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Master's Thesis

Return interdependencies, ARCH and GARCH effects and dynamic conditional correlations among returns of alternative energy, technology index, crude oil and natural gas.

Author: Aarni Pätilä

Supervisor & the 1st examiner: Associate Professor Sheraz Ahmed

The 2nd examiner: Postdoctoral researcher Jan Stoklasa

ABSTRACT

Author	Aarni Pätilä
Title	Return interdependencies, ARCH and GARCH effects and dynamic conditional correlations among returns of alternative energy, technology index, crude oil and natural gas.
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The purpose of this thesis is to examine relationships between alternative energy, technology, crude oil and natural gas over period of January 1, 2006 to December 31, 2015. The modelling process is done using return data generated from alternative energy index prices, technology index prices, crude oil prices and natural gas prices. The research covers two regions: North-America and Europe. Along with modelling return dependencies between variables, volatility spillover effects are also studied using MGARCH–models with BEKK, Diagonal VECH, Constant Conditional Correlation and

Dynamic Conditional Correlation parametrization. Also, a correlation analysis is performed. The correlation coefficients are generated from the basis of constant conditional correlation and dynamic conditional correlation models.

The results reveal both expected and unexpected observations. The mean model generated results indicating similarities compared to the earlier studies. The own past shock seems to have an impact on current return of each of the variables. Also, in both regions the cross-market effects between returns are studied. The deeper analysis for the volatility spillover effects are performed in order to investigate volatility transmission among variables. There are both ARCH and GARCH effects among the variables. The evidence and results from Europe region gained from this study are significant since the deeper analysis between alternative energy index returns and traditional energy index returns are unexamined field of study concerning Europe.

The DCC model is found to be more informative model when correlations between variables are studied. The CCC model provides only a constant value of correlation which seems to be insufficient, when trying to understand the behavior of the time-varying correlations in the long-run. Particularly high correlations are found between alternative energy index returns and crude oil returns in both regions. In addition, correlation between technology index return and natural gas return, and alternative energy index return and natural gas return are found to be negative for certain period of time. The time periods with particular high or, correspondingly, negative correlation provide an interesting viewpoint considering portfolio diversification. This study is important, in economic sense, since studies concerning return dynamics and volatility transmission among alternative energy index and traditional energy sectors are not published in Europe.

TIIVISTELMÄ

Tekijä:	Pätilä Aarni
Tutkielman nimi:	Tuottojen keskinäiset riippuvuudet, ARCH ja GARCH efektit sekä aika-riippuvainen korrelaatio vaihtoehtoisen energiaindeksin, teknologiaindeksin, raakaöljyn ja maakaasun välillä.
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Tämän tutkimuksen tarkoituksena on mallintaa vaihtoehtoisen energiaindeksin, teknologiaindeksin, raakaöljyn sekä maakaasun tuottojen välistä riippuvuutta yhdeksän viime vuoden ajalta. Alueellisesti pro-gradu tutkimus on rajattu kattamaan Euroopan sekä Pohjois-Amerikan. Muuttujien tuottojen välisen mallinnuksen lisäksi tutkimus keskittyy mallintamaan volateliteetin pysyvyyttä muuttujien sisällä. Oleellisessa osassa tutkimuksessa on myös tutkia volateliteetin (pitkä- sekä lyhytaikainen) siirtymistä

muuttujien välillä monimuuttuja GARCH–mallien avulla (BEKK, DVEC, CCC ja DCC). Riippumattomat muuttujat ovat viivästetty yhdellä periodilla suhteessa riippuvaan muuttujaan, jolloin muuttujien välisiä efektejä pystytään mallintamaan tehokkaammin. Tutkimus mallintaa korrelaation vaihtelua tutkimusperiodilla. Korrelaation mallinnus suoritetaan tuottamalla korrelaatiokertoimet CCC– ja DCC–malleista. Tulokset osoittavat, että muuttujien välillä on havaittavissa niin pitkä- kuin lyhytvaikutteista volateliteetin siirtymistä. Lisäksi korrelaatiossa muuttujien välillä on havaittavissa merkittäviä muutoksia tutkimusajalla. Muuttujien omilla aiemmilla tuotto-shokeilla näyttäisi olevan vaikutusta muuttujan nykyiseen tuottoon. Molempien alueiden muuttujilla näyttäisi olevan ARCH– ja GARCH–efektejä. Tilastollisesti merkitsevät tulokset ovat tärkeitä, sillä tämän kaltaisia tutkimuksia on tehty vain Pohjois-Amerikan alueella. Voidaan siis todeta, että muuttujien välillä olevan vahvoja riippuvuussuhteita ja volateliteetin ”läikkyvän” osan muuttujien välillä. DCC–mallin voidaan todeta selittävän syvällisemmin muuttujien välisen korrelaation käyttäytymistä verrattuna CCC–mallin tuottamaan korrelaatiokertoimeen. CCC-mallin tuottama korrelaatiokerroin on vain yksi luku, kun taas DCC–mallin tuottama korrelaatiokerroin selittää korrelaatiota ajan kuluessa. Erityisen korkea korrelaatio on vaihtoehtoisen energiaindeksin tuottojen sekä raakaöljyn tuottojen välillä. Vaihtoehtoisen energiaindeksin tuottojen ja maakaasun tuottojen sekä teknologiaindeksin tuottojen ja maakaasun tuottojen välillä vallitsee ajoittain jatkuva negatiivinen korrelaatio. Nämä korrelaatiota koskevat seikat tarjoavat mielenkiintoisen näkökulman portfolion hajautukseen. Tämä tutkimus on oleellinen, sillä tuottojen vaikutusta toisiinsa, ja volateliteetin siirtymistä vaihtoehtoisten energiaindeksien välillä, on tutkittu Euroopassa erittäin vähän.

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This master's thesis project was a great opportunity to put things that I have learnt during the years in the university into practice. I especially want to thank my beloved girlfriend Sointu for the endless support both during the years in the university, and especially during this project. Also, I want to thank Professor Sheraz Ahmed for his expertise concerning Multivariate GARCH models, and overall good advises.

Before I started to study economics at LUT, I tried a few different field of studies in different universities. Now, after spending five years at LUT, I am confident to say that I made the right choice of switching schools and the study field. I am grateful for my family for the support in the process of finding my path. You have given me strength to believe in myself and my potential to succeed in everything that I do.

Finally, I also want to give special thanks to my friends with whom I have shared so many memorable moments in the university as well as outside the university.

In Helsinki, December 5th, 2016
Aarni Pätilä

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1. INTRODUCTION

I have always had a great interest towards sustainable development and renewable solutions. I wanted to combine my econometric skills with a “greener” field of study. Actually, I got the idea to this thesis after watching *The investment logic for sustainability* by Chris McKnett from TED: *The world is changing really profound ways. And I worry that investors aren’t paying enough attention to some of the biggest drivers of change. Especially, when it comes to sustainability. And by sustainability I mean the really juicy things like environmental and social issues, and corporate governance. I think its reckless to ignore these things, because doing so can jeopardize future long term returns.* (McKnett 2013).

Old and familiar ways of doing things will be replaced by new more innovative and sustainable ways. This same process of changes will be happening also in the investment logic. Understanding the new sustainable investment logic will be crucial for the investors in the future. Some investors have already been starting to pay closer attention to companies’ sustainable background for some time, but during last years, and especially, after Paris Climate Conference in 2015 those issues have been more and more on the frame. Furthermore, as commonly known, crude oil is going to run out in the near future, which will have a great impact on the whole complex energy sector and thus investing.

Renewable energy satisfies one fifth of the world’s total energy consumption, and the share is continuously growing (REN21 2015, 27). This is due to the rapid development of technology in the sustainable energy sector, growing awareness towards sustainable energy and subsidies given by governments into the development of sustainable sectors. Presumably, sustainable energy sector will take over the market share from the traditional energy sectors, like oil, natural gas and coal.

Understanding the behaviour of the traditional energy sectors, emerging sustainable alternative energy sectors and interlinkages between them, will help the public and private investors to constitute a broad picture about price and return dynamics between the energy sectors. Substantial price changes have already happened in several energy sectors within the past 10 years. The greater variation in the prices, and consequently in returns, allow for either greater loss or reward. Furthermore, finding more persistent volatility (high or low) will help investors to predict substantial price changes and utilize that information in their investment decisions. How to gain substantial rewards from the volatile energy markets is another story, but finding return interdependencies between energy sector variables is in the core of this study. Also, the persistency of volatility within an asset, and the volatility transmission (also known as the volatility spillover) between variables will be studied in this thesis.

In order to investigate the interdependencies between energy sector variables and volatility behavior in this study, different econometric models need to be used. Traditional econometric tools, such as regression models for modelling return series' from energy sector, are found impractical due to the fact that energy sector return series' are frequently not normally distributed. The Autoregressive Conditional Heteroscedasticity (ARCH) model [by Engle (1982)] and the Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model [by Bollerslev (1986) and Taylor (1986)] are found to be particular useful modelling non-linear time series, which variance of the errors are not constant. The Multivariate GARCH (MGARCH) models are found to be useful when modelling volatility spillover effects in equity markets (Booth et al. 1997; Cha and Jithendranathan 2009; Karolyi 1995; Karolyi and Stulz 1996; Koutmos and Booth1995; Lin et al. 1994). In addition, MGARCH models are being applied when studying volatility spillover effects in energy economics, such oil prices (Chang et al. 2010; Cifarelli and Paladino 2010; Elder and Serletis 2009; Malik and Hammoudeh 2007; Sadorsky 2006)). Along with previous, MGARCH models are also used when studying electricity prices (Higgs 2009) and natural gas prices (Ewing et al. 2002).

Numerous research papers have been published concerning the interrelationship between oil price movements and stock price movements during past ten years

(Arouri et al. 2010; Kapusuzoglu 2011; Miller and Ratti 2009; Park and Ratti 2008). Oil has been a major economic component, and its price fluctuation has had a great impact on other financial sectors. As commonly known the alternative energy sector provides an alternative option to crude oil. More importantly, alternative energy sector provides a way in producing energy in more sustainable way. Implementation of alternative energy has been driven by the rapidly developing technologies and i.e. tax benefits set by different governments. Yet, the share of alternative energy sector is still small but growing.

The main idea of the study is to model how abrupt price changes transmit between different energy sectors and how the volatility behaves among the variables. More specifically, this study aims to clarify how changes in returns of oil prices, natural gas prices and stock of technology sector influence on stock value of alternative energy companies both in North-America and Europe. Conventional wisdom is that oil price has an impact on alternative energy stocks. According to the latest studies (Henriques and Sadorsky 2008; Sadorsky 2012; Plott 2014) the correlation between oil prices and the stock prices of alternative energy companies is not so strong compared to early 2000's. However, the correlation is expected to be significant. Alternative energy is seen as a substitute for oil. Consequently, consumers start to look for another kind of energy sources when oil price rises.

Henriques and Sadorsky (2008) found out that shocks in the technology sector actually have a larger impact on the stock prices of alternative energy companies than oil prices do. The fact is surprising in the first place. The success or failure of alternative energy companies is related to the level of technical development achieved by technology companies. Actually, alternative energy companies have more in common with technology companies than they do with fossil fuel based energy companies (Sadorsky 2012, 248).

Studies, concerning shock transmission between fossil fuels and alternative energy sector, have focused regionally on North-America (Gormus et al. 2015; Henriquez & Sadorsky 2007; Sadorsky 2012). The firms operating in the alternative energy sector have the longest tradition in the U.S. Also, the availability for the stock prices of alternative energy companies is one reason for the majority of studies are done using data from North-America. The annual investments in the renewable energy have been growing more rapidly in Europe compared to North-America (REN21 2015, 80-81). Actually, studies focusing on volatility dynamics between fossil fuels and alternative energy sector in Europe has not been done before. Therefore, the goal of this study is to fill the void.

1.1 Objectives

Researchers such as Henriques and Sadorsky (2012); Sadorsky (2008) and Plott (2014) have made several profound studies about the interlinkages between prices and returns of fossil fuel based energy and alternative energy. This study takes an advantage of the latest data, which has not been the case in the previous studies. The price of oil has fluctuated considerably; the current price of oil lies in an abnormal low level compared to the long term trend. Therefore, there is a need for a research using the latest data. Also, return interlinkages between natural gas and alternative energy indexes have not been studied. Sustainable or alternative energy is becoming more mainstream, and therefore, it is valuable to study how other energy sources affects to alternative energy.

Research questions are:

1) *Has the correlation between crude oil and alternative energy index been diminishing?*

The correlation between crude oil and alternative energy index prices and returns are thought to be strong. However, lately hints have been turn out that correlation coefficient has been diminishing (Sadorsky 2009).

2) *Do shocks transmit among crude oil, natural gas, technology index and alternative energy index in Europe and North-America?*

Do substantial price changes, and therefore changes in returns of one variable, have an impact to the other? Is the effect one-way (unidirectional) or bidirectional between the variables?

3) *Does the volatility clustering appear? Is the volatility clustering short- or long term? Does the clustering volatility move from one variable to another one (volatility spillover)?*

The base for the Autoregressive Conditional Heteroscedastic models is the feature where volatility appears in bunches meaning the situation where low volatility follows low volatility and high volatility follows high volatility. One of the key elements of this study is to model the behavior of the volatility in order to find out whether the volatility clustering appears within or between variables.

4) *Do shocks and volatility transmit differently depending on region?*

Are there differences in shock transmissions between Europe and North-America?

1.2 Structure

This study is divided into seven sub-sections. First, introduction introduces the topic in general. The introduction covers also the motivation behind this study and some brief reasons why this topic needs a comprehensive and holistic analysis. The second section introduces in general the variables used in this study. Additionally, the second section introduces the main price determinants for each asset. The third section covers the theoretical framework. More specifically, what has been studied earlier related to the same topic and what kind of results have previously been reported. The third section provides also some rough guidelines on what kind of results are expected from this study. The fourth section goes into the methodology of this study. Also, a description to the econometric models used in this study are explained. At first, in the methodology section, the basic univariate ARCH and GARCH models are presented in order to provide general understanding of the autoregressive models. The understanding of the basic models is a requirement in order to be capable of understanding and applying more complex multivariate models, such as Multivariate General Autoregressive Conditional Heteroscedasticity (MGARCH) model with BEKK-, diagonal VECH-, CCC- and DCC- parametrization. Furthermore, requirements for the time series data in order to be harnessed under GARCH models are presented in the fourth section. The fifth section is for the data description and analysis. Data description and analysis-part combine three previous sections applying the theory into the practice. The gathered data is referred to the MGARCH models, and results from the MGARCH models are presented in the sixth section. In the sixth section, alongside with MGARCH results, correlation graphs generated from the Dynamic Conditional Correlation model are presented. Finally, the conclusion section sums up the whole study, and conclusion are drawn.

2. THE GENERAL FEATURES OF THE VARIABLES

For achieving the holistic picture of the return interlinkages and volatility spillovers, the general features of variables are presented. The introduction of variables is brief, because the purpose of this study is to examine the interlinkages of the variables, not to focus on the price determination of variables themselves. However, the general understanding of price determination and trends are needed in order to understand the interlinkages of the variables.

2.1 What is an alternative energy?

In common language renewable energy can be defined as supplementary energy source for traditional energy sources, such as fossil-fuel sources, as coal, oil, and natural gas. More specifically, the alternative energy can be defined as an energy that does not use up natural resources or harm the environment (Twidell and Weir 2015, 3). Keeping this definition in mind, according to Twidell and Weir (2015, 10-11) renewable energy sources are:

- Hydro electricity
- Geothermal energy
- Biofuel and Ethanol
- Wind energy
- Solar energy

To avoid misunderstanding of concepts, it is important to separate two concepts: alternative energy and renewable energy. Those two concepts are frequently mixed. Alternative energy is an energy source that can be used to replace conventional fossil fuel based energy sources (Twidell and Weir 2015, 3). It causes considerably less negative side effects, such as emissions, compared to the fossil fuel based energy sources. In contrast, renewable energy is any type of energy which comes from renewable (natural) sources (Twidell and Weir 2015, 3). It is referred as renewable because it does not deplete compared, for example, to oil reserves.

Keeping the two definitions about renewable energy and alternative energy in mind, nuclear energy could be categorized only into the class of alternative energy. It does not cause undesirable side effects (except nuclear waste). And it can replace the traditional energy sources in some sense. However, uranium source does not last forever so it cannot be categorized to the renewable energy class.

2.2 Trends of alternative energy

Below (figure 1) the notable proportion of the alternative energy (renewable energy included nuclear energy) from the total energy consumption is presented.

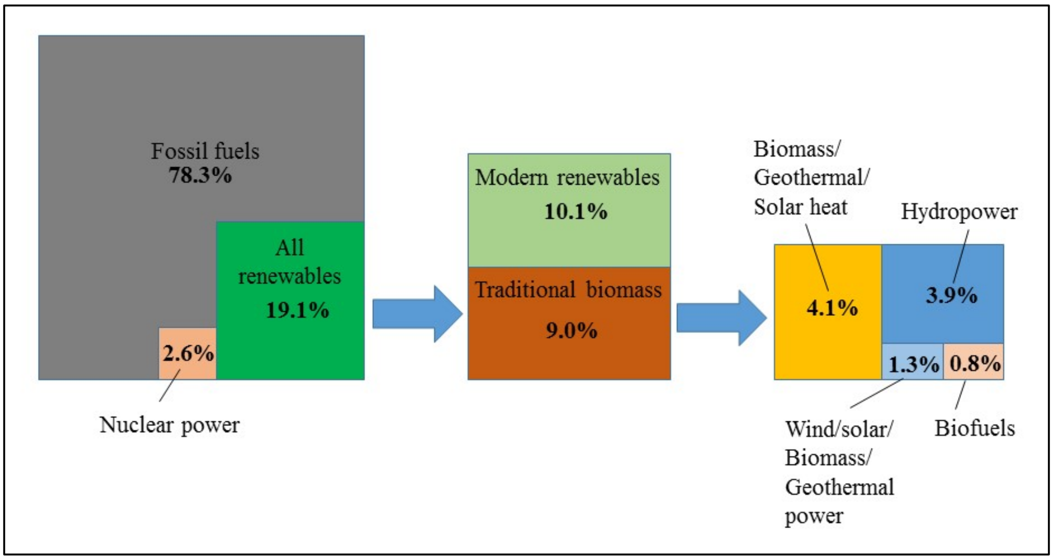

Figure 1. Estimated renewable energy share of global final energy consumption (REN2 2015, 18)

According to REN 21 (2015, 18), in the figure 1, fossil fuels cover 78.3% of the total global final energy consumption. Renewables cover 19.1% and nuclear power covers 2.6%. Two facts will have a great influence of the proportional usage of alternative energy. First, fossil fuels will deplete within decades. Second, the annual production of the nuclear power has remained relatively constant (around 2000 TWh) (World-Nuclear 2016). Both facts mean that renewable energy has to satisfy the need of the world's growing energy demand in the near future.

