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A volatility analysis of energy and stock prices

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Contents

Abstract

In this paper, a new class of multivariate GARCH models is used to model conditional correlations and to analyze the volatility spillovers between oil prices, natural gas and the stock prices of clean energy companies and technology companies. This research use daily data from January 2006 to November 2016 to estimate the dynamic conditional correlations of the indexes above. We also imply Generalized Impulse Response Functions to the conditional correlations, so as to examine what happens between them when there is a shock.
Our findings suggest that all the dynamic conditional correlations are positive, as well as the Impulse response functions of them, with the pair of clean energy companies and technology be the one with the strongest correlation.

2. Introduction

Economic theory suggests that there is a relationship among the prices of natural gas and crude oil. That is due to the fact that both are products which are substitutes in consumption, as well as complements in production. Thus, there are economic factors which connect the prices of natural gas and crude oil, both by demand and supply.

However, there is an asymmetrical relationship between those two products, mainly due to the relative size of each market. The crude oil price is determined on the world market, while natural gas markets tend to be divided regionally. Therefore, the global crude oil market is much bigger than the domestic of natural gas, so events or conditions in the U.S natural gas market seem unlikely to be able to influence the global price of oil. Increases in oil prices may affect the natural gas market in several ways. As for the demand, petroleum and natural gas are competitive substitutes primarily in the electric generation and industrial sectors of the economy. An increase in crude petroleum prices motivates consumers to substitute petroleum with natural gas , which increases natural gas demand and then prices. As for the supply, increases in crude oil prices resulting from an increase in crude oil demand may increase natural gas produced as a co-product of oil, which would tend to decrease natural gas prices.

Energy commodity price volatility is of great concern to oil, natural gas, and electricity market participants, as well as policymakers. Fluctuations in global crude oil prices have always been the focus of the economic and financial news. In our days, because of the depletion and high prices of oil and natural gas, there are few who are looking for the quickest possible search for alternative energy sources, while criticizing governments to move in this direction. The renewable energy sector has become one of the fastest growing segments of the energy industry due to climate change, new technologies and energy security issues. Despite the fact that modern finance focus on modeling and forecasting volatility, very little is known about the volatility dynamics of clean energy stock prices and other important financial markets like oil prices and technology stock prices.

There are several reasons for this particular study. First, most previous work focuses on the oil-stock return links and often neglects the volatility spillover between these markets.

The information contained in empirical results also provides empirical bases from which to address issues regarding hedging strategies, optimal portfolio allocation, and derivatives management in the presence of energy risk. Finally, our review of the literature indicates that little attention has been paid to the interaction of the volatility of oil prices alternative energy resources, natural gas and technology.

2.1 Defying variables of prices of crude oil

Since the first half of the 20th century and thereafter, crude oil has been one of the basic markers of global economic undertaking, due to its significance in the supply of global energy needs. Despite the emergence of alternative sources of energy like wind and solar, petroleum still remains the basic source of energy. Thus, crude oil is one of the most important factors for regulating the functionality of the global economy. It is a product of strategic importance, especially for the national superpowers who attempt to ensure its unobstructed flow. The price of crude oil, as in every commodity, is defined from powers of demand and supply while at the same time from a plethora of geopolitical and other factors.
The fluctuation of oil prices impacts economic and social life and that is why it concerns every citizen as well as a numerous researchers, who study the effects of crude oil prices in macro-economy.

2.1.1 Historical overview of petroleum crises

During the 1850 the production of oil and natural gas originated from processing coal, crude and limestone. A new era came at 1859, when Edwin Drake successfully drilled marketable quantities of crude petroleum, from 69 feet well in Pennsylvania.
The first product of Drake (Enterprises / Inc.) was sold for 50 cents per gallon, and from August 1859 until the end of that year, the price of petroleum rose to 20$ / barrel.
While, the drilling of petroleum from the wells in Pennsylvania during the 1860 rose, the price of petroleum fell to an average of 9.60$/barrel. These prices triggered a drilling fury throughout the region, which was quadruplicated of the production, from half million barrels in 1860 to over 2 million in 1861, and the price quickly dropped to $2/barrel by the end of 1860 and 50 cents a barrel by the end of 1861.
The onset of the U.S. Civil War brought about a surge in prices and commodity demands generally. The effects on the oil market were amplified by the cut-off of supplies of turpentine from the South and more importantly by the introduction of a tax on alcohol, which rose from 20$/gallon in 1862 to $2/gallon by 1865, which resulted, to the elimination of alcohol as a competitor to petroleum as a source for illuminants. Moreover, the price collapse of 1861 had led to the closure of many of the initial drilling operations, while water flooding and other problems forced out many petroleum entrepreneurs. As a result of these big increases in demand and drops in supply, the increase in the relative price of oil during the U.S. Civil War was as big as the rise during the 1970s (Hamilton, 2011).
The petroleum barrel, which at 2008 surpassed the 135 dollars per barrel, cost at 1970 less than two dollars. A review of petroleum prices and the most important dates of the last four decades follow. In 1970, the official price of crude petroleum of Saudi Arabia is set to 1.80 US dollars per barrel while in 1973 the first petroleum crisis occurred, which affected the world economy. The cause of the crisis was the decision of USA to continue supply the Israeli army during the Yom Kippur war. In response the members of the Organization of Petroleum Exporting (hereafter OPEC) or OAPEC (which is composed by the OPEC member plus Egypt and Syria) announced an embargo on petroleum exports which disrupted the flow of petroleum. On 16 October 1973, OPEC announced its decision to raise the price of petroleum by 70%, to 5,11 dollars per barrel. The following day the ministers of Arabic countries agreed

to the embargo, to a reduction of 5% and to continue the reduction of production by 5% per year until the acknowledgement of their economic and political objectives. Taking into consideration that the demand of oil falls when price increases, prices had to increase dramatically to reduce demand to the new, lower level of supply. As a result prices rose from $3 per barrel to $12 per barrel. The embargo had larger consequences in Europe and Japan , which were dependent to a great extend by the Arabic oil and smaller for US since the dependency on Arabic petroleum did not surpassed 10%. The first economic crisis was harsh for the global economy. Due to the inflation during that time, a folk economic theory was that the price rises were responsible for the reduction of financial activity. The global financial system remained in recession and with high inflation rates until the early 80s, with petroleum prices rising until 1986.In 1979 the turbulences in Iran, the second petroleum producer of OPEC, and the invasion of the Soviets in Afghanistan, caused the second petroleum crisis in world history, since the price of crude petroleum in Iran and Iraq had almost stopped. After 1980, six years of decadence picked with a 46% reduction of petroleum price (<10 dollars per barrel) due to reduced demand and overproduction by OPEC. In 1983 is the beginning of the term contract of the American light crude petroleum at the New York Mercantile Exchange (*NYMEX*), while in 1985 starts the third petroleum crisis. OPEC influenced by the world recession and the reduction of demand discards the increased rates policy and lowers the prices to 10 dollars per barrel in order to increase demand. As for the time period of 1990-1991, the turbulences in the area of the Persian Gulf between Iraq and Kuwait resulted in financial consequences. At October 1990 petroleum prices skyrocketed from 15 to 41,7 dollars per barrel prior to the invasion. The consequences to the world economy resulted to US to dispose a part of their strategic stocks, which reduced the price to 20 dollars per barrel. The price crisis was numerically moderate and shorter in comparison with previous petroleum crisis. The duration of the crisis was 3 quarters and assisted in the recession of the 1990. Despite the conservative estimation of the petroleum crisis, the macro-economic consequences were at same level as with the previous petroleum crises.

The sixth petroleum crisis was at 1997-1988, which causes the deceleration of the economy of Asian countries. Due to that, OPEC signed in Jakarta an agreement, which raised output by 10 percent for the first time after four years. That resulted to the increase in petroleum production and the reduction of the crude petroleum prices. The new price was 10 dollars per barrel. In 2000, despite the effort of the European countries to emancipate themselves energetically by the Middle East countries, with investments in renewable sources of energy, petroleum remained the moving force of their finances. From December of 1999 a new unstable state of affairs with continuous falling petroleum prices, forces OPEC to reduce production which resulted to the raise of prices from 14 to 19 dollars per barrel. Later on, the disqualification of Iraq from the production alters the prices to $26/per barrel. Furthermore, in November 2007, petroleum prices surpass 95 dollars per barrel, after the fall of the American commercial resources of crude petroleum and the reduction of the interest rates by the Federal Bank of USA. The price skyrocketed to 98 dollars per barrel at 7th of November.

In the early dates of 2008 the prices reach 100 dollars per barrel of petroleum, due to the attacks in Nigeria. As well the decrease of the available American commercial resources, the persistence of OPEC to maintain unchanged the levels of production, and the rapid rates of the development of the Chinese economy, the price of petroleum reached 145 dollars per barrel expressing a name raise of 625% since the ‘90s and 500% from 1998-1999 (Hamilton, 2011).

2.1.2 Specification Factors of Petroleum Prices

The price of petroleum, like all commodities, is defined by the powers of offer and demand. Simultaneously, it is affected by a plethora of geopolitical and other factors which influence the powers of demand and offer, which in turn impact on the current price of petroleum and its variability, such as weather and seasonality (need of heating during the winter and air conditioning during the summer), military crises, like in Nigeria, Georgia, and Iran. In such occasions of disturbance in demand the sudden reduction of quantity of petroleum leads to the rise of the price per barrel. Moreover, the financial aid and taxation of consumers (their alteration leads in crucial fluctuations of the demanded quantity and the prices of petroleum), as well as the anticipation of consumers regarding the adequacy of future petroleum reserves. The realization of world economy (i.e. that if consumption continues with respective rates of today (approximately 86 million barrels daily), and that petroleum might not be sufficient has lead to revaluations since 2000 and forward. Price of oil also affected by the growth of China and other countries which periodically pressured upwards the demand of petroleum. The swift growth of China in recent years as well as other developing countries such as India, Russia, and Latin America raised the demands of the productive capacity of petroleum producers. It is worth mentioning here that 50% of the ascension in demand of petroleum is attributed to China, while the developing economies claim bigger shares in the petroleum market and energy in order to satisfy their rising demands of industrial production. Last but not least, the availability of refining units for the expansion of the productive power. Since 1990 and afterwards there weren't any major constructions of new refining units. Despite the recent high prices encouraged multiple petroleum-producing countries to improve their infrastructure of production (refinements , producers etc.), the rising prices of the construction materials and the dimensions of such projects as well as the recent economic slow-down creates doubts in regard with the productive capabilities of these countries.
Upheaval in offer or/and demand of petroleum lead to fluctuations in the running price. Specifically, a reduction to the produced quantity and thus the offer of petroleum due to a crisis in Middle East for example, where the 61,5% of the reserves of crude petroleum are located, can lead to the increase of price. On the contrary, a reduction in the demanded quantity can trigger a decrease in the price of petroleum.

