THE IMPACT OF OIL PRICE AND CONSUMABLE FUEL PRICE FLUCTUATIONS ON RENEWABLE ENERGY STOCK PERFORMANCE

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Abstract

In this thesis I have studied the relationship between renewable energy stock prices, technology stock prices, oil prices and other consumable fuel prices. In order to provide an overview of the dynamics among these variables, I have outlined the developments for the market sectors renewable energy, consumable fuels and technology. Subsequently, I used a Vector Autoregressive Model (VAR) to find evidence on how fluctuations in consumable fuel prices (oil, gas and other consumable fuels) effect renewable energy stock performance.
I use two different VAR models with both four variables to test the hypotheses. For each variable, I used index data from January 2010 to August 2018.
My findings are that renewable stock prices are unaffected by oil prices and other consumable fuel prices, however there is a relation between renewable stock prices and technology stock prices. The results provide investors, governments and other stakeholders with a better understanding of renewable stock performance and dynamics.

CONTENTS

1 INTRODUCTION

Energy is one of the most important drivers behind economic welfare, it is a daily necessity for people and companies. The growing world population and emerging markets pushed op energy demand in recent years.

Simultaneously, concern about the environment and the dwindling global oil supplies has led to an increase in interest for renewable energy production. Fossil fuels are a main topic in government debates and new possibilities for renewable energy created wide interest for economic and policy analysis. Therefore, I want to examine the interrelations among the renewable energy industry, technology industry, oil, and other consumable fuels to provide governments and firms with knowledge about the dynamics of the renewable equity market.

An important politic stimulus for introducing more renewable energy is the reduction in carbon dioxide emissions, because of the threat they pose for the climate. Recently there are numerous international agreements to reduce greenhouse gasses, such as the Paris climate agreement which states that all European countries should have a detailed proposal to reduce carbon emissions. The G8 countries want to cut emissions by a considerable 50% before 2050.

Next to the environmental implications, there is also the concern for oil shortages originating from forecasts that oil production will peak between now and 2040 and go down the years after that. Furthermore, present-day estimates have proven that the existing oil reserves will last only for 40 years. In combination with the rapid population growth, which will amount to 10 billion in a timeframe of 50 years, this will lead to an increase in oil demand and eventually an increase in oil prices.

Since oil prices are one of the main determinants for the returns of renewable energy projects, an oil price increase will make the substitution from consumable fuel energy sources to renewable energy sources more profitable (Olah, 2005; Kumar, Managi, & Matsuda, 2012).

While in most countries energy production still relies on fossil fuels, we see a shift towards more sustainable ways of energy production. In the more recent years, not only developed countries engaged in renewable energy projects, but also countries in Asia, Africa and Latin America showed more interest in renewable energy projects. Globally, countries have now reached the point where future energy demand must be in balance with future economic and environmental needs (Sadorsky, 2009).

Although the above mentioned development looks promising for the green energy market, only 12% of the global energy will be produced using renewable energy sources in 2023 according to the International Energy Agency (IEA) (Birol, 2018) if we do not invest more in renewable energy production. One of the reasons that the awareness regarding greenhouse emissions is not resulting in a more rapidly development of renewable energy is that economic growth will often be more important than the reduction of CO_2 emissions (Balcilar, Ozdemir, Ozdemir, & Shahbaz, 2018).

Furthermore, government policies are still the dominant factor for increasing renewable energy investment (Shah, Hiles, & Morley, 2018; Cherp, Jewell, Vinichenko, Bauer, & De Cian, 2016). Without subsidy policies, many renewable energy projects would not have been started. With

increasing returns, renewable energy firms must become profitable in the long-run without government intervention.
Identifying relations and causal effects between oil prices, consumable fuels prices and renewable energy stock performance is therefore useful for policymakers and investors because oil prices and consumable fuel prices could predict demand for renewable energy. With this knowledge robust sustainability frameworks can be made to grow clean energy towards the benchmark of 28% renewable energy in 2040 stated by the IEA. It is clear that a positive business environment is important for companies that produce alternative sustainable energy.
In this thesis I will first analyse the effect of shocks in oil prices on the stock performance of renewable energy companies. Secondly, I conduct similar analysis but instead of using only oil prices to see if there is an effect on renewable energy stock, I will incorporate the prices of other consumable fuels as well, such as gas and coal. Thirdly, since earlier studies have found a significant relation between technology stock price movements and the performance of renewable energy stock, I will incorporate the variable: technology stock prices as well. At last, to develop a robust conclusion, I will apply the model to different sub samples in case the relations among variables differs over time.
In order to carry out the analyses, I will use a Vector Autoregressive Model (VAR). The VAR-model has the advantage that all variables may be endogenous, hence there is no need to clarify which variables are explanatory and which variables are the response variables. In this model, I want to see whether the variables are dependent on the lagged values of the variables in the vector which has the advantage that a much richer data structure can be used to analyse the dynamics in the data (Brooks, 2014).
I conduct my empirical analysis using different indices as a measure for renewable energy stock prices, consumable fuel prices, oil prices and technology stock prices. I use weekly prices from 2010 week 13 to 2018 week 35. The stock market performance of renewable energy companies is examined using the weekly prices of two indexes: The Wilder Hill Clean Energy index and the S&P 500 Global Clean Energy index. The index that I use for the weekly oil prices is the Brent Oil price index. According to an earlier study (Henriques & Sadorsky, 2008), investors may have looked upon renewable energy stock as it was related with technology stock. As a consequence, the NYSE Arca Tech 100 technology index is used as a proxy for the stock performance of technology companies in the VAR-model.
Renewable energy can be used as a substitute for oil and other consumable fuels in the near future. Therefore in the future scenario where oil prices rise, renewable energy investments can become more cost effective because renewable energy becomes relatively less expensive. Although it is accepted that rising oil prices have a positive effect on the financial performance of renewable energy firms, there is no consensus about the effects that oil price fluctuations have on renewables. There is a large and growing amount of literature that has done research on the relation between oil prices and financial markets (Ghosh & Kanjilal, 2014; Sadorsky, 1999). However the first research that focused on the relationship of oil price fluctuations and renewable energy stock performance was done by Henriques and Sadorsky (2008). They could not find a statistically significant impact of oil price fluctuations on stock prices performance. The results did show that stock price shocks of technology companies have a significant impact on the stock price performance of renewable energy companies. The following study by Sadorsky (2012) captured the conditional correlations and volatility spill overs between oil prices, clean energy stock prices and technology stock prices. The results are, again that technology stock prices correlate more with technology stock prices. An additional conclusion in this study concerns the fact that technology companies show a higher return then renewable energy companies

regarding the same grade of risk. With a better investment climate for renewable energy companies, this difference could be reduced.

1.1 Research goal

The contributing value of this thesis to the existing literature lies in updating existing research and adding the variable ‘consumable fuels’ to the model used by Henriques and Sadorsky (2008). Since the renewable energy sector has been developing rapidly, I expect that renewable energy sources have become more a substitute for crude oil and other consumable fuels, therefore the impact of oil price fluctuations will have more effect on stock price performance of renewable energy companies.
As interest has becoming more important, governments are pressured to consider the opportunities of renewable sources. Someday, energy companies could be the main stream energy suppliers (Henriques & Sadorsky, 2008), but at this moment we still rely on fossil fuels. Technology for renewable energy production is relatively new and developing. The shift towards an energy infrastructure that incorporates renewable energy is difficult. Therefore, the alternative energy companies are still considered as highly risky and are compared with new technology stock. Governments can help in promoting renewable energy investments by subsidizing alternative energy investments. Providing decision makers with valid information is key for the backing of renewable energy projects. At this moment the cost efficiency of renewables is mostly lower than that of regular energy sources such as coal and oil (López-Peña, Pérez-Arriaga, & Linares, 2012). Nevertheless, also in the business world, interest is growing and great opportunities lie ahead in this sector.

1.2 Problem statement

With this thesis I want to clarify the dynamics of the renewable energy stock market, especially when it concerns the effect of oil and consumable fuel price shocks. With this better insight, investor and government can construct a better forecast for sustainable energy investments. This will eventually help in promoting renewable energy production and a better investment environment for renewable energy companies. This leads to the following research question:

What is the effect on stock performance of renewable energy companies after fluctuations in consumable fuel prices?

In order to analyse how renewable energy stock responds to fluctuations in oil and consumable price fluctuations three hypotheses are formed, these will follow in the empirical method in section 4.

1.3 Structure

This thesis is structured as follows: In Section 2, the earlier empirical research on the topic will be explained. In section 3 there will be a summary of the relevant concepts and theory, I will explain the VAR model and theoretical relations. Section 4 will explain the data that I use. Section 5 will show the empirical results and their implications. Section 6 will be the conclusion of this thesis.

2 THEORETICAL BACKGROUND

2.1 The fundamentals of oil prices, gas and consumable fuels in general

Fossil fuels or as I refer to 'consumable fuels' are fuels that are formed in the earths soil during a time of several million years. Therefore, they cannot be replenished and their amount is finite. Examples of consumable fuels are oil, coal and gas.
In earlier studies, mostly oil prices are used as a proxy for the fossil fuel based market. However, the fossil fuel markets consists of diverse other consumable fuels. For that reason I will also use the variable 'consumable fuels'. In this thesis I consider the term fossil fuels and consumable fuels as similar. Characteristics of consumable fuels are that the amount available is exhaustible. By generating energy using consumable fuels, carbon dioxide, a greenhouse gas is produced. Next to that, there is the emission of particulate, which is a threat to human wellbeing.

2.1.1 Oil, consumable fuels supply & demand

Off all consumable fuels, oil is the most polluting one in terms of carbon dioxide. Simultaneously, oil is of immense importance in the world for the production of energy as it is historically used in all regions of the world. The largest economies are dependent on access to fossil fuels. Due to economic development, approximate 45% more oil, gas and coal is used today than 20 years ago. Today 80% of the global energy supply is produced by using fossil fuels (IEA, 2013). The largest oil consuming region in the world is North America which accounts for 30% of the world's consumption, but China will most likely overtake the first place in the coming years (Henriques & Sadorsky, 2008).
Although the lower carbon energy alternatives have increased, we still need fossil fuels for quite a long time. Even if the whole world would agree to switch to renewable energy sources, we still would need fossil fuels for the bulk of our energy consumption. Hence, there are alternatives, but not in the magnitude what is required.
Concerns about shortages of oil in the future come from predictions that the maximum oil production will be reached somewhere between now and 2040 (Appenzellar, 2004). To meet the future demand, the output needs to be fulfilled by either new oil discoveries or new developments. At the same time emerging markets such as India and China show a constantly increasing oil demand. Oil is globally traded and therefore the price is determined by global demand and supply. Although changes in the crude oil prices tend to be permanent and difficult to predict (Hamilton J. D., 2008), from classic supply and demand theory it is only logical that the crude oil prices will rise on the long-run.
In the short-run an element that defines the supply of oil comes from the geographic distribution of oil resources. More than half of the oil reserves are situated in just five countries (Saudi Arabia, Iran, Kuwait and the Emirates). Together with the organisation of the petroleum exporting countries (OPEC) they determine the short run supply of oil and with that they have a major influence on the price of oil.

Another way to predict short-run oil prices is to calculate the oil decline rates. The decline rates are affected by the oil price increase and technologic development. Constantly monitoring these decline rates is needed for strategic decisions (IEA, 2013). However, this has proven to be a very difficult task because there is often a misconception on how to calculate the reserves and production of oil fields.

2.1.2 Trends in natural gas and coal demand and supply

Natural gas is becoming a more important consumable fuel used for energy supply, especially in power generation and heating. Twenty years ago, there was not that much interest in gas, but now gas winning projects are more cost efficient due to a more developed technology of transportation (IEA, 2013). Gas is the only fossil fuel in OECD countries for which demand increases. Especially the winning of alternative gas sources such as shale gas has seen a substantial growth. Natural gas is a relatively clean consumable fuel compared to oil, it is less CO2 emitting than oil or coal and produces significantly less fine dust.

Even the production of coal has increased during recent years, forecasted to increase even more in the coming years. Again, the responsible factor is economic growth and emerging markets. The resources of coal are sufficient to last for decades and if environmental issues can be partly resolved, the use of coal will not be ended quickly. For example, new technologies make it possible to reduce carbon dioxide in coal energy plants with approximate 25%.

An important developing technology that can lead to an even a higher demand in these consumable fuels is that of carbon capture and storage (CCS). This technology can bring an important contribution to reduce carbon emissions (IEA, 2013). With CCS underground storage carbon dioxide is possible. CCS is not yet used for commercial purposes, the current cost and performance is therefore unknown.

Natural gas, coal and other consumable fuels might be more comparable with renewable energy since oil and renewable energy operate in different markets (Nyquist, 2015). Oil is commonly used for transportation but only very little for producing power. In contrast, natural gas is an important consumable fuel for power generation (27% in the US and 19% in Europe).

2.1.3 Outlook

Not only the investment in renewable energy becomes more interesting if the consumable fuel prices rise, also investment in winning alternative oil, gas and coal reserves becomes more cost effective.

As highlighted earlier, the production of oil will continue under current policies. Even stronger, the production of oil will increase by more than 3% in 2035 (IEA, 2013) due to technologic development. However sustainable awareness is increasing and many countries and firms have announced their intention to reduce emissions and support alternative sources of energy supply. Environmental responsibility has already become part of project planning (IEA, 2013).

Consumable fuels are still dominant in the world's energy supply. This will continue in the coming decades, resources are plenty and technology in this sector is developing. Policy will eventually determine whether how long the switch to renewable energy takes.

2.1.4 The effect of oil price fluctuations on macroeconomic variables

Literature has taken a broad perspective of analysis on the relationship between oil prices and macroeconomics. Oil is one of the most popular sources of energy, therefore oil price fluctuations have impact on a great deal of factors. Even so, high oil prices are often related with economic recessions (Inchauspe, Ripple, & Trück, 2015). Although the effect of oil price fluctuations is hard to measure, there are some proven theories about the increase of oil price in general. A great amount of studies have been dedicated to the effect of oil prices on a broad scale of variables. According to former studies Oil price changes increase costs for investment and production and causes changes in unemployment, consumption, monetary policies, interest rates, economic growth and inflation (Arouri, 2011; Narayan, Sharma, Poon, & Westerlund, 2014). These relations can have an indirect effect on the stock market performance, however to outline all research topics would be to comprehensive, therefore I selected the most relevant studies.

One of the reasons that oil prices affect such a great deal of variables is because the increase in the crude oil prices is passed on to products as petroleum, household products & other final products. Consequently, the relation between oil prices and other macro-economic variables can be explained trough the supply-side effect. A rise in oil prices results in an increase in a basic production input, which leads to a reduction in possible output (Abel & Bernanke, 2001). Production costs will rise and output and productivity will be lower.

