads to the same conclusion of the ADF test before.

Even though the price is non-stationary, we could make the series stationary by transform the series into the log first difference (see equation number 1), which is actually the compounding return of the stock.

Having transformed the price into the log and first differences, we can see the new graph of figure 3, and compare it with the graph of figure 1. We see that the series now behave more constant than before. This could be a stationary series. But, we still need to conduct the unit root tests like in the previous case.

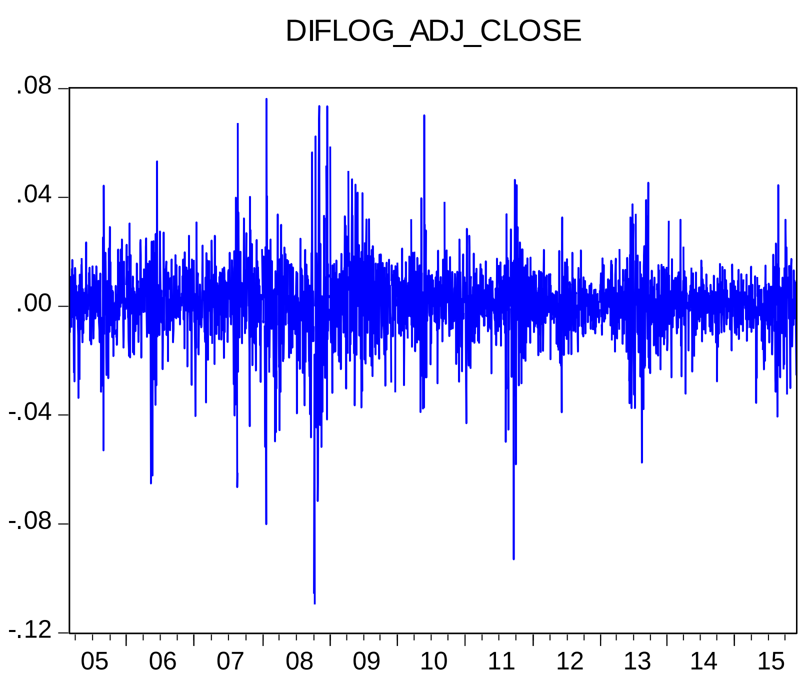
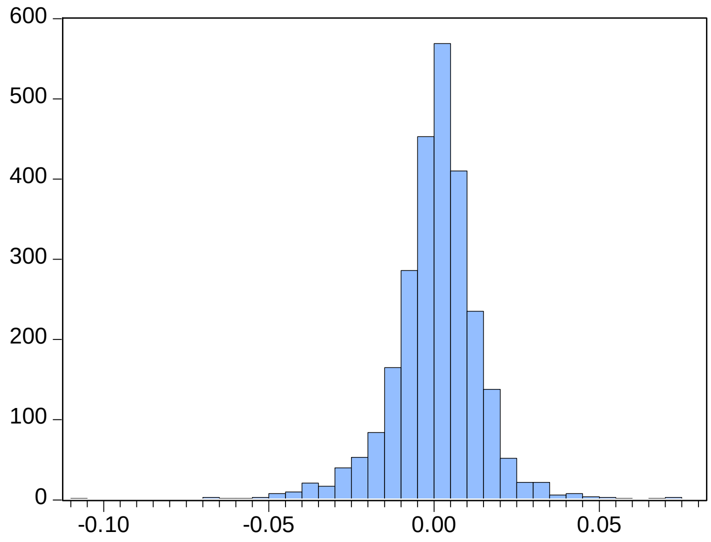


Figure 3 Return of Jakarta Composite Index

By considering the test value of ADF, the probability is lower than 0.05 which leads to rejection of null hypothesis. This means that there is no unit root in this new transformed series. Similarly, in KPSS for the new transformed series, we cannot reject the null because the KPSS test value, 0.059829, is lower than asymptotic critical values, 0.146. That is, both ADF and KPSS test conclude that the new transformed series, log and first difference of price, is stationary.

As the data of transformed series change, we re-do the descriptive analysis. We see in figure 4, that skewness is negative, but still is close to zero. The kurtosis increases dramatically to 9.8211 which point definitely to a leptokurtic empirical distribution. However, the Jarque Bera test show that the probability value is still lower than 0.05 which leads to rejection of null hypothesis. Therefore, the data has still a non-normal distribution.



Series: DIFLOG_ADJ_CLOSE	
Sample 3/01/2005 11/30/2015	
Observations 2630	
Mean	0.000533
Median	0.001283
Maximum	0.076231
Minimum	-0.109540
Std. Dev.	0.014302
Skewness	-0.645958
Kurtosis	9.821108
Jarque-Bera	5281.539
Probability	0.000000

Figure 4 The leptokurtic data distribution of log return of Jakarta Composite Index

Similar to the adjusted closing price, we also do the data analysis for oil price. Most often, as also stated on the introduction chapter, the oil price in Indonesia is constant for a long quiet period. Although we can see that that is non-stationary, we apply ADF and KPSS in unit root test to check the stationarity.

Since the ADF test statistic value is 0.2621, which is larger than 0.05, we do not reject the null hypothesis. This means that the series is not a stationary. Giving the same result, we see that the KPSS test value that is 0.671531 is higher than the asymptotic critical value of 5%. Therefore, the oil price is not a stationary series. To deal with this, we transform it into the first difference, or is called oil price log return (*Ro*) which seems like equation number 1, but use the price of oil.

$$Ro = \log(Po_t) - \log(Po_{t-1}) \qquad (14)$$

Afterward, we keep test the stationary by applying the ADF and KPSS test. As exactly we expect before, the ADF give result statistically significant, which shortly means that the series is stationary. Additionally, KPSS test value is lower than asymptotic critical value which leads to the same conclusion with ADF that it is the stationary series.

Then, in term of descriptive statistic measures, the skewness is nearly zero and the kurtosis point for a leptokurtic. Hence, the data might be non-normally distributed. We also need to reject the null hypothesis of the Jarque-Bera test because the probability value is lower than 0.05. However, this does not affect the statistical inference in the regression that we conduct next due to the sample size.

2. Regression Model Analysis

Having analyzed the data, we then proceed to estimate the model proposed initially (see equation number 13).

Table 2. Regression model

	Coefficient	**t-test**	**Prob.**
Dummy	-0.001386	-1.390179	0.1646
Return_Oil	-0.014080	-0.852905	0.3938
ARCH LM Test – Prob. Chi-Square		Test value = 11.69696	0.0000
R-squared	0.000994		
Adjusted R-squared	0.000233		

First of all, we estimate the regression model for conditional mean equation assuming that the errors are conditional homokedasticity. Based on the obtained results, we found that both estimated coefficients of dummy variable and oil price log return are not statistically significant. Therefore, based on this regression model, both dummy variable and oil price log return cannot be used to explain the return of JKSE. In order to check that this model is appropriate, we test the conditional heteroskedasticity by the ARCH LM test.

Due to the ARCH LM test result, we conclude that errors are conditionally heteroskedastic. Based on this result, we re-estimate the conditional mean equation considering a GARCH specification for the conditional variance of the errors.

