MASTER THESIS

Course code: BE305E

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How does changes in crude oil prices affect renewable energy assets? A VAR-approach.

Date: 02.06.2020

Total number of pages: 61

NORD University

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Abstract

The effects of global warming caused by oil and gas production, along with climate policies are encouraging a shift towards renewable energy. Seeing how oil has an important role as a global energy source, we believe changes in oil price will have an effect on renewable energy assets. Using vector-autoregressive models, we wish to investigate how changes in oil price are affecting renewable energy companies stock performance. We also want to see how carbon prices and interest rates influence this sector. In addition, we analyze how the different sub-sectors of renewable energy relate to oil prices, carbon prices and interest rate.

Our findings from the models testing how changes in oil prices affect the renewable energy assets, show no significant relationship. An analysis on carbon price changes indicate no effect on renewable energy companies. Results from the models in the period between 2014 and 2019, indicate a significant relationship between interest rate and the renewable energy companies. In addition, the models between interest rate and wind, as well as interest rate and the solar sub-sector show a significant relationship. On this basis, we answer our problem statement by saying that changes in oil prices do not seem to affect renewable energy company assets during our sample period.

Acknowledgements

This thesis marks the end of our two-year Master of Science program in Business, with a major in Finance at Nord University. For us, it has been a journey full of new experiences with educational challenges and has overall been a great learning process. It has been interesting to learn about the renewable energy market, gaining some new insight in a sector we had little knowledge about beforehand.

We would like to express our gratitude to our supervisor Oleg Nenadić, who has helped us a lot with our frustration working in R, and many great tips along the way for our models. Additional thank you to Irena Kustec, who has also been very helpful for our thesis. At last we would like to thank family and friends for support during the process.

Nord University, 02.06.2020

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Sammendrag

Effektene av global oppvarming forårsaket av olje- og gassutvinning sammen med klimapolitikk, oppmuntrer til skiftet mot fornybar energi. Siden olje har en viktig rolle som en global energi kilde, tror vi at endringer i oljeprisen vil ha en effekt på selskaper innen fornybar energi. Ved å bruke vektor-autoregressive modeller, ønsker vi å undersøke hvordan endringer i oljeprisen påvirker aksjekursen til selskaper innen fornybar energi. I tillegg ønsker vi å se hvordan karbonpris og obligasjonsrenter påvirker denne sektoren. Vi analyserer også hvordan de forskjellige undersektorene innen fornybar energi reagerer på endringer i oljepris, karbonpris og obligasjonsrenten.

Gjennom våre funn og analyser, så finner vi ingen signifikant forhold mellom oljeprisen og selskaper innen fornybare energi. Analysene som er gjort på karbonpris viser også ingen signifikant effekt på at endringer i karbon prisen påvirker fornybar energi selskaper. Resultatene fra modellene i perioden mellom 2014 og 2019, indikerer et signifikant forhold mellom statsobligasjonsrenten og selskaper innen fornybar energi. I tillegg viser modellene mellom statsobligasjonsrenten og vind, samt mellom statsobligasjonsrenten og sol undersektoren et signifikant forhold. På bakgrunn av dette, svarer vi på vår problemstilling ved å si at endringer i oljeprisen tyder på ingen effekt på fornybar energi selskaper i løpet av vår dataperiode.

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1 Introduction

1.1 Background

A growth in energy demand, caused by population growth is contributing towards global warming (Gurría & Van der Hoeven, 2012). To reduce the amount of warming and subsequent damage, we need to adapt to a more sustainable lifestyle. The United Nations state that by 2030, we shall have substantially increased the share of renewable energy in the global energy mix. This is according to sustainable development goal number 7 (United Nations, 2020). Our society is very dependent on energy, both industrially and residential. Over 80 percent of this energy was derived from natural gases and coal in 2018 (Ritchie & Roser, 2020). Oil and coal stand for a significant amount of the greenhouse gases we produce every day. By switching to renewable energy sources like wind, solar and hydro, we can reduce the release of greenhouse gases substantially and decrease the rate of global warming. Prices of renewable energy has become increasingly lower, and its capacity is increasing. Yet, majority of the worlds power is generated from natural gases. Renewable energies like solar and wind have limited storage capabilities, as well as geographical limitations, which can be a big issue for the growth within this sector.

Technological advancements and political incentives within renewable sources of energy make them more attractive and usable for us as a substitute to fossil fuels. Six out of the ten largest companies worldwide measured by revenue, are within the oil and gas industry. This demonstrates just how big petroleum business is. These companies have a lot of money and influence on politics. Having influence on politics makes it possible for these companies to hinder government incentives towards renewable energy. Since 2010, the five biggest oil and gas companies spent at least €251 million lobbying against climate policies (Laville, 2019). At the same time as companies are lobbying against climate policies, six of the major oil companies have invested billions of dollars towards renewable energy (Murray, 2020). This might seem contradicting but could be an attempt to secure a market position as leading renewable energy companies, before abandoning petroleum.

One might expect that the steep fall in oil prices from 2014 would lead to trouble for the renewable sector, but during 2014, renewable energy investments increased by 16 percent. Here China was the biggest single contributor, with $89.5 billion investment towards renewables. This increase in renewable energy investments demonstrates the flexibility of the sector during fluctuating oil prices, says Ben Warren, head of environmental finances at the consulting firm EY (Downing, 2015). He also suggest that this trend will continue as the technology around this sector becomes cheaper. How investments in the renewable energy sector are during in a market with a more or less stable oil price, is intriguing to us.