2.2 Natural gas and price defining variables

2.2.1 Natural gas and places of origin

Natural gas is a naturally occurring hydrocarbon gas mixture consisting primarily of methane, propane, butane. The alleged physical gas, which is not so physical at birth, is in most cases found below-ground. Remnants of decomposing plant and animal matter once found in earths' surface subsided due to geological transformations and were buried under huge quantities of mud and other sediments and exposed to intense pressure. While we move to the earth's core the temperature rises. Heat and pressure result to the breakage of carbon atoms of the plant and animal mater to produce thermogenic methane, a key component of gas in the

earth's crust. This light gas, as expected, emerges upwards and finally exits in the atmosphere. Unless, it encounters rocks, mainly porous slate, where it is trapped and stays there are waiting to be discovered. Natural gas is found in underground deposits or coexists with crude oil. It is non-toxic, clean, colorless and odorless. Natural gas is lighter than air and its relative density is from 0.59 to 0.605 (air). The liquefied natural gas is the liquid form mixture of saturated carbohydrates of low molecular weight. It is composed mostly by methane with different percentages in other compounds, depending by the processing degree during the liquefaction process and its origin. The liquefied natural gas, when heated, evaporates and returns to its gas form. Physical gas is consumed mostly in 4 areas of economy (USA percentages): Residential use (23%) Trade (16%), Industry (30%), and Production of Electric Power (31%) (Gabriel, 2010). Natural gas can be found in several places worldwide; however regions with redundant quantities and production are limited. According to a review in 2008 about global energy, the current stocks of natural gas are about 6263Tcf worldwide. More than 55% of these reserves are located in three countries: Russia (25, 2%), Iran (15,7%), and Qatar (14,4%). From the 103Tcf of natural gas produced at 2007, Russia produced 21% while Iran and Qatar produced 4% and 2% respectively. In order to supply the demanding regions, like Europe, natural gas has to be transferred with pipelines or as Liquefied Natural Gas (LNG). The creation of the necessary infrastructure for the transfer of natural gas by pipelines or LNG is cost and time effective for prospective energy entrepreneurs. Moreover, there have been indications that in the next 25 years, the worldwide production of conventional natural gas will be reduced. The difference will be covered by three sources: Non conventional gas, Arctic reserves, and LNG. The non conventional gas is Tight gas, Coalbed methane, Shale gas. By the year 2030 approximately 400-500Tcf of natural gas could be retrieved by the usage of technology. As described, the worldwide production is dominated by Russia, USA, and Canada. Surprisingly, USA are the biggest world consumer (22,6%) and then Russia with 15%. The consumption of the rest countries is about 3%. Europe depends to the imported natural gas, especially by Russia (Gabriel, 2010). In conclusion, the worldwide reserves of natural gas are ample and able to satisfy the natural gas demands in the foreseeable future, including the rising increase of LNG.

2.2.2 Defining Variables of Natural Gas Prices

Natural gas prices are mainly a function of market supply and demand. Because there are limited short-term alternatives to natural gas changes in supply or demand over a short period may result in large price changes, which in turn tend to balance supply and demand.
Regarding demand there are three main variables which can affect the price of natural gas: Firstly, the differences of natural gas production, the volume of net imports and lastly the reserve of natural gas. Increases in supply of natural gas tend to pull prices down, and respectively decreases in supply of natural gas tend to push prices up. Factors which affect the prices of natural gas on the demand-side include: levels of economic development, weather conditions: (Winter- Summer) and prices of rival fuels. Increases in demand of natural gas tend to push prices up, and respectively decreases in demand of natural gas tend to pull prices down. Domestic prices of natural gas are mainly affected by demand. The biggest percentage consumed in the USA originates from domestic production. USA dry natural gas production spiked, the highest documented yearly, from 2006 to 2014. The rise of production during that

time was due to the improvement of the drilling techniques. More specifically, production of natural gas can be disrupted by severe weather conditions (hurricanes etc.). For example, in the summer of 2005, hurricanes along the USA Gulf Coast shut down about 4% of total USA natural gas production for almost a year (August 2005- June 2006). Also, the endurance of economy can affect deeply the natural gas markets. During periods of economic growth, increases in demand for goods and services from the commercial and industrial sectors may increase natural gas consumption. The industrial sector for example, uses natural gas as a fuel and a feedstock for making many products, such as fertilizer and pharmaceuticals. Increases in demand can lead in ascending production and prices. Decreasing or weak economic growth tends to have the opposite effect. Winter influences commercial demand of natural gas in residential areas. During cold months, natural gas demand for heating by residential and commercial consumers generally increases overall natural gas demand and can put upward pressure on prices. If unexpected cold or severe weather occurs, the effect on prices intensifies. The effect of weather on natural gas prices may be greater if the natural gas transportation (pipeline) system is already operating at full capacity. Under the aforementioned circumstances, prices tend to rise which decreases the overall demand of natural gas. Natural gas stored during times of lower demand could be used to de-escalate the consequences of high demand during adverse weather conditions.

On the other hand, hot summer weather can increase electric power demand for natural gas. Approximately, 27% of electric energy in the USA was generated with natural gas. Consequently, higher than normal temperatures can increase the demand for air conditioning and thus the demand of electric power, which is generated by natural gas and therefore increase its' price. Moreover, storage of natural gas aids to meet year-round and sudden increases in demand, which otherwise can not be met by internal production and imports. When demand is lower, storage absorbs excess domestic production and, sometimes, imports of lower cost. Storage also aids pipeline operations and center services. Levels of natural gas in storage typically increase from April through October, when overall demand for natural gas is lower and decrease from November through March, when demand for natural gas for heating is lower. Finally, competition with other fuels can influence natural gas prices. Some large-volume fuel consumers such as electricity producers and iron, steel, and paper mills can switch between natural gas, coal, and petroleum, depending on the cost of each fuel. When the cost of the other fuels fall, demand for natural gas may decrease, which may reduce natural gas prices. When the cost of competing fuels rise relative to the cost of natural gas, switching from those fuels to natural gas, may increase natural gas demand and prices.

3. Literature Review

In the last few years, a large volume of literature has appeared mainly focused on volatility in financial markets. One of the pioneering papers in this field, which investigates the impact of oil shocks in economy introduced by Hamilton (1983). According to his research, dramatic rise in oil price volatility since the mid 80's has led to a breakdown in the empirical relationship between oil prices and economic activity in US.

Another two researches Kilian and Park (2009) analyzed oil shocks to stock markets. Most of the literature suggest that Engle's (1982) Autoregressive Conditional Heteroskedasticity (ARCH) model, which was later generalized by Bollerslev (1986) and became known as GARCH model, tend to work better when it comes to modeling high frequency. There is a growing number of studies that have test volatility spillovers by using GARCH models time series data. Early studies have reported a definite correlation between oil price shocks and stock market returns. The study by Jones and Kaul (1996) was the first contribution to examine the reaction of stock markets to oil shocks. The authors consider four developed markets (Canada, Japan, the UK, US) and they found that oil prices have a negative effect on stock returns for all countries. In addition, Hamao (1990) analyzed correlations in price changes and volatility across international markets using GARCH models. Booth, Martikainen and Tse (1997) used Multivariate Exponential Autoregressive Conditionally Heteroskedastic models (EGARCH) to investigate the dynamic interaction of four Scandinavian stock markets. The results indicate that the four markets are related to each other. Moreover, Sadorsky (2001) estimated the expected returns to Canadian oil and gas industry stock prices. The results included the strong impact of exchange rates, oil prices, and interest rates on the Canadian oil and gas industry. He found that oil price increase; positively affect the stock returns of Canadian oil and natural gas companies. Ewing (2002) showed direct and indirect transmission volatility from natural gas to oil markets but only weak evidence of volatility spillover in the inverse direction. According to the authors, these findings can be typically explained by differences in the volatility behavior of the oil and natural gas markets. Another paper, that of Pindyck (2003) used daily data from 1990-2003 and studied the price volatility between oil and natural gas. He showed that crude oil volatility and returns has predictive power to natural gas volatility and returns but not the other way around. Furthermore, Jose A.Villar, Frederick L.Joutz (2006) by using VAR model and analyzing monthly data showed that oil and natural gas are cointegrated, while Matthew Brigida-2013-proved their longrun relationship by using Markov switching cointegration equation. Three other researchers in 2007, Farooq Malik and Hammoudeh analyzed volatility transmission among global crude oil and equity markets of Saudi Arabia, Kuwait and Bahrain using GARCH models with BEKK parameterization. Results show significant interaction between second moments of the US equity and global oil markets. Not surprisingly, in all cases the three Gulf equity markets receive volatility from the oil market. Interestingly, only in the case of Saudi Arabia they found a significant volatility spillover from the Saudi equity market to the global oil market. Henriques and Sadorsky (2008) studied the relationship between clean energy stock prices and oil price using vector autoregressive (VAR) approach over the period January 3, 2001 to May 30, 2007. They find shocks to oil prices have little significant impact on the stock prices of alternative energy companies. Farooq Malik and

Brandley Ewing (2009) by using bivariate GARCH model to estimate conditional variance, examined the volatility transmission mechanism between oil prices and equity sector returns. The results of this research showed significant transmission of stocks and volatility between US sector indexes and oil prices. Victor Lux, Tonn,H.C, Li, Joseph Mc Carzthy (2010) by using wavelet analysis studied futures of oil and futures of natural gas and found high covariance and high frequences among them.

Kumar (2012) extend Henriques and Sadorsky (2008), using data from April 2005 to November 2008 and tracking three energy indexes, oil prices, clean energy stock prices and carbon price. By analyzing a VAR model, his findings conclude to a positive relationship between oil and clean energy firms.
Furthermore Sadorsky (2012) the closest to the present paper, used multivariate GARCH BEKK,DIAGONAL,CCC,DCC- to model conditional correlations and to analyze volatility spillovers between oil, technology and clean energy. He found that clean energy stocks correlate more highly with technology prices than with oil prices. Shunsuke Managi, Tatuyoshi Okimoto (2013) by using Markov switching vector autoregressive models, analyzed the relationships among oil prices, clean energy stock prices and technology stock prices and found a positive relationship between oil prices and clean energy, after structural breaks. Moreover, Olga Efimova and Apostolos Serletis (2014) used daily data for oil natural gas and electricity price and they show by analyzing trivariate BEKK and DCC models, that there is an undirectional spillover from oil to natural gas and from natural gas to electricity prices. Last but not least, Dennis C.Plott (2014), investigated conditional own volatility, spillover volatility, and correlations for a oil, natural gas, coal, alternative energy, and technology series by using a multivariate asymmetric dynamic conditional correlation model. Results for the paper above demonstrate positive relationship among the indexes of energy sector and technology.

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4 Methodology

4.1 Unit root test(Augmented Dickey-Fuller (ADF))

Dickey and Fuller (1979) by using Monte Carlo simulations, found an asymmetric distribution that they used to test the basic unit root hypothesis of the parameter (ρ) of the autoregressive model AR(1), be equal to one (ρ=1). The basic Dickey-Fuller (DF) stationarity test can be estimated from the following equations:

$$Y_t = \rho Y_t + u_t \qquad (4.1.1)$$

So, after subtracting Y_{t-1} from both sides of the equation:

$$Y_t - Y_{t-1} = \rho Y_{t-1} - Y_{t-1} + u_t \qquad (4.1.2)$$

$$Y_t - Y_{t-1} = (\rho - 1) Y_{t-1} + u_t \qquad (4.1.3)$$

$$\Delta Y_t = \delta Y_{t-1} + u_t \qquad (4.1.4)$$

Where δ=ρ-1. In the case where the equation (4.1.3) has a unit root (ρ=1 or δ=0) we take the first difference of the variable that we use for testing. So, the null and the alternative hypotheses that we use in order to run the DF unit root test could be written as:

$H_0: \delta = 0$ (Y_t is not stationary)
$H_0: \delta < 0$ (Y_t is stationary)

In ADF stationarity test, we can reject or fail to reject the null hypothesis (H_0), by comparing the t-student with a critical value. When t-student is smaller than the critical value ($t_{st} < t_{cr}$), then we reject the null hypothesis and the variable we use, is stationary. On the other hand, when t-student is larger than the critical value ($t_{st} > t_{cr}$), then we accept the alternative hypothesis or we fail to reject the null hypothesis and the variable we use, is not stationary. In the case where larger and more complicated time series are used, the augmented Dickey-Fuller unit root test is applied. So, the new higher-order autoregressive model AR (p) is written as:

$$\Delta Y_t = \delta Y_{t-1} + \beta_1 Y_{t-1} + \beta_2 Y_{t-2} + \cdots + \beta_p Y_{t-p} + u_t \qquad (4.1.5)$$

Where β is the coefficient presenting process root and p is the lag order. To determine the existence of a unit root we have to examine the t-values on coefficients. So, in order to test for stationarity we can compare again, as we do in a simple DF test, the t-student with the critical values. Therefore, if t-student is smaller than the critical value ($t_{st} < t_{cr}$), then we reject the null hypothesis (stationary variable) and in the case where t-student is larger than the critical value ($t_{st} > t_{cr}$), we fail to reject the null hypothesis (non-stationary variable). Furthermore, it is possible to conclude to the same result if we take into consideration the Schwartz, Akaike or the Hannan-Quinn information criterion.