We first consider a GARCH (1, 1) symmetric model and the results are shown on table 3. Based on the correlogram of standardized residuals square (see appendix number 13), we see that all probability in every lag is higher than 0.05, so that we cannot reject the null hypothesis of no serial correlation on the squared residuals.

Table 3. Regression model considering GARCH(1,1)

		Coefficient	**z-Statistic**	**Prob.**
Normal Distribution	Dummy	-0.001562	-2.290791	0.0220
	Return_Oil	0.002436	0.147278	0.8829
	Variance Equation			
	RESID(-1)^2	0.131474	12.94853	0.0000
	GARCH(-1)	0.849600	85.67708	0.0000
	ARCH LM Test			
	ARCH LM Test – Prob. Chi-Square		Test value = 0.301021	0.7633
Student's t Distribution	Dummy	-0.001408	-2.192714	0.0283
	Return_Oil	0.004397	0.307554	0.7584
	Variance Equation			
	RESID(-1)^2	0.127626	7.694218	0.0000
	GARCH(-1)	0.851326	51.27901	0.0000
	ARCH LM Test			
	ARCH LM Test – Prob. Chi-Square		Test value = 0.545869	0.5850
Generalized Error Distribution	Dummy	-0.001331	-2.170608	0.0300
	Return_Oil	0.003739	0.248599	0.8037
	Variance Equation			
	RESID(-1)^2	0.127354	7.818872	0.0000
	GARCH(-1)	0.848917	50.29132	0.0000
	ARCH LM Test			
	ARCH LM Test – Prob. Chi-Square		Test value = 0.504806	0.6136

We also see that the estimated coefficient for the dummy variable is now statistically significant, meaning that the dummy which is actually a subsidy existence affects the stock return of JKSE. However, the estimated coefficient of oil price return is not statistically significant since the p-value associated to the t-test is higher than 0.05 significance level. Thus, the return of oil price does not influence the stock return. This answers to our first hypothesis that the subsidy policy do impact JKSE, where it represents the Indonesia Stock Exchange market.

Table 4. Regression model considering GJR(1,1,1)

		Coefficient	**z-statistic**	**Prob.**
Normal Distribution	Dummy	-0.001800	-2.346632	0.0189
	Return_Oil	0.000790	0.049196	0.9608
	Variance Equation			
	RESID(-1)^2	0.063421	5.172261	0.0000
	RESID(-1)^2*(RESID(-1)<0)	0.117240	7.017913	0.0000
	GARCH(-1)	0.843293	87.21360	0.0000
	ARCH LM Test			
	ARCH LM Test – Prob. Chi-Square		Test value = 0.016471	0.9869
Student's t Distribution	Dummy	-0.001549	-2.335261	0.0195
	Return_Oil	0.003642	0.252814	0.8004
	Variance Equation			
	RESID(-1)^2	0.063266	3.198909	0.0014
	RESID(-1)^2*(RESID(-1)<0)	0.117289	4.390532	0.0000
	GARCH(-1)	0.839808	46.73615	0.0000
	ARCH LM Test			
	ARCH LM Test – Prob. Chi-Square		Test value = 0.138701	0.8896
Generalized Error Distribution	Dummy	-0.001469	-2.289818	0.0220
	Return_Oil	0.003835	0.254081	0.7994
	Variance Equation			
	RESID(-1)^2	0.063767	3.144841	0.0017
	RESID(-1)^2*(RESID(-1)<0)	0.109370	4.134151	0.0000
	GARCH(-1)	0.841360	48.53370	0.0000
	ARCH LM Test			
	ARCH LM Test – Prob. Chi-Square		Test value = 0.191728	0.8479

As the Jarque-Berra test result computed before, point for non-normal errors' distribution, even though it is common in finance, we also consider the other theoretical distributions namely Student's t and Generalized Error Distribution (GED) for the conditional distribution of the errors. The main estimated results are presented next. After taking GARCH (1, 1) model for conditional distribution of errors' regression, we run the ARCH LM test to check the ARCH effect on residuals. The result give us that we cannot reject the null hypothesis and this leads us to conclusion of non-conditional heteroskedasticity, or there is no ARCH effect on residuals.

To deal with the news asymmetry, we use the GJR(1,1,1) model by setting the threshold value to 1 in Eviews. The result in table 4 shows that the estimated coefficient for the variable representing the asymmetric effect, RESID(-1)^2 I, where I is a binary variable that assumes the value one if RESID(-1)<0, is statistically significant. We conclude this based on the p-value that associated to the individual test which is lower than 0.05. Consequently, we conclude that there is asymmetric effect on volatility in the series meaning that bad news and good news impact in different ways. The result with the Student's t and GED distribution also correspondingly confirm that we need to reject the null hypothesis, so that it leads to the same conclusion with the result of normal distribution before. This supports to use the asymmetric model rather than the GARCH which is actually proper for the symmetric effect. Nonetheless, we need to check the information criteria beforehand.

Bringing the conclusion of GJR above, it reflects the real world in Indonesia Stock Exchange market. The subsidy removal impacts the corporates not only for operational cost, but also for demand of salary increment. Before the subsidy removal, the price is adjusted by government very rarely, but after the subsidy removal, the price is adjusted periodically in two weeks. This policy change the corporate's financial planning, then might change the decision of investor because the policy is just applied. Investor might react because there is no certainty for the fossil fuel price policy.

In order to check whether there is the ARCH effect in GJR model, we run the ARCH LM test below. As the probability of chi square is higher than 0.05 (see table 4) we do not reject the null hypothesis. Thus, the new series of residuals has no ARCH. Correspondingly in term of correlogram of residuals squared (see appendix number 16), in every lags we do not reject the null hypothesis of no serial correlation.

The test with the student's t and GED conditional errors' distribution also give the same result. We cannot reject the null hypothesis in ARCH LM test and null hypothesis based on correlogram of residuals squared. Consequently, the residuals series has no ARCH effect.

Table 5.Regression model considering EGARCH(1,1,1)

		Coefficient	**z-statistic**	**Prob.**
Normal Distribution	Dummy	-0.001355	-2.088831	0.0367
	Return_Oil	0.002440	0.146938	0.8832
	Variance Equation			
	C(5)	0.223792	15.69027	0.0000
	C(6)	-0.089407	-8.665067	0.0000
	C(7)	0.962216	247.2539	0.0000
	ARCH LM Test			
	Prob. Chi-Square		Test value = 0.203875	0.8384
Student's t Distribution	Dummy	-0.001354	-2.174409	0.0297
	Return_Oil	0.004279	0.292383	0.7700
	Variance Equation			
	C(5)	0.228297	8.647894	0.0000
	C(6)	-0.085670	-5.196381	0.0000
	C(7)	0.961744	131.4959	0.0000
	ARCH LM Test			
	Prob. Chi-Square		Test value = 0.257338	0.7968
Generalized Error Distribution	Dummy	-0.001137	-1.989891	0.0466
	Return_Oil	0.004116	0.264031	0.7918
	Variance Equation			
	C(5)	0.229682	8.974690	0.0000
	C(6)	-0.083656	-4.955147	0.0000
	C(7)	0.960365	133.1171	0.0000
	ARCH LM Test			
	Prob. Chi-Square		Test value = 0.248062	0.8040

Rather than using only one model to predict the asymmetry in the series, we also use EGARCH that is also one of the most popular model for volatility asymmetries. Considering EGARCH(1,1,1) in our regression model, we expect negative value of the estimate for coefficient C(6), despite its impact being positive because it multiplies by the negative RESID(-1). Our target is to find out the leverage effect. We see that C(6) estimated coefficient is statistically significant and it has a negative value. This means that there is leverage effect in conditional volatility. The higher the leverage effect, the greater the volatility of Jakarta Composite Index stock. This means that the bad news (than good news) have a bigger impact on Jakarta Composite Index volatility. If we assume that bad news came from the decision to remove the subsidy, we can conclude that it impacts stronger on market volatility when compared to good news for Jakarta Composite Index. When there is a higher volatility in return, the risk in Jakarta Composite Index goes up, so the investors might shift their fund to other less risky investment. So, we can conclude also that hypothesis 3 holds. This is because based on the result of both EGARCH and GJR, we conclude that the bad news (maybe due to the subsidy removal) give more negative shock to the market than the good news.