Also, the annual investment levels for the renewable energy rose substantially in the first decade of 2000. In Europe global new investments in renewable power and fuels were 57.5 billion USD in 2014 annually (figure 2). The number in the United States was 38.3 billion USD in the same year. The investment level has been relatively constant in the US during past 10 years but in Europe investment level has climbed up to 120.7 billion USD. The most recent observation in 2014 shows that investment level is 57.5 billion USD. Nowadays, majority of the investment funds target to the emerging economies (Ren 21 2015, 79). Nevertheless, the eight-year-trend between 2004 and 2011 (in the figure 2) in investments to renewable and alternative energy sectors has been growing both in Europe and North-America.

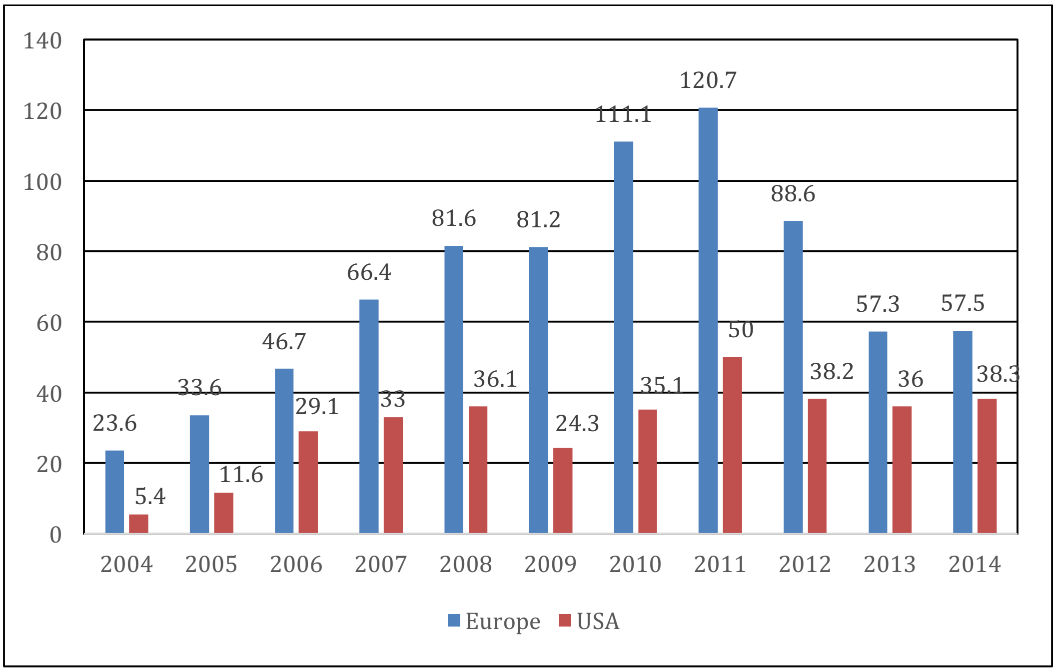

Figure 2.Annual new investments (billions of dollars) in renewable energy in Europe and USA (REN21 2015, 80-81).

Future prospects look promising for the alternative energy sector when costs are compared to other energy sectors i.e. fossil fuel based energy sectors. IEA (2015, 7) states that technologies where high-carbon energy sources are being used become more expensive due to the rising energy prices. Overall, the cost-trend is rising concerning fossil fuel based energy sources. Cost reduction is the norm for alternative energy technologies due to the advancing and cheaper technology. Also, popularity of renewable energy production is growing, and therefore demand for alternative solutions is growing as well. Subsidies have a substantial role in energy business. IEA's World Energy Outlook 2015 – report (IEA 2015, 7) estimates that global subsidy for fossil fuels were $490 billion in 2014 and subsidies endorsing the deployment of renewable energy technologies in the power sector were $135 billion in 2014. The report (IEA 2015, 7) estimates that subsidy for the renewable energy will increase globally by 50% by 2040.

2.3 The price determinants and the latest price trends of the crude oil

Crude oil is one of the driving forces of world's economy. The price of oil has been defining countries' economic status. U.S. Energy Information Administration (EIA) published a review (EIA 2015) of the major oil price determinants that have defined oil prices especially in the 21st century. According the article (EIA 2015), in general, the barrel price of oil has been relatively stable since the early 70s until the 90s. Since the early-20s the oil price has fluctuated remarkably causing uncertainty in the world's economy. The most important determinants (EIA 2015) have been:

- Geopolitical and economic events
- Arbitrage
- Economic growth has a strong impact on oil consumption
- Changes in non-OPEC production an affect oil prices
- Oil production of OPEC countries
- Future expectations

Briefly, all the determinants have realized within last two decades and those have a tendency to deviate the crude oil price from its long term average price. The oil price growth in the beginning of the 20th century can be explained by low spare capacity of crude oil (EIA 2015, 2). Overall economic growth and, especially China's strong economic growth fueled the run-up of the price (EIA 2015, 2). In the figure 3 major trends are clearly visible. There was a peak in the barrel price of the crude oil on July 2008 when the price per barrel was 145 USD. The steep decline started in 2008 due to global financial crisis. Crude oil spot price fell considerably to 30 USD by the end of December 2008. The collapse finally stopped when OPEC cut targets to 4.2 million barrels per day (mbpd). 2014 OPEC refused to cut the production which causes an overproduction and declined oil prices. OPEC actions combined to slow economic activity may keep the oil prices relatively low for some time. Many predictions have been suggested about reserves and sufficiency of the crude oil. British Petroleum (BP 2014) estimated that present rate of consumption oil reserves will last for 53.3 years and it is left 1,687.9 billion barrels. However, the future price of the crude oil is difficult to predict mainly because the future demand is unknown.

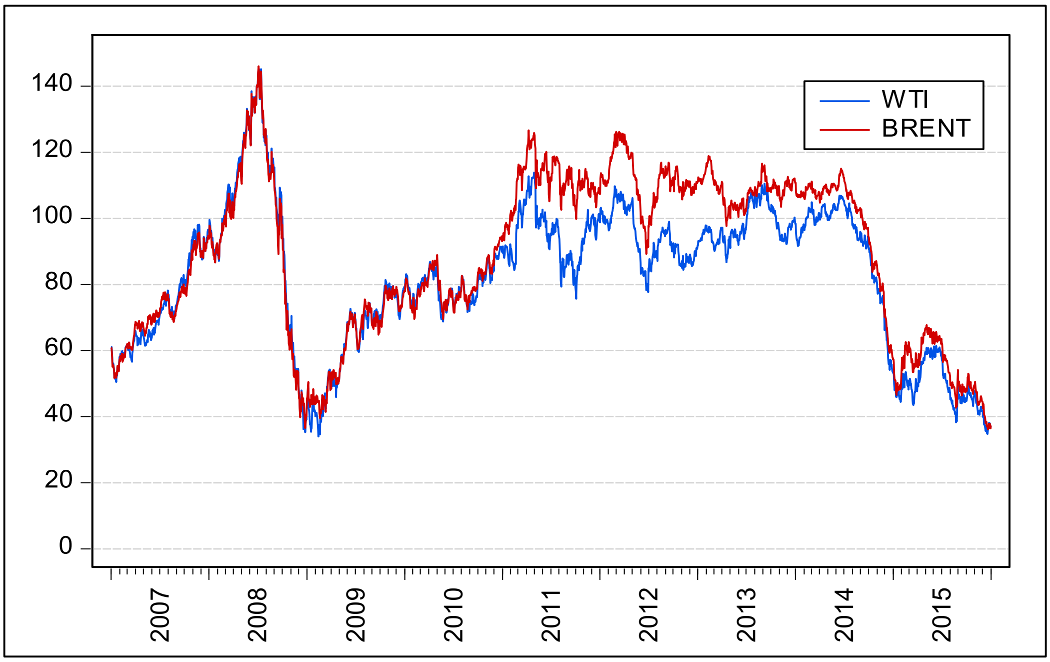

Figure 3. The USD barrel price of WTI (blue line) and Brent (red line) (Datastream 2016).

Historically, the prices of WTI and Brent have had only a little deviation from each other. From the figure 3 is seen that both crude oil qualities have moved together until 2011, then prices start to deviate from each other. The price deviation lasts until 2014. According to U.S. Energy Information Administration (EIA 2015, 8) the main reason for the price deviation was growing deliveries of Canadian crude to Cushing, Oklahoma, and increasing U.S. light sweet crude oil production from tight oil formations caused transportation bottlenecks in the U.S. Midcontinent. These bottlenecks lowered the price of U.S. crude. In 2014 the overproduction of WTI declined and, therefore, the price difference between WTI and Brent evened.

The next important issue after global consumption of fossil fuels is fossil fuel price movement. Proven fossil fuel reserves will fluctuate according to economic conditions, especially fossil fuel prices. In other words, proven reserves will shrink when prices are too low for fossil fuels to be recovered economically and expand when prices deem fossil fuels economically recoverable (IEA 2007). In addition, the trend of fossil fuel prices significantly affects fossil fuel consumption. On the other hand, fossil fuel price fluctuations affect other variables such as international inflation, global GDP growth, etc. Consequently, the size of fossil fuel reserves depends on their prices. (Shafiee and Topal 2009, 182)

Economic conditions in the countries are difficult to predict and, therefore, the demand for crude oil is also difficult to predict. Yet, remarkable shocks are expected and the price of oil is expected to rise, even though, the current price of the crude oil is at low level. As mentioned, oil price has a considerable impact on other energy and financial assets. The fact makes this study even more important, because when considerable shocks will happen, then the knowledge of the interaction will be useful.

2.4 Determinants of natural gas price and interlinkage to crude oil

Natural gas is used to replace more carbon-intensive fuels or backing up the integration of renewables. Also, its consumption has increased substantially compared to other fossil fuels during past ten years (IEA 2015, 4-5). Therefore, natural gas is seen as a good fit for a gradually decarbonizing energy consumption.

For many years, fuel switching between natural gas and residual fuel oil kept natural gas prices closely aligned with those for crude oil. More recently, however, the number of U.S. facilities able to switch between natural gas and residual fuel *oil has declined, and over the past five years, U.S. natural gas prices have been on an upward trend with crude oil prices but with considerable independent movement. (Brown and Yücel 2007, 2)*

Industry and electric power generations switch back and forth between natural gas and residual fuel oil depending on price of particular energy source. Yücel and Guo (2004); Pindyck (2003) tracked that natural gas returns followed the crude oil returns. During the past-ten-year period the natural gas returns have shown independent movement diverging from the crude oil returns. Bachmeir and Griffin (2006) have found only a weak relationship between the crude oil and natural gas prices in U.S. Asche, et al. (2006) found cointegration between natural gas and crude oil prices in the U.K. market after deregulation of the natural gas. Co-movements between natural gas returns and returns from alternative energy sector has not been studied deeply.

3. THEORETICAL FRAMEWORK

The interdependencies between stock price and oil price are a substantially studied field. However, only a few academic researchers have focused on how the oil price movements affect to the stock prices of the alternative energy companies. Publicly accepted presumption is that rising oil prices should increase the stock value of the alternative energy companies, because, as fossil fuel based energy prices increase, then consumers are willing to switch to the alternative energy sources (Sadorsky 2012, 249). Alternative energy sources can be seen as a substitute with the fossil fuels based energy sources.

Perry Sadorsky (2009) introduces the results from International Energy Agency (2006) (IEA) report about the growth of total energy demand in the world. It is projected to grow staggering 50 % (20 trillion USD) between 2004 and 2030 (IEA 2006, 456). Not only does this provide a unique opportunity to expand the renewable energy sector but also force consumers to move towards more sustainable solutions in order to decrease the reliance of fossil fuels based energy sources. Rising prices of fossil fuels encourage the private and public sectors to invest in the research and development of new energy-conserving technologies and alternative fuels. Also, the developing alternative energy sector provides opportunities to the public and private sectors to switch to the low-cost sources (Economic Report of the President 2006, 243). Sadorsky (2009) states that deeper understanding of how the renewable energy consumption behaves is important for several reasons. Concerns for the climate change and rising global temperatures are coming true [The Intergovernmental Panel on Climate Change 2007 and Stern 2006]. Renewable energy is projected to be the fastest growing energy source between now and 2030 (IEA 2006, 66). The growth rate of GDP is the main driver of global demand for energy (IEA 2006, 57). So, the growth of GDP should be taken into account in every model that model the development of fossil fuel or non-fossil fuel energy consumption.

Renewable energy is considered to be a substitute for the crude oil. Therefore, rising oil prices should encourage private and public sectors reducing consumption, purchasing more efficient products and switching to renewable energy sources (Economic Report of the President 2006). Controversially, Henriques & Sadorsky (2008) and Sadorsky (2008) found out that shocks in oil prices surprisingly had only a little significant impact on the stock prices of alternative energy companies. Sadorsky (2008) applied vector autoregressive (VAR) model in order to investigate the power of oil price movements, technology stock prices and interest rates in explaining the movements of the stock prices of alternative energy companies. Actually, Sadorsky (2008) reports, not only the smaller significant results than were expected but he also found out that oil prices having a negative impact on the stock prices of alternative energy companies. According to Sadorsky (2008), rising oil prices should decrease the value of alternative energy companies, and vice versa. Finally, both (Sadorsky 2008 and Henriques & Sadorsky 2008) report the same conclusion: the weak relationship between oil price and movements and the stock prices of the alternative energy companies can be explained by the fact that alternative energy stocks are closely related to general movements in the technology sector than movements in the energy sector.

Gormus & Sarkar (2014) and Gormus (2015) explored the effects of oil price shocks on the performance of the alternative energy companies, including renewable sources. Vector autoregression analysis revealed that oil prices have a remarkable and significant effect on the performance of alternative energy firms. Within alternative energy sector, solar energy related companies gave also remarkable and significant respond to the shocks in the oil prices.

MGARCH models are being used to study volatility transmission and dynamic correlations between energy markets in the North-America (Plott 2014 and Sadorsky 2012). Plot (2014) used MGRACH model with Vector Autoregressive Moving Average parametrization modelling dynamic interrelationship between alternative energy index, technology index, coal, oil, and natural gas futures from 2006 to 2014. Sadorsky (2011) used MGARCH extensions, such as BEKK, Diagonal, Constant Conditional Correlation and Dynamic Conditional Correlation modelling interrelationships between oil prices, stock prices of clean energy companies and stock prices of technology companies. In both studies own conditional ARCH effects within variables were reported. Own conditional ARCH effects were found in natural gas and alternative energy index (Plot 2014) and all variables (Sadorsky 2012). Own conditional ARCH effects indicate influence of “news” or “shocks” on volatility or short term persistence.

Sadorsky (2011) and Plott (2014) found that own long-term GARCH-effects are persistence in all variables. When the own GARCH effect is significant within variables, then volatility can be said to impact on volatility or long-term persistence. BEKK model reveals several instances of significant volatility spillovers. For short-term persistence there is evidence of bidirectional volatility spillovers between alternative energy index and technology (Sadorsky 2012), whereas Plott (2014) reported significant ARCH effects only from coal to oil. The only statistically significant GARCH effect, where volatility in one market effects on volatility in the another market, is from coal to oil (Plott 2014) and bidirectional effect between alternative energy index and technology index. Both studies give similar results considering model specification: The strongest evidence for volatility spillovers is found using the BEKK model. According to AIC and SIC criterion DCC model is found to be the most appropriate model, whereas the BEKK model is the second best.

Ewing et al. (2002) modeled the volatility in the oil and natural gas sectors changes over time and across markets. The univariate and bivariate time-series properties in the oil index and natural gas index returns were examined. According to the multivariate GARCH model with BEKK parameterization, results indicate that volatility (conditional variance) in the oil returns is directly affected by its own volatility. Also, volatility in the natural gas returns significantly affects to the oil returns. Higher levels of conditional volatility in the past affects to the current conditional variance of the current period. Moreover, the coefficients for the covariance term in the conditional variance equation for oil returns is significant and positive. The result implies indirect volatility transmission through the covariance term from natural gas returns to oil returns. Researchers findings suggest that volatility in the natural gas index is directly affected by its own volatility, and indirectly by shocks in the oil sector. Multivariate GARCH model with BEKK parameterization indicates that shocks to volatility are more persistent in the natural gas index returns compared to the oil return index returns. Also, current oil volatility is more dependent for the past volatility than specific events or economic news.

Dynamic conditional correlation measures how the correlation evolves over the time. The results from the DCC model is i.e. used in portfolio diversification. If the results from the dynamic conditional correlation model are negative, then there is a scope for meaningful portfolio diversification. Sadorsky (2012, 253) reports no trend in correlations up until 2008 (study period: 2001-2010). After 2008 there was a slightly positive trend in each pair of correlations. Plott (2014) suggests that that there is a scope for portfolio diversification between crude oil and alternative energy index due to the negative dynamic conditional correlation. Huang, Cheng, Chen & Hu (2012) studied recent relationship between crude oil prices and stock performances of alternative energy companies using econometric Vector Autoregressive (VAR) model. The first decade of the 20th century was divided into three sub samples according the time. Huang et al. (2012) reported the strongest correlation between oil and alternative energy index in the second period. The result is in line with Plott (2014) and Sadorsky (2012) indicates that the correlations has not got stronger during the recent years.