According to Hamilton (2003) oil price effects are not always linear. This phenomenon is further explained by Basher and Sadorsky (2006). In their study, the effect of an increase in oil prices has a direct effect on economic activity, while surprisingly oil price decreases show barely effect on economic parameters. Therefore oil price increases can be better used for forecasting economic variables. However, there is not a suggested functional form that is to be used to determine the effect of oil price changes.

Without doubt, oil price fluctuations impact a great deal of other variables. For this thesis I a mainly interested in the effect of oil price fluctuation on renewable energy stock performance. Nevertheless, to better understand the literature specific for this topic, in the next paragraph, I will outline the effect of oil price fluctuations on stock market performance.

2.1.5 The effect of oil price fluctuations on stock performance

The effect of oil price shocks on stock market returns has been studied by many earlier papers (Barsky & Kilian, 2004; Huang, Masulis, & Stoll, 1996; Jones & Kaul, 1996). Since my thesis is closely related with this literature, I will shortly outline the relevant empirical implications from these papers.

Sadorsky (1999) started with the use of a VAR-model to find the effect of oil prices and oil price volatility on real stock returns and economic activity. He used impulse response functions to investigate how fluctuations in oil prices can lead to response reactions in stock returns. The results show that an oil price shock has a negative and significant impact on stock market returns. Furthermore, positive oil price shocks have more impact on the economy than negative oil price shocks.

Another comprehensive research is done by Nandha & Faff (2008), where one analysed 35 industry indices on the global equity markets. Their findings were that equity returns fell when oil prices rose. In their results they controlled for the differences in industries, with the overall conclusion that oil prices do not have a negative impact on the mining, oil and gas industry sectors. The reason that oil impacts a broad spectrum of the equity market can be explained by the huge amount of services and products that rely on oil supply.

In 2008, Sadorsky started to investigates oil price shocks on stock performance based on firm size. His basic results were similar to the former ones: Higher oil prices will lead to a decrease in stock returns. Furthermore he found that more volatility in the oil prices result in an increased stock price return. Another result was that the effect on stock price returns was greater in case of an increase in oil prices than in case of a decrease in oil prices.

Lee et al. (2012) find that sector equity indexes may be more suitable for finding the impact of oil price fluctuations because oil prices may have effect on different sectors in different ways. Results find that the impact of oil price shocks has effect on different sector indices in the G7 economies.

Henriques and Sadorsky (2011) investigate whether oil price volatility can effect strategic investment decisions. They use real option valuations for their research to explain how movements of the oil price volatility can influence strategic investment decisions. The model they use is based on moment estimation techniques for panel datasets. Results show that the graphic relation among oil price volatility and investment is u-shaped and not linear. Assuming a linear relationship can therefore lead to biased results.

Later, Sadorsky et all. (2012) studied the interrelation among the variables oil prices, exchange rates and emerging stock markets. The goal of their research is to connect two sub research areas: Literature about the relation between oil prices and stock prices and the research on the effect of oil prices on exchange rates. This time they used a structural auto regression to connect both research backgrounds. The results support that an increase in oil prices result to a decrease in stock prices for emerging markets.

The former studies believe that there is a negative relationship between a rise in oil prices and regular stock performance. However this is not necessarily true for renewable energy stock. A rise in oil prices may enhance interest in renewable energy companies due to the substitution effect. To better understand the dynamics among the variables, a short background knowledge of the renewable energy market is needed. Later on I will outline the existing literature about this topic, bit first I will explain the developments in the renewable energy market.

2.2 Renewable energy market

During recent years, several alternative energy sources were more broadly introduced, which primarily consists out of renewables. Driven by the ongoing concerns about environmental issues and energy security, this will eventually lead to a further increase of renewable energy implementation (Bondia, Ghosh, & Kanjilal, 2016). Since the renewable energy sector is growing rapidly in the last decade, I will outline the most relevant developments in the next section.

In this thesis I will refer to renewable energy as to all energy sources that are not finite and can be replenished at a rate that is equal or faster than the rate of consumption of these sources. Renewables include solar energy, hydro-power, energy produced from biomass, geothermal energy and ocean energy. These energy sources can always be replaced, their amount can only be temporarily exhausted. Renewable energy produces little or no waste. In the scope of this thesis I will not consider nuclear energy as a renewable energy source. Unless that nuclear energy is arguably considered as a cleaner alternative to consumable fuels, nuclear energy plants itself are not sustainable. The production of nuclear energy produces radioactive waste which can be extremely toxic for the environment.

2.2.1 Renewable energy supply & demand

There are positive developments in the renewable energy sector, the last decade the average growth rate of renewable energy was 5.4% (Ren21, 2018). More international commitment is made to invest in renewable energy initiatives and also the private sector is taking a more prominent role in the development of renewable energy projects.

In 2016, renewable energy provided 18% of the total global energy supply. Solar power installations and wind power projects now have a capacity that exceeds that of coal, nuclear power and natural gas combined.

However in some sectors, the growth is less positive. In the transport sector technological progress is slow and the increase in biofuels is obstructed by political debates. Also the heating and cooling with renewable energy lags popularity. In both sectors many opportunities are still available to increase the rate of renewable energy consumption.

Also the productions costs of renewable energy is still relative expensive and therefore rarely adopted without government subsidies. Therefore, many countries and regions have implemented policies to enhance renewable energy development and decrease the carbon footprint.

In Europe all countries have a Regional Emissions Trading System (ETS), a national carbon tax or even both. China and New Zealand have implemented an ETS as well and countries in South-America use a national carbon tax. Members of North, Central and South America have launched the "The Carbon Pricing in the Americas" in 2017.

Several countries have already been successful in the implementation of renewable energy, in the top ten of countries with the largest share renewable energy we find Denmark (58%), Germany (28%) and the UK (19%) (Ren21, 2018). Furthermore, China has the highest growth in renewable energy supply.

Good government policies encourage renewable energy investment, these investment are important for the development of renewable energy technologies, therefore I will summarize the current status of renewable energy development around the world in the next paragraphs.

The demand for energy is increasing therefore China has developed an enormous capacity of hydropower and solar power and is the largest producer of bioelectricity since 2017. Other notable developments in Asia are India and Indonesia where India shows an increase of 23% in solar power capacity and Indonesia is prominent in geothermal energy production.

On the contrary, growth in Europe has slowed down last years, although 2017 was the first year that there was more energy produced using wind, solar and biomass than using coal and lignite. Approximately, 30% of Europe's electricity was generated with renewables. Furthermore, 85% of all new electricity capacity is provided using renewable energy.

In the United States renewable energy provides 18% of its electricity capacity in 2018. In 2016 this was 15%. While this increase is limited, the increase in solar power capacity increased with 26%.

In South-America, growth in renewable energy is strong in 2017, markets for all kind of renewables are emerging. Most renewable energy comes from hydropower and renewable energy sources account for nearly 65% of the region's supply. Brazil is the region's largest wind power producer and Chile is ranked third for the world's new geothermal power capacity.

Africa has only some growth in certain countries, non-hydropower capacity grew with 9%, top countries for the increase in this renewable supply are South Africa, Egypt and Kenya. Across Africa. For the rest there are many opportunities for solar power in this region.

In Australia 17% of electricity came from renewables in 2016. After for years of decline in the growth rate, capacity increased with 2% in 2016. Also in Australia Solar power provided the highest increase of capacity. New Zealand is one of the leaders in renewable energy with 85% of the country's electricity produced using renewables. This high amount of renewables comes mostly from hydropower.

In the Middle East renewables are less developed with only 2,5% of the region's energy coming from renewables. This low amount of renewables comes from the political situation in the region and the great amount of oil resources.

On the path towards a low carbon future and lower costs for renewable energy consumption, investment in renewable energy technologies is needed.

One of the current issues is the supply planning for renewable energy. Supply relies on a great amount of external factors, mostly defined by the weather. This makes solar and wind energy generation still hard to forecast.

Therefore storage can secure a constant energy supply. Storage can store surpluses when electricity generation exceeds demand and this stored energy can be used when there is a lack in supply.

Furthermore, the integration of renewables in a countries electricity network can lead towards much higher volatile electricity prices (Hart & Stoutenburg, 2012). This can withhold countries from applying more renewable energy to their network. Once the technology of storage is more advanced countries could grow more in renewable energy supply.

Assuming that the cost effectiveness of renewable energy production will be equal to energy production using consumable fuels, this would mean that consumable fuel based energy and renewable energy are perfect substitutes. If the goods are eventually substitutable, an increase in the oil price should lead to an increase in demand for renewable energy. Because demand is driven by technologic development, earlier studies (Sadorsky, 2008) find that renewable energy stock relates more with technology stock then with crude oil prices. Oil and renewable energy are not substitutes yet, at this moment, oil and renewables can better be considered as complements.

2.2.2 Renewable energy stock performance

Renewable energy has showed an impressive development in the last decade. Global investment has tripled in within five years (Inchauspe, Ripple, & Trück, 2015). Resulting from the several global renewable energy targets, we could expect a great impact of government on investment in the energy sector and therefore a growth in stock prices. As already mentioned good policy environments are the most important encouragements for clean energy technologies.

According to Bürer & Wüstenhagen (2009) investors favour feed-in tariffs above all other sorts of government subsidies. "The stability of the feed-in policy is arguably considered as the key driver of success" (Bürer & Wüstenhagen, 2009). However, the financial crisis has cut feed-in subsidies in most countries. Therefore the financial crisis has changed the investment climate for renewable energy firms (Huisman & Hofman, 2012).

2.2.3 Technology stock

In the 90s it was observed that the equity prices for renewable energy companies moved in the same way as the NASDAQ (Henriques & Sadorsky, 2008). Therefore it might be possible that the stock performance of renewable energy companies is somewhat related to the stock performance of technology companies. In a later study (Bondia, Ghosh, & Kanjilal, 2016) a unidirectional short run causality from technology stock prices to stock prices of alternative energy companies is found. This strengthens the hypothesis that stock prices of renewable energy firms are interrelated with technology stock prices and oil in the short run.

2.3 Literature review

Energy production by renewable sources will increase in the future and there will be a greater reliance on the use of renewable energy (Sadorsky, 2009). This has resulted towards a growing interest for this topic among academics. I already discussed the impact of oil price fluctuations on equity performance of firms. In this part I will summarize the specific literature on the relation between oil price fluctuations and renewable energy stock performance. The overall conclusions in previous studies are that technology stock prices are more related with renewable energy stock prices than oil prices. Secondly, earlier research has shown that whether oil price fluctuations has significant effect on renewable stock performance, depends on the sample period.

The research done by Henriques and Sadorsky (2008) is the basis for my research. They use a four variable vector auto-regression model to find the empirical relationship between renewable energy stock prices, technology stock prices and oil prices. The effect of fluctuations in oil prices on renewable energy stock prices is tested by a one standard deviation in one of the other VAR variables. Their data includes a renewable energy index, a technology index, oil future contract prices and interest rates over a sample period of January 2001 to May 2007. Granger causality tests show statistical significant results for the impact of oil price movement on renewable stock prices. Moreover, the variables oil prices, technology stock prices and interest rates Granger cause the variable renewable energy stock prices. Surprisingly, oil price movements have greater impact on technology stock prices then on renewable energy stock prices. The conclusion in this study is that oil price volatility might not affect renewable energy investment but that renewable energy stocks might be highly related to technology stock. The relation between renewable energy stock and technology can be explained by the fact that for renewable energy improvements, new technology is needed (CleanTech). They conclude that however the oil price fluctuations do no show a direct result, more research on this specific topic is needed.

Later, Sadorsky (2009) studies the important variables that influence renewable energy consumption. In his research, he analysis data for the countries Canada, France, Germany, Italy, Japan, UK and the US. To test the relations among the different variables he uses panel integration estimates. Data is gathered for renewable energy consumption, GDP, population, oil prices and CO2 emissions. However, the variable stock prices of renewable energy companies is not included, renewable energy consumption may have an indirect effect on renewable energy stock prices. The results show a significant relation between CO2 emissions, GDP and renewable energy consumption. Oil prices appeared to have a small effect on renewable energy consumption.

Kumar et al. (2012) continue with a comparable research and continue on the study by Henriques and Sadorsky (2008). They use a VAR-model as well to test the granger causality. In the model they use three different renewable energy indices; the Wilder Hill New Energy Global Innovation Index, The Wilder Hill Clean Energy Index and the S&P 500 Global Clean Energy Index. Impulse responses are correlated if error terms in the VAR-model are serial-correlated. They use the Cholesky decomposition, orthogonalized impulse response functions to solve this problem. Results show that the Wilder Hill New Energy Global Innovation Index and the S&P 500 Global Clean Energy Index are two times more risky than the Wilder Hill Clean Energy Index and the S&P 500 index. With the updated results, they find that changes in stock prices of renewable energy firms can be explained by the lagged values of technology stock prices, oil prices and interest rates. Furthermore, oil price returns are a risk factor for all three renewable energy price indices. A one standard deviation increase in the stock price of oil firms leads to an increase in the renewable energy indices in the first two weeks. After the two weeks the effect become smaller.

In continuing research the relationship among oil prices, renewable energy stock prices and technology is analysed by using a Markov-switching VAR-model (Managi & Okimoto, 2013). The same data of Henriques and Sadorsky (2008) is used although extended with 3 years. Additionally, they use structural breaks as a contribution to the existing literature. These are events in the time series that can lead to a different interrelation between oil prices and clean energy stock. An example of a structural break is the financial crisis in 2008. Surprisingly they find significant results on the relation between oil prices and renewable energy prices in the three years they add to the period used by Henriques and Sadorsky. This structural change can be contributed to the combination of rising oil prices and decreasing renewable energy costs due to technological improvements. Also, they find that there is a strong correlation among the stock price movements of renewable energy stock and technology stock. They reason that the cause for this relations is the similarity in government policies and subsidies for both sectors.

Broadstock et all. (2012) analyses the effect of oil shocks on energy related stock in China. For this research they use time varying conditional correlation and asset pricing models. Similar to the results of Managi & Okimoto (2013) they find that after the financial crisis in 2008, the impact of crude oil shocks is more intense for renewable energy stocks then before the crisis. Driven by economic growth, China became the second largest oil consumer since 2003, the country is highly reliant upon crude oil but also shows serious growth in renewable energy production. Due to these factors, stock prices for renewable energy companies should be more susceptible to oil price fluctuations. Significant results are found for the impact of international oil prices on renewable energy stock. Furthermore an important implication is that these results are only significant after the 2008 financial crisis.