Table 6. Model selection by using AIC and SBC

	Information Criterion	**GARCH(1,1)**	**GJR(1,1,1)**	**EGARCH(1,1,1)**
Normal Distribution	Akaike Information Criterion (AIC)	-5.970571	-5.981317	**-5.985808**
	Scwarz's Bayesian Criterion (SBC)	-5.957169	-5.965681	**-5.970172**
Student's t Distribution	Akaike Information Criterion (AIC)	-6.036935	-6.044081	**-6.046790**
	Scwarz's Bayesian Criterion (SBC)	-6.021299	-6.026211	**-6.028920**
GED	Akaike Information Criterion (AIC)	-6.033425	-6.039551	**-6.042759**
	Scwarz's Bayesian Criterion (SBC)	-6.017788	-6.021682	**-6.024889**

Based on the ARCH LM test, we cannot reject the null hypothesis and this leads us to conclude that there is no ARCH effect on residuals. Likewise, we also get the same conclusion with student's t and GED distribution, which there is no ARCH effect on residual. Regarding to the correlogram of residuals squared (see appendix number 19), we do not reject the null hypothesis in every lag, so there is no serial correlation. This result run in the same way with the model using the student's t and GED distribution as well. Therefore, most of our tested model either using the Gaussian Normal, student's t, or GED distribution give similar result.

In term of the information criterion (see table 6), we can see that the EGARCH(1,1,1), considering three distributions we computed, provides smaller value than GARCH(1,1) and GJR(1,1.1) in both AIC and SBC. This means that the EGARCH(1,1,1) model works better than GARCH(1,1) and GJR(1,1,1). Therefore, in general, we more accept result of EGARCH than GARCH and GJR in this model, because the EGARCH model explain better in this study. Though, we are still able to accept the result from GARCH(1,1) and EGARCH(1,1,1).

The GARCH conclude that the variable impact to Jakarta Composite Index is, in our equation number 13, only the dummy variable, which represents the subsidy removal. Meanwhile, the GJR and EGARCH similarly conclude that there is asymmetric effect on our series. Specifically, the bad news have bigger impact on volatility than good news.

5. CONCLUSIONS

The efficient market hypothesis stated that the prices of the ideal market is completely reflected by available informations (Fama, 1967). Subsidy policy in Indonesia limit the fossil fuel price which is one of the important expense in a company. The fossil fuel price affect the transportation cost, production cost, labor cost and the living cost. Therefore, when the government of Indonesia announced to remove the subsidy, it affects the company's financial plan, which also affects the decision of investor in Indonesia Stock Market.

We perform analysis of the impact of subsidy removal to the Indonesia Stock Market. The price of Indonesia Stock Market is reflected in Jakarta Composite Index (JKSE), which we use as the data. In order to be able to analyze properly, we apply GARCH-type model to deal with the conditional heteroskedasticity. Regarding to the asymmetry effect, we use the GJR and EGARCH.

Based on a regression model with errors GARCH effects, the estimated coefficient for the dummy variable is statistically significant, meaning that the subsidy existence influences statistically the stock return in JKSE. Contrarily, the oil price return does not influence the stock return due to the insignificance of the respective estimated coefficient. Normal, student's t, and GED distributions lead to the similar conclusions in statistical terms.

Then dealing with the asymmetry on volatility, we apply the GJR(1,1,1) model. The result conclude that there is asymmetric effect on volatility in the series meaning that bad news and good news impact differently on conditional volatility. Consistently, we compute with normal, student's t, and GED distributions, and we conclude the same based on those two distributions.

We also use the EGARCH(1,1,1), which is also one of most popular model for asymmetries. The result of our computation lead to the conclusion that there is leverage effect in the series. Specifically, the subsidy removal (bad news for market participants) give a negative shock more that the time when subsidy existed (positive news). The result for EGARCH with normal, student's t, and GED distribution correspondingly lead to the same conclusion.

In order to compare which model can explain better, we take into account the information criterion by using Akaike Information Criterion and Schwarz's Bayesian Criterion. Although the difference of criterion is not absolutely far, we get the result that the EGARCH(1,1,1) provides smaller value than GARCH(1,1) and GJR(1,1,1). This means that the EGARCH model, in this dissertation, can explain the series better. Hence, statistically speaking EGARCH seems statistically more appropriate.

To sum up, the subsidy removal do affect the Indonesia Stock Market. It gives negative shock to the JKSE more than during the subsidy. The subsidy removal generates higher variance so that the risk in JKSE goes up. Therefore, this might makes the investors decide to shift their fund to other less risky investment.

Limitations and Future Research

Nevertheless, we believe that this study is not perfect describing the reality in the market. Therefore, there are some limitations, and suggestions for future research.

Firstly, our study's result is limited to the effect of independent variables which are the subsidy removal and oil price return. However, in reality, there are many other factors could affect the market. Especially in 2015, there is slower economic growth in Indonesia caused by some macroeconomic factor, such as the depreciation of Rupiah, lower export, and intern political issues. Secondly, the subsidy removal policy has just been applied for eleven months during this research, and the market might adapt to act differently in the future. Consequently, the volatility due to subsidy removal might not be the same as the data we compute in this study. Lastly, even though the subsidy is now removed, the fossil fuel price in Indonesia still follows the announcement from government of Indonesia, and it does not follow the supply and demand.

This study and its empirical result tends to be useful for those who want to get deeper in analyzing the government's policy regarding to the subsidy removal. Besides, it is useful to test the GARCH, GJR and EGARCH model empirically in one analysis out-of-sample (after the observation period).

Considering that this study might be continued and be improved in future research, we think that cointegration analysis could be a methodological alternative. If the series are cointegrated, we may trust the long-run relationship of the variables under study, specially the prices.

Bibliography

Ali, M. (2010). *http://uk.reuters.com/*. Retrieved from Reuters: http://uk.reuters.com/article/2010/03/23/indonesia-economy-subsidy-idUKJAK42720420100323

Antonakakis, N., Chatziantonion, I., & Filis, G. 2014. **D*ynamic Spillovers of Oil Price Shocks and Economic Policy Uncertainty*****.** Energy Economics, 433-447.

Asri, M., & Setiawan, F. 1998. ***Reaksi Pasar Modal Indonesia Terhadap Peristiwa Politik Dalam Negeri (Event Study pada Peristiwa 27 Juli 1996)***. Kelola, 137-153.