Huang et al. (2012); Boyer and Fillion (2007); Park and Ratti (2008) registered an interesting fact considering dynamics of the oil returns to the alternative energy index: The magnitude of oil price volatility has an effect to the alternative energy index. In the other words, when oil prices are rather stable and inexpensive, the stock performances for both green energy firms and oil companies do not interact with oil prices considerably. Whereas, during the volatile -era, oil price is greater determinant of stock price of alternative energy company. In summary, the greater uncertainties of oil price movements generate greater impacts on stock returns of alternative energy companies.

Economic theories (Villar and Joutz 2006; Bachmeier and Griffin 2006) suggest that natural gas and cruel oil prices move together. Natural gas and crude oil should be treated as complements. However, there have been times when natural gas prices have decoupled from crude oil prices. For example, Villar and Joutz (2006) compared crude oil prices and natural gas prices from 2000 to 2006. The deviation was considerable. How do the changes in oil prices affect to natural gas supply? Production of natural gas may increase due to natural gas status as oil's co-product, or may decrease as a result of higher-cost productive resources (Villar and Joutz 2006, 39).

The demand side of the natural gas is logical. There is positive relation between oil and natural gas prices. In the short run, natural gas demand is driven by oil prices (Villar and Joutz 2006; Bachmeier and Griffin 2006). Historically natural gas and crude oil have had a stable relationship, despite periods where they have decoupled. Important feature that researchers also find is hypothesis of the nonstationarity of natural gas and crude oil time series (Villar and Joutz 2006; Bachmeier and Griffin 2006). Consequently, it is even more important to take into account nonstationarity of time series in order to capture important features and properties of the data.

As a summary, Gormus (2015), Gormus and Sarkar (2014) and Sadorsky (2008) have used Vector autoregression analysis in order to study return effects between alternative energy and crude oil. Results considering how the return movements of crude oil affects to alternative energy index differs between studies. Perry Sadorsky has made several studies from the interdependencies between alternative energy and crude oil (i.e. 2008 and 2012). Also Plott (2014) and Sadorsky and Henriques (2008) has made studies using Multivariate GARCH extensions in order to study return interdependencies and volatility transmissions. Based on those studies, own conditional ARCH- and GARCH- effects are in-line among studies. However, there are differences in volatility spillover effects. In other words, general rule for the volatility contagion between variables is not found. Also studies cover only North-America, and, therefore, applying other region as well, will increase the reliability of the results and provide comprehensive understanding for the return dynamics and volatility contagion among selected variables. Many researchers have used the MGARCH extensions, and usually, the most applied extension has been the BEKK model in order to investigate volatility contagion (Plott (2014); Sadorsky (2012); Ewing (2002). The Dynamic Conditional Correlation model is used in order to generate time-varying conditional correlation coefficients. The purpose is to examine how the correlation has changed over the time. Sadorsky (2012) reports positive correlation between alternative energy index returns and crude oil return between 2008-2010. Huang et al. (2012) divided the first decade of the 20th century into three sub-periods according time. Huang et al. (2012) reported the strongest correlation between oil and alternative energy index in the second period. The correlation results provide meaningful viewpoint for studying how the correlation between alternative energy index and crude oil has been changing during the most recent years.

4. METHODOLOGY

The methodology section covers the reasons why ARCH and GARCH models are needed, and why, for example, simple linear regression model cannot be used modelling interrelationships between returns. The methodology section follows the logical line. First, ARCH and GARCH models are presented, and then more complex extensions to the multivariate GARCH models are explained.

4.1 The reason for GARCH models

Many non-linear models can be made linear by using suitable transformation i.e. taking logarithms. However, many relationships in finance are intrinsically non-linear and incapable of explaining certain features (Brooks 2002, 437). Those features are:

- Leptokurtosis – tendency for financial asset returns to have distribution that exhibit fat tails and peakedness at the mean.
- Volatility clustering – the tendency for volatility in financial markets to appear in bunches (Mandelbrot 1963). Therefore, large returns are expected to follow large returns. Analogously, small returns are expected to follow small returns.
- Leverage effects – the tendency for volatility to rise more following a large price fall than following a price rise of the same magnitude (Black 1976).

Few researchers have noticed that same features appear in energy economics. (Chang et al. 2010; Cifarelli and Paladino 2010; Elder and Serletis 2009; Malik, and Hammoudeh 2007; Sadorsky 2006). The selection for model being able to capture features such as leptokurtosis, volatility clustering and leverage effects is crucial for this study.

There are many possible models for non-linear time series. However, only a few are capable to model financial data (Brooks 2002, 438). The most popular models are Autoregressive Conditional Heteroskedasticity (ARCH) model and Generalized

Autoregressive Conditional Heteroskedasticity (GARCH) model. These models are used for modelling and forecasting volatility (Brooks 2002, 438). When the estimators of the classical linear regression model (CLRM) are unbiased, then the estimators are said to be the best linear unbiased estimators (BLUE). If assumptions are violated, then the estimators are no longer BLUE. If the violations are ignored, then it may lead to misleading standard errors, and possibly wrong assumptions about the results from the regression model.

One common problem in financial time series data, and energy economics, is heteroscedasticity. Heteroscedasticity means that the variance of errors is not constant. The ARCH-model (Engle 1982) was the first model being able to systematically model the volatility. The ARCH model takes into account the inconsistency of the variance of errors, and models the heteroscedasticity. Tim Bollerslev (1986) developed a generalized version of Engle's ARCH-model in 1986, known as Generalized Autoregressive Heteroskedasticity (GARCH) model. The GARCH-model is improved version from the ARCH model. Bollerslev (1986) developed the ARCH-model by correcting two deficiencies. The first deficiency, is that in the original ARCH-model estimated parameters cannot be negative. While number of lags increases, probability of the negative estimated parameters become more possible. The second deficiency of the original ARCH model is the difficulty to determine the correct amounts of lags.

4.2 The ARCH model

Under the ARCH model by Engle (1982), the autocorrelation in volatility is modelled by allowing the conditional variance of error term, σ^2, depend on the previous ones. A full structural model with ARCH(q) parametrization consists of two equations. In the equation 1, the error term ε_t is split into two pieces: z_t and σ_t. z_t is a sequence of random variables with normal distribution, zero mean and unit variance. σ_t denotes the time-varying function of the information set. In the equation 2, conditional variance σ_t^2 depends on constant α_0 and q lags of one period lagged squared errors ε_{t-i}^2. α_i is obviously the ARCH term. Both constant α_0 and the ARCH term are assumed to be positive.

$$\varepsilon_t = z_t \sigma_t \quad \varepsilon_t \sim N(0,1) \tag{1}$$

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \, \varepsilon_{t-i}^2 \tag{2}$$

where $\alpha_0 > 0$ and $\alpha_i \geq 0, \ldots, \alpha_q \geq 0$.

Usually conditional variance σ_t^2 is called h_t for the simplicity, and the same simplification is done in this study from now on.

The ARCH-model provides a framework for the volatility analysis of time series models. Plain ARCH- models have rarely been used. There are several deficiencies which should be taken into account when a plain ARCH-model is used. According to Brooks (2002, 452), the major deficiencies are:

- Difficulty to select the number of lags of the squared residuals in the model.

- The number of lags of the squared error that are required to capture all of the dependence in the conditional variance, might be very large. This would result in a large conditional variance model that was not parsimonious.

- Non-negativity constraints might be violated. When there are more parameters in the conditional variance equation, the more likely it is that one or more of them will have negative estimated values.

The GARCH model is more widely employed in practice compared to ARCH model since it takes into account some deficiencies that plain ARCH model cannot take.

4.3 The GARCH model

The GARCH model was first developed by Bollerslev (1986) and Taylor (1986). The GARCH model takes into account some of the deficiencies that the ARCH model does not, e.g. the GARCH model is parsimonious and avoids overfitting (Brooks 2002, 453). In this case, parsimonious means that model is less likely to breach non-negativity constrain. The main difference compared to the ARCH model is the dependency of the conditional variance upon its own previous lags. Again, disturbances are retrieved from the mean equation. The GARCH(p,q) equation, according to Bollerslev et al. (1988), is as following:

$$\varepsilon_t | \psi_{t-1} \sim N(0, h_t), \quad (3)$$

$$h_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i u_{t-i}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2, \quad (4)$$

Where

$p \geq 0, \quad q > 0$
$\alpha_0 > 0, \quad \alpha_1 \geq 0, \quad i = 1,\ldots, p$
$\beta_j \geq 0, \quad i = 1,\ldots, q$

In the equation 4 the current conditional variance is parameterized to depend upon p lags of the squared errors and q lags of conditional variances. h_t is known as the conditional variance because it is a one period ahead estimate for the variance calculated based on past information though relevant. The GARCH model can be interpreted as following: α_0 is a long term average value, α_i is the ARCH term, u_{t-i}^2 is one period lagged and squared error term (the volatility information during the previous period), β_j is GARCH term and σ_{t-j}^2 is the fitted variance from the model during the previous period. Non-negativity constraints are also included into the model. Usually, higher order models are not used since GARCH(1.1) is capable to capture both ARCH and GARCH effects.

4.4 Parameter estimation using maximum likelihood

Ordinary least squares (OLS) approach cannot be used for estimating parameters in ARCH or GARCH models since the model is no longer in usual linear form. Briefly, in the OLS method sum of squared errors is minimized. The residual sum of squares (RSS) depends only on the parameters in the conditional mean equation, and not the conditional variance, and hence RSS minimization is no longer an appropriate objective (Brooks 2002, 455). GARCH family models require a different approach for the model estimation. In the maximum likelihood technique, the most likely values of the parameters are found, given the actual data. More specifically, a log-likelihood function is formed and the values of the parameters that maximize it are sought (Brooks 2002, 456). The approach can be used in both, linear and non-linear models.

4.5 Multivariate GARCH (MGARCH) models

Generally speaking, the MGARCH models are in spirit very similar compared to their univariate counterparts, excepts that the MGARCH models also specify equations for how the covariances move over time (Brooks 2002, 506). Actually, covariances may vary substantially over time and those have a significant role in how the risk premium move over time (Bollerslev et. al. 1988). The multivariate GARCH models allow to study the volatility contagion between several markets. Compared to univariate GARCH models, where volatility and fitted variance influence only within one market, MGARCH models provide an interesting viewpoint how information about volatility and fitted variance move from one market to another.

It is worth mentioning that the MGARCH models include some unfavorable features that need to be taken into account when the model is constructed. Teräsvirta & Silvennoinen (2009) have listed the unwanted features:

- The number of parameters in the MGARCH model often increases rapidly with the dimension of the model.
- The model specification should be parsimonious in order to allow easy estimation of the model. However, seeking for parsimoniousity may lead to over-simplification where relevant dynamics in the covariance structure is lost.
- By definition, covariance matrices need to be positive.

Creating a model that would satisfy above-mentioned conditions has been problematic. The first GARCH model extension for the conditional covariance matrices was the VEC model by Bollerslev, Engle and Woolridge (1988). The VEC model by Bollerslev, Engle and Woolridge (1988) was based on the original ARCH model by Engle, Granger, and Kraft (1984).

Bollerslev, Engle and Woolridge (1988) created the general multivariate GARCH model for the conditional covariance matrices:

$$y_t = \mu_t + \epsilon_t \tag{5}$$

$$\epsilon_t | \phi_{t-1} \sim N(0, h_t) \tag{6}$$

In the equation 5, μ_t is the N x 1 vector of conditional expectation of y at time period t. ϵ_t denotes the N x 1 vector of shocks at time t. ϕ captures all available information at time t – 1. Disturbances are expected to be normally distributed with zero mean and constant variance.

The model specification can be started by representing the model used in this study. The model consists of two parts. First, the Vector autoregression model allows for modelling return dependencies between variables. In the VAR model independent variables are lagged with one period compared to dependent variable. The VAR model allows autocorrelations and cross correlation in the returns. Then, the

MGARCH model is applied in order to model time-varying variances and covariances.

$$r_{it} = \alpha_{i0} + \sum_{j=1}^{4} \alpha_{ij} r_{jt-1} + \varepsilon_{it}, \varepsilon_{it} \mid I_{it-1} \sim N(0, h_{it}) \quad i = 1,2,3,4 \tag{7}$$

$$\varepsilon_{it} = v_{it} h_{it}^{1/2} \quad v_{it} \sim N(0,1) \tag{8}$$

$$h_{it} = c_{ii} + \sum_{j=1}^{4} \alpha_{ij} \varepsilon_{jt-1}^{2} + \sum_{j=1}^{4} \beta_{ij} h_{jt-1} \tag{9}$$

In the equation 7, r_t is return series for i (in this case i= 1,2,3,4) an error term (ε_{it}) with conditional variance h_{it}. The equation 8 v_t is normally distributed with zero mean and unit variance. Then ε_{it} need to be also normally distributed with zero mean and variance h_t. The variance equation (equation 9) specifies the GARCH(1.1) model, conditional variance h_t depends on previous squared error terms (ε_{t-1}^{2}) and previous conditional variance terms (h_{t-1}). Next paragraphs the variance equations are studied more closely.

There are four MGARCH parametrizations used studying time-varying variances and covariances: the VECH model of Bollerslev, Engle and Wooldridge (1988), the constant conditional correlation (CCC) model by Bollerslev (1990), the dynamic conditional correlation (DCC) model by Engle (2002), and the BEKK model by Baba, Engle, Kraft and Kroner (1990) and Engle and Kroner (1995). Kroner and Ng (1998) stated that choice of a multivariate volatility model can lead to substantially different conclusion. Therefore, it is crucial to use multiple MGARCH models to confirm the result. The BEKK model is being used as the benchmark model since it assumes that variance-covariance matrix is not always positive, but may also be negative.

4.5.1 The Diagonal VECH (DVECH) model

Bollerslev, Engle and Wooldridge (1988) developed the VECH model from the basis of the univariate GARCH model. In the VECH model components in conditional variance-covariance matrix are the linear function of all lagged squared errors and returns, as well as the cross- products of squared errors, also known as innovations. The VECH model is flexible but it still has its weaknesses. Firstly, number of parameters may increase substantially when the number of modelled assets increases. The number of parameters of VECH model can be calculated as $\frac{3}{2}\mathrm{N}(\mathrm{N}+1)$ (Kroner and Ng 1998, 820). Secondly, the condition for the positive definitiveness for the variance covariance matrix is threatened, especially when the number of parameters increases (Silvennoinen and Teräsvirta 2009).

Bollerslev, Engle and Wooldridge (1988) created the Diagonal VECH (DVECH) model by restring the number of parameters of the original VECH model. In the DVECH model, the variance-covariance matrix depends on only its own lags, as well as previous value of $\epsilon_{it}\epsilon_{jt}$, while A_i and B_j are assumed to be diagonal (equation 10). In the other words, dynamic independence between volatilities are not allowed in the model. The diagonal GARCH-VECH (DVECH) model is simpler compared to i.e. the standard VECH model.

$$h_{ij,t} = C_{ij} + A_{ij}\epsilon_{it-1}\epsilon_{jt-1} + B_{ij}h_{ij,t-1} \tag{10}$$

When the equation consists of four variables (N=4), then the representation would be as following:

$$\begin{bmatrix} h_{11,t} \\ h_{12,t} \\ \vdots \\ h_{44,t} \end{bmatrix} = \begin{bmatrix} c_{11} \\ c_{12} \\ \vdots \\ c_{44} \end{bmatrix} + \begin{bmatrix} a_{11} & 0 & \cdots & 0 \\ 0 & a_{22} & \cdots & 0 \\ \vdots & \vdots & \ddots & 0 \\ 0 & 0 & 0 & a_{44} \end{bmatrix} \begin{bmatrix} \epsilon^2_{1,t-1} \\ \epsilon_{1,t-1} \quad \epsilon_{2,t-1} \\ \vdots \\ \epsilon^2_{4,t-1} \end{bmatrix} + \begin{bmatrix} b_{11} & 0 & \cdots & 0 \\ 0 & b_{22} & \cdots & 0 \\ \vdots & \vdots & \ddots & 0 \\ 0 & 0 & 0 & b_{44} \end{bmatrix} \begin{bmatrix} h_{11,t-1} \\ h_{12,t-1} \\ \vdots \\ h_{44,t-1} \end{bmatrix} \tag{11}$$

And equations are written as:

$$
\begin{aligned}
h_{11,t}^2 &= c_{11}^0 + a_{11}\epsilon_{1,t-1}^2 + b_{11}h_{1,t-1}^2 \\
h_{12,t} &= c_{12}^0 + a_{12}\epsilon_{1,t-1}\epsilon_{2,t-1} \quad + b_{12}h_{12,t-1} \\
h_{13,t} &= c_{13}^0 + a_{13}\epsilon_{1,t-1}\epsilon_{3,t-1} \quad + b_{13}h_{13,t-1} \\
h_{14,t} &= c_{14}^0 + a_{14}\epsilon_{1,t-1}\epsilon_{4,t-1} \quad + b_{14}h_{14,t-1} \\
h_{22,t}^2 &= c_{22}^0 + a_{22}\epsilon_{2,t-1}^2 + b_{22}h_{2,t-1}^2 \\
&\vdots \\
h_{44t}^2 &= c_{44} + a_{44}\epsilon_{4,t-1}^2 + b_{44}h_{4,t-1}^2
\end{aligned}
\tag{12}
$$

It is important to notice that model assumes that individual conditional variances and covariances only depend on their own lags and lagged squared residuals. Therefore, the possibility of missing important information is possible. The model is simple but it does not ensure the existence of a positive definite variance covariance matrix in each step. So numerical problems may occur.