Subsequently Sadorsky (2012) continued his research on clean energy companies. In this study, a multivariate GARCH model is used to find the volatility spill-overs. Especially the dynamics of the volatility between renewable energy stock, oil prices and technology stock is examined. The Wilder Hill Clean Energy Index, NYSE Arca Tech 100 and the West Texas Intermediate crude oil indices are used for the variables respectively: Renewable energy stock, technology stock and crude oil prices. The results are similar to earlier studies: the correlations between renewable energy stock and technology stock are higher than for renewable energy stock and oil prices. Again, proof is found that renewable companies relate more with technology firms than with oil related companies. Intuitively failure or success in the renewable energy market depends on technologic development. Furthermore, from investment perspective, technology companies show higher returns than renewable energy companies while having the same amount of risk. Therefore it is important to decrease the gap between innovation, adoption and diffusion of clean energy technologies.

More recently, Inchauspe et all. (2015) published a paper that studies the excess returns for the Wilder Hill New Energy Global Innovation Index. They extend the research done by Henriques and Sadorsky (2008) and use a dynamic multi-factor setting based on a state-space model with time-varying coefficients. The Wilder Hill New Energy Global Innovation index consists of companies in the renewable energy sector and is one of the global technology benchmarks for this sector. They find that the impact of oil price fluctuations on renewable energy stock is lower than stock price fluctuations of technology stock. However, oil had more impact on renewable energy stock after 2007 then before 2007. Moreover, high oil prices are related with economic recessions, leading to a positive shift in the energy mix towards renewable energy. There is even the possibility that investors use oil prices as a proxy for a governments willingness to switch to renewable energy production.

3 METHODOLOGICAL FRAMEWORK

This research makes several important contributions about the knowledge of market implications for supporting renewable energy sources. Renewable energy source researches are scarce, while the technology of creating energy from alternative sources is growing substantially. Furthermore, the existing literature lacks a final conclusion about the impact of oil and consumable fuel prices on renewable energy stock.
In this section the empirical methods will be explained that are used in this thesis to test the relation between oil prices and consumable fuel price fluctuations and stock performance of renewable energy companies.
The methods that I use are derived from earlier research (Henriques & Sadorsky, 2008). The mechanisms between the variables can intuitively be explained. Higher oil prices or consumable fuel prices increases production costs for companies that rely on these fuels for producing energy. Considered that firms will not entirely transfer the increased costs to the customer, profit will decline. Consequently, an oil price increase or an oil price shock will have a negative effect on the stock market. However since renewable energy could be more of a substitute for oil and consumable fuels, a rise in oil prices could have a positive effect on renewable energy stock. This results from the fact that once energy production using oil becomes more expensive, renewable energy production becomes more cost effective.

3.1 The model and dynamics

The main question I want to answer in this thesis is: How does consumable fuel prices affect renewable energy stock performance. As introduced earlier, to find this relation, I will use a Vector Auto Regression (VAR) model. The variables in this model are all endogenous and therefore I will also analyse the interactions among the variables. Furthermore earlier studies show in their results that the impact of a positive oil price change is not immediate but rather follows a lagged pattern (Basher & Sadorsky, 2006)

3.1.1 Variables

Variables in the model are:

1. Oil prices
2. Consumable fuel prices
3. Stock prices of renewable energy companies
4. Stock prices of technology companies

The reasons for using these variables are based upon the extensive literature in the literature review section.
An increase in oil prices is believed to have a positive effect on renewable energy stock prices (Henriques & Sadorsky, 2008; Managi & Okimoto, 2013; Inchauspe, Ripple, & Trück, 2015). This is explained by the substitution effect, when oil prices increase, consumers and investors have more reason to substitute consumable fuel bases energy sources with renewable energy. However earlier studies state that this substitution effect is imperfect, since renewable energy sources cannot be used as a perfect substitute for conventional energy sources. Furthermore as explained earlier, an increase in oil prices has a larger effect than a decrease in oil prices.
Consumable fuel prices include all kinds of conventional energy sources such as oil, gas and coal. The effect of a consumable fuel price increase will therefore lead to a positive effect on renewable energy stock prices. Because oil and clean energy operate in a somewhat different markets, consumable fuel prices might be more comparable with renewable energy stock prices (Nyquist, 2015). If consumable fuel prices are more related to renewable energy stock prices, a fluctuation in consumable fuel prices must have more effect on renewable energy stock than a fluctuation in oil prices.
Stock prices of technology companies are included in the model because all past studies have found a positive relation between technology stock prices and renewable energy stock prices (Henriques & Sadorsky, 2008; Kumar, Managi, & Matsuda, 2012; Inchauspe, Ripple, & Trück, 2015; Managi & Okimoto, 2013). An increase in technology stock prices will therefore lead to an increase in renewable energy stock prices. Both sectors are driven by the success of technologic developments and rely on the same kind of government policies. Furthermore renewable energy firms and technology firms are both depending on high-skilled talent and research and development. Because of the above mentioned similarities, investors might see renewable energy firms similar to technology firms.

3.1.2 Hypotheses

The method to test the hypothesis is the VAR, before I explain all the steps in using this method, I will first outline the research question:

What is the effect on stock performance of renewable energy companies after fluctuations in consumable fuel prices?

To find the answer to this question, I constructed various hypothesis. As mentioned in the introduction renewable energy stock prices might correlate more with technology stock prices than with oil prices.

Therefore the following hypothesis is used:

(H1) Renewable energy stock is more correlated to fluctuations in technology stock prices than fluctuations in the oil price.

Furthermore, since literature states that not only the renewable energy market is growing, but there is also a visible shift from energy producing by using oil towards natural gas and coal, I have chosen to incorporate an index for consumable fuels instead of only oil prices. Consequently, the following hypothesis is:

(H2) Renewable energy stock is more correlated to fluctuations in consumable fuel prices than fluctuations in the oil price.

Taken in account that this study is done using almost 8 years of data, there might have been significant structural changes in the former mentioned relationships. These structural changes are referred to as structural breaks. According to Bondia et al. (2016), a research can have misleading results if the possibility of structural breaks is ignored. To test for structural breaks the following hypothesis is used:

(H3) The impact of oil fluctuations on renewable stock prices has more effect in different time periods.

The results to these hypothesis will be explained in section 5 of this thesis. In section 4 the data that is used to test the hypothesis is outlined.

3.2 Vector auto-regression model explained

VAR models are widely used among academics for multivariate time series. VAR models are often used as an alternative to large-scale simultaneous equation structural models. In a VAR model all variables are jointly endogenous and there are not restrictions on structural dependence. It is therefore not necessary to specify which variables are explanatory and which ones are the response variables.
This approach is especially useful for the study among commodities, whose prices are often related because of the substitution or complementary effects in production and consumption. However the coefficients that are estimated do often lack statistical significance, Granger Causality and Impulse Response functions can reveal something about how variables move together.
The Granger Causality determines if the lags of a certain variable can explain the value of another variable at the present time. It is most commonly implemented by an F-test on the lags of the other variable on the variables of interest. In this case it tests if oil prices can forecast renewable energy stock prices. With this, the dynamics of the data can be described using a VAR Model (Brooks, 2014).
Impulse response functions are used to explain the effect of the shocks in a particular variable. Alongside, the impulse response functions are used to observe the response effect of one variable from an innovation in another. In other words, it forecasts the value of a variable at the present time or in the future based upon other lagged variables. If the error terms in the VAR are serially correlated, the impulse response functions are also correlated (Brooks, 2014).
The structure of a VAR can best be described as a linear function of past lags of a particular variable and past lags of other variables. Structural VAR models are used to find response of variables to a

shock in another variable. They are often used to explain time series correlations under the condition that all variables in a VAR-model are used symmetrically, for each variable there is an equation that explains the evolution based on the historical results of all variables in the model.
The model that I use is a VAR model with four variables. It consists of y_{1t} , $y_{2t,}$ $y_{3t,}$ y_{4t} and the values are dependent on the combinations of previous lags of the variable and error terms. I will explain this model to give some background about the dynamics. When performing the test for the empirical results, I will use four different variables, where for example the following variables are used: y_{1t}=oil prices, y_{2t}=renewable energy stock y_{3t}=consumable fuel prices, y_{4t}=technology stock prices, which using one lag can be described as:

(1) $Y_{1t}=\beta_{10}+ \beta_{11}y_{1t-1}\ldots+ \beta_{12}y_{2t-1}+ \beta_{13}y_{3t-1}+ \beta_{14}y_{4t-1}+ e_{1t}$
(2) $Y_{2t}=\beta_{20}+ \beta_{21}y_{1t-1}\ldots+ \beta_{22}y_{2t-1}+ \beta_{23}y_{3t-1}+ \beta_{24}y_{4t-1}+ e_{2t}$
(3) $Y_{3t}=\beta_{30}+ \beta_{31}y_{1t-1}\ldots+ \beta_{32}y_{2t-1}+ \beta_{33}y_{3t-1}+ \beta_{14}y_{4t-1}+ e_{3t}$
(4) $Y_{4t}=\beta_{40}+ \beta_{41}y_{1t-1}\ldots+ \beta_{42}y_{2t-1}+ \beta_{43}y_{3t-1}+ \beta_{44}y_{4t-1}+ e_{4t}$

In this model, I assume that all variables are stationary, this means that the error terms, e_{1t}, e_{2t}, e_{3t}, and e_{4t} are uncorrelated noise errors with standard deviations of SD_{1t} and SD_{2t} with an average of zero. The first order VAR model with two variable can be expanded by implementing more variables. In this multivariate VAR model, the variables are allowed to affect each other. The terms that are used to capture immediate feedback effects are so called contemporaneous feedback terms. This is a way to measure the value of a variable based on the value of another variable.

The VAR model that estimates the relationship between the four variables looks like the following:

<u>For Model 1:</u>

(5) $\Delta REI= \beta^{REI}_{0} + \beta^{REI}_{1}\Delta REI_{t-1}+\beta^{REI}_{2}\Delta OIL_{t-1}+\beta^{REI}_{3}\Delta CF_{t-1}+ \beta^{REI}_{4}\Delta TECH_{t-1}+e_{REI}$
(6) $\Delta OIL= \beta^{OIL}_{0} + \beta^{OIL}_{1}\Delta REI_{t-1}+\beta^{OIL}_{2}\Delta OIL_{t-1}+\beta^{OIL}_{3}\Delta CF_{t-1}+ \beta^{OIL}_{4}\Delta TECH_{t-1}+e_{OIL}$
(7) $\Delta CF= \beta^{CF}_{0} + \beta^{CF}_{1}\Delta REI_{t-1}+\beta^{CF}_{2}\Delta OIL_{t-1}+\beta^{CF}_{3}\Delta CF_{t-1}+ \beta^{CF}_{4}\Delta TECH_{t-1}+e_{CF}$
(8) $\Delta TECH= \beta^{TECH}_{0} + \beta^{TECH}_{1}\Delta REI_{t-1}+\beta^{TECH}_{2}\Delta OIL_{t-1}+\beta^{TECH}_{3}\Delta CF_{t-1}+ \beta^{TECH}_{4}\Delta TECH_{t-1}+e_{TECH}$

<u>Model 2:</u>

(9) $\Delta REII= \beta^{REI}_{0} + \beta^{REI}_{1}\Delta REII_{t-1}+\beta^{REI}_{2}\Delta OIL_{t-1}+\beta^{REI}_{3}\Delta CF_{t-1}+ \beta^{REI}_{4}\Delta TECH_{t-1}+e_{REI}$
(10) $\Delta OIL= \beta^{OIL}_{0} + \beta^{OIL}_{1}\Delta REII_{t-1}+\beta^{OIL}_{2}\Delta OIL_{t-1}+\beta^{OIL}_{3}\Delta CF_{t-1}+ \beta^{OIL}_{4}\Delta TECH_{t-1}+e_{OIL}$
(11) $\Delta CF= \beta^{CF}_{0} + \beta^{CF}_{1}\Delta REII_{t-1}+\beta^{CF}_{2}\Delta OIL_{t-1}+\beta^{CF}_{3}\Delta CF_{t-1}+ \beta^{CF}_{4}\Delta TECH_{t-1}+e_{CF}$
(12) $\Delta TECH= \beta^{TECH}_{0} + \beta^{TECH}_{1}\Delta REII_{t-1}+\beta^{TECH}_{2}\Delta OIL_{t-1}+\beta^{TECH}_{3}\Delta CF_{t-1}+ \beta^{TECH}_{4}\Delta TECH_{t-1}+e_{TECH}$

With:
S&P Global Clean Energy price index: RE1
Brent Oil Fund: OIL
S&P500 Oil, Gas & Consumable fuels price index: CF
Wilder Hill Clean Energy price index: REII
NYSE Arca Technology 100 price index: TECH

3.2.1 Requirements of the VAR model

To use the VAR model to test the data, there are some requirements that need to be satisfied, the first one is that the expected value of the error term is zero.

(13) $E(e_{1t,} e_{2t,} e_{3t,} e_{4t}) = 0$

Furthermore there must be no serial correlation and the time series in the models should be stationary. Stock market prices and commodity prices are typically non-stationary, using the difference of the stock prices will mostly solve the problems. However to be sure, a Dicky-Fuller test is performed to determine if the data is stationary.

The requirements in short:

1 $E(e_{1t,} e_{2t,} e_{3t,} e_{4t}) = 0$
2 Time series in the model are stationary
3 No serial correlation

3.2.2 Stationarity

One of the assumptions when conducting a VAR analysis, is that the data must be stationary. A stationary process has the property that the variance, mean and autocorrelation does not change in different time periods. There are two sorts of stationarity: Strict stationarity and weak stationarity. In case of strict stationarity, the stochastic process has a joint probability distribution that is not affected by time.
In other words: the mean and variance do not change over time, whereby the fluctuations move around the mean with a constant range.
Weak stationarity or covariance stationarity occurs in case you are only interested in the mean, variance and covariance of the data. In these cases, I only want to know if the movements of a variable are independent from time, instead of independent throughout the entire distribution. A stochastic process has weak stationary for t=1, ∞ if the following requirements are met:

1 $E(y_t)=u$
2 $E(y_t-u)(y_t-u)=SD^2 < \infty$
3 $E(y_{t1-u})(y_{t2}-u)= Y_{t2-t1}\ A_{t1,\ t2}$

The first two requirements must have a constant and finite mean and variance in the process. The last one requires that the auto covariance depends only on the distance in time between two observations. In other words, the mean variance and auto covariance may not depend on time. Autocovariance measures if there is dependency between two observations. It clarifies how y is related to its previous values. Autocorrelation is the normalization of the autocovariances by dividing the variance.
If the data does not meet these requirements, it is not stationary. In my data it is clear that the data is not since the mean is different at distinctive points in time. In most economic time series this is the case. For a graphic overview of the datasets, see Chapter 3, figure 1.
In most literature, stationary is referred to as weak stationarity or covariance stationarity. The reason that I want to know if the data is stationary is because as a researcher you want to avoid so called

spurious regression. This happens if the data for two variables are random series with one of the variables regressed on the other, and a false effect is observed. In this case the t-ratio of the coefficient will be not significantly different from zero and R^2 is also expected to be low. If the data follows a certain trend, the model could haven high R^2. If standard techniques are used when the data is non-stationary, this can lead to a misleading and faulty result (Brooks, 2014).
To use a VAR and get reliable results, it is therefore important to adjust the data to make the data stationary, this can be done for example by de-trending the data. However there is an exception for some sort of data. If two non-stationary time series follow a similar growth in time, the combination of the trend can be still stationary. This is called cointegration. As I will use the daily differences in index prices, the data I use is assumable stationary and therefore I will leave the cointegration test out.