Bangun, A. 2008. ***Pengaruh Pengumuman Harga BBM Industri (Non Subsidi) Terhadap Indeks Harga Saham Di Bursa Efek Indonesia*****.** Thesis Master of Management, Universitas Gadjah Mada, Yogyakarta, Indonesia.

Barragan, B., Ramos, S. B., & Veiga, H. 201). ***Correlations Between Oil and Stock Markets: A Wavelet-based approach***. Statistic and Econometric Series 04.

Barunik, J., Kocenda, E., & Vacha, L. 2015. ***Volatility Across Petroleum Markets***. Energy Journal, 36, 309-329.

Beaton, C., & Lontoh, L. 2010. ***Lesson Learned form Indonesia's Attempts to Reform Fossil-Fuel Subsidies***. International Institute for Sustainable Development.

Bentes, S. R., Menezes, R., & Ferreira, N. B. 2013. ***On The Asymmetric Behaviour of Stock Market Volatility: Evidence From Three Countries***. International Journal of Academic Research, 5, 24-32.

Black, F. 1976. **Studies of Stock Price Volatility Changes**. Massachusets Institute of Technology.

Bollerslev, T. 1986. ***Generalized Autoregressive Conditional Heteroskedasticity***. Journal of Econometrics, 307-327.

Caporale, G. M., Ali, F. M., & Spagnolo, N. 2015. ***Oil Price Uncertainty and Sectoral Stock Returns in China: A Time-Varying Approach***. Economic and Finance Working Paper Series, Brunel University London.

Chiarella, C., Kang, B., Niktopoulos, C. S., & To, T.-D. 2013. ***The Return-Volatility Relation in Commodity Future Markets.*** Quantitative Finance Research Center.

Cooke, E. F., Hague, S., Cockburn, J., Lahga, A.-R. E., & Tiberti, L. 2014. ***Estimating the Impact on Poverty of Ghana's Fuel Subsidy Reform and a Mitigating Response***. Policy Paper: Partnership for Economic Policy.

Cramer, D. 1997. ***Basic Statistics for Social Research***. Routledge.

Dartanto, T. 2013. ***Reducing Fuel Subsidies and the Implication on Fiscal Balance and Poverty in Indonesia: A Simulation Analysis***. Energy Policy, 117-134.

Degiannakis, S., Filis, G., & Kizys, R. 2014. ***The Effects of Oil Price Shocks on Stock Market Volatility: Evidence from European Data***. The Energy Journal, Vol. 35, No. 1.

Dobrota, M., Poledica, A., Bulajic, M., & Petrovic, B. 2012. ***Modelling Volatility Using GARCH Model: NASDAQ-100 Application***. University of Belgrade: Faculty of Organizational Science.

Fama, E. F. 1970. ***Efficient Capital Markets: A Review of Theory and Empirical Work***. The Journal of Finance, 383-417.

Glosten, L. R., Jagannathan, R., & Runkle, D. E. 1993. ***On the Relation between the Expeced Value and the Volatility of the Nominal Excess Return on Stocks***. The Journal of Finance, 48, 1779-1801.

Grek, A. 2014. ***Forecasting Accuracy for ARCH models and GARCH(1,1) Family - Which Model Does Best Capture the Volatility of the Swedish Stock Market?*** Orebro University: School of Business and Economics.

Hafezian, P., Salamon, H., & Shitan, M. 2015. ***Estimating Value at Risk for Sukuk Market Using generalized Auto Regressive Conditional Heteroskedasticity Models.*** The Economics and Finance Letters, 8-23.

Hammoudeh, S. M., Yuan, Y., & McAleer, M. 2008. ***Shock and Volatility Spillovers Among Equity Sectors*** . *EI 2008-29*.

Hansen, P. R., & Lunde, A. 2001. ***A Comparison of Volatility Models: Does Anything Beat A GARCH(1,1)?*** Center of Analytical Finance.

Imarhiagbe, S. 2015. ***Examining the Impact of Crude Oil Price on External Reserves: Evidence from Nigeria.*** International Journal of Economics and Finance.

Jiang , Z., & Tan, J. 2013. ***How the Removal of Energy Subsidy Affects General Price in China: A Study Based on Input-Output Model.*** Energy Policy, 599-606.

Jiang, W. 2012. ***Using the GARCH Model to Analyze and Predict the Different.*** Master Thesis in Statistics, Uppsala University, Sweden.

Jones, C. 2007. ***Investment, Analysis and Portfolio Management, 10th ed***. New York: John Wiley and Sons.

Kang, W., & Ratti, R. A. 2013. ***Oil Shocks, Policy Uncertainty and Stock Market Returns.*** Munich Personal RePEc Archive. Retrieved 10 24, 2015, from http://mpra.ub.uni-muenchen.de/49008/

Kendall, M., & Hill, A. B. 1953. ***The Analysis of Economic Time-Series-Part I: Prices.*** Journal of the Royal Statistical Society, Series A (General), 11-34.

Kritzman, M. 1994. ***What Practitioners Need to Know about Event Studies***. Financial Analyst Journal, 17-20.

Lee, C.-C., & Zeng, J.-H. 2011. ***The Impact of Oil Price Shocks on Stock Market Activities: Asymmetric Effect with Quantile Regression***. Elsevier.

Lee, Y.-H., & Chiou, J.-S. 2010. ***Oil Sensitivity and Its Asymmetric Impact on The Stock Market***. Elsevier.

Lin, B., & Jiang , Z. 2011. ***Estimates of Energy Subsidies in China and Impact of energy Subsidy Reform.*** Energy economics*: Elsevier*, 273-283.

Majmudar, U., & Banerjee, A. 2004. ***VIX Forecasting***. Available at SSRN: http://ssrn.com/abstract=533583 or http://dx.doi.org/10.2139/ssrn.533583.

Matias, R. B. 2012. ***A Comparison About The Predictive Ability of FCGARCH, Facing EGARCH and GJR***. Lisbon: ISCTE Busines School - Instituto Universitario de Lisboa.

Miron, D., & Tudor, C. 2010. ***Asymmetric Conditional Volatility Models: Empirical Estimation And Comparison of Forecasting Accuracy***. Romanian Journal of Economic Forecasting.

Morgan, T. 2007. ***Energy Subsidies: Their Magnitude, How They Affect Energy Investment and Greenhouse Gas Emissions, and Prospects for Reform.*** UNFCCC Secretariat Financial and Technical Support Programme.

Mourorugane, A. 2010. ***Phasing Out Energy Subsidies in Indonesi***a. OECD Economics Department Working Paper*, No. 808*.

Ou, P., & Wang, H. 2010. **F*inancial volatility Forecasting by Least Square Support Vector Machine Based on GARCH, EGARCH and GJR Models: Evidence from ASEAN Stock Markets.*** Internation Journal of Economics and Finance.

Peters, J.-P. 2001. ***Estimating and Forecasting Volatility of Stock Indices Using Asymmetric GARCH Models and (Skewed) Student-t.*** Belgium: Ecole d'Administration des Affaires, University of Li`ege.