4.5.2 The BEKK model

As mentioned earlier, BEKK (Baba; Engle; Kraft; Kroner 1990) provides the solution for the positive definiteness problem. The BEKK model is presented below

$$
\begin{aligned}
H_t = CC' + \sum_{i=1}^{p} A_i\,(\epsilon_{t-i}\epsilon_{t-i}')A_i' \\
+ \sum_{j=1}^{q} B_j\,H_{t-j}B_j'
\end{aligned}
\tag{13}
$$

In the equation 13, *C* is the lower triangular and *C'* is the upper triangular, but also one of the *(N x N)* parameter matrixes with A_i and B_j. The BEKK model operates under GARCH(1.1). Therefore, p=1 and q=1. The positive definiteness of the covariance matrix is ensured owing to the quadratic nature of the terms on the equation's right hand side. In the case of two variables (N = 4) and p = 1 and q =1, the complete formula would be expressed as:

$$\begin{bmatrix} h_{11,t} & \cdots & h_{14,t} \\ \vdots & \ddots & \vdots \\ \cdot & \cdots & h_{44,t} \end{bmatrix} = \begin{bmatrix} c_{11} & \cdots & c_{14} \\ \vdots & \ddots & \vdots \\ \cdot & \cdots & c_{44} \end{bmatrix} + \begin{bmatrix} c_{11} & \cdots & c_{14} \\ \vdots & \ddots & \vdots \\ \cdot & \cdots & c_{44} \end{bmatrix}' +$$
$$\begin{bmatrix} a_{11} & \cdots & a_{14} \\ \vdots & \ddots & \vdots \\ \cdot & \cdots & a_{44} \end{bmatrix} \begin{bmatrix} \epsilon^2_{1,t-1} & \cdots & \epsilon_{1,t-1}\varepsilon_{4,t-1} \\ \vdots & \ddots & \vdots \\ \epsilon_{4,t-1}\varepsilon_{1,t-1} & \cdots & \epsilon^2_{4,t-1} \end{bmatrix} \begin{bmatrix} a_{11} & \cdots & a_{14} \\ \vdots & \ddots & \vdots \\ \cdot & \cdots & a_{44} \end{bmatrix}' + \qquad (14)$$
$$\begin{bmatrix} b_{11} & \cdots & b_{14} \\ \vdots & \ddots & \vdots \\ \cdot & \cdots & b_{44} \end{bmatrix} \begin{bmatrix} h_{11,t-1} & \cdots & h_{14,t-1} \\ \vdots & \ddots & \vdots \\ \cdot & \cdots & h_{44,t-1} \end{bmatrix} \begin{bmatrix} b_{11} & \cdots & b_{14} \\ \vdots & \ddots & \vdots \\ \cdot & \cdots & b_{44} \end{bmatrix}'$$

This model (equation 14) assumes the conditional covariance matrix of asset returns is determined by the outer product matrices of the vector of past return shocks. Because the second and third terms on the right-hand side of the equation 14 are expressed in quadratic forms, the positive definiteness of the conditional covariance matrix of asset returns is guaranteed, provided that *CC'* is positive definite. Even though, this model overcomes the major weakness (large number of parameters) of the VECH model, it still has (5/2) * N^2 + (N / 2) parameters (Kroner and Ng 1988, 821). In this study only 4 assets are used, and the BEKK model still has 42 parameters. Especially, studies where multiple assets are modelled, the number of parameters restricts the applicability of the BEKK model.

4.5.3 The Constant Conditional Correlation (CCC) model

The CCC (Bollerslev 1990) model sets the assumption that correlations between each pair of returns are constant. Therefore, the CCC model consists only of the equations for the variances. The actual CCC-GARCH model (Bollerslev 1990) can be presented as follows:

$$H_t = D_t P D_t \tag{15}$$

where D_t is the diagonal matrix with time-varying standard deviations in the diagonal (equation x).

$$D_t = diag(h_{1,t}^{1/2},\ldots, h_{N,t}^{1/2}) \tag{16}$$

and P is positive definite with $\rho_{ii} = 1$, $i = 1, \ldots, N$.

In the equation 16 variance terms $h_{1,t}^{1/2},\ldots, h_{N,t}^{1/2}$ are the univariate GARCH(p,q) terms. In this case conditional variances can be written in a vector form:

$$h_t = \omega + \sum_{j=1}^{q} A_j r_{t-j}^{(2)} + \sum_{j=1}^{p} B_j h_{t-j} \tag{17}$$

ω is a N × 1 vector, A and B are diagonal N × N matrices, and $r_t^{(2)} = r \odot r$. Logically, when P referring to conditional correlation matrix is positive definite, ω and the diagonal elements of A_j and B_j are positive, the conditional covariance matrix H_t is positive definite.

In the case of four variables the CCC-GARCH(1.1) model can be expressed as:

$$H_t = \begin{bmatrix} \sqrt{h_{11,t}} & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & \sqrt{h_{44,t}} \end{bmatrix} \begin{bmatrix} 1 & \cdots & \rho_{14} \\ \vdots & \ddots & \vdots \\ \rho_{41} & \cdots & 1 \end{bmatrix} \begin{bmatrix} \sqrt{h_{11,t}} & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & \sqrt{h_{44,t}} \end{bmatrix} \tag{18}$$

Estimated variances come from either Exponentially Weighted Moving Average (EWMA) or univariate GARCH schemes. In the both schemes, each covariance is obtained by multiplying the correlation coefficient between standardized or non-standardized returns by the product of the standard deviations obtained from the conditional volatility models previously estimated by EWMA or GARCH schemes. The representation is widely employed because number of estimated parameters is smaller compared to other models.

4.5.4 The Dynamic Conditional Correlation (DCC) model

The dynamic conditional correlation (Engle 2002) model allows for the dynamic dependencies in the correlations. Basically, an EWMA representation can be used in estimating variances of individual returns. Also, variances of individual returns can be estimated through univariate GARCH models. Engle (2002) generalized the CCC model to the Dynamic Conditional Correlation model (DCC). In the DCC model the conditional quasicorrelations R_t follow a GARCH(1,1)- like process [Engle (2009) and Aielli (2009)] described that parameters in R_t are not standardized to be correlations, and, therefore, are known as quasicorrelations) (Stata 2012). Preserving parsimony, all the conditional quasicorrelations are restricted to follow the same dynamics (Stata 2012). The dynamic conditional correlation model can be executed in two phases. First, the GARCH parameters are estimated. The following step is the estimation of the correlation coefficients for the model.

$$H_t = D_t R_t D_t \tag{19}$$

In the equation 19 H_t is N x N conditional covariance matrix, R_t is the conditional correlation matrix and D_t is the diagonal matrix with time-varying standard deviations in the diagonal (similar as presented in the equation x). R_t can be expressed as following:

$$R_t = diag(Q_t)^{-1} Q_t diag(Q_t)^{-1} \tag{20}$$

where Q is a symmetric positive definete matrix. The representation for Q is:

$$Q_t = (1 - \theta_1 - \theta_2)\bar{Q} + \theta_1 \xi_{t-1} \xi'_{t-1} + \theta_2 Q_{t-1} \tag{21}$$

Q is the N x N unconditional correlation matrix of the standardized residuals ξ_{ij}. The parameters θ_1 and θ_2 are non-negative scalar parameters with a sum of less than unity. The correlation estimator is:

$$p_{ij,t} = \frac{q_{ij,t}}{\sqrt{q_{ii,t} q_{jj,t}}} \tag{22}$$

In the CCC case, $R_t = R$ and $R_{ij} = \rho_{ij}$ and in the Diagonal model ρ_{ij}= 0 fort all *i* and *j*. The choice between conditional correlation models (constant or dynamic) affects a determinant way to the results obtained by the models.

5 DATA DESCRIPTION AND ANALYSIS

In the data description part are introduced the factors that affected to data collection. Also, data description part clarifies how and where the data is collected. Variables are also presented regionally, and descriptive statistical analysis and correlation analysis is performed for each of the variable.

5.1 Data Collection

All of the time-series data, except European Renewable Index, used in this study is retrieved from Thomson & Reuters Datastream database. European Renewable Index is retrieved from its website (*www.sgindex.com*). Data type for an alternative energy indexes and technology indexes is Price Index (PI) which is the default type for the equity indexes. Price index was chosen because its availability. Total return index (TRI) was another option. However, it was not available for all the indexes. Therefore, price index was chosen. Nearest contract to maturity forward prices were used to describe commodity prices, such as Brent crude oil (Brent), West Texas Intermediate (WTI), and Henry Hub natural gas prices. Forward prices were used instead of spot prices for several reasons. Sadorsky (2001) and Scholtsens & Wang (2008) found out that future prices reflects oil prices more authentically compared to spot prices. Sadorsky (2001), Scholtsen & Wang (2008) also found out that spot prices of oil are sensitive to the short-term supply-demand shocks. Gurcan (1998) and Crowder and Hamed (1993) noticed that crude oil futures are unbiased predictors of future spot prices. Data type for commodity futures is price.

Observations were collected over period of December 31, 2006 to December 31, 2015. So, each time series covers 9 years and includes 2350 observations. Data frequency is daily in order to ensure sufficient amount of observations for the requirements of MGARCH model. A few research papers have been published concerning the influence of data frequency to the ARCH-effects. Andersen and Bollerslev (1998); Arouri and Nguyen (2010) argued that high frequency data may lead to some problems in the GARCH modelling. I.e. forecasts may be inaccurate in multivariate GARCH models. However, daily data frequency is used in order to model return and volatility dynamics with the latest data. Also, the usage of the daily observations ensures that that number of observations is sufficient for the requirements for the econometric GARCH models. Any missing data point is being replaced with the observation of the most recent trading session. All the obtained time series are denoted in US Dollars. Regional aspect has considered when time series are selected. Time series are obtained from two regions: North-America and Europe. RATS pro version 9.10 was used producing results from the mean and variance equations.

In this study continuously compounded daily returns are being used. Continuously compounded daily returns (r) are calculated by taking logarithm from the division where price (P) at the moment t is divided by the earlier moment's price (P_{t-1}).

$$r = (log(P_t \,/\, P_{t-1})) * 100 \tag{23}$$

5.2 Selection of variables

Alternative energy indexes and technology indexes are regional. Brent Crude oil is used for Europe, and WTI is used for North-America. Brent and WTI returns are highly correlated (Maslyuk & Smyth 2009, 20) so both crude oil types could be used for both regions. However, temporal reconciliation is between variables within region is more accurate when the pricing of the assets follows the region's time zone. Henry Hub Natural Gas Spot prices and returns have the most continuous history. Furthermore, Henry Hub Natural gas spot- and future prices have been used in similar studies compared to this. Therefore, it is acceptable to use Henry Hub Natural Gas returns and prices for both regions.

Variables used for Europe and North-America are listed below:

1. Europe
   a) ERIX European Renewable Energy Index, ALT(ERI)
   b) Stoxx Europe 600, TEC(SE6)
   c) Brent Blend Crude Oil, OIL(BRE)
   d) Henry Hub Natural Gas, GAS(HHB)

2. North-America
   a) WilderHill Clean Energy Index, ALT(WIL)
   b) New York Stock Exchange Arca Technology 100, TEC(ARC)
   c) West Texas Intermediate Crude Oil, OIL(WTI)
   d) Henry Hub Natural Gas, GAS(HHB)

5.2.1 Variables; Europe

European Renewable Index ALT(ERI) is one of the few renewable energy indexes whose constituents locate only in Europe. This index comprises public companies engaged in six sectors: a) Biomass, b) Geothermal, c) Sea Energy, d) Solar, e) Water, and d) Wind (Societe Generale, Corporate & Investment Banking, 2016). ALT(ERI) tracks the performance of the largest stocks in the European renewable energy sector. Furthermore, ALT(ERI) consist of the largest companies in the area of renewable energy sector in Europe. Each component has a minimum weight of 5%, and the remaining weight is allocated according to market capitalization (Societe Generale, Corporate & Investment Banking, 2016).

The index was founded in September 1, 2003. Plotted raw data (prices) and continuously compounded daily returns are shown in the figure 4. Downward price trend is clearly visible on the left half of the figure 4. Consistently, daily returns generated from the daily prices are expected to be negative. When the financial crises in 2008 really actualized (LHS of the figure 4), the index value of ALT_ERI crashed and following four years (2008 - 2012) the trend was declining. On the right side daily returns are presented. Observing the RHS of the figure 4, high volatility clusters are present in 2008, 2010 and 2011.

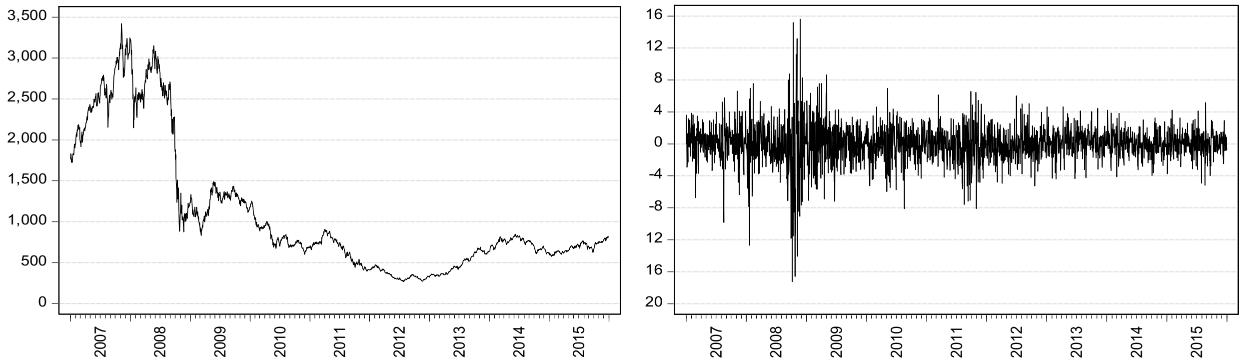

Figure 4. Raw index value plot (LHS) & daily percentual returns (RHS) for ALT(ERI)

Stoxx ® Europe 600 Technology Index TEC(SE6) is one of the 19 Stoxx supersector indices. TEC(SE6) is owned by subsidiary of Deutche Börse Group and consists of 22 European companies whose primary source of the revenue comes from technology (Stoxx, 2016). Index is weighted quarterly according to free-float capitalization and the base value for the index was dated on December 31, 1991 as 100 (Stoxx, 2016). The constituent list is produced for the index with a fixed number of constituents in order to determine replacements for any stock deleted from the indices due to a corporate action (Stoxx, 2016). Plotted raw data and continuously compounded daily returns are shown in figure 5. Similarly compared to ALT(ERI) substantial index value crash happened in 2008 but after financial crises the trend has been upward sloping. High volatility clusters are clearly visible during the years 2008, 2011 and 2015 (LHS of the figure 5).

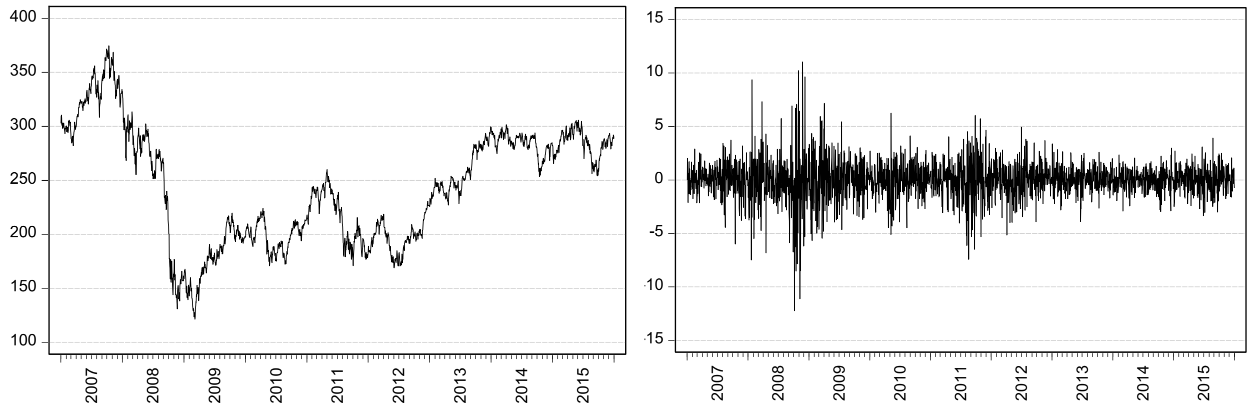

Figure 5. Raw index value plot (LHS) & percentual daily returns (RHS) for TEC(SE6)

Brent Crude is a major trading classification of sweet light crude oil. Brent crude is drilled from North-Sea and is equivalent to West Texas Intermediate (Speight 2011, 126). Brent is the primary energy source for about 1/3 of the world's needs (Speight 2011, 126). Historically, the price development of oil has been unstable. The highest (nearest contract to maturity) future price for the barrel was 146 USD in the study period, and was recorded in July 2008 (LHS of the figure 6). Analogously, returns generated from daily future prices have also been volatile. Maximum and minimum returns are located at global financial crises in September 2008 (RHS of the figure 6). High volatility clusters appear in 2008, 2011 and 2015.