4.2 GARCH Models

GARCH models are tools for forecasting and analyzing volatility of time series when the volatility varies over time. There are many multivariate GARCH models. An important goal in creating multivariate GARCH models is to make them parsimonious, as well as flexible enough. Another aspect is to ensure the conditional covariance matrix to be positive definite. DCC-GARCH model is a generalization of the CCC-GARCH model, which allows the correlation matrix to depend on the time. The DCC-GARCH model have clear computational advantages in that the number of parameters to be estimated in the correlation process is independent of the number of series to be correlated. In this way very large correlation matrices can be estimated. It is known that volatility varies over time and tends to cluster in periods; small changes tend to be followed by small changes and large changes by large ones. This phenomenon when the standard deviation varies over time is called heteroscedastisity. Heteroscedasticity means ''fluctuating variance". Moreover, the volatility has shown to be autocorrelated, which means that today's volatility depends on the past volatility. Considering the fact that the volatility is not directly observable, the need of a good model to predict the future volatilities is crucial. One model that has shown to be successful in capturing volatility clustering and predicting future volatilities is the univariate GARCH (Generalized Autoregressive Conditional Heteroscedasticity) model introduced by Bollerslev in 1986. It is known that financial volatilities move together more or less closely over time across assets and markets. Hence it is essential to take into account the dependence in the comovements of asset returns. One method to estimate the covariance matrix between the assets is to extend the univariate GARCH into a multivariate GARCH model. Extending from univariate to multivariate GARCH opens the door to better decision tools such as asset pricing models, portfolio selection, hedging, and Value-at-Risk forecasts.. The main challenge in composing multivariate GARCH models is to make them parsimonious enough, but still maintain the flexibility. One approach is to disintegrate the conditional covariance matrix into conditional standard deviations and a conditional correlation matrix. The first model of this type was the Constant Conditional Correlation (CCC) model introduced by Bollerslev in 1990. In this model, the conditional correlation is assumed to be constant over time, and only the conditional standard deviation is time-varying. The assumption that the conditional correlation is constant over time is not always reasonable. In 2001, Engle and Sheppard introduced the DCC-GARCH model, which is an extension of the CCC-GARCH model, for which the conditional correlation matrix is designed to vary over the time.

Multivariate GARCH Model

$$r_t = \mu_t + a_t \qquad (4.2.1)$$

$$a_t = H_t^{1/2} z_t \qquad (4.2.2)$$

Firstly, r_t denotes a $n \times 1$ vector of log returns of n assets at time and term α, expresses a $n \times 1$ vector of mean-corrected returns of n assets at time t, i.e. $E[\alpha_t] = 0$, $Cov[\alpha] = H_t$. Furthermore, μ_t , is a $n \times 1$ vector of the expected value of the conditional r_t, while H_t indicates a $n \times n$ matrix of conditional variances of a_t at time t and $H_t^{1/2}$ determines any $n \times n$ matrix at time t such that H_t is the conditional variance matrix of α_t. Finally, z_t is a $n \times 1$ vector of iid errors such that $E[z_t] = 0$ and $E = [z_t z_t^T] = I$. As in the univariate case, α_t is uncorrelated in time. However this does not mean that there is no serial dependence, but that the dependence is non-linear. The conditional covariance matrix H_t is the last to be specified. The parameters in the conditional covariance matrices increase very rapidly as the a_t increases. Since H_t is dependent of time *t*, it has to be inverted in each iteration, which makes the computation demanding unless *n* is small. This creates difficulties in the estimation of the models, and therefore an important goal in constructing the MGARCH models is to make them parsimonious enough, but still maintain the flexibility. Another aspect is to ensure the conditional covariance matrix to be positive definite. The different specifications of MGARCH models can be divided into four categories:

1. **Models of the conditional covariance matrix:** In this case the conditional covariance matrices H_t are modeled directly. This category includes the VEC and BEKK models. These models were among the first parametric MGARCH models.
2. **Factor models:** The idea of factor models comes from economic theory. In this case the conditional covariance matrices are motivated by parsimony. The vector a_t is assumed to be generated by a (small) number of unobserved heteroskedastic factors; hence these models are called factor models. These factors can be studied and one may make assumptions that some characteristics of the data are captured, similar as for principal component analysis. This approach has the advantage that it reduces the dimensionality of the problem when the number of factors relative to the dimension of the return vector a_t is small.
3. **Models of conditional variances and correlations:** The models in this category are built on the idea of modeling the conditional variances and correlations instead of straightforward modeling the conditional covariance matrix.
4. **Nonparametric and semi parametric approaches:** Models in this class form an alternative to parametric estimation of the conditional covariance structure. The advantage of these models is that they do not impose a particular structure (that can be misspecified) on the data.

4.2.1 Models of conditional variances and correlations

The models in this class are built on the idea of modeling the conditional variances and correlations instead of model directly the conditional covariance matrix. The conditional covariance matrix is decomposed into conditional standard deviations and a correlation matrix as:

$H_t = D_t R_t D_t$ (4.2.1)

$D_t = \mathrm{diag}(h_{1t}^{1/2}, \dots, h_{nt}^{1/2})$ (4.2.2)

Is the conditional standard deviation, and R_t is the correlation matrix. Models in this class can be classified in two groups; those with a constant correlation matrix and those when the correlation matrix is time-varying.

4.2.2 Constant correlation matrix

Models in this class includes the Constant Conditional Correlation (CCC) GARCH of Bollerslev and its extensions. The conditional correlation matrix is time invariant, i.e. $R_t = R$.

Hence (4.2.1) becomes: $H_t = D_t R D_t$ (4.2.2.1)

The correlation matrix, $R = [\rho_{ij}]$, is positive definite with $\rho_{ii} = 1, i = 1, \dots n$
The off-diagonal elements of the conditional covariance matrix, H_t are given by:

$H_t = h_{it}^{1/2} h_{jt}^{1/2} \rho_{ij}, i \neq j$ (4.2.2.2)

The process $\{a_{it}\}$ is modeled as univariate GARCH. Hence the conditional variances can be written in a vector form:

$h_t = c + \sum_{j=1}^{q} A_j \alpha_{t-j}^{(2)} + \sum_{j=1}^{p} B_j h_{t-j}$ (4.2.2.3)

Where c is $n \times 1$ vector, A_j and B_j are diagonal $n \times n$ matrices, and $\alpha_{t-j}^{(2)} = \alpha_{t-j} \odot a_{t-j}$ is the element–wise product. H_t is ensured positive definite when the elements of c and A_j and B_j are positive, since R is positive definite. There exists also an extended CCC-GARCH model for which A_j and B_j do not need to be diagonal. The estimation of models in this class is computationally attractive because the correlation matrix is constant. However the CCC-GARCH model may be too restrictive in some cases. The model may then be generalized by assuming the correlation matrix to vary with time.

4.2.3 Time-varying correlation matrix

When the correlation matrix, R_t, is time-varying, H_t is positive definite if R_t is positive definite at each point in time and the conditional variances, $h_{it}, i = 1, \dots n$ are well-defined. Compared to the CCC-GARCH model, the advantage of numerically simple estimation is lost, as the correlation matrix has to be inverted for each time, t, during every iteration.
Several specifications of R_t have been suggested in the literature. In this thesis we will study one specification; the DCC-GARCH model.

4.3 DCC GARCH model

The Dynamic Conditional Correlation (DCC) GARCH belongs to the class "Models of conditional variances and correlations". It was introduced by Engle and Sheppard in 2001. The idea of the models in this class is that the covariance matrix, H_t, can be decomposed into conditional standard deviations, D_t and a correlation matrix, R_t. In the DCC-GARCH model both $D_t$and R_t are designed to be time-varying. Suppose we have returns, α_t, from n assets with expected value 0 and covariance matrix H_t, then the Dynamic Conditional Correlation (DCC) GARCH model is defined as:

$$r_t = \mu_t + a_t \quad (4.3.1)$$

$$a_t = H_t^{1/2} z_t \quad (4.3.2)$$

$$H_t = D_t R_t D_t$$

Where, r_t denotes a $n \times 1$ vector of log returns of n assets at time t. Term a_t , expresses a $n \times 1$ vector of mean-corrected returns of n assets at time t, i.e. $E[a_t] = 0$, $Cov[a_t] = H_t$, while μ_t implies a $n \times 1$ vector of the expected value of the conditional r_t. Additionally, H_t indicates a $n \times n$ matrix of conditional variances of a_t at time t, while $H_t^{1/2}$ expresses any $n \times n$ matrix at time t such that H_t is the conditional variance matrix of a_t.Moreover, D_t determines a $n \times n$ diagonal matrix of conditional standard deviations of α_t at time t and R_t, a $n \times n$ conditional correlation matrix of α_t at time t. Finally, term z_t denotes a $n \times 1$ vector of iid errors such that $E[z_t] = 0$ and $E = [z_t z_t^T] = I$.

The elements in the diagonal matrix D_t are standard deviations from univariate GARCH models.

$$D_t = \begin{bmatrix} \sqrt{h_{1t}} & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & \sqrt{h_{nt}} \end{bmatrix} \quad (4.3.3)$$

Where

$$h_t = \alpha_{i0} + \sum_{q=1}^{Q_i} \alpha_{iq}\alpha_{i,t-q}^2 + \sum_{p=1}^{P_i} \beta_{ip}\, h_{i,t-p} \quad (4.3.4)$$

The univariate GARCH models can have different orders. Often the simplest model, GARCH(1,1), is sufficient.
It is worth mentioning, that $R_t$is the conditional correlation matrix of the standardized disturbances ϵ_t , i.e $\epsilon_t = D_t^{-1}\alpha_t \sim N(0, R_t)$ and it is symmetric.

$$R_t = \begin{bmatrix} 1 & \rho_{12,t} & \rho_{13,t} & \cdots & \rho_{1n,t} \\ \rho_{12,t} & 1 & \rho_{23,t} & \cdots & \rho_{2n,t} \\ \rho_{13,t} & \rho_{23,t} & 1 & & \rho_{2n,t} \\ \vdots & \vdots & \ddots & \ddots & \vdots \\ \rho_{1n,t} & \rho_{2n,t} & \dots & & 1 \end{bmatrix} \quad (4.3.5)$$

The elements of $H_t = D_t R_t D_t$

Is $[H_t]_{ij} = \sqrt{h_{it}h_{jt}}\rho_{ij}$, where $\rho_{ii} = 1$

This form of matrix R_t exists if two conditions are specified. Firstly, H_t has to be positive definite because it is a covariance matrix. To establish that H_t will be positive definite, R_t has to be positive definite too. (D_t is positive definite since all the diagonal elements are positive).Secondly, all the elements in the correlation matrix R_t have to be equal or less than one by definition. To ensure both of these requirements in the DCC-GARCH model R_t is decomposed into:

$$R_t = Q_t^{*-1} Q_t Q_t^{*-1} \quad (4.3.6)$$

$$Q_t = (1 - \theta_1 - \theta_2)\overline{Q} + \theta_1 \epsilon_{t-1} + \epsilon_{t-1}^T + \theta_2 Q_{t-1} \quad (4.3.7)$$

Where $Q_t = \mathrm{Cov}[\epsilon_t \epsilon_t^T] = E[\epsilon_t \epsilon_t^T]$ is the unconditional covariance matrix of the standardized errors ϵ_t, and $\overline{Q}$ can be estimated as $\overline{Q} = \frac{1}{T}\sum_{t=1}^{T} \epsilon_t\, \epsilon_t^T$.