Said, M. E., & Leigh, D. 2006. ***Fuel Price Subsidies in Gabon: Fiscal Cost and Distributional Impact***. *IMF Working Paper*.

Salgado, J. 2011. ***What Best Predicts Realized and Implied Volatility: GARCH, GJR or FCGARCH***. Lisbon: ISCTE Business School - Instituto Universitario de Lisboa.

Appendix

1. Result of ADF Test to price of Jakarta Composite Index

Null Hypothesis: ADJ_CLOSE has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 3 (Automatic based on SIC, MAXLAG=27)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.009278	0.5954
Test critical values:	1% level	-3.961537	
	5% level	-3.411518	
	10% level	-3.127621	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(ADJ_CLOSE)
Method: Least Squares
Date: 12/27/15 Time: 04:29
Sample (adjusted): 3/07/2005 11/30/2015
Included observations: 2627 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
ADJ_CLOSE(-1)	-0.003839	0.001911	-2.009278	0.0446
D(ADJ_CLOSE(-1))	0.072310	0.019497	3.708717	0.0002
D(ADJ_CLOSE(-2))	0.008033	0.019550	0.410896	0.6812
D(ADJ_CLOSE(-3))	-0.085157	0.019507	-4.365362	0.0000
C	5.288324	2.258578	2.341440	0.0193
@TREND(3/01/2005)	0.006038	0.003465	1.742641	0.0815

R-squared	0.014145	Mean dependent var	1.272726
Adjusted R-squared	0.012265	S.D. dependent var	41.01011
S.E. of regression	40.75784	Akaike info criterion	10.25546
Sum squared resid	4354010.	Schwarz criterion	10.26887
Log likelihood	-13464.54	Hannan-Quinn criter.	10.26031
F-statistic	7.521401	Durbin-Watson stat	2.002750
Prob(F-statistic)	0.000001		

2. Result of KPSS Test to price of Jakarta Composite Index

Null Hypothesis: ADJ_CLOSE is stationary
Exogenous: Constant, Linear Trend
Bandwidth: 41 (Newey-West using Bartlett kernel)

		LM-Stat.
Kwiatkowski-Phillips-Schmidt-Shin test statistic		0.289323
Asymptotic critical values*:	1% level	0.216000
	5% level	0.146000
	10% level	0.119000

*Kwiatkowski-Phillips-Schmidt-Shin (1992, Table 1)

Residual variance (no correction)	175100.2
HAC corrected variance (Bartlett kernel)	6809759.

KPSS Test Equation
Dependent Variable: ADJ_CLOSE
Method: Least Squares
Date: 12/27/15 Time: 04:30
Sample: 3/01/2005 11/30/2015
Included observations: 2631

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	843.9092	16.31752	51.71797	0.0000
@TREND(3/01/2005)	1.726099	0.010745	160.6379	0.0000

R-squared	0.907539	Mean dependent var	3113.730
Adjusted R-squared	0.907504	S.D. dependent var	1376.404
S.E. of regression	418.6089	Akaike info criterion	14.91251
Sum squared resid	4.61E+08	Schwarz criterion	14.91698
Log likelihood	-19615.41	Hannan-Quinn criter.	14.91413
F-statistic	25804.52	Durbin-Watson stat	0.009589
Prob(F-statistic)	0.000000		

3. Result of ADF Test of log return

Null Hypothesis: DIFLOG_ADJ_CLOSE has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic based on SIC, MAXLAG=27)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-46.22354	0.0000
Test critical values:	1% level	-3.961534	
	5% level	-3.411517	
	10% level	-3.127620	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(DIFLOG_ADJ_CLOSE)
Method: Least Squares
Date: 12/27/15 Time: 04:31
Sample (adjusted): 3/03/2005 11/30/2015
Included observations: 2629 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
DIFLOG_ADJ_CLOSE(-1)	-0.897736	0.019422	-46.22354	0.0000
C	0.000964	0.000556	1.733948	0.0830
@TREND(3/01/2005)	-3.66E-07	3.66E-07	-1.001729	0.3166

R-squared	0.448623	Mean dependent var	-5.95E-06
Adjusted R-squared	0.448203	S.D. dependent var	0.019158
S.E. of regression	0.014231	Akaike info criterion	-5.665651
Sum squared resid	0.531819	Schwarz criterion	-5.658947
Log likelihood	7450.498	Hannan-Quinn criter.	-5.663223
F-statistic	1068.312	Durbin-Watson stat	2.001745
Prob(F-statistic)	0.000000		

4. Result of KPSS test of log return

Null Hypothesis: DIFLOG_ADJ_CLOSE is stationary
Exogenous: Constant, Linear Trend
Bandwidth: 19 (Newey-West using Bartlett kernel)

		LM-Stat.
Kwiatkowski-Phillips-Schmidt-Shin test statistic		0.059829
Asymptotic critical values*:	1% level	0.216000
	5% level	0.146000
	10% level	0.119000

*Kwiatkowski-Phillips-Schmidt-Shin (1992, Table 1)

Residual variance (no correction)	0.000204
HAC corrected variance (Bartlett kernel)	0.000226

KPSS Test Equation
Dependent Variable: DIFLOG_ADJ_CLOSE
Method: Least Squares
Date: 12/27/15 Time: 04:31
Sample (adjusted): 3/02/2005 11/30/2015
Included observations: 2630 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.001053	0.000558	1.888082	0.0591
@TREND(3/01/2005)	-3.95E-07	3.67E-07	-1.076051	0.2820

R-squared	0.000440	Mean dependent var	0.000533
Adjusted R-squared	0.000060	S.D. dependent var	0.014302
S.E. of regression	0.014302	Akaike info criterion	-5.656075
Sum squared resid	0.537550	Schwarz criterion	-5.651608
Log likelihood	7439.739	Hannan-Quinn criter.	-5.654457
F-statistic	1.157886	Durbin-Watson stat	1.794308
Prob(F-statistic)	0.282003		

5. Result of ADF Test of fossil fuel price

Null Hypothesis: OIL_PRICE has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic based on SIC, MAXLAG=27)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.640680	0.2621
Test critical values:	1% level	-3.961533	
	5% level	-3.411516	
	10% level	-3.127620	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(OIL_PRICE)
Method: Least Squares
Date: 12/27/15 Time: 04:35
Sample (adjusted): 3/02/2005 11/30/2015
Included observations: 2630 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
OIL_PRICE(-1)	-0.005134	0.001944	-2.640680	0.0083
C	20.06015	7.474629	2.683765	0.0073
@TREND(3/01/2005)	0.005664	0.003067	1.846884	0.0649

R-squared	0.002653	Mean dependent var	1.863118
Adjusted R-squared	0.001894	S.D. dependent var	81.58955
S.E. of regression	81.51226	Akaike info criterion	11.64052
Sum squared resid	17454441	Schwarz criterion	11.64723
Log likelihood	-15304.29	Hannan-Quinn criter.	11.64295
F-statistic	3.493951	Durbin-Watson stat	1.996091
Prob(F-statistic)	0.030522		

6. Result of KPSS test of fossil fuel price

Null Hypothesis: OIL_PRICE is stationary
Exogenous: Constant, Linear Trend
Bandwidth: 41 (Newey-West using Bartlett kernel)