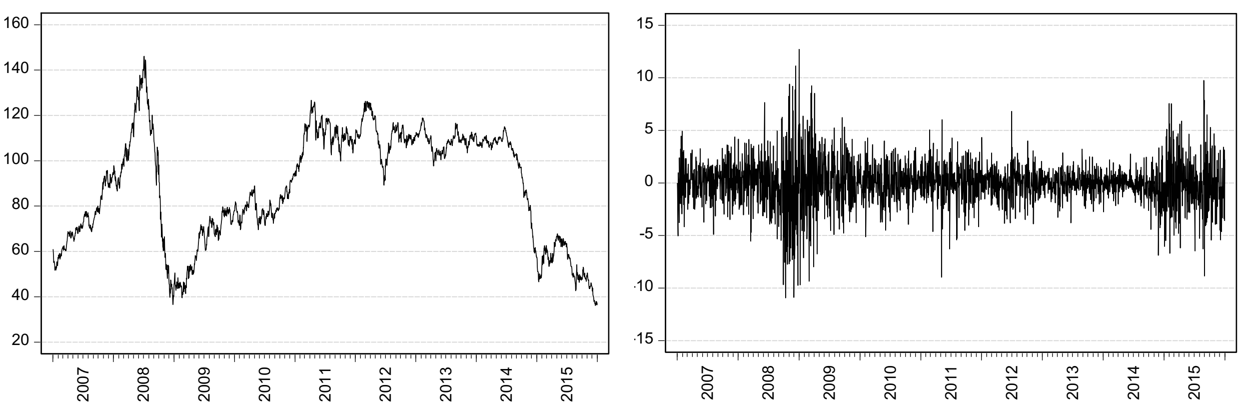

Figure 6. Raw index value plot (LHS) & percentual daily returns (RHS) for OIL(BRE)

The Henry Hub is a distribution hub on the natural gas pipeline system in Erath, Lousiana U.S. It is owned by Sabine Pipe Line LLC, a subsidiary of EnLink

Midstream Partners LP who purchased the pipeline system from Chevron Corporation in 2014 (EIA 2015, 70). Future prices for natural gas distributed by Sabine Pipe Line are listed in U.S. dollars per millions of British thermal units ($/mmbtu). Interpreting the price graph from the figure 7 (LHS), GAS(HHB) prices have fluctuated more compared to other variables in this study. Sharp upward and downward return spikes appear in 2009, 2011, 2014 and 2015 (figure 7, RHS). Interestingly, the spikes are singular referring to less present ARCH effects.

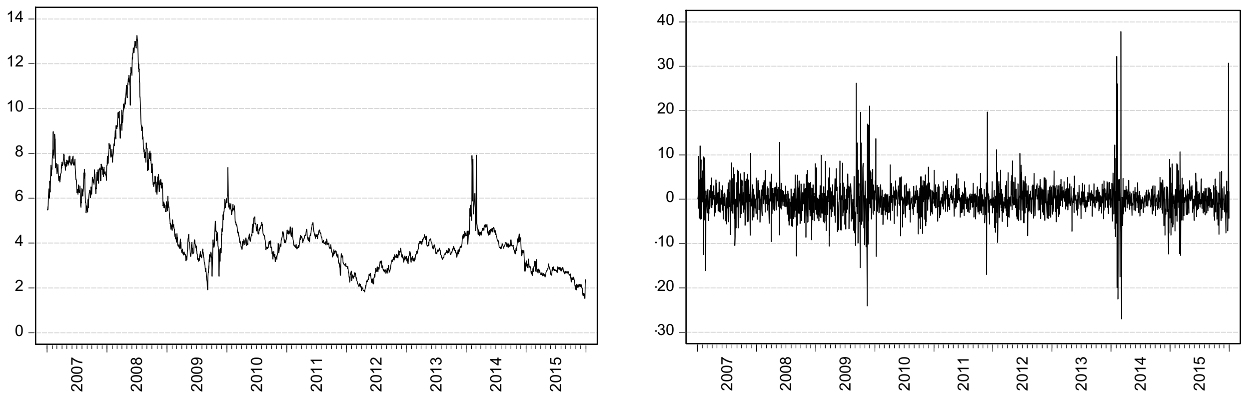

Figure 7. Raw price data plot (LHS) & percentual daily returns (RHS) for GAS(HHB)

5.2.2 Variables; North-America

WilderHill Clean Energy Index ALT(WIL) is a modified dollar weighted index of 54 companies engaged in the clean (renewable) energy business in the U.S. The index is the oldest solely tracking clean energy companies. No single stock may not exceed 4 % of the Clean Energy Index weight at the start of quarterly rebalancing. In order to get chosen to ALT(WIL) index stock needs to be identified as one that has a significant exposure to clean energy, or contribute to the advancement of clean energy, or be important to the development of clean energy. The index is generally comprised of companies that operate in the following sectors: Renewable Energy Supplies, Energy storage, Cleaner Fuels, Energy Conversion, Power Delivery and Conversion and Greener Utilities. The index is calculated using a modified equal dollar weighting methodology. The market capitalization for a majority of ALT(WIL) is typically over $ 200 million. (WilderShares, 2016)

The behavior of the raw price data plot of the ALT(WIL) (LHS of the figure 8) is similar compared to its counterpart [ALT(ERI)]. Volatility bunches are clearly visible around 2008-2009, 2010, 2011-2012 (RHS of the figure 8).

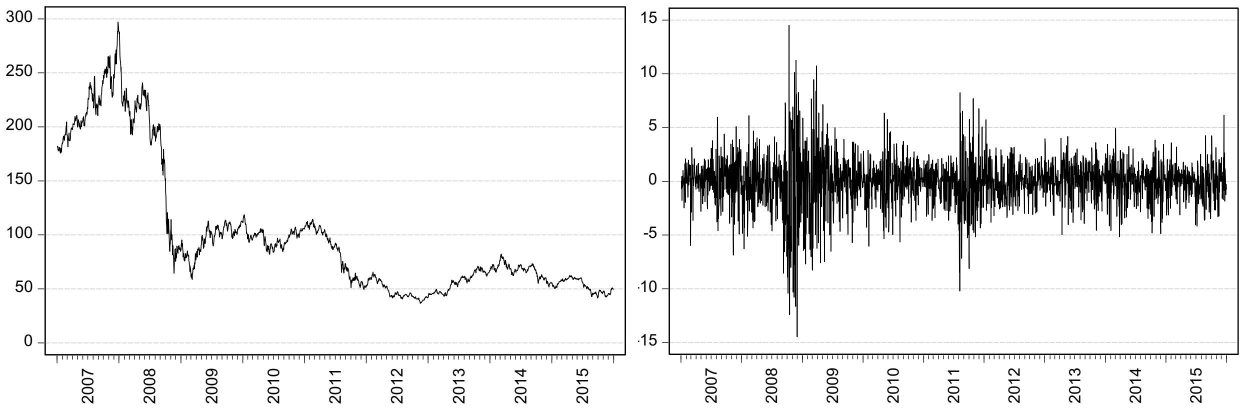

Figure 8. Raw price data plot (LHS) & daily percentual returns (RHS) for ALT(WIL)

New York Stock Exchange Arca Technology 100 [TEC(ARC)] is a price weighted index that consists of the common stocks of U.S technology companies. The NYSE Arca Technology 100 Index is one of the oldest US based technology indexes. It was founded by the Pacific Stock Exchange and named by the Pacific Stock exchange in 1982. The index consists of leading Technology companies mainly in U.S region. Several technology industries are taken into consideration; computer hardware, software, semiconductors, telecommunications, electronics, aerospace, defense, healthcare and biotechnology. (New York Stock Exchange, 2016)

The financial crisis did not cause substantial price collapse to TEC(ARC) in 2008 compared to other assets under this study. Raw price data plot indicates strong growth since 2009 in the price of the index (LHS of the figure 9). High volatility clusters are present in 2008-2009, 2011-2012 and 2015 (RHS of the figure 9).

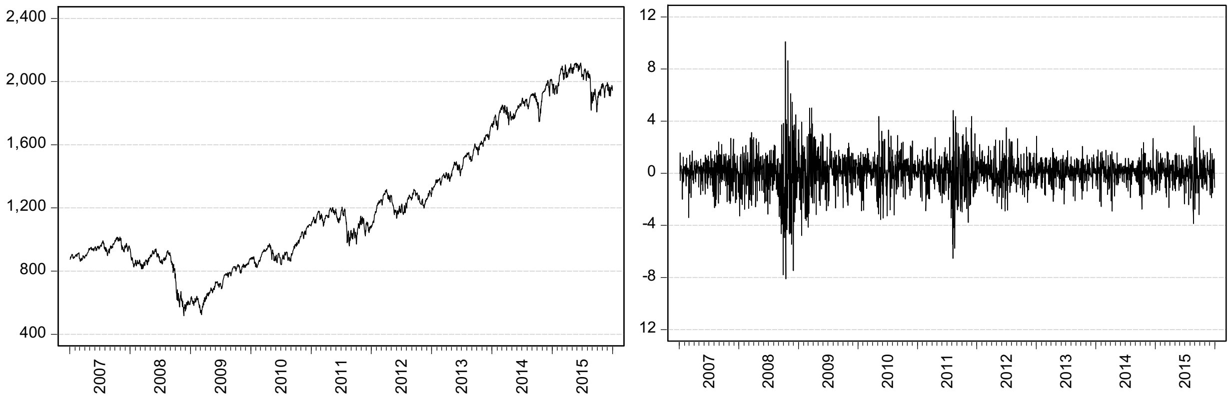

Figure 9. Raw price data plot (LHS) & percentual daily returns (RHS) for TEC(ARC)

West Texas Intermediate crude oil OIL(WTI) is another benchmark index for the crude oil, besides Brent crude oil. It is also known as "Texas Light Sweet". WTI is recognized as a high grade crude oil. WTI is refined mostly in the Midwest and Gulf Coast regions of the USA and the bulk of WTI crude oil is consumed in the USA (Speight 2011, 127).

Qualities of WTI are optimal for producing products such as low-Sulphur gasoline and low-Sulphur diesel. Therefore, the difference in grade quality compared with others, such as Brent crude or Dubai Crude, leads to the position where WTI is traded with premium over the benchmark oil indexes (Speight 2011, 127).

Price and return graphs (figure 10) are similar. And as earlier is noticed, prices are highly correlated between future prices of Brent crude and WTI. High volatility clusters appear in 2008-2009 and 2014-2015 (RHS of the figure 10).

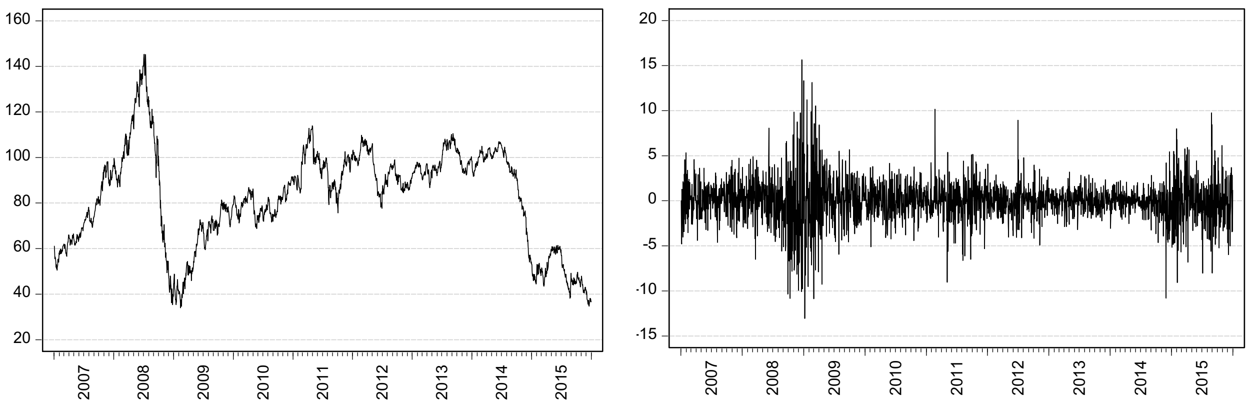

Figure 10. Raw price data plot (LHS) & daily percentual returns (RHS) for OIL(WTI)

5.3 Correlation analyses

In the table 1. results from the correlation analyses between variables regionally are presented. The correlation coefficients in the table 1 are in-line with earlier studies done in North-America (Sadorsky 2009; Sadorsky 2012). Also correlation coefficients seem to be relative similar in both regions.

Table 1. Correlation between daily returns in Europe (upper table) and North America (lower table)

Europe	**ALT_ERI**	**TEC_SE6**	**OIL_BRE**	**GAS_HHB**
ALT_ERI	1			
TEC_SE6	0.756	1		
OIL_BRE	0.351	0.354	1	
GAS_HHB	0.094	0.066	0.203	1
North-America	**ALT_WIL**	**TEC_ARC**	**OIL_WTI**	**GAS_HHB**
ALT_WIL	1			
TEC_ARC	0.828	1		
OIL_WTI	0.373	0.316	1	
GAS_HHB	0.021	0.053	0.208	1

The correlation coefficient is high between ALT_ERI and TEC_SE6 (0.756), and ALT_WIL and TEC_ARC (0.828). In the other words, correlation is strong between alternative energy index returns and technology index returns in Europe and North-America. As expected, correlation between alternative energy index returns and crude oil returns are lower compared to correlation coefficients between alternative technology indexes and alternative energy indexes in both regions. The correlation between ALT_ERI and OIL_BRE is 0.351, and correlation between ALT_WIL and OIL_WTI is 0.373. Between Technology index returns and crude oil returns seems to have parallel correlation coefficient compared to the correlation coefficient between alternative energy index returns and crude oil returns. Natural gas returns seem to have low correlation coefficient with all other variables. Interesting observation is that there is low correlation between oil and natural gas in both regions.

5.4 Descriptive Statistics

In the table 2 are presented descriptive statistics from the continuously compounded daily returns. All the seven variables are presented.

Table 2. Descriptive statistics generated from continuously compounded daily returns

	ALT_ERI	TEC_SE6	OIL_BRE	GAS_HHB	ALT_WIL	TEC_ARC	OIL_WTI
Mean (%)	-0,033	-0,002	-0,021	-0,042	-0,056	0,034	-0,021
Median (%)	0	0,012	0	0	0,017	0,049	0
Maximum (%)	15,613	11,037	12,707	26,771	14,52	10,099	15,659
Minimum (%)	-17,249	-12,228	-10,946	-14,893	-14,467	-8,12	-13,065
Std. Dev.	2,337	1,755	2,145	3,039	2,264	1,313	2,369
Skewness	-0,426	-0,196	-0,064	0,659	-0,339	-0,196	0,041
Kurtosis	9,953	8,26	6,852	7,851	7,525	8,634	7,752
Jarque-Bera	4802,648	2723,283	1453,672	2473,289	2048,539	3121,264	2210,448
Probability	0	0	0	0	0	0	0
Observations	2349	2349	2349	2349	2349	2349	2349
Autocorrelation coeff. (Level data)	**ALT_ERI**	**TEC_SE6**	**OIL_BRE**	**GAS_HHB**	**ALT_WIL**	**TEC_ARC**	**OIL_WTI**
lag 1	***0.068	-0,019	***-0.067	***-0.085	0,03	***-0.064	***-0.065
lag 2	***-0.022	*-0.045	***-0.006	***0.046	0,024	***-0.029	***-0.018
lag3	***-0.03	**-0.034	**0.005	***-0.046	-0,035	***-0.009	***0.022
lag 4	***0.064	**0.038	***0.061	***0.016	0,008	**-0.002	***0.052
lag 5	***-0.063	**-0.033	***-0.049	***-0.065	-0,043	**-0.01	***-0.055
lag 6	***-0.032	**-0.031	***0.029	***0.001	0,011	**-0.016	***0.015
lag 7	***0.012	*0.03	***-0.037	***0.018	0,009	*-0.002	***-0.05
lag 8	***0.026	*0.047	***0.006	***-0.005	0,005	*0.018	***0.021
*** denotes significance at 1% risk level, ** at 5% risk level and * at 10% risk level							
Autocorrelation coeff. Squared r (Level data)	**ALT_ERI**	**TEC_SE6**	**OIL_BRE**	**GAS_HHB**	**ALT_WIL**	**TEC_ARC**	**OIL_WTI**
lag 1	***0.221	***0.117	***0.181	***0.072	***0.297	***0.209	***0.208
lag 2	***0.29	***0.185	***0.245	***0.119	***0.339	***0.344	***0.238
lag3	***0.306	***0.207	***0.284	***0.083	***0.319	***0.232	***0.245
lag 4	***0.255	***0.153	***0.211	***0.109	***0.3	***0.238	***0.186
lag 5	***0.397	***0.279	***0.352	***0.083	***0.4	***0.324	***0.316
lag 6	***0.272	***0.193	***0.159	***0.062	***0.331	***0.284	***0.192
lag 7	***0.266	***0.156	***0.212	***0.102	***0.366	***0.28	***0.199
lag 8	***0.28	***0.164	***0.266	***0.079	***0.29	***0.248	***0.282
*** denotes significance at 1% risk level, ** at 5% risk level and * at 10% risk level							
ADF test stat. (26 lags)	***-45.253	***-49.38	***-51.765	***-51.712	***-47.009	***-54.643	***-51.690
Phillips-Perron	***-45.200	***-49.504	***-51.738	***-52.845	***-47.013	***-51.856	***-51.700

All mean values, except TEC(ARC) are negative. The observation is in-line with the downward trends of asset prices. All mean and median values are close to zero. The standard deviation values are higher than those corresponding to the means. The standard deviation of GAS(HHB) is higher compared to other variables. The standard deviation of GAS_HHB is 3.039 and returns vary in the range from -14.893 % to 26.771 %. Returns of other variables are concentrated closer to the mean. Therefore, standard deviation values are smaller compared to GAS_HHB. In fact, TEC_ARC has the smallest standard deviation which is 1.313. Each series displays small amount of skewness and a large amount of kurtosis which is typical to financial time series' data. Negative skewness can be explained by the fact that negative news causes a greater decline for the returns compared to increase due positive news. Jarque-Bera test is test to inspect the normality of the sample. According to Jarque-Bera p-value, returns are not normally distributed for any series.

The second panel of the table 2 shows the autocorrelation functions of variables. Coefficients are generated from the level data. Majority of the coefficients are statistically significant at 1 percent confidence level. The result refers to the autocorrelation in time series up till lag eight. ALT_WIL is an exception. ALT_WIL time series does not express signs of the autocorrelation. However, squared return series of ALT_WIL express signs of the autocorrelation and, therefore, it can be used in the GARCH settings. Autocorrelation is also present in all squared returns (table 2, panel 3). The null hypothesis of no autocorrelation between squared residuals can be rejected in 99 % confidence level.