Additionally, the parameters θ_1 and θ_2 are scalars to capture the effects of previous shocks and previous dynamic conditional correlations on the current dynamic conditional correlation and Q_t^*, is a diagonal matrix with the square root of the diagonal elements of Q_t at the diagonal.

$$Q_t^* = \begin{bmatrix} \sqrt{q_{11t}} & 0 & \dots & 0 \\ 0 & \sqrt{q_{22t}} & \dots & 0 \\ \vdots & \ddots & \ddots & \vdots \\ 0 & \dots & 0 & \sqrt{q_{nnt}} \end{bmatrix} \quad (4.3.8)$$

And the correlation estimator is: $\left|\rho_{ij}\right| = \left|\frac{q_{ijt}}{\sqrt{q_{iit}\, q_{jjt}}}\right| \leq 1$

Furthermore Q_t has to be positive definite to ensure R_t to be positive. In addition to the conditions for the univariate GARCH model to ensure positive unconditional variances, the scalars $\theta_1$and θ_2 must satisfy the conditions below: $\theta_1 > 0$, $\theta_2 > 0$ and $\theta_1 + \theta_2 < 1$. At last, the estimation of the parameters is done in two steps by quasi-maximum likelihood (QML), assuming that the innovations are Gaussian. The joint log-likelihood of the model can be split into two parts and maximized sequentially. First, the univariate volatilities are modeled for each series of returns and then, the parameters of the correlation process are estimated.

4.4 Vector Autoregressive model

A VAR model describes the evolution of a set of *k* variables (called endogenous variables) over the same sample period (*t* = 1... *T*) as a linear function of only their past values.

$$y_t = c + A_1 y_{t-1} + A_2 y_{t-2} + \cdots + A_p y_{t-p} + e_t \quad (4.4.1)$$

Where each y_i is a vector of length k and each A_i is a k x k matrix.
Properties of the VAR model are usually summarized using structural analysis, such as forecast error variance decompositions, Granger causality and impulse response functions.

4.5 Granger Causality test

Granger (1969) based on a linear regression model, formed a statistical hypothesis concept of causality, through which he could determine the potential predictive power one time series might have on another. In particular his model states that, if the variable X_t Granger-causes another variable Ψ_t, then the lag values of X_t contains information that can predict future values of Ψ_t . In order to perform the Granger causality test we have to determine first, if the variables we are using are stationary or not. In the case where the time series is stationary, we are using the level values and on the other hand when the time series is non-stationary we take the first differences of the variables. To determine the optimal lag length to be included, we take into consideration information criteria, such as Schwarz information criterion or the Akaike information criterion. So, in order to test the null hypothesis that variable X_t does not Granger-cause variable Ψ_t, we perform a univariate auto regression, that includes also the optimal lagged values of the time series X_t:

$$\Psi_t = \alpha_0 + \alpha_1 \Psi_{t-1} + \alpha_2 \Psi_{t-2} + \cdots + a_m \Psi_{t-m} + b_1 X_{t-1} b_2 X_{t-2} + \cdots + b_n X_{t-n} + \varepsilon_t \quad (4.5.1)$$

Where α_0 is a constant and ε_t is the residual.

5. Data

The data for this study includes the daily closing prices of the Winderhill Clean energy Index (ECO), the NYSE Arca Technology Index (PSE), the nearest contract to maturity on the West Texas Intermediate crude oil futures contract (OIL) and the Henry Hub Natural Gas Index (NG).

The **WilderHill Clean Energy Index (ECO)** is a modified dollar weighted index of 54 companies engaged in the clean (renewable) energy business. It was generate at 2004 to track clean energy companies and now is benchmark. It is generally comprised of companies in the areas of renewable energy supplies-harvesting, energy storage, cleaner fuels, energy conversion and power delivery and conservation. Individuals cannot invest in this index directly but they can invest in the Powershares WilderHill Clean Energy exchange traded fund (ETF) with ticker symbol PBW that tracks this index. The **NYSE Arca Tech 100 Index (PSE)** is a price weighted index composed of common stocks and ADRs of technology-related companies listed on US stock exchanges. As it is tracked since 1982, Nyse Arca is one of the oldest technology indexes, initiated by the Pacific Exchange. The index include leading companies from several industries, such as computer hardware, semiconductors, telecommunications, software, electronics, aerospace and defense, health care equipment, and biotechnology. It is worth noting that there are no companies included in both ECO and PSE. The third index that we are going to use in our analysis is the **West Texas Intermediate (WTI)**, also known as Texas light sweet, which is a grade of crude oil used as a benchmark in oil pricing. In addition, the **Natural Gas Index (NG)** "Henry Hub", originates from the gas pipeline with the same name which runs through Erath, Louisiana. This pipeline has great influence on the price for natural gas futures, which are traded on the world's largest commodity futures exchange, the New York Mercantile Exchange (NYMEX). As of June 2007, the Henry Hub Pipeline has also been connected to four other domestic pipelines and nine other international.

The sample period for the data set covers January 3, 2006 to November 3, 2016 containing a total of 2749 daily observations. For the stock market prices we use data from the New York Stock Exchange (NYSE) and for the price of oil and natural gas we obtain data from the U.S Energy Information Administration (EIA) data services.

Crude oil prices are expressed in USD dollar per barrel.

The returns of daily price index and crude oil prices are calculated by a continuous compound basis, defined as $r_t = \ln(\frac{P_t}{P_{t-1}})$, where P_t is the daily closing price.

6. Empirical Analysis

6.1 Augmented Dickey-Fuller Test

The first step we have to take in order to determine if the two time series are stationary or not, is the standard unit root testing procedures based on the Augmented Dickey-Fuller (ADF) test. At first sight, crude oil, natural gas, technology and the clean energy time series seem to be non-stationary, because they have not a constant mean and constant variance. On the other hand their logarithmic differences do seem as stationary ones. In order though to demonstrate a more solid and cognitive judgment about the order of integration of the two variables, we have to proceed to the Augmented Dickey Fuller (ADF) (Dickey and Fuller, 1979) unit root test. The above unit root test will be implemented firstly to the levels and afterwards to the first logarithmic differences of the two time series.

Table 1: Unit root test

Variables	T- statistic	Probability
eco	-1,146215	0,6994
deco	-47,07319	**0,0001***
ng	-2,405295	0,1403
dng	-33,55106	**0,0000***
oil	-1,920022	0,3232
doil	-51,27326	**0,0001***
pse	0,137962	0,9685
dpse	-52,84481	**0,0001***

So, when we apply the ADF test (no trend) to the level of our variables, we fail to reject null hypothesis (has a unit root) for the 1% 5% and 10% of significance level. Our next step is to run again unit root tests until we are able to reject the null hypothesis. Now, the test should be performed at the first logarithmic difference. As we can see from the tables above we reject the null hypothesis. In other words, natural log difference of level variable is stationary.

6.2 Descriptive statistics

To examine the validity and the accuracy of the sample, we use measures of central tendency as the mean, the median and the mode, as well as measures of spread such as standard deviation. Moreover, the descriptive statistics table presents the skewness and the kurtosis of the sample which are helpful tools to identify the location and the variability of the data. In particular, skewness is a measure of symmetry, or more precisely, the lack of symmetry (a set

of data is symmetric if it looks the same to the left and right of the center point), and kurtosis is a measure of whether the data are picked or flat relative to a normal distribution. Data with high kurtosis are determined of a distinct peak near the mean, heavy tales and they slope downward. On the other hand, those with low kurtosis have skinny tails and a distribution concentrated toward the mean.

Table 3.2, summarizes the descriptive statistics of the stock market indices. Along with the standard statistics, the tables report the skewness and kurtosis coefficients, the Jarque-Bera statistic and the corresponding p-value for the normality hypothesis.

Table 2: Summary statistics for daily returns

	Mean	Median	Max	Min	Std.Dev	Skewn.	Kurt.	J.Ber	Prob.	Obs
deco	-0.000523	0.000672	0,145195	-0,144673	0,022525	-0,332061	7,325216	1982,673	0,00000	2485
doil	-0,000111	0,000111	0,164137	-0,128267	0,023901	0,072112	8,131510	2728,653	0,00000	2485
dng	-0,000660	0,000000	0,390069	-0,278437	0,040919	0,754576	16,45384	18977,47	0,00000	2485
dpse	0,000343	0,000852	0,100988	-0,081202	0,013012	-0,185204	8,532448	3183,408	0,00000	2485

Statistics clearly indicate non-normality of the returns, since the values of skewness and kurtosis deviate from the normal. For each of the series, the mean and the median values are close to zero and the standard deviation values are higher than those corresponding to the mean. Moreover, the three series show a scanty amount of skewness and a larger amount of kurtosis. The non-normality is further confirmed by the Jarque-Bera test statistics, since the corresponding p-value rejects the null-hypothesis of normality. Finally, from now on we establish our variables as ECO, for the variable deco, PSE, for dpse, OIL for doil and NG for dng, so as to be more readable.

6.3 Estimation Results

Taking into account the characteristics of the data series, the family of Generalized Autoregressive Conditional Heteroskedastic (GARCH) models (Bollerslev, 1986) has been proven to be particularly appropriate to model time varying volatility. These models capture

the three most common features in return series which are fat tails, excess kurtosis and volatility clustering. The Dynamic Conditional Correlation (DCC) model of Engle (2002) is one of the most cited works related to the parametric modeling of time-varying correlations for multivariate portfolios. It is a generalization of the Constant Conditional Correlation (CCC) model of Bollerslev (1990), where volatilities are time-varying but conditional correlations are assumed to be constant.

The DCC model is written as follow:

$$H_t = D_t R_t D_t \qquad (6.3.1)$$

$$R_t = \mathrm{diag}\{Q_t\}^{-1/2} Q_t \mathrm{diag}\{Q_t\}^{-1/2} \qquad (6.3.2)$$

$$Q_t = (1 - \theta_1 - \theta_2)\overline{Q} + \theta_1 \varepsilon_{t-1} \varepsilon'_{t-1} + \theta_2 Q_{t-1} \qquad (6.3.3)$$

and the correlation estimator is:

$$\rho_{i,j,t} = \frac{q_{i,j,t}}{\sqrt{q_{i,i,t} q_{j,j,t}}} \qquad (6.3.4)$$

The first step is the estimation of the DCC GARCH models of our four variables and for pairs of stock prices, oil and natural gas we estimate dynamic correlations. It is worth mentioning that the conditions θ_1, θ_2>0 and $\theta_1 + \theta_2 < 1$ are satisfied.