3.2.2.1 Stationary

To see if the data is stationary or not, we first can look at the data (figure 1). Secondly, because graphical analysis is not sufficient to conclude that the data is stationary, a unit root tests needs to be performed. A commonly used test to see if the data is stationary is known as the Dicky Fuller test. In this thesis I will use the augmented Dicky fuller test because this test offers higher power than the standard Dicky Fuller test. This results in a more likely rejection of the null hypothesis of a unit root against a stationary alternative.

3.2.2.2 The Dicky Fuller test explained

The Dicky Fuller test is the most commonly used method for unit root testing. The test helps to find out in which order the variables are integrated when they appear to be non-stationary. Brooks (2014) states that if an economic non-stationary time series needs to be converted to a stationary time series, one can best use the first difference. The time series is then integrated of order d, which can be notated as $y_t \sim I\ (d)$. Furthermore the value: I(0) means the process has no unit root and a value of I(1) means that it does. The original design of the test is to test the null hypothesis, $H_0 : \delta = 0$. If the null hypothesis is not rejected, the variable or data can be seen as non-stationary, I(1). The alternative hypothesis, $H_a : \delta < 1$, implies that the variable is stationary. When the null hypothesis cannot be rejected, I will perform the following test: $H_0 : X_t \sim I\ (2)$ vs. $H_a : X_t \sim I\ (1)$, in order to determine if the series are integrated of the second order. If this test is also rejected, the conclusion is that the variable contains one unit root, but if the rejection fails, the test needs to be done for the third order and so on. The distribution of the rejection regions follow a non-standard form. The critical values are derived with simulations. This theory can be used to time series with a random walk, with a random walk with drift and time series with a random walk with drift and a deterministic trend.

The notations are:

(14) $x_t - x_{t-1} = (\rho - 1)\ x_{t-1} + \varepsilon_t = \delta x_{t-1} + \lambda T + \varepsilon_t$

(15) $x_t - x_{t-1} = \boldsymbol{\mu} + (\rho - 1)\ x_{t-1} + \varepsilon_t = \boldsymbol{\mu} + \delta x_{t-1} + \varepsilon_t$

(16) $x_t - x_{t-1} = \mu + (\rho - 1)\ x_{t-1} + \boldsymbol{\lambda t} + \varepsilon_t = \mu + \delta x_{t-1} + \boldsymbol{\lambda T} + \varepsilon_t$

The tests are valid if the error term is only white noise, which means that the error term is not auto correlated. With the augmented Dicky Fuller test, I can solve this problem. The augmented Dicky Fuller test adds lagged variables, $\Delta x_t = x_t - x_{t-1}$, which leads to no autocorrelation for the error term, $\varepsilon_{t.}$

The full test is notated as:

(17) $\Delta x_t = \mu + \delta x_{t-1} + \lambda t + \gamma_1 \Delta x_{t-1} + \gamma_2 \Delta x_{t-2} \ldots + \gamma_n \Delta x_{n-k} + \varepsilon_t$

3.2.3 Lag selection

In order to perform a sound VAR analysis, I need to determine the optimal number of lags that is needed for the dependent variable (Brooks, 2014). This is important because the tests that I use depends on the number of lags that I select. Using a too large number of lags will lead to an increase of the standard error of the coefficient. On the other hand, using too few lags will not clear all the autocorrelation, which can lead to misleading results.
The basic method to find the appropriate number of lags is by using information criteria. The information criteria is divided in two factors: (1) A term that is a function of the residual sum of squares, (2) A ‘penalty’ for the loss of degrees of freedom that results from adding the independent variable.
Adding a new variable or lag will therefore lead to the effects that the residual sum of squares will decline and the penalty term will increase.
The optimal number of lags or parameters is the number that has the lowest value for the information criteria.
The commonly used method from earlier research by Schwert (1989) allows the information criteria to be calculated for the value range of p, with $p < p_{max}$ to p=0 and $p_{max}=[12*\left(\frac{T}{100}\right)^{1/4}]$.
In the next step, I need to decide the right amount of lags. According to Brooks (2014), it is best to use the same number of lags for each equation and therefore the multivariate versions of the information criteria is used:

1. MAIC=log $[\sum\text{^}]\frac{2p'}{T}$
2. MSBIC= log $[\sum\text{^}]+\frac{p'}{T}$ ln T
3. HQIC= log $[\sum\text{^}]+\frac{2p'}{T}$ log(log(T))

And:
$\sum$^ being the variance-covariance matrix of all the residuals
T is the number of observations
P’ is the number of regressions = k^2p+k
k is the number of equations in the auto regression of the vector, with p lags.

In this thesis I use two different VAR models, therefore two separate lag selection criteria tests will be used.

3.2.4 Autocorrelation

Autocorrelation refers to the problem that the error term is correlated between different time periods. To determine if the previous value (t-1) will affect the next value (t), a look graphical analysis can be used. If the time series includes autocorrelation, the plot of the graph shows a pattern that crosses the x-axis only a few times. In case of negative autocorrelation, the plot shows a graph that crosses the x-axis many times. A negative autocorrelation means that the current value of the residual is the opposite of the previous value. For example, if the first value is positive, the second one is likely to be negative. This results in a fluctuating graph.
When the time series do not have autocorrelation, the plots show a scattered pattern across all quadrants.
However, the graphical analysis might be delusive sometimes because the plot isn't totally clear when distinguishing between autocorrelation or no autocorrelation.
A method to statistically test for autocorrelation is the Lagrange Multiplier. This test helps to analyse the relationship between $\hat{u}_t$ and the lagged values at the same time period (Johanson, 1995).

3.2.5 Stability of the VAR-model

It is important for the results that the VAR is stable. If the VAR is stable, the impact of a shock should gradually decline. In the case that the VAR is unstable, shocks will increase over time and the projections become unrealistic extreme results. In the end, this will lead to an invalid model. We test the stability of the model by analysing the eigenvalues, which must be lower than one and inside the unit circle.

3.2.6 Impulse response functions

The impulse response functions of the variables in the model show how each variable responds on another variable. It says something about the responsiveness of the variables to shocks and that is something I am interested in. The impulse response functions visualise the response of a variable to an exogenous shock over time. For each of the impulse response functions, a unit shock is applied to the error term. By doing so, the effects on the different variables within the VAR model can be defined, which shows if the effect is positive or not and how long the effect lasts in time (Brooks, 2014).
To explain how impulse response functions are calculated consider the following VAR with four variables:

$$y_t = A_1 y_{t-1} + yt \qquad (18)$$

With $A_1 = \begin{pmatrix} 0.4 & 0.3 & 0.4 & 0.3 \\ 0.5 & 0.4 & 0.5 & 0.4 \\ 0.3 & 0.2 & 0.3 & 0.2 \\ 0.4 & 0.5 & 0.4 & 0.5 \end{pmatrix}$

This can be written as:

$$(19) \qquad \begin{pmatrix} y1t \\ y2t \\ y3t \\ y4t \end{pmatrix} \begin{pmatrix} 0.4 & 0.3 & 0.4 & 0.3 \\ 0.5 & 0.4 & 0.5 & 0.4 \\ 0.3 & 0.2 & 0.3 & 0.2 \\ 0.4 & 0.5 & 0.4 & 0.5 \end{pmatrix} \begin{pmatrix} y1t-1 \\ y2t-1 \\ y3t-1 \\ y4t-1 \end{pmatrix} + \begin{pmatrix} e1t \\ e2t \\ e3t \\ e4t \end{pmatrix}$$

A unit shock to y_{1t} at time t=0 will be:

$$(20) \qquad y_0 = \begin{pmatrix} e1t \\ e2t \\ e3t \\ e4t \end{pmatrix} = \begin{pmatrix} 1 \\ 0 \\ 0 \\ 0 \end{pmatrix}$$

$$(21) \qquad y_1 = A_1 y_0 = \begin{pmatrix} 0.4 & 0.3 & 0.4 & 0.3 \\ 0.5 & 0.4 & 0.5 & 0.4 \\ 0.3 & 0.2 & 0.3 & 0.2 \\ 0.4 & 0.5 & 0.4 & 0.5 \end{pmatrix} \begin{pmatrix} 0.4 \\ 0.5 \\ 0.3 \\ 0.4 \end{pmatrix}$$

Eventually, the impulse response functions can be described as functions of y_{1t}, y_{2t}, y_{3t} and y_{4t} to a unit shock in y_{1t}.

3.2.7 Normality distribution test

A normality distribution test is standard in statistic testing when conducting a VAR analysis, whereby, a commonly known used test to is the Bera Jarque test (Jarque & Bera, 1980). This statistical procedure is used to test the goodness of fit of a model. In order words, to determine if the data is skewed and if the kurtosis is the same as model with normal distributed data. The skewness measures if the distribution is somehow symmetric and kurtosis measures how thick the 'tails' of the distribution are. A normal distribution has kurtosis of 3 and is not skewed.

3.2.8 Granger causality

Granger causality is a statistical measure to determine the causality between two variables. It measures if the lagged values of one variable can explain an effect in other non-lagged variable.

In other words, there exists a granger causality for oil prices on renewable energy stock if renewable energy stock can be better predicted by the lagged values of oil prices and renewable energy stock prices than only by the lagged value of renewable stock prices. Economic intuition as explained in the theoretical background suggests that oil prices and consumable prices have a positive effect on renewable energy stock prices. Furthermore technology stock prices might also have a positive effect on renewable energy stock prices.

To test the causal relations of the variables in the VAR model, writing down the equations for each variable, I performed the Ordinary Least Squares test to obtain the coefficients. Granger Causality makes use of the F-statistics to determine whether the (independent) variables are useful predictors.

4 DATA

4.1 Data

The dataset that I have used for this thesis consists of daily closing prices of renewable stock, oil, gas and consumable fuel. All the data is gathered from Datastream. The sample period covers almost 8 years, dating from January 2010 to August 2018, containing a total of 435 weekly observations per model. I use date in this period because studies explained in section 2, conclude that the investment climate for renewable energy has changed after the crisis. The crisis is defined as a structural break in the data; an event that changes the dynamics among variables (Managi & Okimoto, 2013). According to Bondia et al. (2016) a structural break should not be ignored. They investigate the long-term relationship of alternative energy stock prices with oil prices. The research finds a conformation to the fact that structural brakes in large time's series should not be ignored. If structural breaks are ignored, this can lead to biased results.

Additionally, I use weekly date as this seems the perfect trade of between enough observations and too many observations. Earlier studies used daily, weekly, monthly and quarterly data, however the overall consensus is that weekly data is the best fit for the analysis. The first difference of the weekly values is used for the tests in order to exclude co-integration.

The choices for the indices used rely solely on earlier research, in the next paragraphs I will explain the characteristics of each benchmark. I think the indices are a good measure for the chosen variables in my models.

4.1.1 Description of renewable energy datasets

The Wilder Hill Clean Energy Index (ECO) is the first index that is used to track the performance of clean energy firms. It's one of the first renewable energy indexes and therefore it has a relatively large timespan. The index is an equal-dollar-weighted index consisting of a set of corporations engaged in the production of cleaner energy such as solar power, wind power, hydrogen power, fuel cells, biofuels but also pollution prevention. The Wilder Hill index consists of 40 different stock in the first quarter of 2018. It is a capitalization weighted equity index and is used in a large amount of literature regarding the renewable energy subject.

As second dataset for renewable energy stock I use the S&P 500 Global Clean energy index. The index is formed by the weighted equity value of 30 renewable energy firms. The firms in the index are operating globally and range from clean energy equipment to hydropower facilities. Also this index is a capitalization weighted index.