On the fourth panel of the table 2 are listed two tests for stationarity. Augmented Dickey Fuller (ADF) test up to 26 lags expresses that null hypothesis, about presence of unit root, can be rejected for all the seven-time-series. In the other words, time series are stationary. Phillips-Perron (PP) test results are in-line with ADF-test, and indicate that time series' are free from unit root.

6 EMPIRICAL RESULTS

In this section, results from the MGARCH models are presented. First, the results of multiple linear regression model are generated. Then current conditional variance is set to depend upon q lags of the squared error (from the regression model) and p lags of the conditional variance. Using the linear regression model, the broad picture can be created how lagged returns of the variable affects to the current return of the same or another variable. However, linear regression model does not model features such as volatility clustering and leptokurtosis. Daily return plots (figures 4-10) and autocorrelation coefficients (table 2, panel 3) suggest that volatility clustering is present. MGARCH models are capable of modelling both ARCH and GARCH effects among variables which measures short- and long-term persistence in the volatilities. In addition, MGARCH models provide a tool to model time varying variances and covariances. The BEKK model is chosen as the benchmark model since the following reasons: It is not restricted model as VECH, CCC and DCC are and it assumes a positive definite variance. Furthermore, it is the widely utilized MGARCH model in alternative energy economics (Ewing et al. 2002; Sadorsky 2012; Plott 2014).

6.1 The MGARCH results

In the table 3 and 4 results from the mean and variance models of BEKK, DVECH, CCC and DCC are presented. The order of variables is following: Alternative energy index (1), Technology index (2), Crude oil (3) and Natural gas (4). First, the return effects of the mean model, m, are shown. In the variance equations, c denotes constants, a denotes the ARCH terms and b denotes the GARCH terms. The interpretation of table is done as following: i.e. m_{23} denotes the effect of a one period lag of crude oil return on the current period of technology index, a_{12} denotes the short-term volatility spillover from the technology index return to the alternative energy index return. Whereas, b_{24} denotes the long-term volatility spillover from the natural gas returns to the technology index returns.

6.1.1 Results from mean and variance models: Europe

Table 3. Europe: MGARCH parameter estimates (*** denotes significance at 1% risk level, ** at 5% risk level and * at 10% risk level).

	BEKK			Diag.			CCC			DCC		
Mean	Coeff.	T-stat.	Signif.	Coeff.	T-stat.	Signif.	Coeff.	T-stat	Signif.	Coeff.	T-stat	Signif.
m_{10}	0,034	1,107	0,268	0,048	1,281	0,200	0,046	1,566	0,117	0,030	1,105	0,269
m_{11}	0,036 ***	2,802	0,005	0,031	1,069	0,285	0,029	1,069	0,285	0,031	1,244	0,213
m_{12}	-0,001	-0,078	0,938	-0,006	-0,158	0,875	-0,009	-0,257	0,797	-0,005	-0,155	0,877
m_{13}	0,054 ***	4,729	0,000	0,056 ***	2,852	0,004	0,063 ***	4,323	0,000	0,055 ***	2,675	0,007
m_{14}	0,004	0,392	0,695	0,001	0,103	0,918	0,001	0,087	0,930	-0,003	-0,347	0,729
m_{20}	0,044 **	2,003	0,045	0,048	1,540	0,123	0,051 **	2,375	0,018	0,050 **	2,328	0,020
m_{21}	-0,029 ***	-2,596	0,009	-0,025	-1,203	0,229	-0,030	-1,488	0,137	-0,025	-1,306	0,191
m_{22}	-0,019	-1,319	0,187	-0,017	-0,603	0,547	-0,018	-0,652	0,514	-0,023	-0,875	0,382
m_{23}	0,021 **	2,411	0,016	0,020	1,285	0,199	0,021 **	2,057	0,040	0,017	1,090	0,276
m_{24}	0,005	0,622	0,534	-0,001	-0,079	0,937	0,001	0,117	0,907	-0,002	-0,237	0,813
m_{30}	0,034	1,167	0,243	0,019	0,568	0,570	0,031	1,068	0,286	0,034	1,192	0,233
m_{31}	-0,042 ***	-2,708	0,007	-0,047 **	-2,240	0,025	-0,045 **	-2,449	0,014	-0,044 **	-2,533	0,011
m_{32}	0,059 ***	2,756	0,006	0,067 **	2,302	0,021	0,061 **	2,332	0,020	0,059 **	2,402	0,016
m_{33}	-0,048 ***	-2,676	0,007	-0,054 **	-2,336	0,019	-0,049 **	-2,213	0,027	-0,047 **	-2,213	0,027
m_{34}	0,016	1,526	0,127	0,017	1,454	0,146	0,016	1,464	0,143	0,013	1,237	0,216
m_{40}	-0,048	-0,888	0,375	-0,027	-0,458	0,647	-0,010	-0,194	0,846	-0,030	-0,629	0,529
m_{41}	0,066 ***	2,712	0,007	0,057 *	1,959	0,050	0,061 **	2,344	0,019	0,064 ***	2,803	0,005
m_{42}	-0,076 **	-2,346	0,019	-0,046	-1,174	0,240	-0,049	-1,438	0,150	-0,056 *	-1,671	0,095
m_{43}	0,009	0,363	0,717	0,003	0,117	0,907	0,002	0,067	0,946	0,003	0,139	0,889
m_{44}	-0,059 ***	-2,923	0,003	-0,061 ***	-2,912	0,004	-0,060 **	-2,538	0,011	-0,062 **	-2,553	0,011
Variance												
c_{11}	0,330 ***	5,457	0,000	0,082 ***	3,637	0,000	0,139 ***	3,835	0,000	0,064 ***	3,453	0,001
c_{21}	0,070 **	2,265	0,024									
c_{22}	0,116 ***	6,555	0,000	0,021 ***	2,728	0,006	0,046 ***	3,977	0,000	0,022 ***	3,242	0,001
c_{31}	-0,070 *	-1,912	0,056									
c_{32}	0,085 ***	3,950	0,000									
c_{33}	0,121 ***	5,705	0,000	0,017 ***	2,754	0,006	0,029 ***	3,988	0,000	0,023 ***	3,142	0,002
c_{41}	-0,189 ***	-2,726	0,006									
c_{42}	0,131	1,626	0,104									
c_{43}	-0,120	-1,281	0,200									
c_{44}	0,321 ***	3,997	0,000	0,155 ***	3,785	0,000	0,162 ***	4,060	0,000	0,149 ***	3,821	0,000
a_{11}	0,173 ***	5,986	0,000	0,072 ***	7,487	0,000	0,053 ***	5,923	0,000	0,047 ***	6,859	0,000
a_{12}	0,029	1,622	0,105									
a_{13}	0,001	0,053	0,958									
a_{14}	-0,022	-0,755	0,450									
a_{21}	0,116 ***	3,543	0,000									
a_{22}	0,146 ***	7,453	0,000	0,065 ***	7,704	0,000	0,046 ***	5,852	0,000	0,045 ***	7,041	0,000
a_{23}	-0,040 *	-1,821	0,069									
a_{24}	-0,077 **	-2,047	0,041									
a_{31}	0,038 ***	2,662	0,008									
a_{32}	0,038 ***	3,868	0,000									
a_{33}	0,225 ***	17,312	0,000	0,055 ***	7,421	0,000	0,055 ***	8,481	0,000	0,056 ***	7,322	0,000
a_{34}	0,017	0,727	0,467									
a_{41}	-0,007	-0,773	0,439									
a_{42}	-0,002	-0,372	0,710									
a_{43}	-0,007	-0,971	0,331									
a_{44}	0,223 ***	16,131	0,000	0,067 ***	7,246	0,000	0,068 ***	7,919	0,000	0,069 ***	7,537	0,000
b_{11}	0,963 ***	63,624	0,000	0,909 ***	72,296	0,000	0,912 ***	54,811	0,000	0,941 ***	102,241	0,000
b_{12}	0,004	0,502	0,615									
b_{13}	0,016 *	1,935	0,053									
b_{14}	0,050 ***	4,023	0,000									
b_{21}	-0,015	-1,198	0,231									
b_{22}	0,977 ***	144,214	0,000	0,929 ***	100,576	0,000	0,934 ***	83,965	0,000	0,949 ***	126,397	0,000
b_{23}	-0,007	-1,190	0,234									
b_{24}	-0,028 **	-2,501	0,012									
b_{31}	-0,001	-0,326	0,745									
b_{32}	-0,008 ***	-2,841	0,004									
b_{33}	0,970 ***	265,143	0,000	0,942 ***	122,493	0,000	0,937 ***	141,277	0,000	0,939 ***	114,815	0,000
b_{34}	-0,009	-1,306	0,192									
b_{41}	0,003	0,899	0,369									
b_{42}	0,001	0,275	0,783									
b_{43}	0,001	0,679	0,497									
b_{44}	0,963 ***	231,819	0,000	0,917 ***	87,822	0,000	0,916 ***	93,838	0,000	0,917 ***	92,832	0,000
p_{21}							0,700 ***	84,053	0,000			
p_{31}							0,288 ***	18,631	0,000			
p_{32}							0,310 ***	20,058	0,000			
p_{41}							0,079 ***	4,379	0,000			
p_{42}							0,043 **	2,434	0,015			
p_{43}							0,194 ***	10,533	0,000			
DCC(A)										0,016 ***	6,164	0,000
DCC(B)										0,977 ***	215,192	0,000
Log.L	-18690			-19688			-18741			-18675		
AIC	15,973			16,797			15,996			15,936		
SIC	16,125			16,876			16,089			16,020		

First, results from the mean regression models are presented. The results from the mean equations are important in establishing a relationship between current period returns and last period returns within variables or between variables. In the first glance both mean equation tables (the upper part of tables 3 and 4) look rather similar.

m_{11} is positive and significant in Europe meaning that the previous period return of the alternative energy index has a relationship to the current period return of alternative energy index (table 3). One period lagged oil return (m_{33}) seems to have a significant and negative relationship to current period oil return in Europe. The negative relationship means that when the last period return of the crude oil return is positive then the current period of the crude oil return is negative or when the last period is negative then the current period is positive. Similarly, natural gas (m_{44}) has the same (negative and significant) relationship between current return and one period lagged return.

The previous period crude oil return has unidirectional effect on alternative energy index in Europe (m_{13}). Alternative energy index return seems to have dependency on the technology index return (m_{21}). The relationship is negative meaning that when the lagged period return of alternative energy index is positive then current period of technology index is negative and vice versa. Similarly, one period lagged return of the crude oil return seems to have relationship on the current returns of the technology index in Europe (m_{23}). The previous period of the alternative energy index return has a significant and negative relationship on the current period crude oil return (m_{31}). One period lagged technology index return has a positive and significant relationship on the current period crude oil return (m_{32}). Previous period alternative energy index return and technology index return have a significant relationship on the current period of natural gas return [(a_{41}) and (a_{42})].

Results from the mean equation and variance equation tables are interpreted at 10% significance level. None of the mean equation regression coefficients are not remarkably high but provides an evidence to execute a deeper analysis on the relationship among selected variables.

In the lower panel of the table 3 are presented results from the variance equations. First, own conditional effects are being studied because own conditional ARCH a(,) and GARCH b(,) have a key role in explaining conditional volatility. The ARCH-effect is related to the short term persistence of volatility. Accordingly, the GARCH effect is related to the long term persistence of volatility. Own ARCH- and GARCH- effects are statistically significant at 10% level for four MGARCH models in Europe. On the other words, long- and short-term volatility are persistence in the all variables in Europe.

Next, unidirectional and bidirectional spillover effects are being studied. Unidirectional spillover effect means only one-way volatility shifting (can be long- or short-term) from one variable to another one. i.e. short-term volatility spillover effect from one period lagged technology index return to the current period alternative energy index return (a_{12}). Whereas bidirectional spillover effect (can be long- or short-term), i.e. [(b_{12}) and (b_{21})], means long-term volatility spillover effect i.e. from one period lagged return of technology index return to current period alternative index return, and from one period lagged return of alternative energy index to current period of technology index return. On the other words, the direction of shifting volatility is bidirectional.

The only bidirectional effect, ARCH effect, is present between technology index return and crude oil return in Europe (a_{23} and a_{32}) (table 3) indicating short-term volatility spillover effects between variables. In general, directional ARCH effects are found from alternative energy index return to technology index return (a_{21}), and from natural gas return to technology index return (a_{24}). For short-term persistence there is also evidence of volatility spillovers from alternative energy index return to the crude oil return (a_{31}).

The evidence of unidirectional long-term volatility persistence in Europe is found from crude oil return to alternative energy index return (b_{13}), and from natural gas return to the alternative index return (b_{14}). This result is expected because crude oil return has expected to have an interlinkage with alternative energy index return.

Also directional GARCH effect is found from natural gas return to the technology index return (b_{24}) and from technology index return to the crude oil return (b_{32}).

6.1.2 Results from mean and variance models: North-America

Table 4. North-America: MGARCH parameter estimates (*** denotes significance at 1% risk level, ** at 5% risk level and * at 10% risk level).

	BEKK				Diag.				CCC				DCC			
Mean	Coeff.		T-stat.	Signif.	Coeff.		T-stat.	Signif.	Coeff.		T-stat	Signif.	Coeff.		T-stat	Signif.
m_{10}	0,011		0,484	0,628	-0,002		-0,060	0,952	0,020		0,745	0,456	0,007		0,252	0,801
m_{11}	0,032		1,242	0,214	0,046		1,569	0,117	0,029		0,921	0,357	0,028		0,957	0,339
m_{12}	0,038		0,908	0,364	0,058		1,199	0,231	0,085	*	1,785	0,074	0,073		1,510	0,131
m_{13}	-0,002		-0,223	0,824	-0,013		-0,781	0,435	-0,013		-1,101	0,271	-0,010		-0,569	0,570
m_{14}	-0,009		-0,974	0,330	-0,018		-1,479	0,139	-0,020	**	-2,328	0,020	-0,012		-1,341	0,180
m_{20}	0,072	***	5,577	0,000	0,076	***	3,684	0,000	0,079	***	4,929	0,000	0,079	***	4,787	0,000
m_{21}	-0,042	***	-2,914	0,004	-0,037	***	-3,329	0,001	-0,043	***	-2,604	0,009	-0,041	**	-2,497	0,013
m_{22}	0,030		1,270	0,204	0,023		1,096	0,273	0,042		1,389	0,165	0,043		1,465	0,143
m_{23}	0,006		1,040	0,299	-0,005		-0,537	0,592	-0,004		-0,662	0,508	-0,002		-0,151	0,880
m_{24}	0,004		0,725	0,468	0,000		0,063	0,950	-0,001		-0,124	0,901	0,001		0,214	0,831
m_{30}	0,022		0,636	0,525	0,021		0,599	0,549	0,034		0,967	0,334	0,020		0,589	0,556
m_{31}	0,003		0,169	0,866	0,001		0,030	0,976	-0,007		-0,283	0,777	-0,008		-0,297	0,766
m_{32}	0,068	**	2,060	0,039	0,059		1,312	0,189	0,095	**	2,337	0,019	0,087	*	1,848	0,065
m_{33}	-0,065	***	-3,913	0,000	-0,060	**	-2,543	0,011	-0,064	***	-2,944	0,003	-0,067	***	-3,065	0,002
m_{34}	0,021	*	1,750	0,080	0,018		1,510	0,131	0,016		1,323	0,186	0,021	*	1,852	0,064
m_{40}	-0,029		-0,558	0,577	-0,017		-0,365	0,715	-0,001		-0,018	0,986	-0,007		-0,129	0,898
m_{41}	0,110	***	3,885	0,000	0,145	***	3,464	0,001	0,133	***	3,971	0,000	0,123	***	3,165	0,002
m_{42}	-0,167	***	-3,452	0,001	-0,169	**	-2,534	0,011	-0,161	***	-2,925	0,003	-0,168	**	-2,543	0,011
m_{43}	0,014		0,614	0,539	0,002		0,103	0,918	0,004		0,142	0,887	0,011		0,424	0,672
m_{44}	-0,050	**	-2,451	0,014	-0,062	***	-2,642	0,008	-0,060	**	-2,371	0,018	-0,057	**	-2,401	0,016
Variance																
c_{11}	0,228	***	10,273	0,000	0,093	***	4,030	0,000	0,159	***	4,514	0,000	0,074	***	4,430	0,000
c_{21}	0,144	***	8,676	0,000												
c_{22}	0,126	***	12,884	0,000	0,032	***	4,549	0,000	0,058	***	6,660	0,000	0,034	***	5,197	0,000
c_{31}	0,061	***	2,925	0,003												
c_{32}	0,060	*	1,917	0,055												
c_{33}	0,143	***	7,578	0,000	0,025	***	2,898	0,004	0,047	***	3,932	0,000	0,037	***	3,273	0,001
c_{41}	-0,056		-0,807	0,420												
c_{42}	0,065		0,918	0,359												
c_{43}	-0,132	*	-1,707	0,088												
c_{44}	0,375	***	6,270	0,000	0,154	***	3,774	0,000	0,158	***	3,856	0,000	0,151	***	3,882	0,000
a_{11}	0,220	***	17,291	0,000	0,094	***	7,376	0,000	0,074	***	6,114	0,000	0,06408	***	7,59139	0
a_{12}	0,035	***	3,638	0,000												
a_{13}	0,019		1,141	0,254												
a_{14}	0,041		1,061	0,289												
a_{21}	0,036	*	1,700	0,089												
a_{22}	0,228	***	15,060	0,000	0,094	***	8,397	0,000	0,080	***	8,364	0,000	0,077	***	8,810	0,000
a_{23}	0,005		0,169	0,866												
a_{24}	0,054		0,759	0,448												
a_{31}	0,014		1,234	0,217												
a_{32}	0,016	**	1,964	0,049												
a_{33}	0,212	***	17,252	0,000	0,061	***	7,424	0,000	0,066	***	8,577	0,000	0,068	***	8,036	0,000
a_{34}	-0,037	*	-1,803	0,071												
a_{41}	-0,006		-0,754	0,451												
a_{42}	-0,011	**	-1,994	0,046												
a_{43}	-0,010		-1,262	0,207												
a_{44}	0,196	***	13,165	0,000	0,068	***	7,876	0,000	0,068	***	8,179	0,000	0,070	***	7,341	0,000
b_{11}	0,976	***	351,595	0,000	0,884	***	56,496	0,000	0,883	***	45,721	0,000	0,922	***	87,528	0,000
b_{12}	0,002	***	3,101	0,002												
b_{13}	0,004		0,654	0,513												
b_{14}	0,011		0,651	0,515												
b_{21}	-0,022	***	-3,246	0,001												
b_{22}	0,944	***	298,296	0,000	0,884	***	67,938	0,000	0,873	***	64,153	0,000	0,904	***	84,847	0,000
b_{23}	-0,021		-1,623	0,105												
b_{24}	-0,061	*	-1,898	0,058												
b_{31}	-0,003		-1,487	0,137												
b_{32}	-0,003	**	-2,375	0,018												
b_{33}	0,975	***	340,106	0,000	0,935	***	109,741	0,000	0,924	***	108,543	0,000	0,926	***	103,993	0,000
b_{34}	0,013	**	2,454	0,014												
b_{41}	0,004		1,498	0,134												
b_{42}	0,005	**	2,327	0,020												
b_{43}	0,004		1,590	0,112												
b_{44}	0,969	***	226,620	0,000	0,917	***	92,011	0,000	0,916	***	100,252	0,000	0,916	***	87,766	0,000
p_{21}									0,786	***	132,666	0,000				
p_{31}									0,356	***	37,354	0,000				
p_{32}									0,294	***	28,103	0,000				
p_{41}									0,051	***	3,493	0,000				
p_{42}									0,022		1,509	0,131				
p_{43}									0,207	***	10,655	0,000				
DCC(A)													0,017	***	7,320	0,000
DCC(B)													0,977	***	271,560	0,000
Log.L	-17708				-19078				-17761				-17663			
AIC	15,137				16,277				15,161				15,074			
SIC	15,289				16,356				15,254				15,158			

In North-America (table 4) one period lagged return of crude oil and natural gas have an effect to the current period return. The relationship between lagged period return and current period return of crude oil (m_{33}) and natural gas (m_{44}) are in both cases significant and negative. All the other MGARCH models (DVEC, CCC and DCC) confirm the same result.