Table 3: Estimation results of unconditional correlations

	ECO	NG	OIL	PSE
ECO	1.000000	0,018168	0,357621	0,815552
NG	0,018168	1,000000	0,046912	0,006097
OIL	0,357621	0,046912	1,000000	0,294527
PSE	0,815552	0,006097	0,294527	1,000000

Table 3 above, represents the static correlations of our model. We note that the closer to 1 the correlation is, the more positive the correlation between the variables is. It is obvious that there is a strong and positive correlation between ECO and PSE, since their correlation is 0,8 which is very close to 1.OIL and ECO has also positive correlation as all the others, and is almost the one third of the correlation ECO/PSE. The pair with the lowest correlation in comparison with all the others is NG and PSE, which is very close to zero but still positive.

Table 4: Estimation results of DCC-GARCH(1,1) models

	Coefficients	Std.Error	z-Statistic	Probability
θ_1	0,060000	0,032581	1,841543	0,0655
θ_2	0,060000	0,263986	0,227285	0,8202
θ_3	0,060000	0,020663	2,903785	0,0037

dcc01:Dcc for NG and PSE

	Coefficients	Std.Error	z-Statistic	Probability
θ_1	0,024562	0,004571	5,373040	0,0000
θ_2	0,967098	0,006836	141,4749	0,0000

dcc02:Dcc for ECO and OIL

	Coefficients	Std.Error	z-Statistic	Probability
θ_1	0,051713	0,007805	6,626047	0,0000
θ_2	0,922673	0,012719	72,54415	0,0000

dcc03:Dcc for ECO and PSE

	Coefficients	Std.Error	z-Statistic	Probability
θ_1	0,002234	0,001813	1,231922	0,2180
θ_2	0,996424	0,003848	258,9616	0,0000

dcc04:Dcc for NG and OIL

	Coefficients	Std.Error	z-Statistic	Probability
θ_1	0,030522	0,005324	5,733131	0,0000
θ_2	0,959905	0,007596	126,3661	0,0000

dcc05:Dcc for PSE and OIL

	Coefficients	Std.Error	z-Statistic	Probability
θ_1	0,000838	0,007398	0,113333	0,9098
θ_2	0,931872	0,272136	3,424288	0,0006

dcc06:Dcc for ECO and NG

As we can see from the results above, the conditions of our model are satisfied, so figure 1 illustrates the conditional correlations from the DCC model. It is worth mentioning, that the correlation NG/PSE is too close to zero, meaning that the correlation is too low and this is the reason for the appearance of the coefficient θ_3, since the model gave unsatisfactory estimates in our first estimation. All the figures of Dynamic conditional correlations include in Appendix.

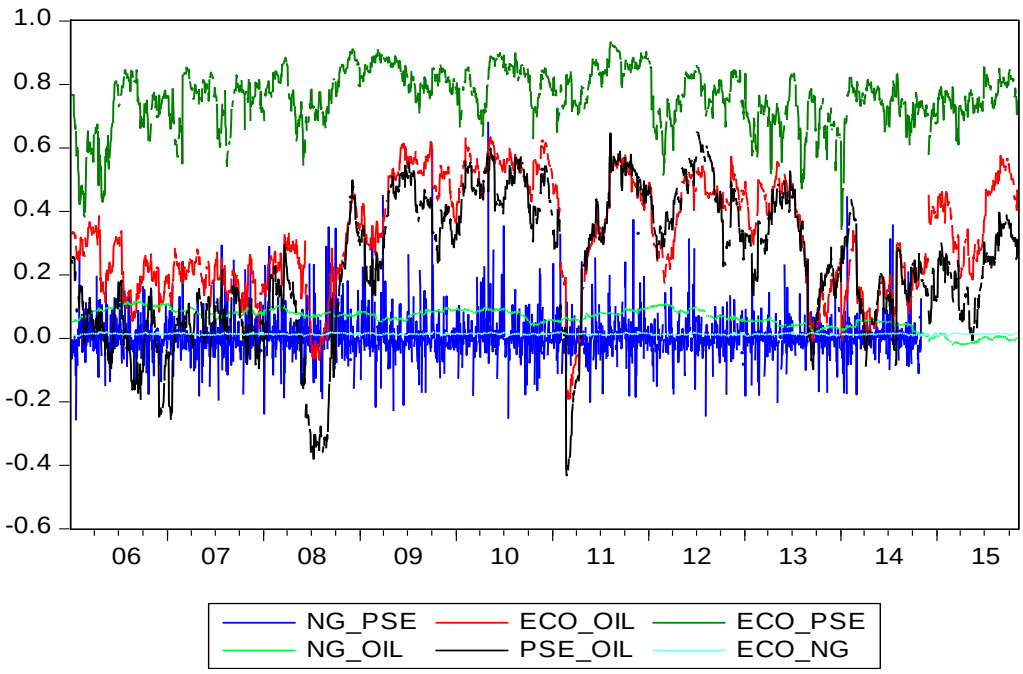


Figure 1:

Time-varying conditional correlations from the DCC model

Firstly, the dark green line characterize the conditional correlation of the returns of clean energy and technology while red line illustrates the conditional correlation of the returns of clean energy and crude oil. As we can see from the figure above, the dynamic conditional correlations between ECO and PSE are all positive and generally larger than 0.6. This indicates that there is little scope for portfolio diversification between these two series. The dynamic conditional correlations between ECO and OIL do alternate in sign and cover a range of values between -0,2 and 0,6. Furthermore, the red line moves in the same way with the black one, which depicts the returns of the conditional correlation of technology index and crude oil index. It is worth mentioning that there is a negative and steep change of red and black line during the period of Economic Crisis, specifically at 2008 and 2010-2011.

In addition, the conditional correlation of the returns of natural gas index and technology index, which is demonstrated from the dark blue line, as well as, the light blue line and the

light green one, are close to zero which means that the correlations are not affected from the other factors. It is worth mentioning that we were forced to cut the sample period for the correlation NG/PSE until 2014 and change the initial coefficients of our model to 0,6, because our results weren't the appropriate for our model.

Until now, we have seen that the variables reflect correlations (non constant). Including them in a Vector Autoregressive model (VAR), is basically saying that the correlations are non constant and interact and interdependent with all the others. So, after extracting the conditional correlations of the model, the next step of our research is to develop a Variance Decomposition under a Vector Autoregressive model (VAR) for the conditional correlations above. After that we are able to run a Granger Causality test and Impulse Responses Functions so as to analyze what happens to all the other correlations when there is a shock and conclude to some interesting econometric results.

We assure that all correlations are stationary in nature because VAR model needs stationary data. We run a VAR (1) ,with one lag which occurred from the best lag-length criteria of Schwarz.

6.3.1 Vector Autoregressive model (VAR)

$$Y_t = a_0 + \beta_1 Y_{t-1} + e_t \quad (6.3.1)$$

$$Y_t = \begin{pmatrix} NG/PSE \\ PSE/OIL \\ OIL/NG \\ OIL/ECO \\ ECO/NG \\ ECO/PSE \end{pmatrix} \qquad (6.3.2)$$

a_0 →6x1 vector of constant terms

β_1→6x6 matrix of coefficients

e_t→6x1 vector of iid error terms

6.3.2 Variance decomposition

The variance decomposition indicates the amount of information each variable contributes to the other variables in the autoregression. Table 5 illustrates that the volatility of the correlation of technology and oil is explained by 55% of the other correlations. Moreover, Table 6 demonstrates the results in which the volatility of natural gas and clean energy is explained by 45% of the other correlations.

Table 5: Variance decomposition of correlation PSE/OIL to

ECO/OIL

56.04915
55.96780
55.91709
55.87406
55.83323
55.79285
55.75229
55.71128
55.66975
55.62770
55.58517
55.54223

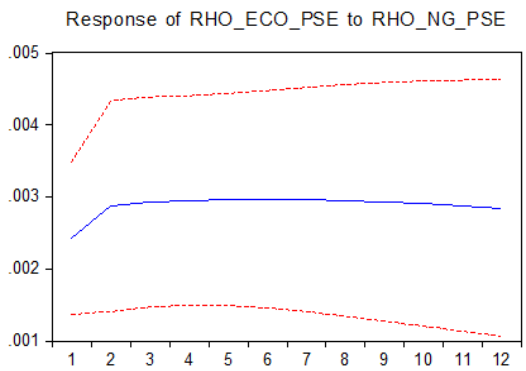
Table 6: Variance decomposition of correlation ECO/NG to

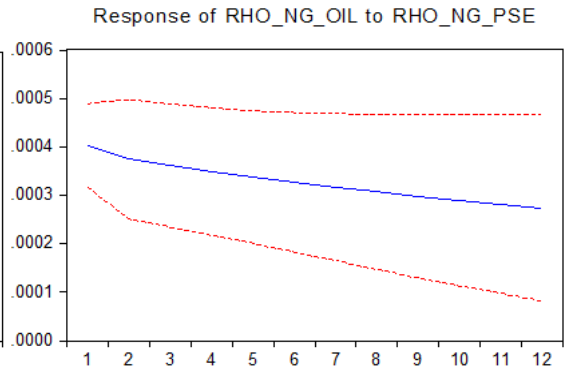
NG/PSE

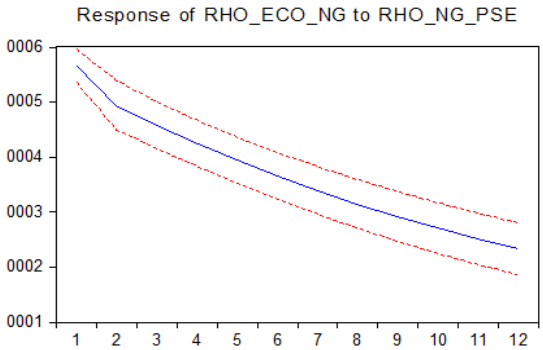
47.61317
46.18863
45.61408
45.29369
45.07775
44.91435
44.78104
44.66655
44.56467
44.47169
44.38531
44.30402

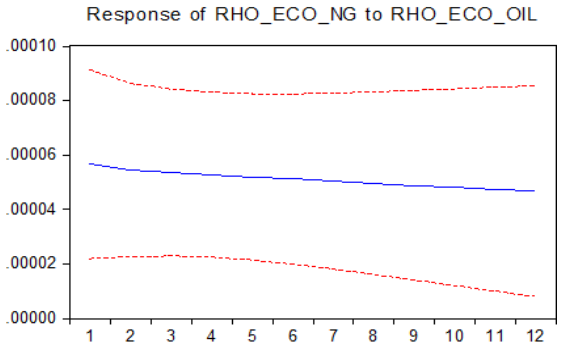
6.3.3 Impulse Response Functions

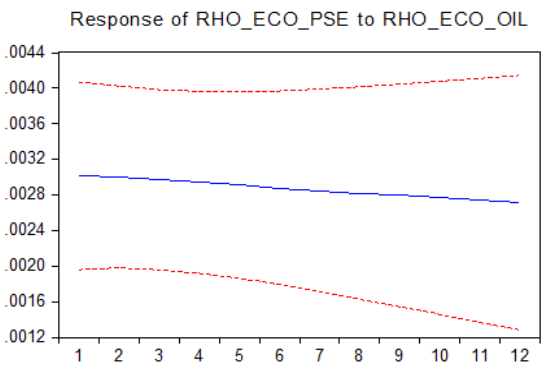
An impulse response is the reaction of any dynamic system in response to some external change. The Regimes below illustrate the effect of one standard deviation shock of one of the variables to each of the others. For obvious reasons, we represent only the statistically significant Regimes of Generalized Impulse Response Functions. All the others are included in the Appendix.