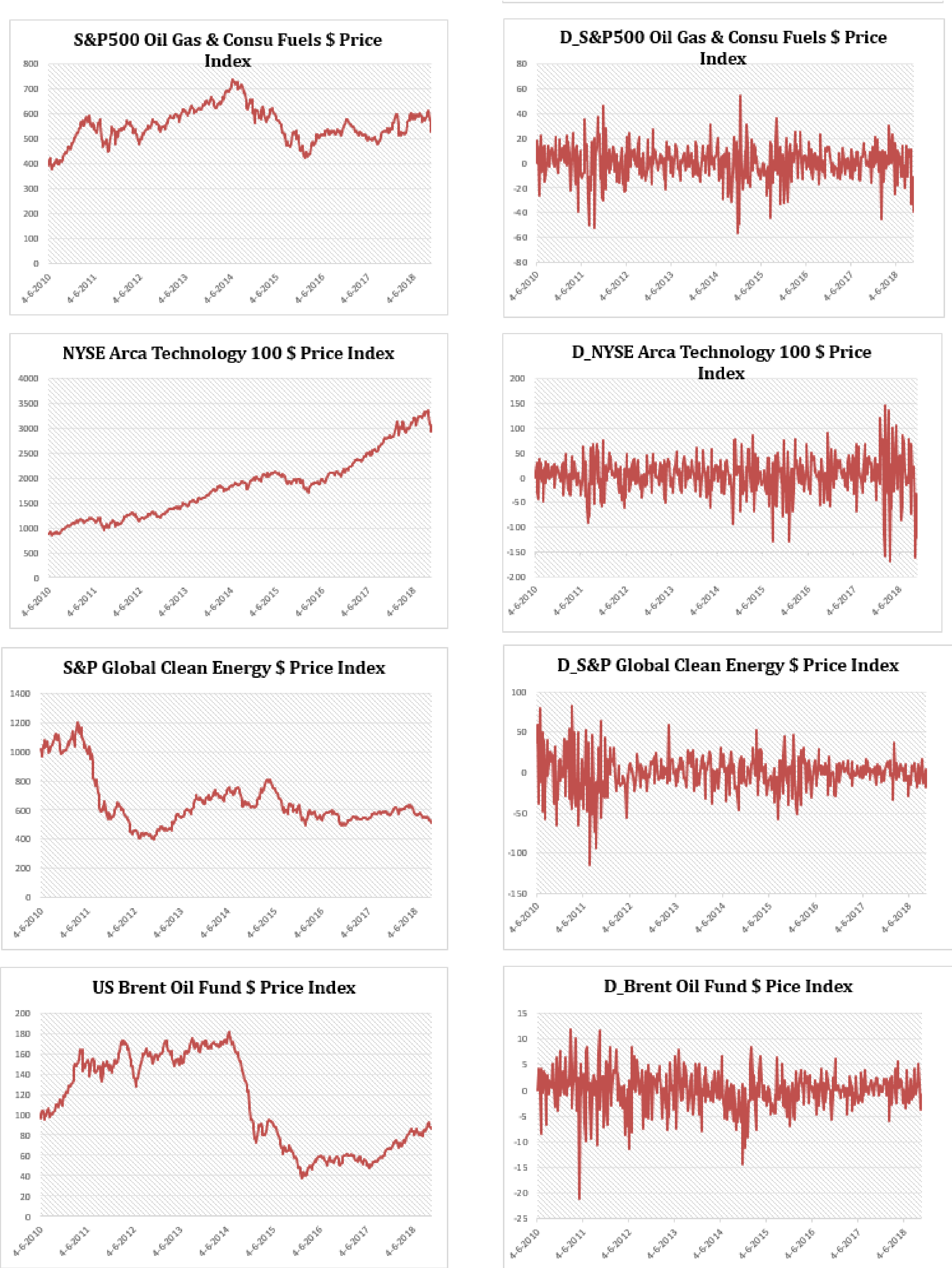
4.1.2 Description of the tech dataset

The NYSE Arca Tech 100 (PSE) index is one of the oldest US-Based technology index. This index is price-weighted and includes common stock and ADRs of technology firms, operating in several different industries. It is listed in the U.S. stock exchange. I incorporate this dataset in my thesis because renewable energy companies may look a lot like tech companies, even more (Sadorsky, Correlations and volatility spillovers between oil prices and the stockprices of clean energy and technology companies., 2012). The success of renewable energy companies relies on the same fundamentals as that of tech firms. Both renewable energy and tech firms are competing for the same resources such as infrastructure, government support and developing talent. The behaviour of the late 1990s and early 2000 US equity market supports the similarity among renewable energy and technology equity (Ferrer, Shahzad, López, & Jareño, 2018).

4.1.3 The oil, gas & consumable fuels data

The U.S. Brent Oil index (BNO) is used for the oil daily oil price data. The Brent oil price index is one of the major benchmarks for U.S. crude oil prices and is used in a wide variety of earlier research.
Because besides oil, the market performance of conventional energy firms might influence the equity of renewable energy firms I use the S&P 500 Oil, Gas & Consumable Fuels sector index (CESI). This index consist of companies that are active in the exploration and production of energy by using Oil, gas or other conventional energy sources. CESI is according to earlier papers, the leading benchmark for the conventional energy production.

Figure 1: A graphical view of the variables and the weekly differences



5 RESULTS & INTERPRETATION

With this part of the thesis will present the results that come from the empirical methodology. A VAR model is used to explain the endogenous variables, based on their own historic values. To avoid Co-integration when applying the VAR-model, the weekly decline or increase is used for the different values.

5.1 Stationarity

Since the VAR model is designed to test variables which are stationary, a unit root test is performed. As I explained before, the time series for all variables look stationary based on graphical analysis in chapter 3, but to determine if the data is stationary, I performed the Augmented Dicky Fuller test
By using lags of the order p, the test formulation allows for a higher order autoregressive process. The Augmented Dicky Fuller test is used to test for a unit root, I(0) means there is no unit root and I(1) means there is.
If I run the unit root test with the null hypothesis against the alternative hypothesis, it can be compared to the critical value of the test. If the test statistic is less than the critical value, the null hypothesis can be rejected and there is no unit root.
The first variable which is tested is the difference in price of renewable energy stock, the second variable analyses using the Augmented Dicky Fuller test is Oil Price. To examine if the different variables used in the VAR analysis are stationary, two different procedures are used. With the first, a time series line graph is used, where one examines if a variable renders a trend which is dependent on time. In other words, if a variable has a unit root, time acts as a causal effect on the variable. The Dickey Fuller test is the second one which will be used to test for stationarity.

Variable	Exogenous variable	Lag length	Test Statistics	P
D_S&P Global Clean Energy	None	1	-14.041	0.0000
D_Brent Oil	None	1	-14.324	0.0000
D_S&P 500 Oil, Gas & Consumable fuels	None	1	-14.542	0.0000
D_Wilder Hill Clean Energy	None	1	-14.224	0.0000
D_Arca Tech 100	None	1	-16.027	0.0000

Table 1: Augmented Dicky-Fuller Test for all variables with siginificant level 1%

There are various ways to ensure that a variable is stationary. One of them is to compute a new variable, where the difference is taken from t=1 and t=2 of a particular variable – a one-year lag. Since I mainly use the daily weekly differences as values, these variables were tested again on stationarity. If you look at the time series line graph on the next page, one can observe that no time trend is visible anymore for each of the variables which is also the conclusion of the Dickey Fuller tests. The test indicates that with a probability of 0.000 it's below the 0.001 significantly level. Therefore, the null hypothesis can be rejected, which implies that the variables are stationary for a p-value of <0.01

Another way of transforming variables with the aim of making them stationary, is taking the percentage increase between t=1 and t=2. To test if the transformed variables are really stationary, line graphs were plotted and Dickey-Fuller tests were computed. The line graphs showed that the variables were without a time trend, and by approximation stationary. This conclusion was again underscored by the Dickey Fuller tests (with a p-value of <0.001), which show that each of the variables are stationary after transformation.

Now it's clear that the two types of transformed variables -by taking the first difference and the percentage increase of two-time frames- are stationary. Therefore, henceforth I can use these two types of variables in the VAR analyses.

Figure 2: non-stationary variables:

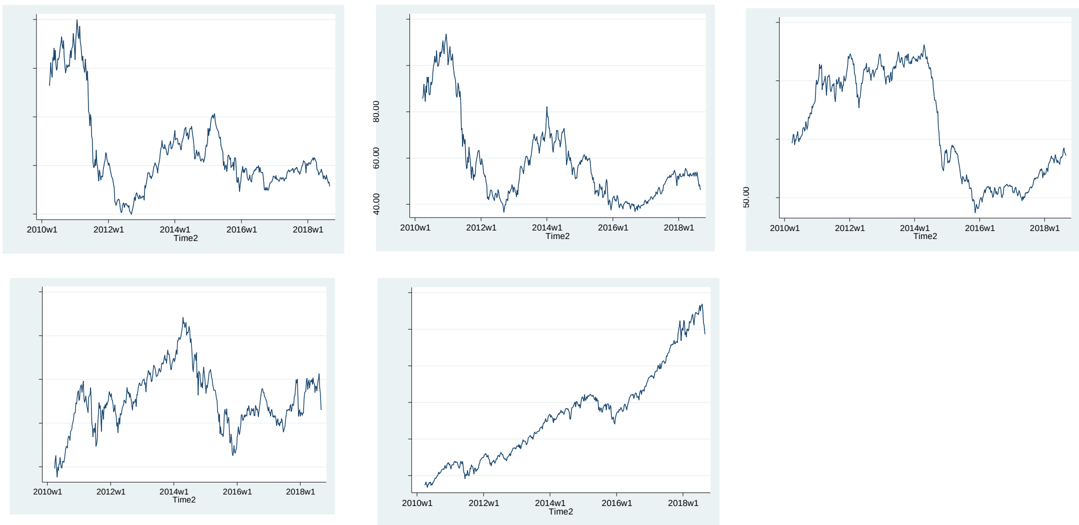
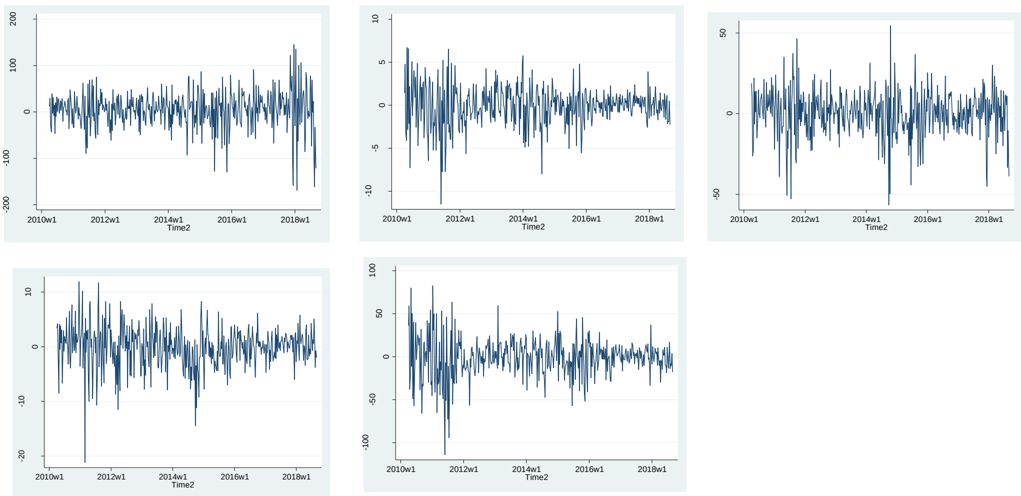


Figure 3: stationary variables:



5.2 Lag selection

In section 3 I explained the method that I use for an appropriate lag selection. This is important because if the lag length is too short, the model does not capture the dynamics of the model while using a longer lag length than optimally would make the estimation to complicated. This eventually can lead to misleading results.
To determine how many lags are appropriate, an information criterion is used. The criteria are calculated for each lags, where under normal circumstances they generates the same outcome. In this case, the criteria: AIC, HQIC and SBIC are used. When the optimal number of lags differ between the different criteria, the AIC criteria has the definite vote.
Because in this thesis, two kind of VAR models are used, two separate lag selection criteria tests are computed. The first model looks at the effect of the oil, gas and consumable fuels index and the tech index on the S&P 500 Global Clean Energy Price index. The second one, looks at the effect of the oil, gas and consumable fuels index on the Wilder Hill Clean Energy Price index. For the former, all of the criteria suggested that including one lag in the model would be most optimal (because an asterisk denotes the most optimal lag selection per criteria). For the latter, a lag selection of one is also the most optimal choice. This is because both the AIC, HQIC and SBIC indicate that the lowest value of the criteria -when minimizing the error term- is reached when using a VAR model with a lag value of one (rendered by the asterisks).

VAR Model 1								
Lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	-10637.1000				2.1E+16	48.9244	38.9292	48.9619
1	-6843.2900	7587.5*	16.0000	0.0000	5.9e+08*	31.5554*	31.6293*	31.7428*
2	-6839.4600	7.6740	16.0000	0.9580	6.30E+08	31.6113	31.7444	31.9486
3	-6828.9400	21.0450	16.0000	0.1770	6.50E+08	31.6365	31.8288	32.1237
4	-6820.2400	17.3860	16.0000	0.3610	6.70E+08	31.6701	31.9215	32.3071
VAR Model 2								
Lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	-9825.89				2.00E+14	44.2754	44.2901	44.3128
1	-5809.84	7632.1*	16	0	5.1e+06*	26.8039*	26.8778*	26.9912*
2	-5805.77	8.1428	16	0.945	5.40E+06	26.8587	26.9918	27.196
3	-5796.49	18.549	16	0.293	5.60E+06	26.8896	27.0819	27.3768
4	-5788.4	16.18	16	0.44	5.80E+06	26.926	27.1774	27.5631

Table 2: Selection order criteria, sample 2010w17 to 2018w35 for VAR model 1 and 2

5.3 Autocorrelation

5.3.1 Lagrange multiplier

The time series should not be affected by autocorrelation. To achieve unbiased empirical results, I examine if all variables have ‘random’ data and aren’t serially correlated. I perform the serial correlation LM test on all VAR residuals with the conclusion that all variables fit the model. Hence, I can accept the null hypothesis of no serial correlations. In addition, to test if autocorrelation is present in the different models, the Lagrange-multiplier test was computed. This statistical procedure is used because the model is only statistically valid when the residuals don’t display any form of autocorrelation. Hence, it’s necessary to determine if the VAR model doesn’t suffer from this. For model one, one can conclude that he H_0 hypothesis can’t be rejected, because the p-value has a value of 0.194. The same can be said of model two, where the H_0 hypothesis again cannot be rejected, because of the p-value of 0.102. Hence, one can conclude that there is no autocorrelation in both models.

VAR model 1				VAR model 2		
lag	chi2	df	prob>chi2	chi2	df	prob>chi2
1	20.6079	16	0.19408	23.4188	16	0.10299
2	17.3728	16	0.36188	19.6952	16	0.23426

Table 3: Lagrange-Multiplier test, H0 no autocorrelation at lag order

5.3.2 Stability

As described earlier in the methodological section, it’s important that a VAR model is stable. The criteria which has to be uphold is that the eigenvalues of both models are less than one. In the tables below, one can observe the different eigenvalues per model. What can be concluded here, is that both models meet that criteria, because all the values are below one. Furthermore, all the eigenvalues for both models lie inside the unit root circle as shown in figure 4 and 5. If this was not the case, this would mean that one of the variables is integrated in the first order, I(1).

VAR model 1		VAR model 2	
Eigenvalue	Modulus	Eigenvalue	Modulus
-0.6817149	0.068171	-0.06174901	0.061749
0.05705068	0.057051	.01213094 + .03204727i	0.034266
.02048172 + .03398984i	0.039684	.01213094 - .03204727i	0.034266
.02048172 - .03398984i	0.039684	0.02445165	0.024452

Table 4: Eigenvalue stability condition vor 2 VAR models

All the eigenvalues lie inside the unit circle.
VAR satisfies stability condition.

Figure 4: unit root circle model 1

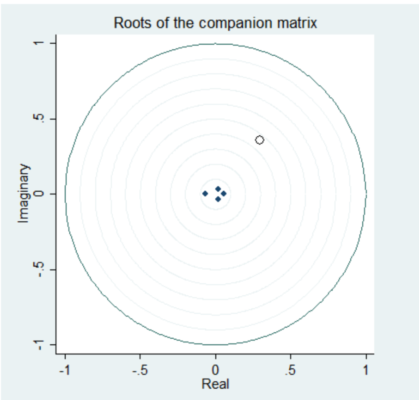
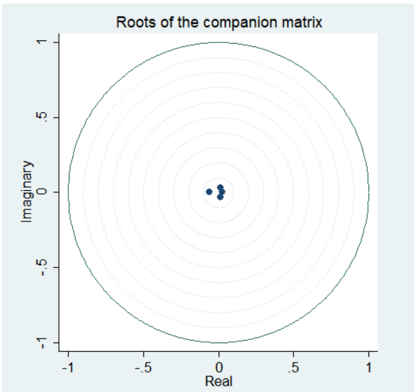


Figure 5: unit root circle model 2



5.4 Normality distribution tests

A normality distribution test is a standard test when computing a VAR analysis. It measures if the data is skewed and if the kurtosis is approximately equal to a normal distribution. For our analysis, a Bera Jarque test is used, which measures the 'goodness of fit' of a model. One potential problem can lie in the fact that our distribution has fatter tails and is more peaked than what is acceptable in a normal distribution. This can occur when returns with short-term intervals (daily or weekly) are used.