The upper, mean equation, table states that alternative energy index return seems to have dependency on the technology index return (m_{21}). Also, one period lagged technology index has a positive and significant relationship on the current period crude oil return (m_{32}).

Similarly, unidirectional effects on natural gas returns in North-America are identical (considering significancy and sign) compared to Europe. Previous period alternative index return and technology index return have a significant relationship on the current period of natural gas return [(m_{42}) (m_{43})].

Again, results are interpreted at 10% significance level. None of the mean equation regression coefficients are not remarkably high but provides an interesting information from the relationships among variables.

Bidirectional ARCH- (a_{12} and a_{21}) and GARCH (b_{12} and b_{21}) effects are found in North-America (table 4) between alternative energy index returns and technology index returns. The fact is important because i.e. Sadorsky (2012) has stated that one of the strongest driver behind the alternative index returns is technology index returns. Bidirectional ARCH- and GARCH effects between variables indicate an evidence of bidirectional short- and long-term persistence in volatility spillovers.

For short-term volatility persistence in North-America there is an evidence of volatility spillovers from technology index return to the crude oil return (a_{32}), and from natural gas return to the crude oil return (a_{34}). Also from technology index return to natural gas return (a_{42}).

Bidirectional GARCH-effects are found also between technology index return and natural gas return (b_{24} and b_{42}). Unidirectional GARCH effects are found from natural gas return to the crude oil return (b_{34}), and from technology index return to crude oil returns (b_{32}) in North-America.

6.1.3 Results from the CCC- and the DCC models

Sadorsky and Henriques (2008, 1003) found out that the highest correlation is between alternative energy index and technology index, and the second highest correlation with alternative energy index is crude oil return. Sadorsky (2012, 252) remade the study with slight modification and came to same conclusion. In this study, CCC-model generates significant and positive correlation coefficients among all variables [p(,,) in the table 3 and 4]. Results are similar between both regions. The highest correlation coefficient is between alternative energy index and technology index (p_{21}) in Europe (0.700) and North-America (0.786). The correlation coefficients between alternative energy index and crude oil (p_{31}) are 0.288 in Europe and 0.356 in North-America. Also, high correlation coefficient (p_{43}) lies between natural gas and crude oil [Europe (0.310) and North-America (0.294)]. The result is somehow expected because natural gas is known as the byproduct of the oil production.

Fairly high correlation coefficient between technology index and natural gas (p_{42}) in both regions is interesting because interlinkages between natural gas and technology index is still pretty unexamined field of study. Important observation is also the small size of the correlation coefficient between natural gas alternative energy index (p_{41}) in the both region [Europe (0.076) and North-America (0.051)]. For the DCC model both coefficients are positive and statistically significant at 1% level. Coefficients sum to less than one, meaning that the dynamic conditional correlation is mean reverting.

In case of Europe, the DCC model is the best model according to AIC and SIC criteria. The second best model, according the same criteria, is the BEKK model. The rank order of the MGARCH models is the same in North-America

6.1.4 The Diagnostic test for models

The diagnostic test revels whether the serial correlation is present.

Table 5. Europe: Diagnostic test for standardized residuals

	BEKK				Diag				CCC				DCC			
	alt_ eri	tec_ se6	oil_ bre	gas_ hhbn	alt_ eri	tec_ se6	oil_ bre	gas_ hhbn	alt_ eri	tec_ se6	oil_ bre	gas_ hhbn	alt_ eri	tec_ se6	oil_ bre	gas_ hhbn
Q(20)r	18,134	13,817	21,639	23,769	25,262	12,033	21,779	22,991	26,774	13,735	21,902	23,013	25,308	13,300	21,574	22,895
p-values	0,579	0,840	0,360	0,253	0,192	0,915	0,353	0,289	0,142	0,844	0,346	0,288	0,190	0,864	0,364	0,294
Q(20)r^2	12,931	41,866	19,035	14,440	11,602	19,965	16,168	12,921	41,896	43,144	15,681	13,094	35,971	37,358	15,872	13,014
p-values	0,228	0,003	0,520	0,808	0,929	0,460	0,706	0,881	0,003	0,002	0,736	0,873	0,016	0,011	0,725	0,877

Table 6. North-America: Diagnostic test for standardized residuals

	BEKK				Diag.				CCC				DCC			
	alt_ wil	tec_ arc	oil_ wti	gas_ hhbn	alt_ wil	tec_ arc	oil_ wti	gas_ hhbn	alt_ wil	tec_ arc	oil_ wti	gas_ hhbn	alt_ wil	tec_ arc	oil_ wti	gas_ hhbn
Q(20)r	17,521	21,150	12,969	25,841	17,074	21,279	13,349	23,401	17,849	21,567	13,892	23,402	17,219	21,981	13,964	23,283
p-values	0,619	0,388	0,879	0,171	0,648	0,381	0,862	0,270	0,597	0,364	0,836	0,270	0,639	0,342	0,832	0,275
Q(20)r^2	44,498	29,055	25,178	18,419	18,150	18,013	20,519	12,651	36,612	43,444	18,886	12,805	38,481	32,546	19,545	12,961
p-values	0,001	0,087	0,195	0,560	0,578	0,587	0,426	0,892	0,013	0,002	0,529	0,886	0,008	0,038	0,487	0,879

All the residuals are free from serial correlation. However, the BEKK model and the DCC model contain some autocorrelation in the squared residuals. Consequently, models should fit fairly well to the data. Finally, the DCC model is chosen for the best model considered. The DCC model is used to construct dynamic conditional correlation.

6.2 The Dynamic Conditional correlation

The dynamic conditional correlations are constructed from the basis of DCC model. In the DCC model dynamic dependencies in the correlations are allowed. Correlations are time varying. Therefore, dynamic conditional correlations provide more useful information compared to the constant conditional correlation. To be more precise, dynamic conditional correlations can vary a lot from the constant conditional correlations. Below, dynamic constant correlations between each pair in both regions are presented. Figures 10-21 show evidence of considerable changing correlation coefficients. Therefore, the deeper analysis of the behavior of correlation is justified. Keeping in mind the research question about the changing correlation, dynamic conditional correlation is a way to find out how each pair of correlations have been changing over the past years.

6.2.1 Pairwise dynamic conditional correlations in Europe

The dynamic conditional correlation between ALT(ERI) and TEC(SE6) (figure 11) varies between 0.55 (March 2011) and 0.89 (December 2008). The constant conditional correlation between ALT(ERI) and TEC(SE6) (p_{21}) is 0.70 (table 3). The graph in the figure 11 shows a fluctuation in the correlation. Two major down and up spikes and are clearly visible in August 2008 and March 2011. The fluctuation of the DCC is heavier before 2012. Then fluctuation levels closer to the constant correlation coefficient. Due to the great fluctuation in the correlation graph, detecting distinct trend is difficult.

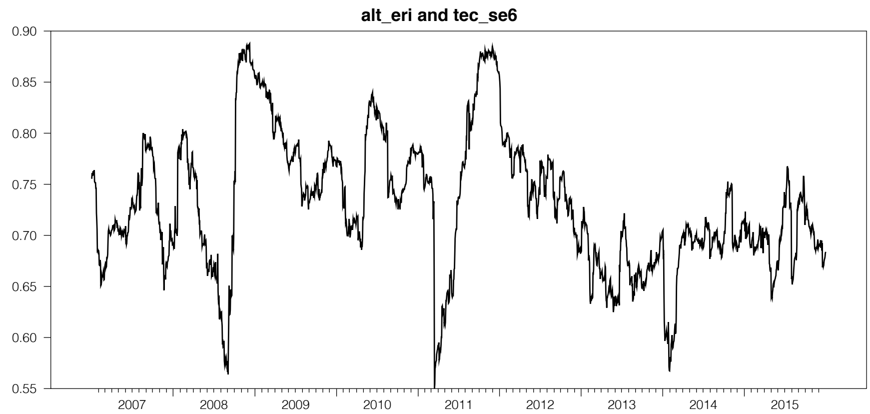

Figure 11. The DCC graph between ALT(ERI) and TEC(SE6)

The dynamic conditional correlation between ALT(ERI) and OIL(BRE) (figure 12) varies between 0.1 (July 2008) and 0.7 (December 2008). Worth noticing is the sequence of the highest and lowest value in 2008. The constant conditional correlation (p_{32}) is 0.29 (table 3) for the whole study period. The dynamic conditional correlation varies considerable from the constant conditional correlation during the beginning of the study period. Declining trend starts in the end of 2011 and continues until the end of 2015.

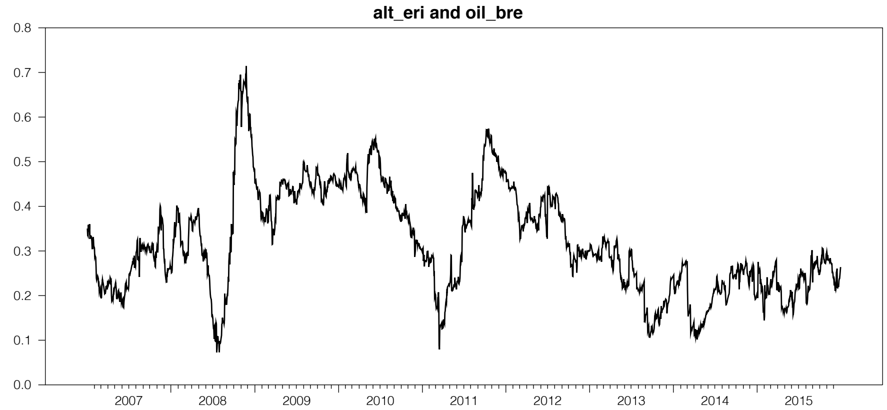

Figure 12. The DCC graph between ALT(ERI) and OIL(BRE)

The dynamic conditional correlation between ALT(ERI) and GAS(HHBN) (figure 13) varies between –0.15 (August 2007) and 0.45 (November 2008). In general, the behavior of correlation graph in the figure 13 is more stable compared to the behavior of correlation graphs in the figures 11 and 12. Consequently, the DCC graph moves closer to the CCC coefficient (p_{42}) (0.08). The general the trend of the DCC correlation graph is declining. So, while approaching the present moment the dynamic conditional correlation between selected variables declines, and values are closer-to-zero.

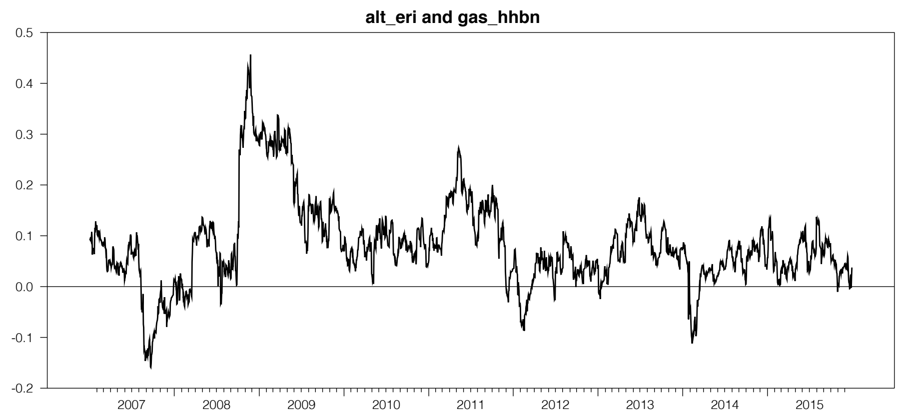

Figure 13. The DCC graph between ALT(ERI) and GAS(HHBN)

The dynamic conditional correlation between TEC(SE6) and OIL(BRE) reaches the smallest value (0.00) in August 2008, and immediately thereafter the highest value 0.65 in November 2008. Then the trend of the DCC is declining closer to zero. The declining trend is clearly visible in the figure 14. The graph experiences sharp fluctuations between 2008 and 2011. From the year 2012 to the year 2015 the trend is clearly declining.

Figure 14. The DCC graph between TEC(SE6) and OIL(BRE*)*

The constant conditional correlation between TEC(SE6) and GAS(HHBN) (p_{32}) is 0.04 (table 3). The fluctuation is relative small except the year 2009 when correlation reaches the highest value 0.4 (figure 15). Otherwise the graph wanders near zero. The correlation stays negative for some time in 2012 and 2015. Time periods with negative correlation provides a scope for meaningful portfolio diversification. In addition, dynamic conditional correlation graph reaches negative value more often compared to other European dynamic conditional correlation graphs.

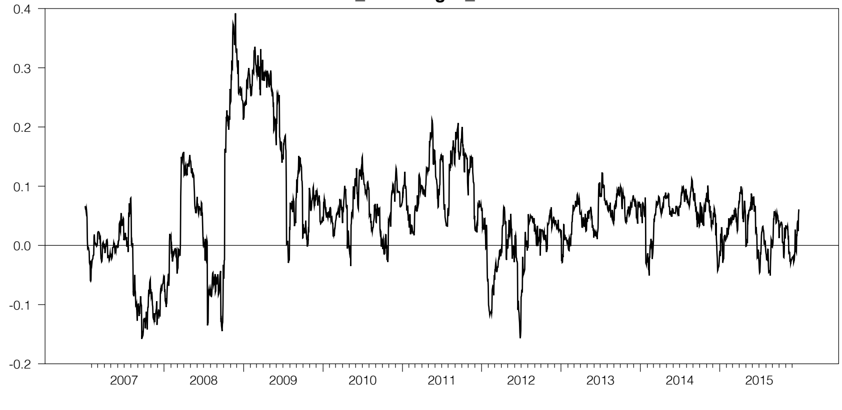

Figure 15. The DCC graph between TEC(SE6) and GAS(HHBN)

The dynamic conditional correlation between OIL(BRE) and GAS(HHBN) (figure 16) reaches its high-value 0.68 in October 2008. After that the trend of dynamic conditional correlation is declining and more stable compared to the years in the first decade of the 21st century. The values of dynamic conditional correlation are closer to constant conditional correlation in the end of the study period. The correlation graph doesn't reach negative values in the study period at all.

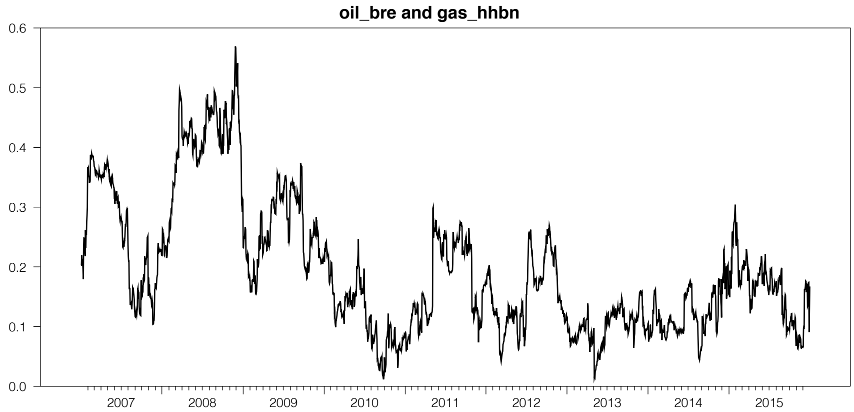

Figure 16. The DCC graph between OIL(BRE) and GAS(HHBN)

6.2.2 Pairwise dynamic conditional correlations in North-America

The dynamic conditional correlation between ALT(WIL) and TEC(ARC) is at high level over the whole study period (figure 17). The lowest value 0.62 is recorded in August 2007. Again, as many cases in Europe, the trend of the correlation graph is declining after 2008. However, the highest value is reached in August 2011 when the value of dynamic conditional correlation reaches almost the value of 0.95. The high correlation value means that assets move in tandem. In the other words, when correlation coefficient between variables is close to 1, then returns follow each other identically. The value of constant conditional correlation between ALT(WIL) and TEC(ARC) (p_{21}) is 0.79 (table 4). The correlation graphs behave similarly between alternative energy index returns and technology index returns in both regions (figure 11 and 17). High and low values are located at the same time periods in both of the regions. Also, CCC and DCC coefficients are high in both regions.