		LM-Stat.
Kwiatkowski-Phillips-Schmidt-Shin test statistic		0.671531
Asymptotic critical values*:	1% level	0.216000
	5% level	0.146000
	10% level	0.119000

*Kwiatkowski-Phillips-Schmidt-Shin (1992, Table 1)

Residual variance (no correction)	668262.5
HAC corrected variance (Bartlett kernel)	25812251

KPSS Test Equation
Dependent Variable: OIL_PRICE
Method: Least Squares
Date: 12/27/15 Time: 04:35
Sample: 3/01/2005 11/30/2015
Included observations: 2631

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	3479.700	31.87752	109.1584	0.0000
@TREND(3/01/2005)	1.153318	0.020992	54.94157	0.0000

R-squared	0.534491	Mean dependent var	4996.313
Adjusted R-squared	0.534313	S.D. dependent var	1198.373
S.E. of regression	817.7841	Akaike info criterion	16.25183
Sum squared resid	1.76E+09	Schwarz criterion	16.25630
Log likelihood	-21377.29	Hannan-Quinn criter.	16.25345
F-statistic	3018.576	Durbin-Watson stat	0.009955
Prob(F-statistic)	0.000000		

7. Result of ADF test of fossil fuel price log return

Null Hypothesis: DIFLOG_RETURN_OIL has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic based on SIC, MAXLAG=27)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-51.28347	0.0000
Test critical values:	1% level	-3.961534	
	5% level	-3.411517	
	10% level	-3.127620	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(DIFLOG_RETURN_OIL)
Method: Least Squares
Date: 01/17/16 Time: 21:08
Sample (adjusted): 3/03/2005 11/30/2015
Included observations: 2629 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
DIFLOG_RETURN_OIL(-1)	-1.000759	0.019514	-51.28347	0.0000
C	0.000761	0.000660	1.153221	0.2489
@TREND(3/01/2005)	-2.57E-07	4.35E-07	-0.590958	0.5546

R-squared	0.500380	Mean dependent var	0.000000
Adjusted R-squared	0.499999	S.D. dependent var	0.023910
S.E. of regression	0.016907	Akaike info criterion	-5.321034
Sum squared resid	0.750636	Schwarz criterion	-5.314331
Log likelihood	6997.499	Hannan-Quinn criter.	-5.318606
F-statistic	1314.997	Durbin-Watson stat	2.000002
Prob(F-statistic)	0.000000		

8. Result of KPSS test of fossil fuel price return

Null Hypothesis: DIFLOG_RETURN_OIL is stationary
Exogenous: Constant, Linear Trend
Bandwidth: 2 (Newey-West using Bartlett kernel)

		LM-Stat.
Kwiatkowski-Phillips-Schmidt-Shin test statistic		0.076943
Asymptotic critical values*:	1% level	0.216000
	5% level	0.146000
	10% level	0.119000

*Kwiatkowski-Phillips-Schmidt-Shin (1992, Table 1)

Residual variance (no correction)	0.000285
HAC corrected variance (Bartlett kernel)	0.000285

KPSS Test Equation
Dependent Variable: DIFLOG_RETURN_OIL
Method: Least Squares
Date: 01/17/16 Time: 21:13
Sample (adjusted): 3/02/2005 11/30/2015
Included observations: 2630 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.000760	0.000659	1.152198	0.2493
@TREND(3/01/2005)	-2.56E-07	4.34E-07	-0.589592	0.5555

R-squared	0.000132	Mean dependent var	0.000423
Adjusted R-squared	-0.000248	S.D. dependent var	0.016899
S.E. of regression	0.016901	Akaike info criterion	-5.322174
Sum squared resid	0.750637	Schwarz criterion	-5.317707
Log likelihood	7000.659	Hannan-Quinn criter.	-5.320556
F-statistic	0.347619	Durbin-Watson stat	2.001518
Prob(F-statistic)	0.555515		

9. Result of least squares regression model

Dependent Variable: DIFLOG_ADJ_CLOSE
Method: Least Squares
Date: 01/17/16 Time: 21:22
Sample (adjusted): 3/02/2005 11/30/2015
Included observations: 2630 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
DUMMY	-0.001386	0.000997	-1.390179	0.1646
DIFLOG_RETURN_OIL	-0.014080	0.016508	-0.852905	0.3938
C	0.000658	0.000292	2.255387	0.0242

R-squared	0.000994	Mean dependent var	0.000533
Adjusted R-squared	0.000233	S.D. dependent var	0.014302
S.E. of regression	0.014301	Akaike info criterion	-5.655869
Sum squared resid	0.537252	Schwarz criterion	-5.649167
Log likelihood	7440.467	Hannan-Quinn criter.	-5.653442
F-statistic	1.306941	Durbin-Watson stat	1.793839
Prob(F-statistic)	0.270823		

10. Correlogram of standardized residuals squared for least square regression model

Date: 01/17/16 Time: 21:57
Sample: 3/02/2005 11/30/2015
Included observations: 2630

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.222	0.222	130.32	0.000
		2	0.275	0.237	329.65	0.000
		3	0.208	0.121	443.64	0.000
		4	0.140	0.028	495.63	0.000
		5	0.202	0.114	603.33	0.000
		6	0.116	0.015	638.91	0.000
		7	0.153	0.056	700.74	0.000
		8	0.116	0.022	736.37	0.000
		9	0.127	0.043	779.08	0.000
		10	0.105	0.011	807.96	0.000
		11	0.187	0.122	900.74	0.000
		12	0.141	0.041	953.55	0.000
		13	0.176	0.071	1035.9	0.000
		14	0.151	0.031	1096.0	0.000
		15	0.102	-0.014	1123.7	0.000
		16	0.104	-0.017	1152.3	0.000
		17	0.161	0.091	1220.9	0.000
		18	0.090	-0.021	1242.4	0.000
		19	0.101	-0.002	1269.3	0.000
		20	0.084	-0.006	1287.8	0.000
		21	0.050	-0.025	1294.5	0.000
		22	0.080	-0.004	1311.5	0.000
		23	0.030	-0.031	1313.8	0.000
		24	0.018	-0.062	1314.7	0.000
		25	0.094	0.060	1338.3	0.000
		26	0.066	0.026	1350.0	0.000
		27	0.071	0.008	1363.3	0.000
		28	0.059	-0.013	1372.7	0.000
		29	0.087	0.048	1392.9	0.000
		30	0.078	0.004	1409.2	0.000
		31	0.071	0.007	1422.5	0.000
		32	0.045	-0.017	1427.9	0.000
		33	0.042	-0.007	1432.5	0.000
		34	0.092	0.056	1455.0	0.000
		35	0.047	0.017	1460.9	0.000
		36	0.080	0.020	1478.1	0.000

11. Result of serial Breusch-Godfrey correlation LM Test to natural regression model

Breusch-Godfrey Serial Correlation LM Test:

F-statistic	14.33147	Prob. F(2,2625)	0.0000
Obs*R-squared	28.40736	Prob. Chi-Square(2)	0.0000

Test Equation:
Dependent Variable: RESID
Method: Least Squares
Date: 01/17/16 Time: 21:24
Sample: 3/02/2005 11/30/2015
Included observations: 2630
Presample missing value lagged residuals set to zero.