In the graphs below one can observe two normality plots of the variables: 1) Difference of the S&P 500 Global Clean Energy Price and 2) Difference of the Wilder Hill Clean Energy Price, where both are approximately normally distributed. Yet, one cannot rely in full on the graphical representation of normal distribution test. Hence, Jarque-Bera test were computed for both models. According to these tests, both models have normally distributed data, because the p-value is significant is all cases.

Figure 6: distribution S&P 500 Global Clean Energy Price

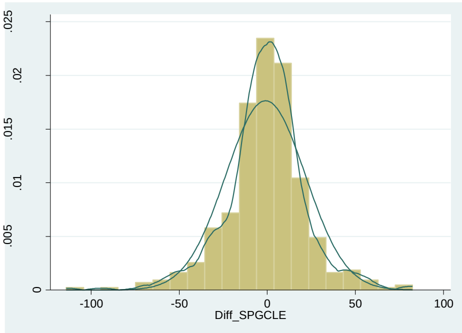
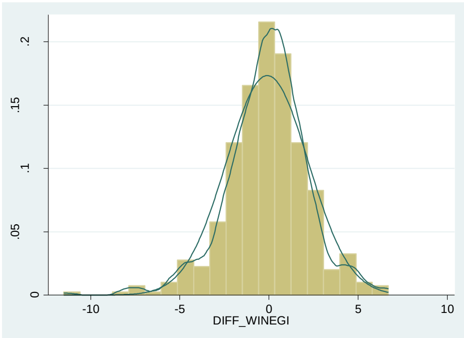


Figure 7: distribution Wilder Hill Clean Energy Price



VAR model 1				VAR model 2			
Equation	chi2	df	Prob > chi2	Equation	chi2	df	Prob > chi2
DIFF SPGCLE	157.194	2	0.0000	DIFF_WINEGI	102.711	2	0.0000
DIFF_BNO	100.983	2	0.0000	DIFF_BNO	115.129	2	0.0000
DIFF_SP5IOIL	63.41	2	0.0000	DIFF_SP5IOIL	29.536	2	0.0000
DIFF_PACXTEC	202.284	2	0.0000	DIFF_PACXTEC	239.246	2	0.0000
ALL	523.871	8	0.0000	ALL	486.622	8	0.0000

Table 5: Jarque-Bera test results for model 1 and 2

5.5 Granger causality

A Granger causality test is used to examine the causal relationship between different variables in the VAR model. Essentially, it's a useful parameter in determining if one time series can forecast another. Granger causality therefore implies that it's measuring the ability to predict futures values of variables when using prior values of that same variable or other variables. In this case for example, consumable fuel prices are said to ''Granger cause'' renewable energy stock prices if it can be concluded that because of a series of T- and F-tests, lagged values provide statistical information about future values.

In this thesis, two different models are used to determine the effect of the fluctuation of oil, gas and other consumable fuels on the return on renewable energy indices. What one can observe in model 1 is that none of the lag values has a significant p-value (beneath the 0.05 threshold). This conclusion also holds for model 2, where none of the variables have significant p-values.

(H1) Renewable energy stock is more correlated to fluctuations in technology stock prices than fluctuations in the oil price.

(H2) Renewable energy stock is more correlated to fluctuations in consumable fuel prices than fluctuations in the oil price.

Regarding the hypotheses, the following can be said. Hypotheses 1 cannot be accepted, because the p-values are not significant. However, one can observe different scores between the technology stocks on the one hand and oil prices on the other. For instance, in model 1, the granger causality of technology stock on the renewable energy stock is lower than the price of oil on renewable energy stock. This effect is however reversed in model 2, where the granger causality of technology stock is higher than the price of oil on renewable energy stock.
Also, hypothesis 2 has to be rejected. First, this is because of the high p-values and therefore non-significant values of the different variables. In addition, this is because the price of oil has a lower p-value than the consumable fuel prices in model 1. This effect is however reversed in model 2, where consumable fuels have a relatively higher effect on the renewable energy stock. Hence, due to this inconsistently, I cannot infer a conclusion that there is a causal relation among oil prices, consumable fuel prices, technology stock prices and renewable stock prices.

VAR model 1					VAR model 2				
Equation	Excluded	chi2	df	Prob > chi2	Equation	Excludes	chi2	df	Prob > chi2
DIFF SPGCLE	DIFF_BNO	0.12006	1	0.729	DIFF_WINEGI	DIFF_BNO	0.00381	1	0.951
DIFF SPGCLE	DIFF_SP5IOIL	0.00029	1	0.986	DIFF_WINEGI	DIFF_SP5IOIL	0.22547	1	0.613
DIFF SPGCLE	DIFF_PACXTEC	0.0034	1	0.985	DIFF_WINEGI	DIFF_PACXTEC	0.59128	1	0.442
DIFF SPGCLE	ALL	0.16534	3	0.983	DIFF_WINEGI	ALL	1.5811	3	0.664
DIFF_BNO	DIFF SPGCLE	0.15791	1	0.681	DIFF_BNO	DIFF_WINEGI	0.3634	1	0.547
DIFF_BNO	DIFF_SP5IOIL	0.95268	1	0.329	DIFF_BNO	DIFF_SP5IOIL	1.084	1	0.298
DIFF_BNO	DIFF_PACXTEC	0.99411	1	0.319	DIFF_BNO	DIFF_PACXTEC	0.65578	1	0.418
DIFF_BNO	ALL	1.5421	3	0.673	DIFF_BNO	ALL	1.7483	3	0.626
DIFF_SP5IOIL	DIFF SPGCLE	0.00644	1	0.936	DIFF_SP5IOIL	DIFF_WINEGI	0.66005	1	0.417
DIFF_SP5IOIL	DIFF_BNO	0.82599	1	0.363	DIFF_SP5IOIL	DIFF_BNO	0.79152	1	0.374
DIFF_SP5IOIL	DIFF_PACXTEC	0.11205	1	0.738	DIFF_SP5IOIL	DIFF_PACXTEC	0.00047	1	0.983
DIFF_SP5IOIL	ALL	0.89439	3	0.827	DIFF_SP5IOIL	ALL	1.5493	3	0.671
DIFF_PACXTEC	DIFF SPGCLE	0.2975	1	0.585	DIFF_PACXTEC	DIFF_WINEGI	0.08032	1	0.777
DIFF_PACXTEC	DIFF_BNO	0.4416	1	0.834	DIFF_PACXTEC	DIFF_BNO	0.05866	1	0.809
DIFF_PACXTEC	DIFF_SP5IOIL	0.15699	1	0.692	DIFF_PACXTEC	DIFF_SP5IOIL	0.39701	1	0.529
DIFF_PACXTEC	ALL	1.1295	3	0.770	DIFF_PACXTEC	ALL	0.91195	3	0.823

Table 6: Granger causality Wald tests for both models

5.6 Impulse response function results

Granger Causality may not be enough to conclude about the interactions among the different variables. Impulse response functions have a similar purpose as Granger Causality are calculated differently. With the impulse response function one administers a shock to the renewable energy stock and propagate it through the used VAR model for a number of periods. This can be traced trough the VAR and you can see whether it impacts the other variables in a statistically significant way.

5.6.1 Full sample period

In this case particular I like to analyse the impulse response relationship between the oil prices and renewable energy stock prices plus the response between consumable fuel prices and the renewable energy stock prices. Now I have tested both models for statistical validity, I can describe both VAR models as:

Model 1

$\Delta REI= -0.77462*\Delta REI_{(-1)} -0.1274062*\Delta OIL_{(-1)} + 0.0020857*\Delta CF_{(-1)} +0.0006688*\Delta TECH_{(-1)}$

$\Delta OIL= 0.0039412*\Delta REI_{(-1)} +0.084937*\Delta OIL_{(-1)} -0.199403*\Delta CF_{(-1)} +0.0060259*\Delta TECH_{(-1)}$

$\Delta CF= 0.0030261 *\Delta REI_{(-1)} +0.2131383*\Delta OIL_{(-1)} -0.0887215*\Delta CF_{(-1)} +0.0076949 *\Delta TECH_{(-1)}$

$\Delta TECH= -0.0564794*\Delta REI_{(-1)} -0.1352775*\Delta OIL_{(-1)} -0.0844325*\Delta CF_{(-1)} -0.015048*\Delta TECH_{(-1)}$

Model 2

$\Delta REI= -0.0686202*\Delta REI_{(-1)} -0.0023108*\Delta OIL_{(-1)} -0.006319*\Delta CF_{(-1)} -0029667*\Delta TECH_{(-1)}$

$\Delta OIL= 0.0649673*\Delta REI_{(-1)} +0.0849131*\Delta OIL_{(-1)} -0.0214174*\Delta CF_{(-1)} +0.0051409*\Delta TECH_{(-1)}$

$\Delta CF= 0.3328517*\Delta REI_{(-1)} +0.2083797*\Delta OIL_{(-1)} -0.1061832*\Delta CF_{(-1)} +0.0005222 *\Delta TECH_{(-1)}$

$\Delta TECH= 0.3190364*\Delta REI_{(-1)} -0.1558753*\Delta OIL_{(-1)} -0.1353948*\Delta CF_{(-1)} -0.0175075*\Delta TECH_{(-1)}$

With:
SPGLCLE: S&P Global Clean Energy price index: RE1
BNO: Brent Oil Fund: OIL
SP5IOIL: S&P500 Oil, Gas & Consumable fuels price index: CF
WINEGI: Wilder Hill Clean Energy price index: REII
PACXTEC: NYSE Arca Technology 100 price index: TECH

The shock amounts to one standard deviation of the response variable. In this thesis, two models are used where in each case, a unit shock is applied to the error term. In total, this would amount to 16 different impulse response functions per model. An interesting point to raise here though, is that Stata uses positive shocks by default. Thus, the figures below render the responses of a positive shock to one the impulse variables, where they show how long an effect lasts and if the shock has a positive or negative effect on the response variable. Furthermore a 95% confidence interval is used.

What one can observe in the figures below are the effects of a shock in one variable in relation to another. For model 1, one can observe the following: in the first column, the effect of a shock in the impulse variables 1: S&P 500 Global Clean Energy Price index 2: S&P 500 Oil Gas Consumable fuels index 3: Nyse Arca Technology 100 index on the response variable: 'United States Brent Oil Fund' is rendered. Here, one can observe that almost no effect is visible between those variables, implying none to negligible effects.

In the second column of model 1, one can observe the effect of a shock of the impulse variables on the 'Nyse Arca Technology 100' index. Here, one can notice a fairly larger effect than the previous one. The shock administered to the impulse variables results in a 10% or even 30% change of the response variable in t=1, which can be considered large. The increase in one of the variables shows an immediate increase in technology stock prices. However the other way around, a positive shock in technology stock prices does not cause an effect on the other variables.

The outcome of these impulse response functions show implication for the first hypothesis: *Renewable energy stock is more correlated to fluctuations in technology stock prices than fluctuations in the oil price* since I cannot see any effect between oil prices and renewable energy stock prices. This findings supports the studies in the literature review that renewable energy stock prices might correlate more with technology stock prices than with oil prices. The rationale behind the results is that renewable energy companies still rely on the development of technology before renewable energy can become a substitute for oil.

In the third column, one can observe the effect of the different impulse variables on the 'S&P 500 Oil Gas and Consumable fuels' index. Here, effects are visible between the response variable and the different impulse variables, such as 1: the United States Brent Oil Fund, 2: the S&P 500 Oil Gas Consumable fuels index and 3: the S&P 500 Global Clean Energy Price' index. However, the effect isn't quite large -with a maximum increase of 10%.

In the last column, one can observe only one clear effect, namely the effect of the 'S&P 500 Global Clean Energy Price' index on the variable itself -with an almost 25% increase in t=1, which implies that the lagged version of the variable has an effect on itself in a later timeframe. At last, another interesting observation is that most of the shocks administrated in the impulse response function have a positive effect on the response variable in the early stages of t=1, in the later stages though, this effect diminishes and even becomes negative for a short amount of time.

In model 2, the following can be observed. In the first column, one administrated a shock of the impulse variables on the 'United States Brent Oil Fund' index. Here, none tot negligible effects could be observed.

This changes however in the second column, where the effects of a shock to the impulse variables on the response variable: 'Nyse Arca Technology 100' index are rendered. Here, effects in the magnitude of 5% or even 30% increase of the response variable is visible in t=1, which can be considered large. Regarding the third column, one can observe that much smaller effects are visible. Here, the: 'S&P 500 Oil Gas and Consumable fuels' index acts as the response variable and one can notice that the impulse variables: 'S&P Global Clean Energy Price' index, the United States Brent Oil price have a clear effect on the 'response variable, with a 0-10% percentage increases in t=1. For the last column, where one examines the effect of the different impulse variables on the response variable: Wilder Hill Clean Energy Price index, none to negligible effects could be observed.

Considering the next hypothesis: *Renewable energy stock is more correlated to fluctuations in consumable fuel prices than fluctuations in the oil price,* the results do not draw a consensus.

Fluctuations in oil prices and consumable fuel prices have no effect to renewable energy stock prices. However, a shock to the variable renewable energy stock has a minor effect to the variable consumable fuel prices.