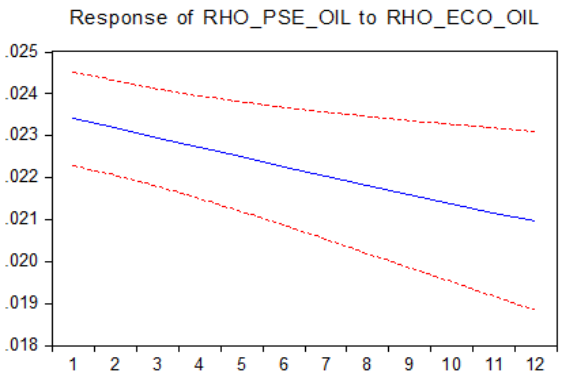




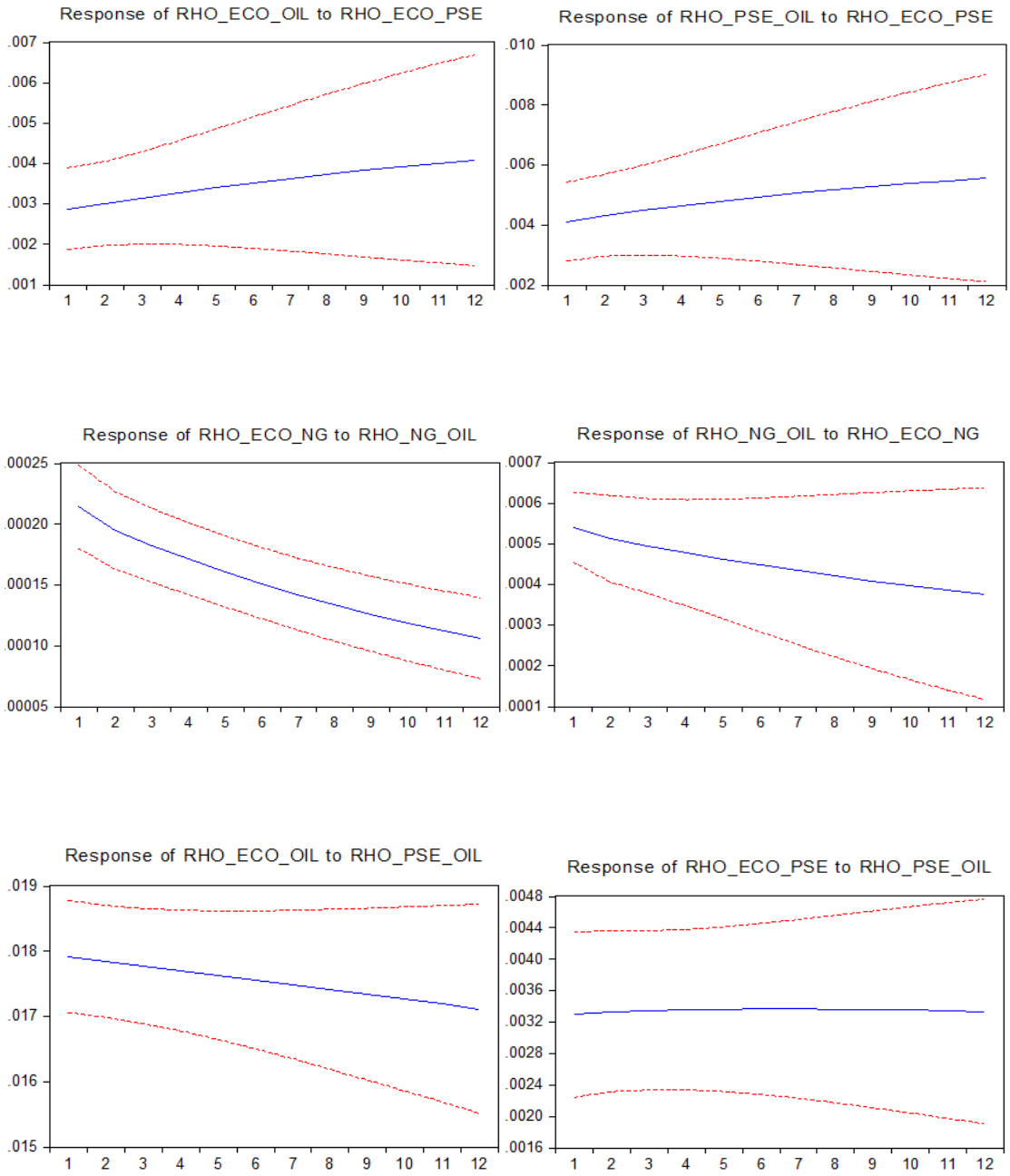








Generalized IRFs



The first Regime illustrates a one standard deviation shock to the correlation of NG/PSE, which has a significant positive effect but stable over time on the correlation of ECO/PSE. In the same way are moving the Regimes of shocks of ECO/OIL to ECO/NG, ECO/OIL to ECO/PSE, PSE/OIL to ECO/PSE. All these responses of correlations to shocks are positive but stable through time. In contrast, the GIRF for the third Regime depicts that a one standard deviation shock to the correlation NG/PSE although has positive effects on correlation ECO/NG, it decreases with time. The same pattern follows the regime with the shock to ECO/OIL and response of PSE/OIL, the shock which happens to NG/OIL with response of the correlation ECO/NG and last but not least, to the correlation of ECO/NG with response of NG/OIL. Finally, there are two Regimes that move upward over the time staying always positive, as all the others. It is worth mentioning that, the Regimes that go downward or stay stable, respond to the figure 1, where we note that some of these variables have almost zero correlation or negative especially in crisis periods where correlations collapse.

6.3.4 Granger Causality

In our last section we are going to test for causality between the correlations of our four variables. We assure that all the conditions are satisfied in case to run a Granger causality test. Our statistically significant results are demonstrated at the table below.

Table 7:

Dependent variable:
ECO/OIL

Excluded	Chi-sq	df	Prob
PSE/OIL	4,074417	1	0,0435

Table 8:

Dependent variable:
ECO/PSE

Excluded	Chi-sq	df	Prob
NG/OIL	2,835324	1	0,0922

Table 9:

Dependent variable:
ECO/NG

Excluded	Chi-sq	df	Prob
NG/PSE	3,041472	1	0,0812
ECO/OIL	3,541847	1	0,0598

The empirical results for daily data, reveal statistically significant uni-directional causality from the correlation of PSE/OIL to ECO/OIL and from NG/OIL to ECO/PSE at 10% level of significance, as we can see from Table 7 and Table 8. In addition, the results of Table 9 show that there is a uni-directional causality from the correlation of NG/PSE to ECO/NG at 10% level of significance and from correlation ECO/OIL to ECO/NG at 5% level of significance.

7. Concluding Remarks

As the amount of money invested in the clean energy sector grows, it is important to have a better understanding of the volatility dynamics of the stock prices of clean energy companies. This paper uses a new class of multivariate GARCH models, the Dynamic Conditional Correlation models, to investigate correlations and the volatility spillovers between oil prices, natural gas and the stock prices of clean energy companies and technology companies.

For each pair of series, the dynamic conditional correlations reached their highest values in the fall of 2010, as the effects of the greatest economic downturn since the Great Depression of 1930‟s were being felt. The dynamic conditional correlations between clean energy stock prices and technology stock prices are higher than the dynamic conditional correlations between clean energy stock prices and oil or natural gas prices. These results are important in establishing that clean energy companies have more in common (correlate more closely) with technology companies than they do with the oil and natural gas markets. Additionally, Impulse Response Functions show that positive correlations cause positive shocks. In crisis periods where correlations collapse, shocks has negative effect in correlations but not statistically significant. In contrast with, good times where correlations move upwards and cause positive shocks. As for the Granger causality tests we have developed, results show that only the correlation of technology and oil can cause the correlation of alternative energy companies and oil, natural gas and oil conditional correlation can cause the correlation of alternative energy companies and technology and last but not least, correlations of natural gas and technology, as well as correlation of alternative energy companies and oil either cause the correlation of alternative energy companies and technology. For the above results there is not corresponding literature review so we can not compare our results. For our research between the correlations, our findings are absolutely consistent with the previous papers, so these results can be add to a small but growing literature showing that oil price movements are not as important as once thought because investors may view alternative energy companies as similar to other high technology companies. These results should be of use to investors managers and policy makers.