Variable	Coefficient	Std. Error	t-Statistic	Prob.
DUMMY	-1.50E-05	0.000992	-0.015105	0.9879
DIFLOG_RETURN_OIL	-0.000956	0.016427	-0.058205	0.9536
C	5.33E-07	0.000290	0.001837	0.9985
RESID(-1)	0.100771	0.019527	5.160559	0.0000
RESID(-2)	0.017380	0.019527	0.890062	0.3735

R-squared	0.010801	Mean dependent var	2.66E-19
Adjusted R-squared	0.009294	S.D. dependent var	0.014295
S.E. of regression	0.014229	Akaike info criterion	-5.665208
Sum squared resid	0.531449	Schwarz criterion	-5.654039
Log likelihood	7454.748	Hannan-Quinn criter.	-5.661163
F-statistic	7.165737	Durbin-Watson stat	1.996768
Prob(F-statistic)	0.000010		

12. Result of regression model considering GARCH

Dependent Variable: DIFLOG_ADJ_CLOSE
Method: ML - ARCH (Marquardt) - Normal distribution
Date: 01/17/16 Time: 21:25
Sample (adjusted): 3/02/2005 11/30/2015
Included observations: 2630 after adjustments
Convergence achieved after 28 iterations
Presample variance: backcast (parameter = 0.7)
GARCH = C(4) + C(5)*RESID(-1)^2 + C(6)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
DUMMY	-0.001562	0.000682	-2.290791	0.0220
DIFLOG_RETURN_OIL	0.002436	0.016538	0.147278	0.8829
C	0.001039	0.000232	4.481786	0.0000
Variance Equation				
C	4.85E-06	6.35E-07	7.638720	0.0000
RESID(-1)^2	0.131474	0.010154	12.94853	0.0000
GARCH(-1)	0.849600	0.009916	85.67708	0.0000

R-squared	-0.000082	Mean dependent var	0.000533
Adjusted R-squared	-0.001988	S.D. dependent var	0.014302
S.E. of regression	0.014317	Akaike info criterion	-5.970571
Sum squared resid	0.537831	Schwarz criterion	-5.957169
Log likelihood	7857.301	Hannan-Quinn criter.	-5.965718
Durbin-Watson stat	1.793761		

13. Correlogram of standardized residuals squared for regression considering GARCH

Date: 01/17/16 Time: 21:58
Sample: 3/02/2005 11/30/2015
Included observations: 2630

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.006	0.006	0.0905	0.764
		2	0.003	0.003	0.1221	0.941
		3	0.016	0.016	0.7617	0.859
		4	-0.001	-0.001	0.7626	0.943
		5	0.001	0.001	0.7671	0.979
		6	-0.013	-0.014	1.2348	0.975
		7	-0.006	-0.005	1.3183	0.988
		8	-0.012	-0.011	1.6687	0.990
		9	-0.024	-0.023	3.1367	0.959
		10	-0.016	-0.016	3.8156	0.955
		11	0.019	0.020	4.7782	0.941
		12	-0.013	-0.013	5.2318	0.950
		13	-0.002	-0.002	5.2470	0.969
		14	0.014	0.013	5.7621	0.972
		15	0.001	0.001	5.7676	0.983
		16	-0.016	-0.017	6.4541	0.982
		17	-0.004	-0.004	6.4928	0.989
		18	0.007	0.006	6.6291	0.993
		19	-0.010	-0.010	6.8770	0.995
		20	0.018	0.019	7.7104	0.994
		21	-0.012	-0.012	8.1062	0.995
		22	0.001	0.000	8.1074	0.997
		23	-0.017	-0.017	8.8756	0.996
		24	-0.025	-0.024	10.478	0.992
		25	0.006	0.004	10.562	0.995
		26	0.004	0.005	10.604	0.997
		27	-0.002	-0.001	10.620	0.998
		28	0.016	0.016	11.337	0.998
		29	0.056	0.056	19.770	0.900
		30	-0.031	-0.032	22.404	0.839
		31	0.013	0.011	22.846	0.855
		32	0.000	-0.002	22.846	0.883
		33	-0.018	-0.019	23.716	0.883
		34	0.013	0.013	24.169	0.894
		35	0.016	0.019	24.881	0.898
		36	0.013	0.013	25.351	0.907

14. Result of ARCH LM test of GARCH

Heteroskedasticity Test: ARCH

F-statistic	0.090614	Prob. F(1,2627)	0.7634
Obs*R-squared	0.090680	Prob. Chi-Square(1)	0.7633

Test Equation:
Dependent Variable: WGT_RESID^2
Method: Least Squares
Date: 01/17/16 Time: 21:26
Sample (adjusted): 3/03/2005 11/30/2015
Included observations: 2629 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.993933	0.045380	21.90233	0.0000
WGT_RESID^2(-1)	0.005884	0.019546	0.301021	0.7634

R-squared	0.000034	Mean dependent var	0.999802
Adjusted R-squared	-0.000346	S.D. dependent var	2.100765
S.E. of regression	2.101129	Akaike info criterion	4.323587
Sum squared resid	11597.53	Schwarz criterion	4.328056
Log likelihood	-5681.355	Hannan-Quinn criter.	4.325205
F-statistic	0.090614	Durbin-Watson stat	1.996387
Prob(F-statistic)	0.763422		

15. Result of regression model considering GJR

Dependent Variable: DIFLOG_ADJ_CLOSE
Method: ML - ARCH (Marquardt) - Normal distribution
Date: 01/17/16 Time: 21:36
Sample (adjusted): 3/02/2005 11/30/2015
Included observations: 2630 after adjustments
Convergence achieved after 26 iterations
Presample variance: backcast (parameter = 0.7)
GARCH = C(4) + C(5)*RESID(-1)^2 + C(6)*RESID(-1)^2*(RESID(-1)<0) +
C(7)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
DUMMY	-0.001800	0.000767	-2.346632	0.0189
DIFLOG_RETURN_OIL	0.000790	0.016063	0.049196	0.9608
C	0.000844	0.000237	3.561120	0.0004
Variance Equation				
C	6.45E-06	6.51E-07	9.914403	0.0000
RESID(-1)^2	0.063421	0.012262	5.172261	0.0000
RESID(-1)^2*(RESID(-1)<0)	0.117240	0.016706	7.017913	0.0000
GARCH(-1)	0.843293	0.009669	87.21360	0.0000

R-squared	0.000493	Mean dependent var	0.000533
Adjusted R-squared	-0.001793	S.D. dependent var	0.014302
S.E. of regression	0.014315	Akaike info criterion	-5.981317
Sum squared resid	0.537521	Schwarz criterion	-5.965681
Log likelihood	7872.432	Hannan-Quinn criter.	-5.975655
F-statistic	0.215646	Durbin-Watson stat	1.794545
Prob(F-statistic)	0.971958		

16. Correlogram of standardized residuals square for regression considering GJR

Date: 01/17/16 Time: 22:00
Sample: 3/02/2005 11/30/2015
Included observations: 2630