Figure 8: model 1

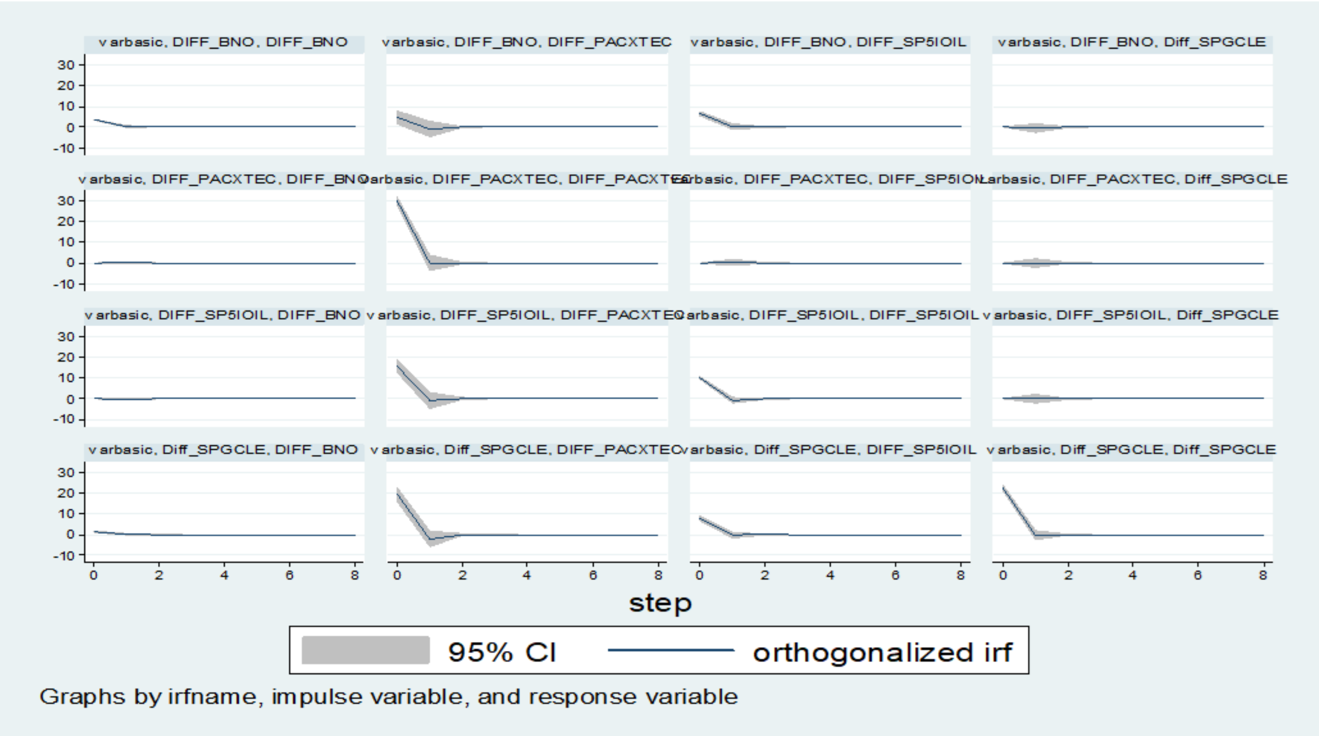
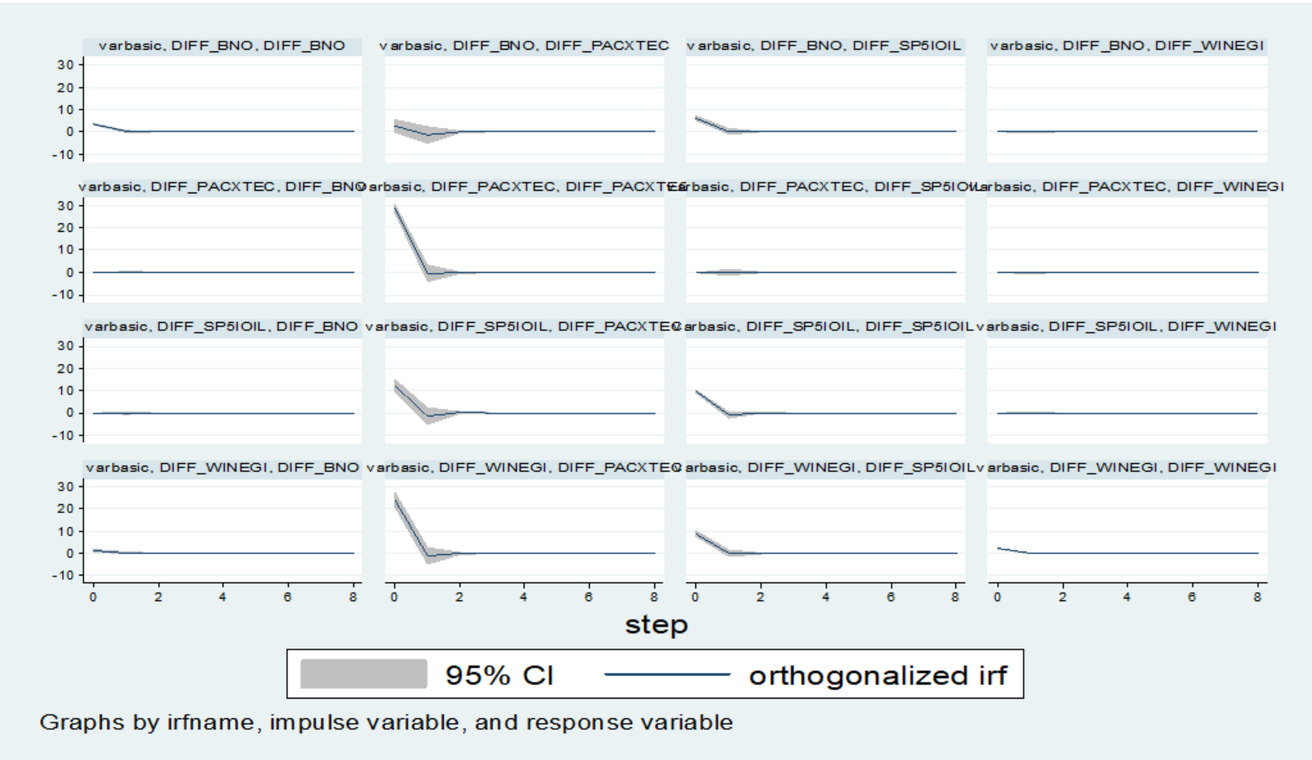


Figure 9: model 2



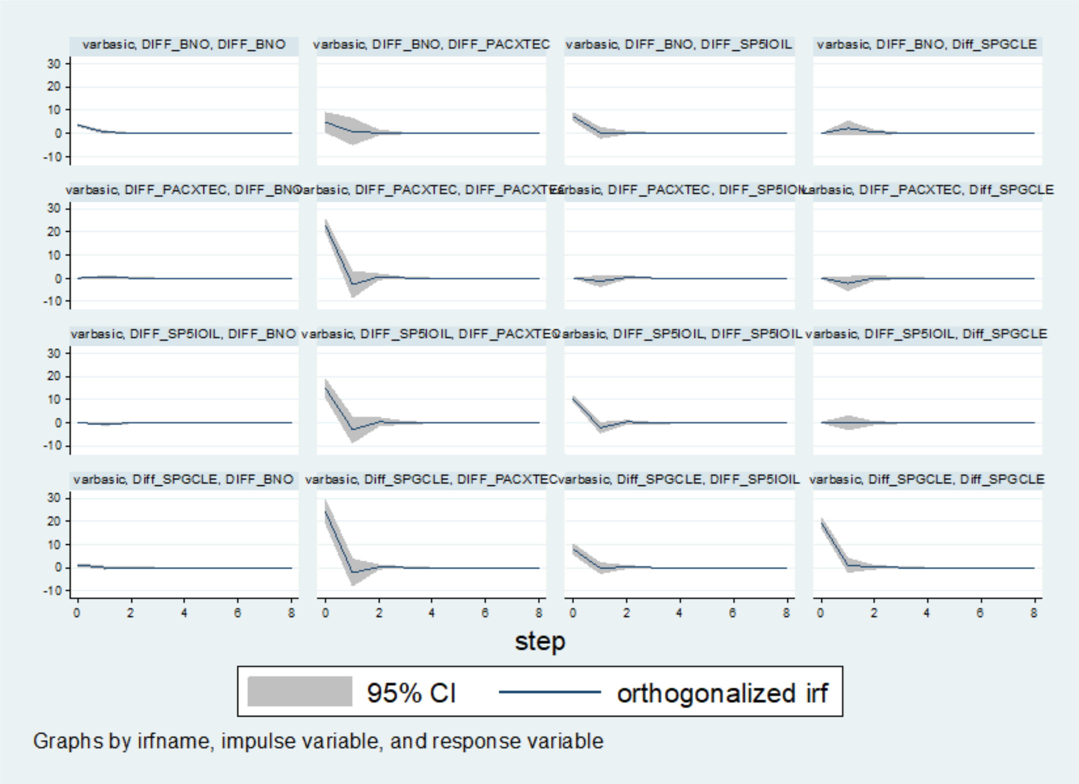
5.6.2 Sub sample period

The next hypothesis that is analysed is: *The impact of oil fluctuations on renewable stock prices has more effect in different time periods*. Consequently, I applied the two VAR models to three different sub samples. In earlier studies, impulse respond functions tend to differ over time, although in this research I do not find different relationships among the variables in different time periods.

Figure 7 shows the response to each variable in the system to a one standard deviation of the variables in the system. The impulse responses in this sub samples are quite similar to the impulse responses in the full sample period. However, the effect of the shock of SPGCLE to PAXTEC is more dramatic in sub sample 2013w1-2015w52 and 2010w15-2012w52. The third sub sample does not differ from the full sample period and is therefore included in the appendix.

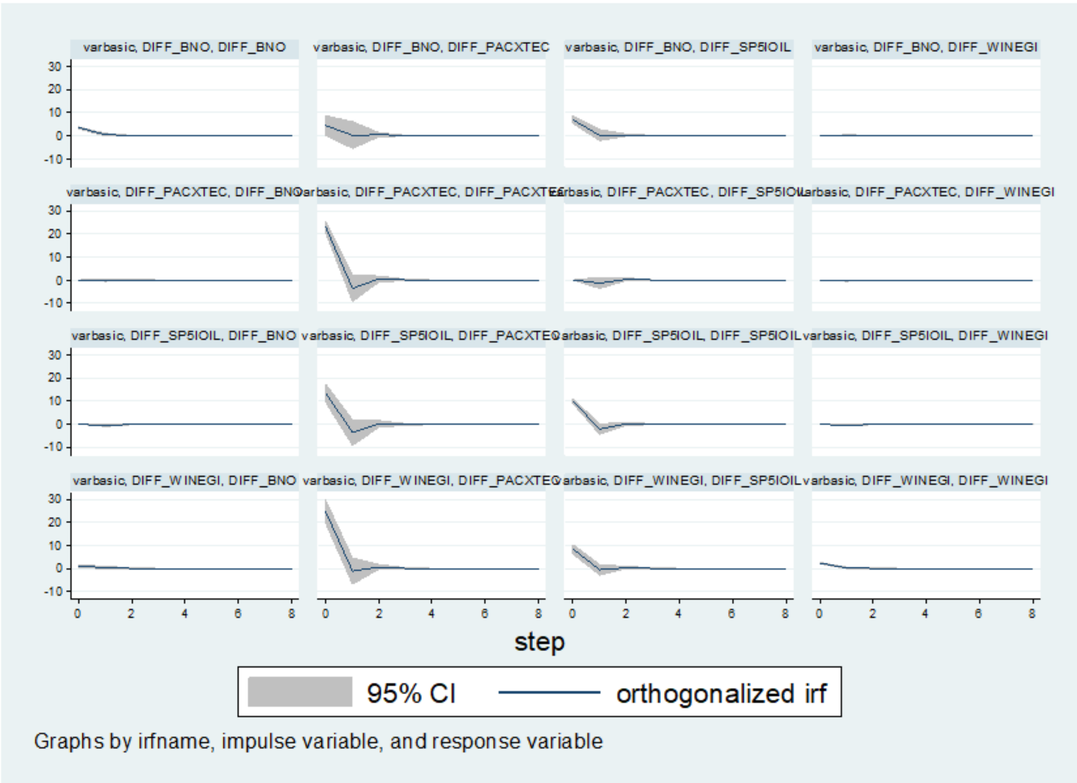
An explanation why no different relations could be found is because earlier studies use older sample periods, therefore it might be possible that there are no structural breaks in my sample period. Also I only used data from after the crisis, while the crisis years are considered to be a structural break (Managi & Okimoto, 2013).