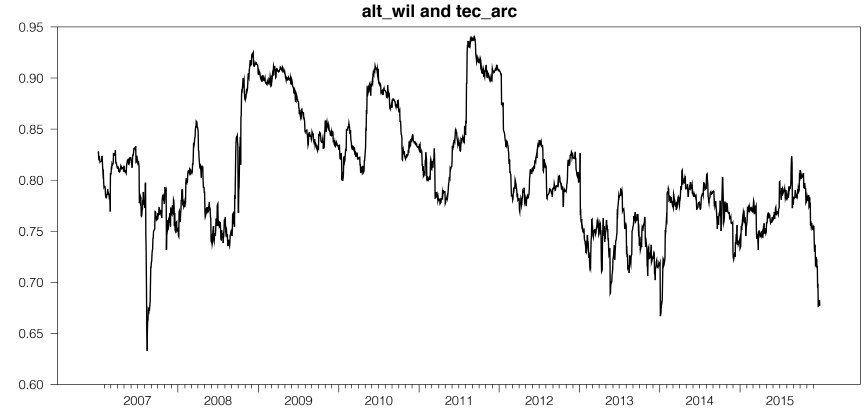

Figure 17. The DCC graph between ALT(WIL) and TEC(ARC)

The constant conditional correlation between ALT(WIL) and OIL(WTI) is 0.36 (table 4). The lowest value of the dynamic conditional correlation is 0 and the highest value is 0.6 (figure 18). The DCC graph wanders near to the constant conditional correlation. The DCC value oscillates around 0.4 and 0.5 for long period (2009 - 2013). There are differences between correlations when regions are compared. In the Europe the correlation between variables is smaller [CCC coefficient (p_{42}) is 0.29 (table 3)]. Also the fluctuations are smaller in Europe compared to North-America.

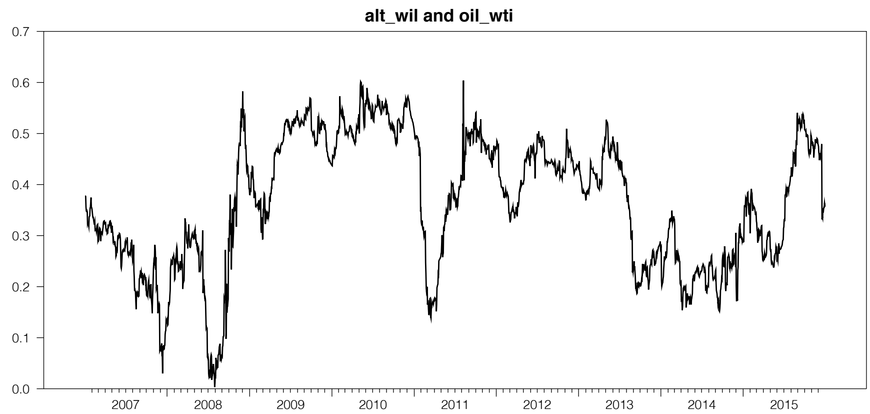

Figure 18. The DCC graph between ALT(WIL) and OIL(WTI)

The dynamic conditional correlation graph in the figure 19 fluctuates considerably. Indicating an unstable correlation between ALT(WIL) and GAS(HHBN). The mean of the DCC is positive in the first half of the study period. The highest DCC spike is 0.29 in June 2011. After 2009 the positive trend turns into negative. In addition, during the years 2012, 2013 and 2014 there are times when the correlation graph lies on the negative side relatively long periods. Especially longer times with negative correlation provides an opportunity for meaningful portfolio diversification.

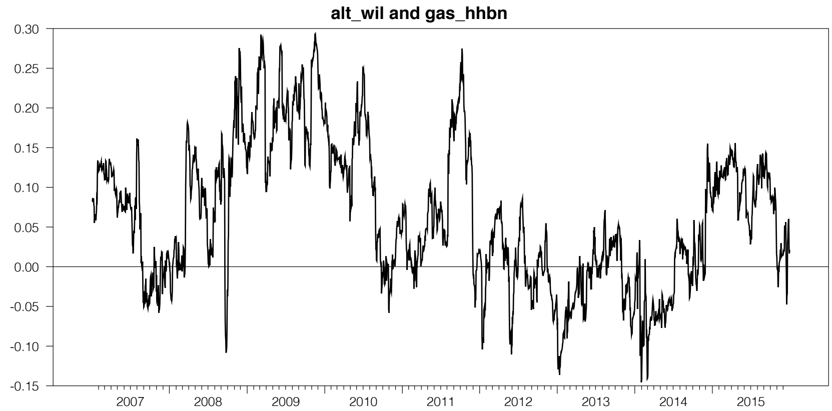

Figure 19. The DCC graph between ALT(WIL) and GAS(HHBN)

The correlation graph between TEC(ARC) and OIL(WTI) in the figure 20 is similar compared to its European counterpart (figure 14). The dynamic conditional correlation reaches the lowest value in August 2008 and thereafter the correlation between TEC(ARC) and OIL(WTI) fluctuates around 0.5 for 4 years until 2013. From 2012 the trend of the correlation is decreasing.

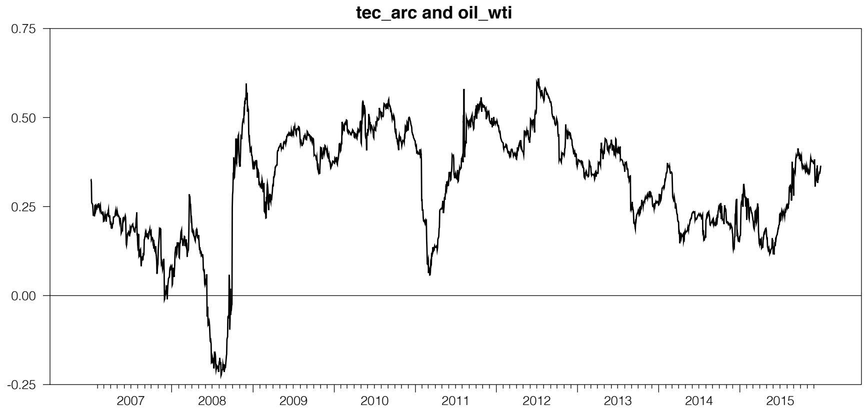

Figure 20. The DCC graph between TEC(ARC) and OIL(WTI)

The dynamic conditional correlation graph between TEC(ARC) and GAS(HHBN) (figure 21) is similar compared to its European counterpart (figure 15). The steep drop happens in the summer of 2008 and then the correlation fluctuates around 0.4 until 2013. There is also a notable drop between 2010 and 2011when the dynamic conditional correlation reaches zero. During the years 2012 and 2013, the mean of the DCC seems to lie under zero. After the downward spike in the beginning of the year 2014, the DCC graph moves around zero. The dynamic conditional correlation graph moves relative close to the constant conditional correlation (p_{42}) value which is 0.02 (table 4).

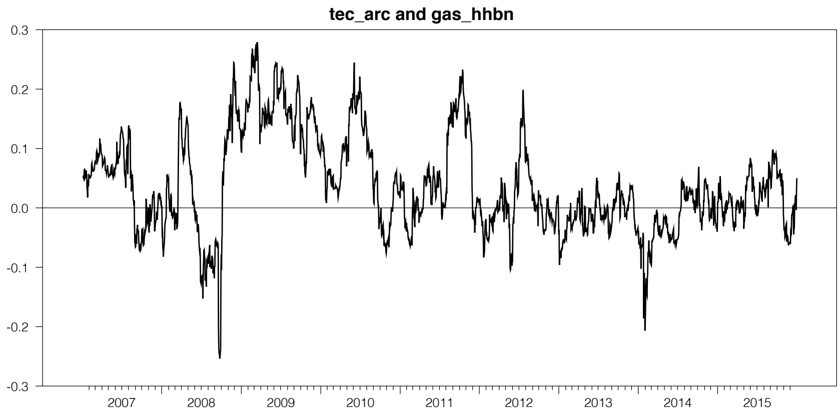

Figure 21. The DCC graph between TEC(ARC) and GAS(HHBN)

As expected the correlation graph between OIL(WTI) and GAS(HHBN) (figure 22) is similar compared to European one (figure 16). The dynamic conditional correlation graph fluctuates between slightly negative value in September 2010 and 0.55 in November 2008. The trend of the first half of the graph is negative and thereafter the dynamic conditional correlation lies around the constant conditional (p_{43}) correlation which is 0.2 (table 4).

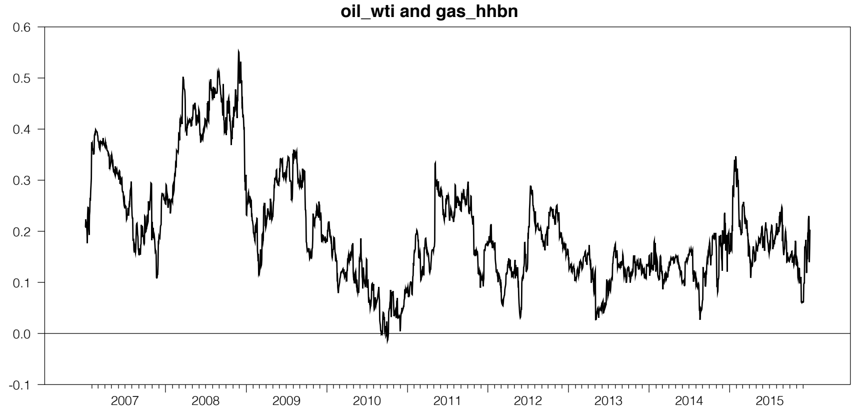

Figure 22. The DCC graph between OIL(WTI) and GAS(HHBN)

Common features can be found in correlations between variables in the particular region. Also identical features can be found from the same variable in both regions. In general, it can be said that the major fall is followed by the steep rise of correlation around the year 2008. Furthermore, the middle section of the study period is stable considering the fluctuation of the correlation graph. Typically, thereafter follows downward trend of the correlation graph. The major changes in 2008 can be explained by the financial crises. In addition, dynamic conditional correlations reveal that relying only on constant conditional correlation over the study period can be misleading. Dynamic conditional correlations provide more useful information compared to constant conditional correlation about the certain value of correlation at the certain moment.

The correlation pair of ALT(ERI) and TEC(SE6) (figure 11) is an illustrative example. The value of constant conditional correlation is 0.7 but as seen from the figure 11, the dynamic conditional correlation varies a lot from the constant conditional correlation. In the other words, not only constant conditional correlation should be used as a basis of portfolio diversification but also further analysis of the correlation behavior should be applied. In that case the dynamic conditional correlation is a great tool for achieving a deeper understanding of the correlation's behavior during the certain period of time.

7. CONCLUSION

The alternative energy is constantly taking over the growing share of total energy consumption. Especially, alternative energy is seizing market share from traditional energy sectors such as natural gas and its derivatives. The growing share of alternative energy sector from total energy consumption can be explained by the increasing level of technology which makes alternative energy technology more competitive compared the traditional energy sectors. The developed alternative energy technologies allow to produce energy more efficiently, and therefore in cheaper ways. Also major fluctuations have been happening in the petroleum prices as well in the derivative of petroleum, natural gas, prices. Factors, such as crude oil and natural gas, are expected to have an influence to the prices of the alternative energy sector prices. Also, drying up the oil reservoirs is looming in the horizon. The above mentioned factors force the human kind to move towards using more sustainable energy sources. Understanding the dynamics of alternative energy sectors and fossil fuel based energy sectors helps to predict the price behavior of alternative energy sector. In North-America studies concerning volatility spillovers and conditional correlations are done a few but in Europe similar studies are not done. Studying volatility contagion and conditional correlation is important in order to constitute a clear picture how different markets interact.

The MGARCH model with BEKK, DVECH, CCC and DCC parametrization provides interesting, and more or less expected, results concerning the volatility dynamics and time-varying correlations among variables. The first observation that stands out is that daily mean and volatility spillover effects among returns are present in both regions (table 7). Interestingly, effects are not totally identical when regions are compared. In the other words, interdependencies between variables are not totally same when regions are compared.

Autocorrelation is present within returns and squared returns, referring to clustering volatility in time-series used in both regions. It is justified to say that volatility also spills over between variables. In some cases, volatility spillovers are unidirectional but also bidirectional spillovers occur. Furthermore, both, ARCH effects (short-term persistence of volatility) and GARCH effects (long-term persistence of volatility) are present among some variables. In the table 7, the summary of daily mean and volatility spillovers are presented.

First, mean spillovers are studied in Europe and North-America in the upper parts of table 7. The one period lagged return of alternative index has an effect to current period technology index return in both regions (table 7). Bidirectional return effect is present between technology index returns and crude oil returns in Europe. Also, directional return effect from alternative energy index to natural gas can be found in Europe. Mean model states bidirectional (Europe) and unidirectional (North-America) return effects from technology index to crude oil. Unidirectional effect from technology index returns to natural gas returns is found. Finally, unidirectional returns effect is seen from natural gas to crude oil in North-America.

Table 7. Daily mean and volatility spillovers among returns of alternative energy index, technology index, oil and gas in Europe (left) and North-America (right) during 2006-2015.

Combinations	BEKK	Diag.	CCC	DCC
Mean				
Alt(1) – Tech(2)	=>			
Alt(1) – Oil(3)	<=>	<=>	<=>	<=>
Alt(1) – Gas(4)	=>	=>	=>	=>
Tech(2) – Oil(3)	<=>	=>	<=>	=>
Tech(2) – Gas(4)	=>			=>
Oil(3) – Gas(4)				
Short-term				
Alt(1) – Tech(2)	=>			
Alt(1) – Oil(3)	=>			
Alt(1) – Gas(4)				
Tech(2) – Oil(3)	<=>			
Tech(2) – Gas(4)	<=			
Oil(3) – Gas(4)				
Long-term				
Alt(1) – Tech(2)				
Alt(1) – Oil(3)	<=			
Alt(1) – Gas(4)	<=			
Tech(2) – Oil(3)	=>			
Tech(2) – Gas(4)	<=			
Oil(3) – Gas(4)				

Combinations	BEKK	Diag.	CCC	DCC
		Mean		
Alt(1) – Tech(2)	=>	=>	<=>	=>
Alt(1) – Oil(3)				
Alt(1) – Gas(4)			<=	
Tech(2) – Oil(3)	=>		=>	=>
Tech(2) – Gas(4)	=>	=>	=>	=>
Oil(3) – Gas(4)	<=			<=
		Short-term		
Alt(1) – Tech(2)	<=>			
Alt(1) – Oil(3)				
Alt(1) – Gas(4)				
Tech(2) – Oil(3)	=>			
Tech(2) – Gas(4)	=>			
Oil(3) – Gas(4)	<=			
		Long-term		
Alt(1) – Tech(2)	<=>			
Alt(1) – Oil(3)				
Alt(1) – Gas(4)				
Tech(2) – Oil(3)	=>			
Tech(2) – Gas(4)	<=>			
Oil(3) – Gas(4)	<=			

Interpreting the long and short term volatility persistence to alternative energy sector in Europe and North-America, the results are not fully identical. The mean equation reveals that return dynamics (table 7) are more in-line with earlier studies (Sadorsky 2009 & 2012) in Europe. On the other hand, volatility dynamics are more similar compared to earlier studies (Sadorsky 2009 & 2012) in North-America.

Sadorsky (2012) and Plott (2014) both found out that crude oil returns and technology index returns have an effect to alternative energy index. There is a bidirectional long- and short-term (ARCH and GARCH) volatility spillover effects between technology index return and alternative energy index return in North-America (right-hand side). Meaning short-term and long-term persistence in the volatility from technology index to alternative energy index and from alternative energy sector to technology index return.

Long-run persistence in volatility spillovers to alternative energy index returns are present in both regions. In Europe (left-hand side) the effect is identified coming from crude oil return. The result is somewhere expected because similar results are generated in earlier studies done in North-America. Totally new observation is the unidirectional volatility spillover effect (GARCH) from natural gas to alternative energy index in Europe. The observation is important because now it is justified to consider taking natural gas into account when the behavior of alternative energy index returns is further studied.

Dynamic conditional correlation graphs also reveal important features from the dynamics between variables. Relying on only constant conditional correlation when the correlation between variables are studied is misleading. The more fundamental way is to make conclusions on the basis of time-varying conditional correlation in order to constitute an accurate observation in each period of time. In general, the trend in the dynamic constant correlation has been declining since the global financial crisis. The declining correlation means that joint movements of variables' returns are more independent from each other. The dynamic conditional correlation graphs reveal that the correlation between alternative energy index returns and crude oil returns is certainly declining in both regions. The high correlation between alternative energy index returns and technology index returns stands out. The interlinkages between alternative energy index returns and natural gas index returns is not so string in terms of correlation coefficients. However, dynamic conditional correlation is negative in times. Negative correlation provides a scope for meaningful portfolio diversification.

For further studies taking into account different regions, i.e. Asia or Middle East would be informative and useful. Also, analysis how efficient portfolio, including alternative energy companies, could be constructed using portfolio diversification tools would be useful. Also, as mentioned few times in this study, renewable ways producing energy is seizing market share. Therefore, substantial changes in interdependencies between variables are likely. So, producing updated research results is also important in future.

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