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.000	0.000	0.0003	0.987
		2	-0.004	-0.004	0.0447	0.978
		3	0.011	0.011	0.3660	0.947
		4	-0.003	-0.003	0.3900	0.983
		5	0.002	0.002	0.3979	0.995
		6	-0.016	-0.016	1.0762	0.983
		7	-0.006	-0.006	1.1765	0.991
		8	-0.002	-0.002	1.1893	0.997
		9	-0.025	-0.024	2.7888	0.972
		10	-0.010	-0.010	3.0725	0.980
		11	0.018	0.018	3.9567	0.971
		12	-0.012	-0.012	4.3419	0.976
		13	0.007	0.007	4.4549	0.985
		14	0.018	0.017	5.2943	0.981
		15	0.004	0.004	5.3439	0.989
		16	-0.019	-0.020	6.3040	0.984
		17	-0.004	-0.004	6.3470	0.991
		18	0.018	0.017	7.2107	0.988
		19	-0.001	-0.001	7.2116	0.993
		20	0.017	0.018	7.9437	0.992
		21	-0.002	-0.003	7.9593	0.995
		22	0.004	0.003	7.9995	0.997
		23	-0.009	-0.008	8.1989	0.998
		24	-0.026	-0.025	9.9638	0.995
		25	0.014	0.012	10.451	0.995
		26	0.005	0.006	10.531	0.997
		27	-0.003	-0.001	10.561	0.998
		28	0.019	0.019	11.570	0.997
		29	0.050	0.051	18.329	0.937
		30	-0.027	-0.027	20.307	0.908
		31	0.018	0.018	21.171	0.907
		32	-0.001	-0.003	21.175	0.928
		33	-0.011	-0.012	21.507	0.938
		34	0.020	0.021	22.612	0.932
		35	0.016	0.019	23.256	0.936
		36	0.010	0.010	23.537	0.945

17. Result of ARCH LM Test of GJR

Heteroskedasticity Test: ARCH

F-statistic	0.000271	Prob. F(1,2627)	0.9869
Obs*R-squared	0.000271	Prob. Chi-Square(1)	0.9869

Test Equation:
Dependent Variable: WGT_RESID^2
Method: Least Squares
Date: 01/17/16 Time: 21:36
Sample (adjusted): 3/03/2005 11/30/2015
Included observations: 2629 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.999490	0.044935	22.24314	0.0000
WGT_RESID^2(-1)	0.000322	0.019547	0.016471	0.9869

R-squared	0.000000	Mean dependent var	0.999811
Adjusted R-squared	-0.000381	S.D. dependent var	2.075372
S.E. of regression	2.075767	Akaike info criterion	4.299299
Sum squared resid	11319.24	Schwarz criterion	4.303768
Log likelihood	-5649.428	Hannan-Quinn criter.	4.300917
F-statistic	0.000271	Durbin-Watson stat	1.996252
Prob(F-statistic)	0.986860		

18. Result of regression model considering EGARCH

Dependent Variable: DIFLOG_ADJ_CLOSE
Method: ML - ARCH (Marquardt) - Normal distribution
Date: 01/17/16 Time: 21:37
Sample (adjusted): 3/02/2005 11/30/2015
Included observations: 2630 after adjustments
Convergence achieved after 25 iterations
Presample variance: backcast (parameter = 0.7)
LOG(GARCH) = C(4) + C(5)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(6)
*RESID(-1)/@SQRT(GARCH(-1)) + C(7)*LOG(GARCH(-1))

Variable	Coefficient	Std. Error	z-Statistic	Prob.
DUMMY	-0.001355	0.000649	-2.088831	0.0367
DIFLOG_RETURN_OIL	0.002440	0.016607	0.146938	0.8832
C	0.000809	0.000230	3.510191	0.0004
Variance Equation				
C(4)	-0.501367	0.037920	-13.22181	0.0000
C(5)	0.223792	0.014263	15.69027	0.0000
C(6)	-0.089407	0.010318	-8.665067	0.0000
C(7)	0.962216	0.003892	247.2539	0.0000

R-squared	0.000487	Mean dependent var	0.000533
Adjusted R-squared	-0.001799	S.D. dependent var	0.014302
S.E. of regression	0.014315	Akaike info criterion	-5.985808
Sum squared resid	0.537525	Schwarz criterion	-5.970172
Log likelihood	7878.337	Hannan-Quinn criter.	-5.980146
F-statistic	0.213114	Durbin-Watson stat	1.794781
Prob(F-statistic)	0.972784		

19. Correlogram of standardized residuals square for regression considering EGARCH

Date: 01/17/16 Time: 22:01
Sample: 3/02/2005 11/30/2015
Included observations: 2630

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.004	0.004	0.0415	0.839
		2	0.009	0.009	0.2690	0.874
		3	0.022	0.022	1.5867	0.662
		4	-0.001	-0.001	1.5901	0.811
		5	0.008	0.008	1.7706	0.880
		6	-0.016	-0.017	2.4780	0.871
		7	-0.000	-0.000	2.4786	0.929
		8	0.000	0.000	2.4790	0.963
		9	-0.024	-0.023	4.0256	0.910
		10	-0.007	-0.007	4.1424	0.941
		11	0.027	0.027	6.0208	0.872
		12	-0.012	-0.011	6.3814	0.896
		13	0.005	0.005	6.4538	0.928
		14	0.022	0.022	7.7813	0.900
		15	0.002	0.002	7.7921	0.932
		16	-0.016	-0.018	8.4904	0.933
		17	-0.002	-0.002	8.4993	0.955
		18	0.027	0.027	10.485	0.915
		19	0.003	0.003	10.511	0.939
		20	0.020	0.022	11.578	0.930
		21	-0.001	-0.002	11.579	0.950
		22	0.008	0.006	11.729	0.963
		23	-0.011	-0.011	12.079	0.969
		24	-0.023	-0.022	13.427	0.959
		25	0.012	0.010	13.815	0.965
		26	-0.001	0.000	13.821	0.975
		27	0.002	0.005	13.831	0.983
		28	0.018	0.017	14.656	0.982
		29	0.034	0.033	17.666	0.951
		30	-0.028	-0.028	19.744	0.923
		31	0.020	0.018	20.762	0.918
		32	-0.002	-0.005	20.775	0.936
		33	-0.014	-0.015	21.294	0.942
		34	0.025	0.026	22.976	0.924
		35	0.015	0.018	23.594	0.929
		36	0.015	0.013	24.205	0.933

20. Result of ARCH LM Test of EGARCH

Heteroskedasticity Test: ARCH

F-statistic	0.041565	Prob. F(1,2627)	0.8385
Obs*R-squared	0.041596	Prob. Chi-Square(1)	0.8384

Test Equation:
Dependent Variable: WGT_RESID^2
Method: Least Squares
Date: 01/17/16 Time: 21:38
Sample (adjusted): 3/03/2005 11/30/2015
Included observations: 2629 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.995854	0.044535	22.36107	0.0000
WGT_RESID^2(-1)	0.003984	0.019543	0.203875	0.8385

R-squared	0.000016	Mean dependent var	0.999829
Adjusted R-squared	-0.000365	S.D. dependent var	2.052654
S.E. of regression	2.053028	Akaike info criterion	4.277269
Sum squared resid	11072.61	Schwarz criterion	4.281738
Log likelihood	-5620.471	Hannan-Quinn criter.	4.278888
F-statistic	0.041565	Durbin-Watson stat	1.996703
Prob(F-statistic)	0.838467		