Figure 10 Sub sample 2013w1-2015w52 model 1



Graphs by irfname, impulse variable, and response variable

Figure 10 Sub sample 2013w1-2015w52 model 2



Graphs by irfname, impulse variable, and response variable

Figure 11 Sub sample 2010w15-2012w52 model 2

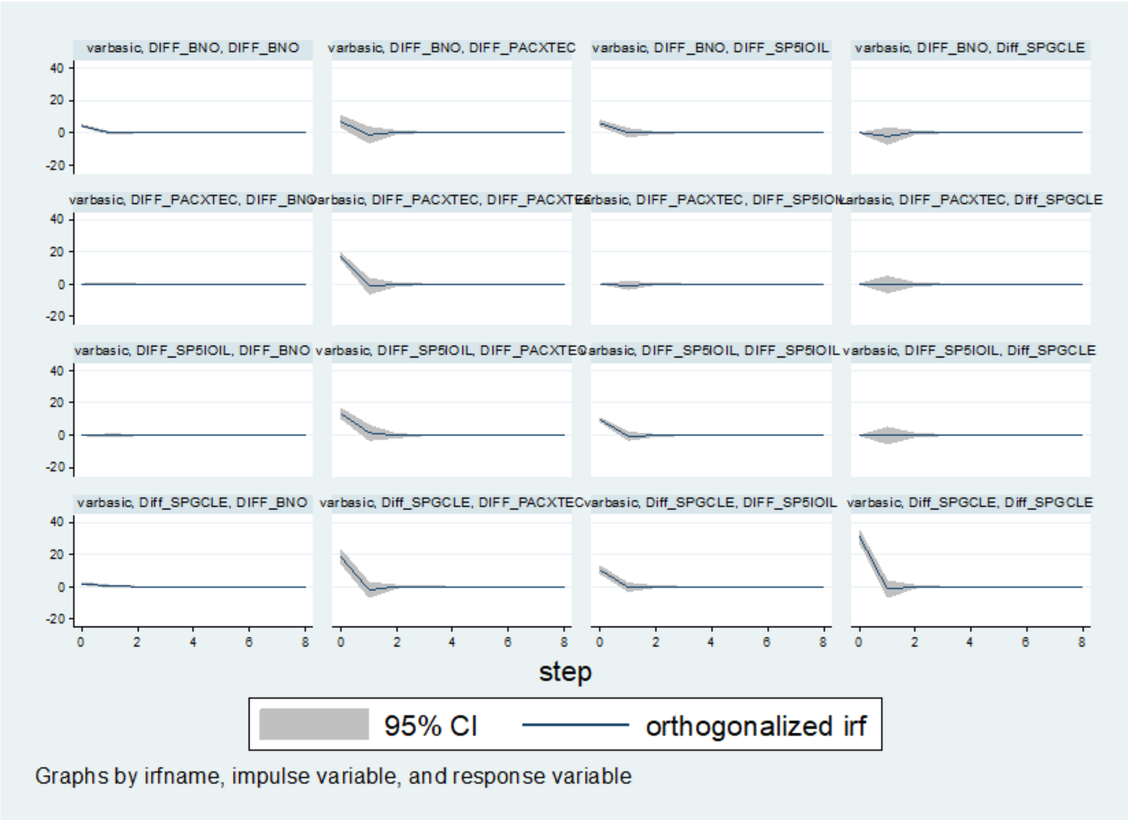
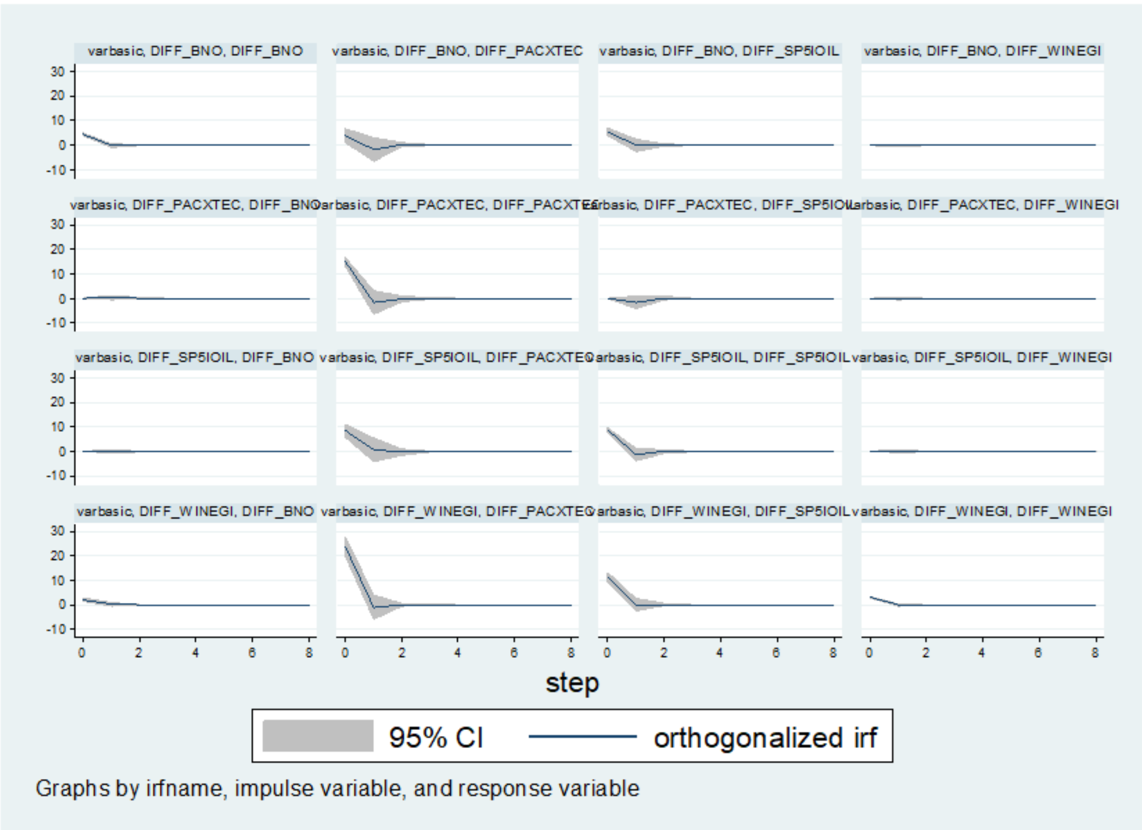


Figure 12 Sub sample 2010w15-2012w52 model 2



6 CONCLUSION

In this thesis I have analysed the relationship between renewable energy stock performance, oil prices, consumables fuel prices and technology stock prices. The focus of this thesis is to improve renewable energy policy and investment decisions. Environmental concerns and energy security already led to substantial growth of investment and interest in the renewable energy sector. Although development in the renewable energy sector goes well, a better understanding of the interrelations among the variables is wanted.

I used two different vector auto regression models with both 4 variables and investigated the reciprocal relationships. The two models I used differ in the variable renewable energy stock prices where I use the weekly data from the S&P 500 Renewable energy index for model 1 and the data from the Wilder Hill clean energy index for model 2.

Data was retrieved from five different indices using DataStream and has covered the period from January 2010 to August 2018 after the crisis because earlier studied advocated that structural breaks, events such as the crisis could cause biased results.

Granger causality tests did not lead to a better understanding of the interactions among the variables since I did not find significant results that one of the variables granger causes another. Therefore renewable energy stock prices cannot be explained by fluctuations in oil prices or consumable fuel prices. This questions the logic of a substitutional movement from consumable fuel and oil towards renewable in energy in case oil prices increase. Furthermore the believe that a fluctuation in consumable fuel prices has more effect on renewable energy stock prices than oil prices is not confirmed.

Also, the impulse response functions show very modest significant results, however I find a revealing relationship among the variables renewable energy stock prices and technology stock prices. A shock in renewable energy stock prices causes a temporary increase in the prices for technology stock. Surprisingly a shock in technology stock prices did not result to a significant change in renewable energy stock prices.

To increase the robustness of my empirical outcomes I tested my model for 3 different sub samples, despite that the effect of technology stock price shocks was more dramatic in one sub sample, the implications are equal as for the full sample period.

Some studies did assume that once renewable energy stock is mass adopted, it could become a perfect substitute for consumable fuels. Other research states that renewable energy is still too dependent on technologic development to be considered a substitute for consumable fuels. My results support earlier believes that technology stock and renewable energy stock are indeed related. Investors may consider renewable energy stock similar to technology stock because renewable energy firms are dependent on technologic development.

For now, consumable fuel price changes are unable to explain renewable energy stock prices. At this moment renewably energy stock still involve high uncertainty as was the case more than ten years ago in the study by Henriques and Sadorsky (2008). Technologic development will eventually demonstrate if renewable energy can be a substitute for oil and other consumable fuels. Once renewable energy is more of a substitute for oil and consumable fuels, oil might impact renewable energy stock in the near future. There is much upward potential for investors in clean energy, but only if government policies can increase technologic development. At the same time, technologic development will lead to a reduction in environmental pollution during the production of energy using consumable fuels, conserving interest in consumable fuels.

One of the limitations of my research is that I did not divided the data for renewable energy stock in sub categories. It might be possible that some categories in the renewable energy sector are more developed than another. For example, companies active in the wind energy industry can respond differently to consumable fuel price shocks than photovoltaic energy firms.
Furthermore, research for renewable energy stock could concentrate on geographical regions where renewable energy is more common. For example, New Zealand having 85% of its total energy output coming from renewables, therefore renewable energy will act more as a substitute for consumable fuels and causal relations will be easier to find. Lastly new research could concentrate on the similarity between renewable energy firms and technology firms.

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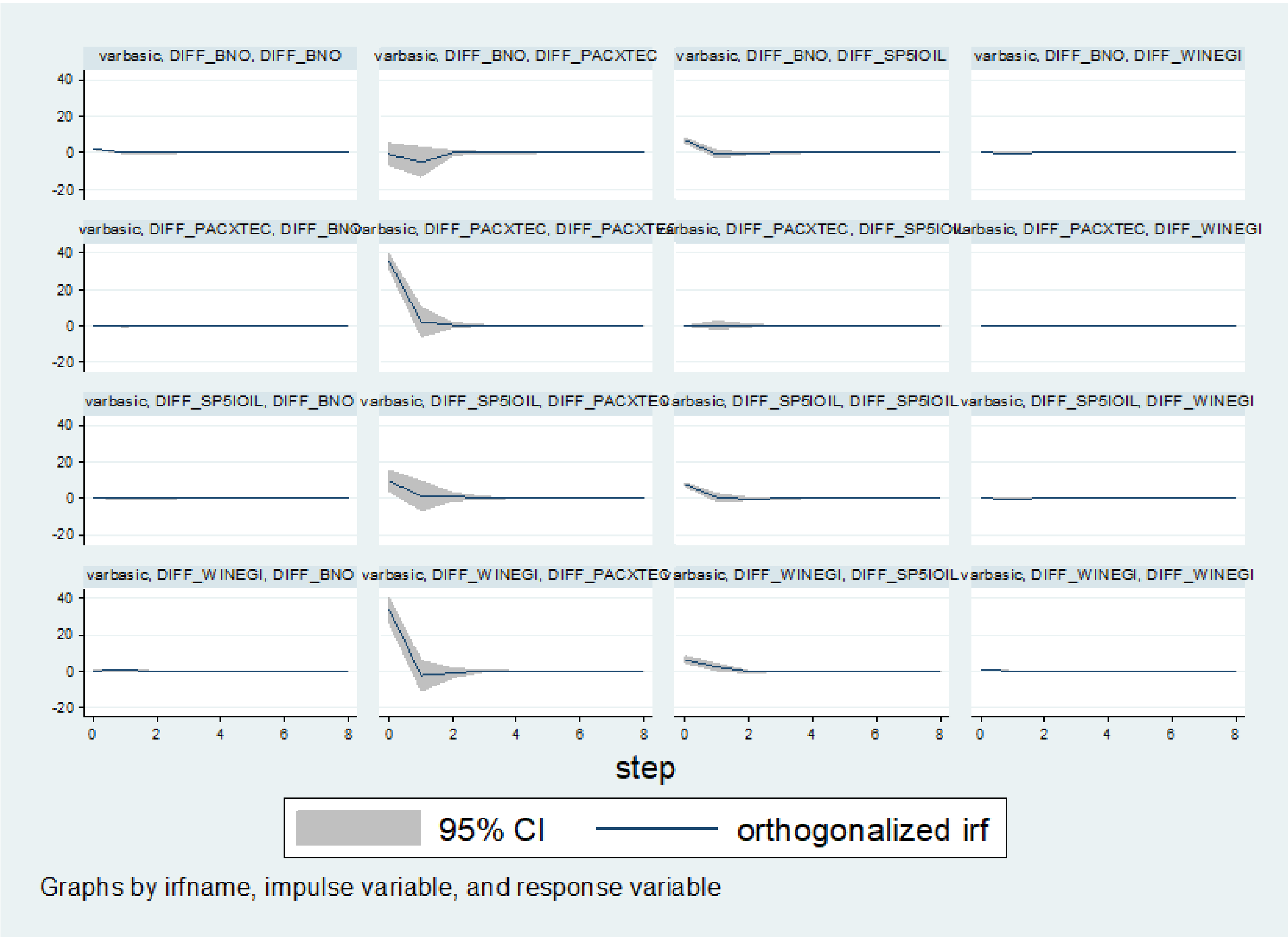
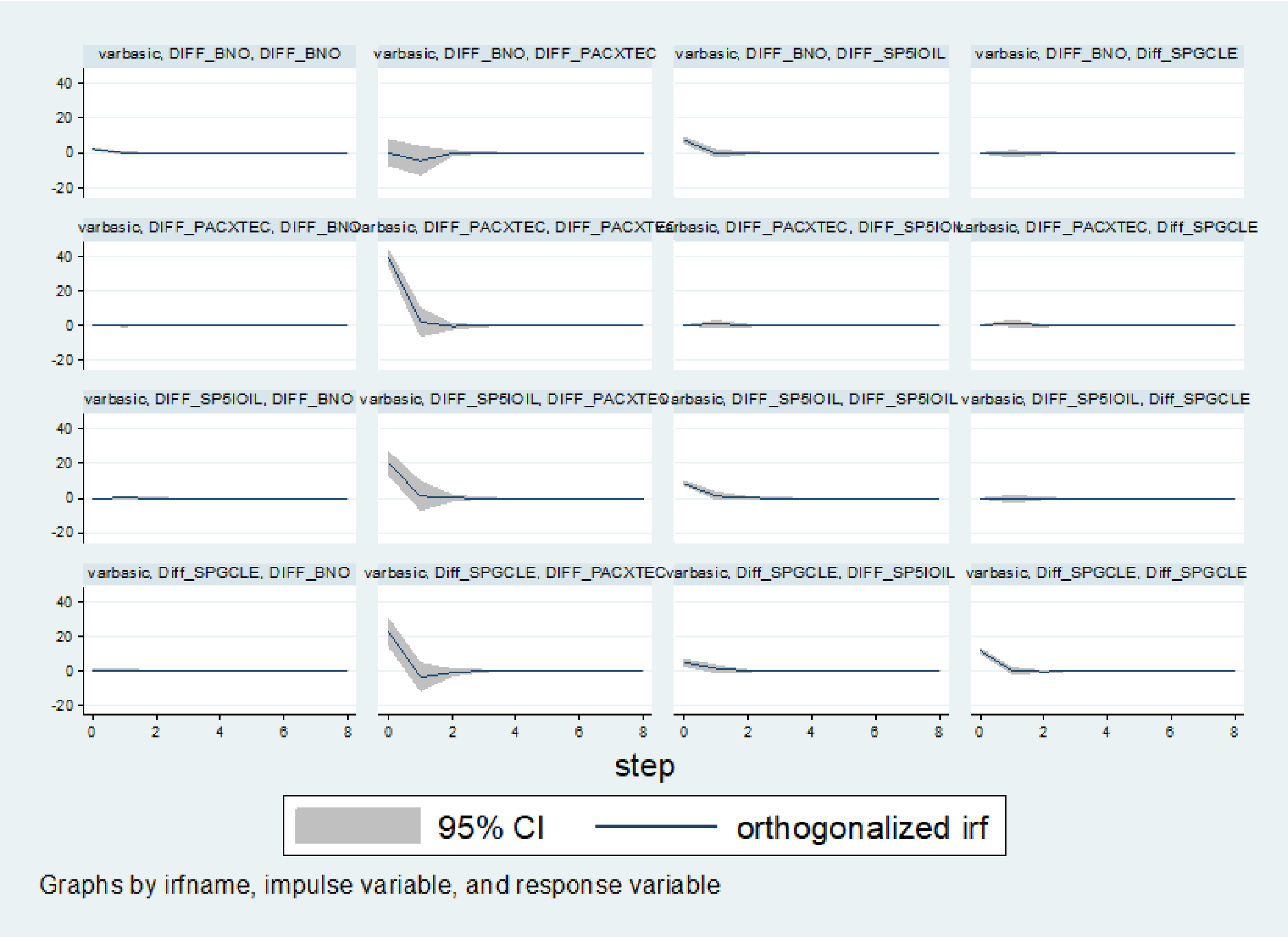
8 APPENDIX

8.1 Impulse responses sub sample 2016w1 – 2018w35




varbasic, DIFF_BNO, DIFF_BNO
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40
20
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-20
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2
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6
8
step
95% CI
orthogonalized irf
Graphs by irfname, impulse variable, and response variable