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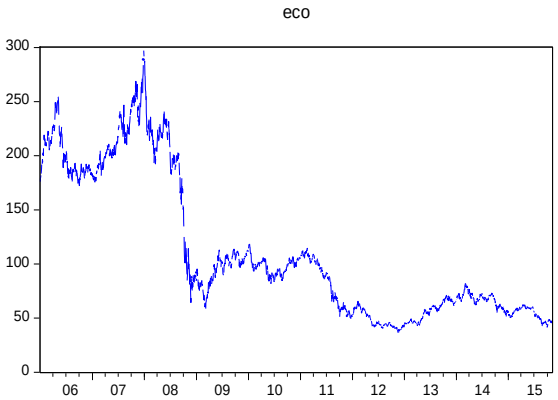
Appendix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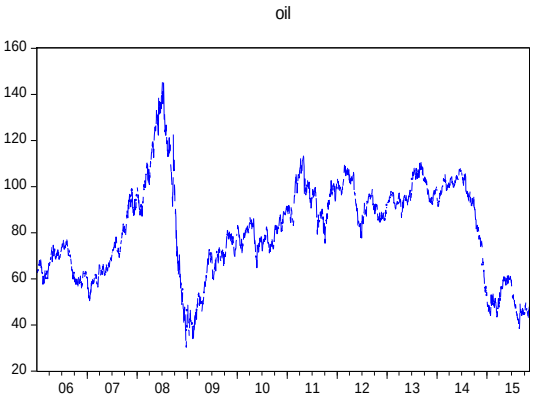
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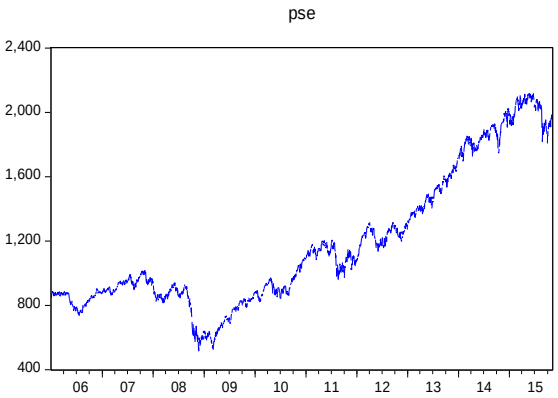
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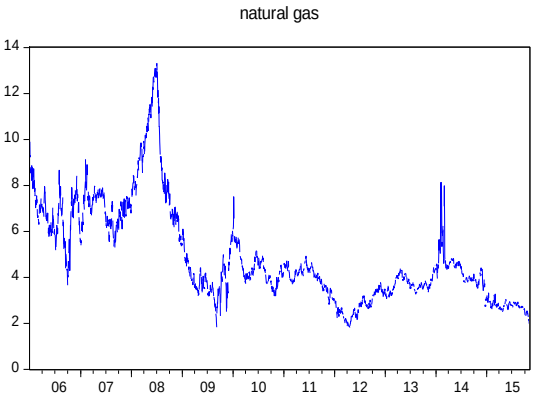
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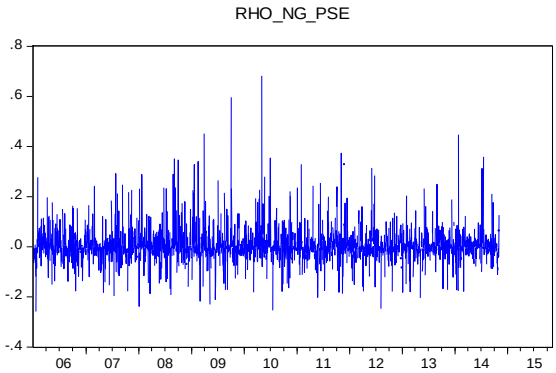
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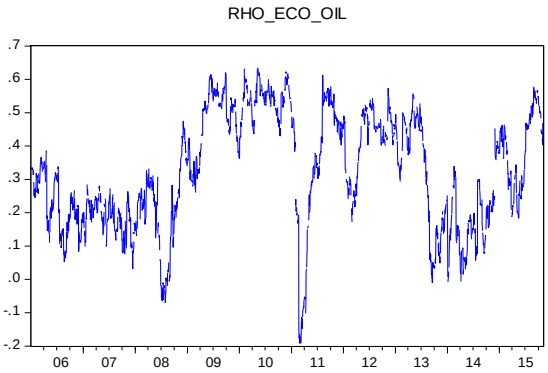
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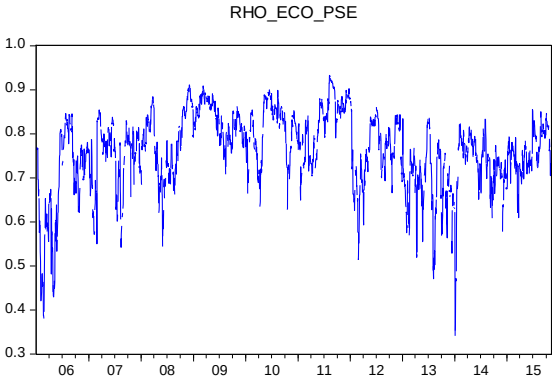
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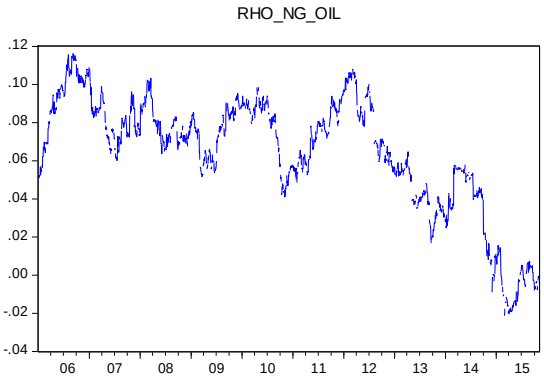
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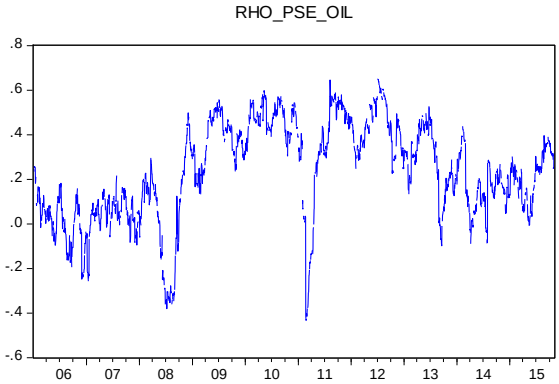
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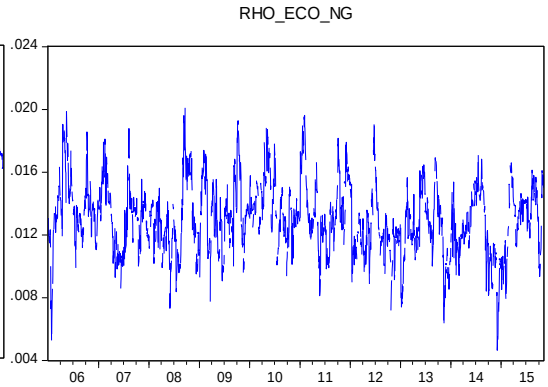
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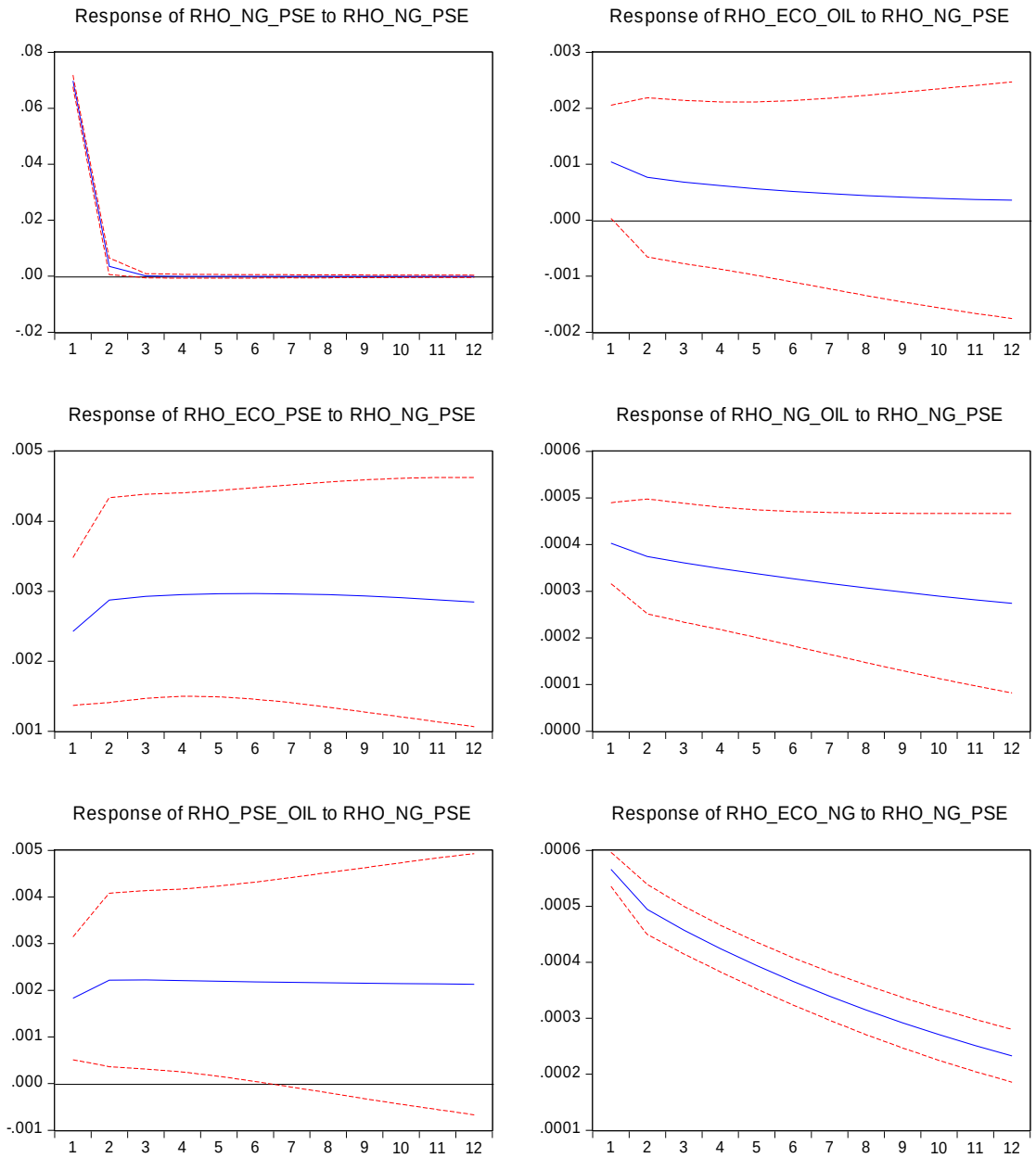

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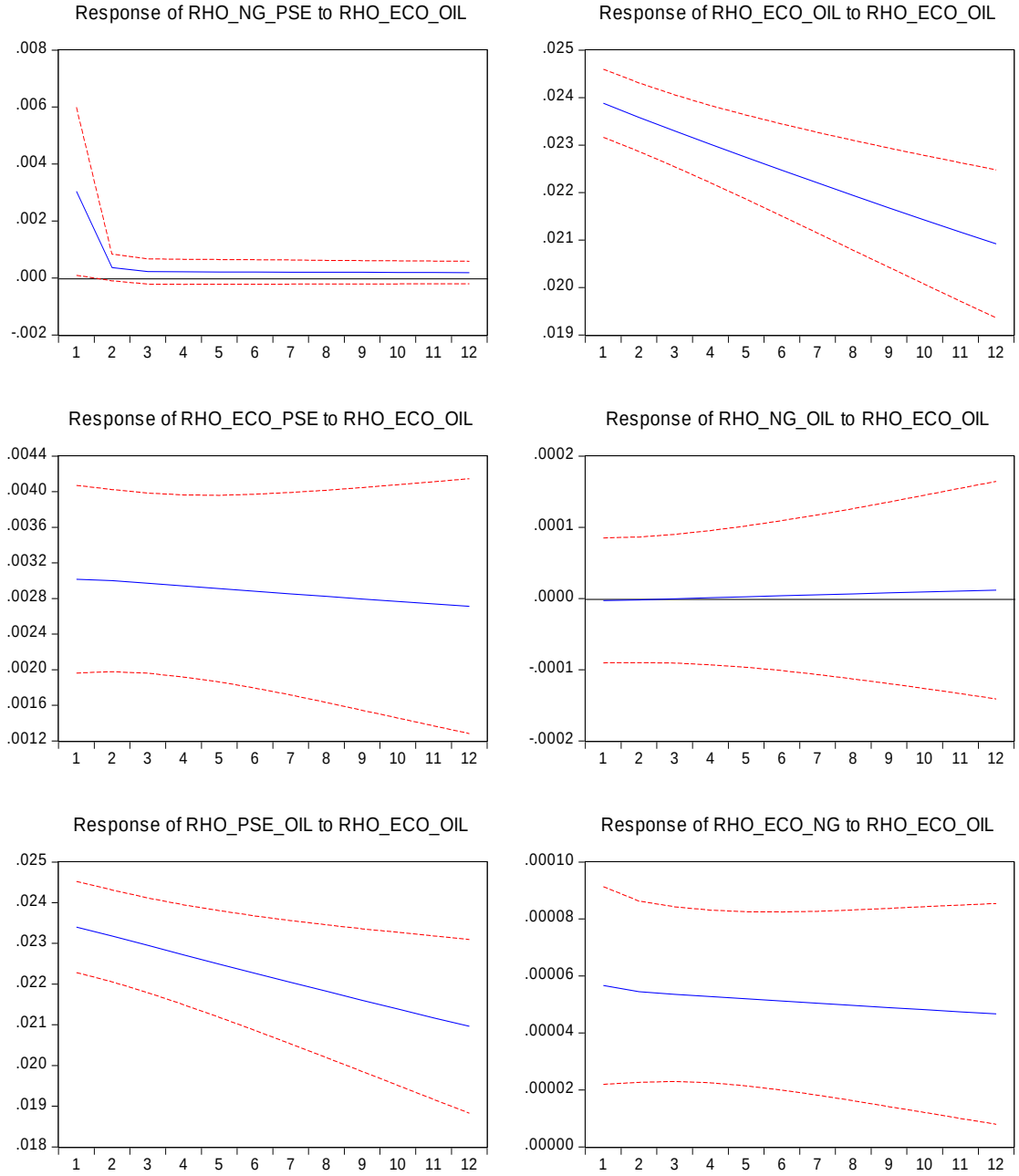

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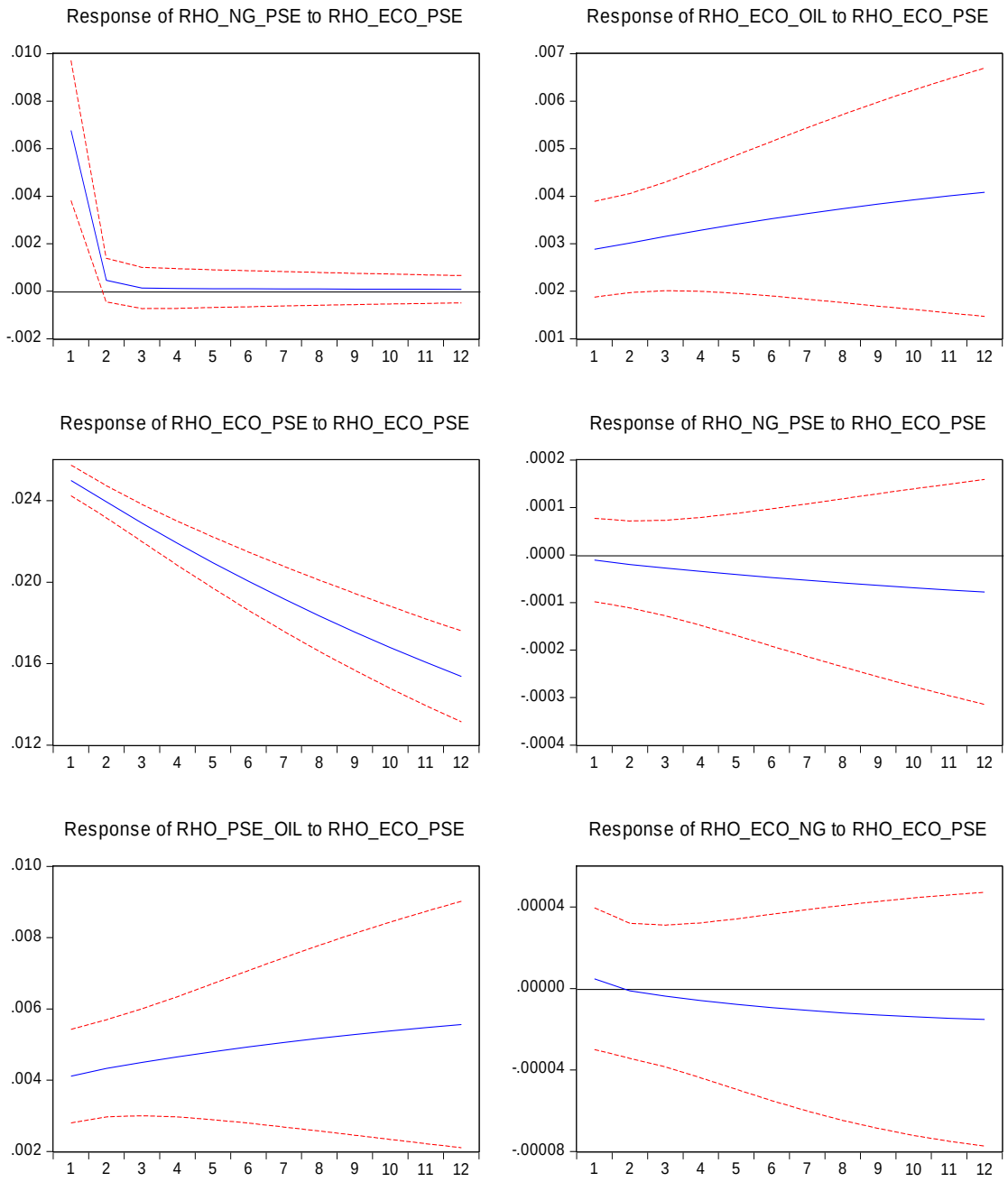

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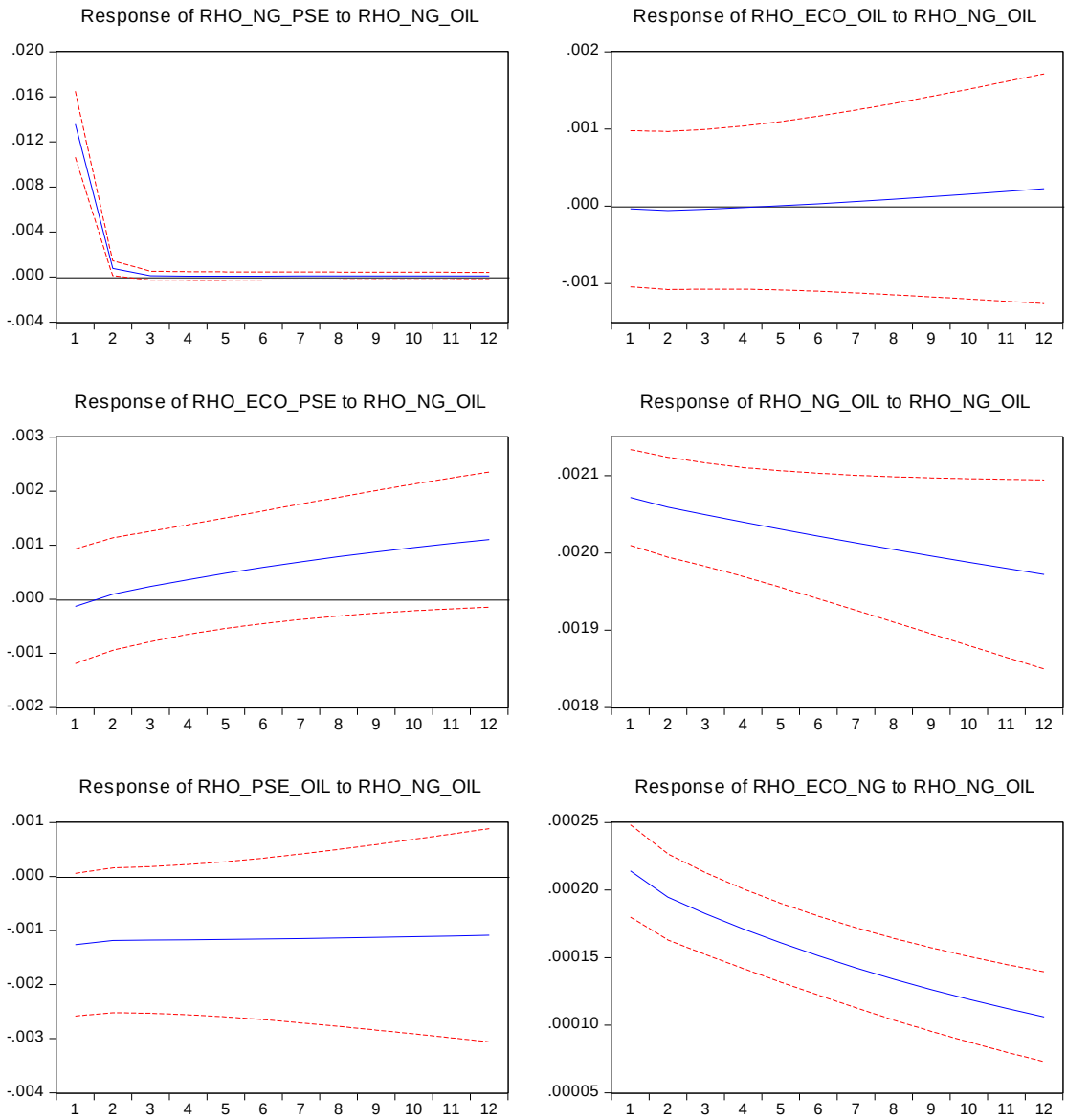

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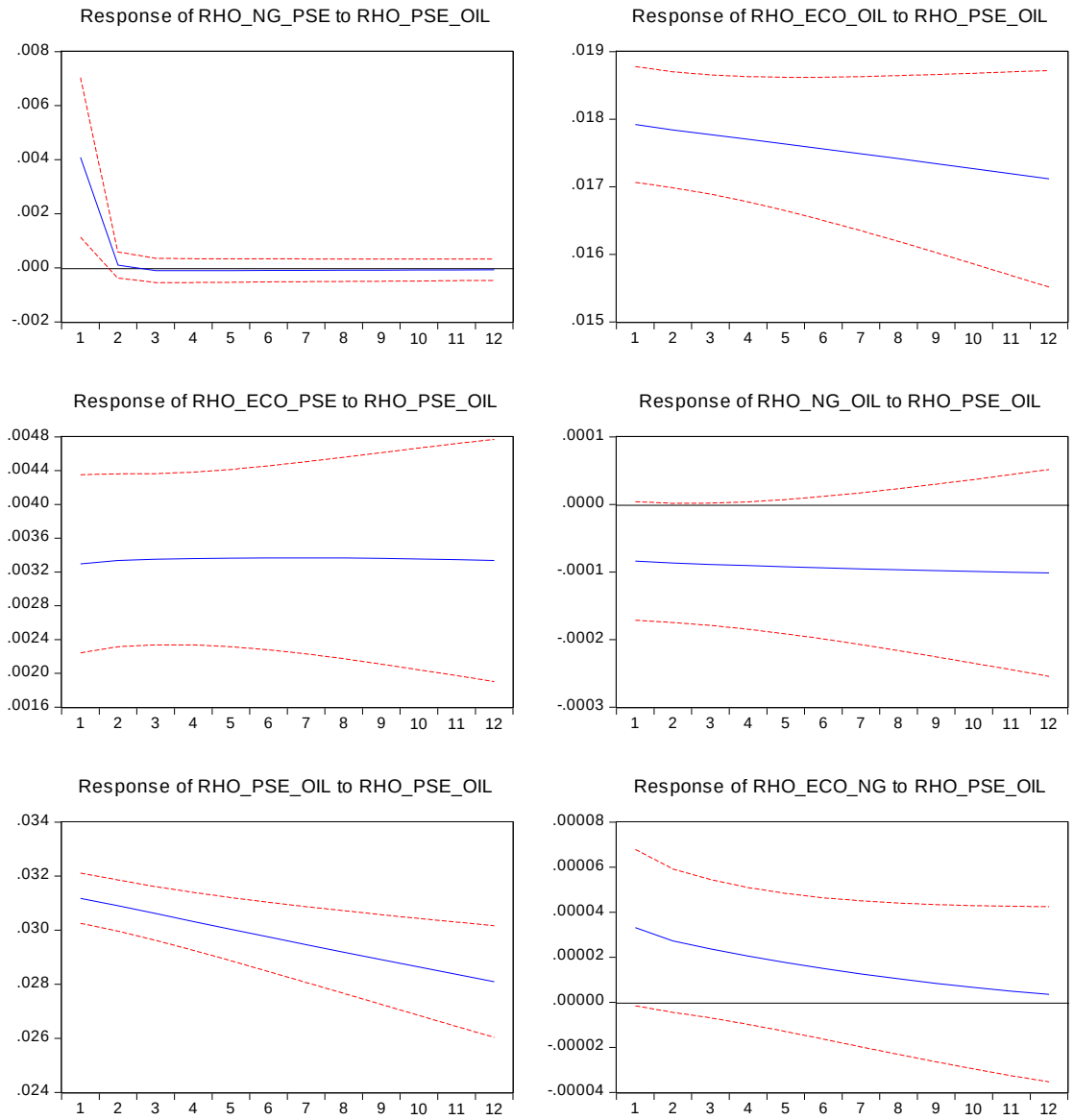

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