Renewable energy is an industry in growth, seeing a lot of innovation and investments over the years. In the context of climate change, this industry is an important part of our future. Innovations have driven renewable energy companies towards becoming a worthy competitor against oil as the future of energy. In this thesis we are interested in seeing how the changes in oil prices affect renewable energy sector stocks. Occasionally we encounter headlines in the media commenting on how stock markets are falling, caused by decreased oil prices. This relates to how many large oil companies' profits are plummeting, causing their shares to fall which drags the market down with it (Associated Press, 2016).

1.2 Problem statement

The renewable energy sector has gone from being a sector with high costs and low profit, to a sector facing big technological advancements and expanding revenues. We find it intriguing to investigate whether factors influence the renewable energy assets. Earlier studies show that fluctuations in crude oil price affect assets on the stock market. We want to look specifically at the renewable energy sector, and how they react to fluctuations. Renewables like solar energy and wind energy are the sources experiencing the largest growth. We want to see the difference in how these renewable sub-sectors react to changes. Solar and Wind energies is the two renewable energy sectors that is having the highest growth rate between renewable energies, and can be very important for the energy sector in the future (International Renewable Energy Agency, 2019). Therefore, we will include them in our analysis.

Our problem statement:

How does changes in crude oil prices affect renewable energy assets?
A VAR-approach.

As an attempt to answer this problem statement, we are using a vector autoregressive model (VAR-model) to see how the variables affect each other. We find that using a VAR-model to be appropriate as we can use the methodology to show if oil prices have any direct effect on any renewable energy assets. In addition, the model allows us to use lagged value from both the dependent variables and independent ones. Using lagged values can give a more robust model in finding relationship between variables and to forecast.

Looking at this from a financial standpoint, we have another hypothesis. We propose that fluctuating oil prices may cause energy demanding companies to search for alternative sources of energy for investment. Investing towards renewable energy sources, that could have a more stable energy price, may lead to lower costs for companies. This could result in an increased demand for renewable energy. Increased demand would increase profits for renewable energy companies, which could increase their stock prices and in turn improve the company market value. In other words, we want to see if an increase in spot price of crude oil has any effect on renewable energy companies stock performance.

We hope that by using a data sample from a more recent time period than previous research, we will contribute to this literature with an updated analysis. Until recently, prices of renewable energies have been high and therefore a barrier for many to adapt renewables. Today, renewable energy has become cheaper, gained more capacity and become easier to maintain than before (International Renewable Energy Agency, 2018). Our hypothesis support that rising oil prices should encourage the investments towards renewable energy sources. This would mean that an increase in oil prices should increase revenues of renewable energy companies, which can increase stock value. Whereas some research done in past time periods confirm this, at the same time as other research do not find any impact.

1.3 Hypothesis

The main objective of this thesis is to investigate whether renewable energy companies stock performance is affected by the oil price changes. Since we look into the renewable energy sector, it is likely that other factors than the oil price could impact the stock prices too. By using indexes and factors that earlier research use, we expect to see similar results. When the oil price increases, it may be natural for the alternative energy stock prices to increase as well. This is based on an assumption that companies will search for ways to reduce their overall costs. When the oil price is increasing, companies might search for other solutions. Additionally a shift towards renewable energy sources might reflect good on the company. Kumar et al. (2012) and Managi & Okimoto (2013) find that an increase in oil price influence the alternative energy companies positively. Since the renewable energy companies are in competition with fossil fuel companies, the oil price could have an effect on their performance.

H1: *An increase in oil prices have a positive effect on renewable energy index prices*

In our analysis, we include indexes of the overall renewable energy sector, as well as sub-sectors within renewable energy. The solar energy companies and fuel cell companies have a negative trend during the last years. while wind energy companies show a positive trend. Based on this, we wish to see how different sub-sector indexes react differently to oil price volatility. Interest rates effect as an instrument has a wide effect on the economy and financial (Norges Bank, 2003), and our believe is that a rise in interest rate would result in lower stock prices. This is based on an assumption that higher interest rate will make financial debt more expensive. As stated above, renewable energies are more sensitive to interest rate variation (Schmidt et al., 2019). This can indicate that the renewable energy companies do not have the possibility to invest in new projects when the interest rate is high. Consequently, we are interested in testing how interest rates affect renewables.

H2: *An increase in interest rate have a negative effect on renewable energy index prices.*

Kumar et al. (2012) investigate if carbon prices encourage investments towards clean energy sectors. This is because setting a price to carbon can have an effect encouraging companies to invest in more environmentally friendly solutions. They could not find any relationship between carbon price and the clean energy companies (Kumar et al., 2012). By looking at more recent data, we hope to reveal whether the effect of carbon price on renewable energy companies is different now. The focus on environmentally friendly solutions increases every year, and we expect that a higher carbon price may lead to more renewable investments. Furthermore, we think that if companies get penalties for having high concentration of carbon in their production it can make them shift to cleaner energy.

H3: *An increase in carbon price have a positive effect on renewable energy index prices*.

2 Literature review

There are numerous papers studying how the oil price affect the renewable energy stocks. Henriques et. al. (2008) use a four-variable vector autoregression model to investigate the relationship between oil price, alternative energy stock price, technology stock price, and interest rate. They conclude that shocks to oil prices have a little significant impact on the stock prices of alternative energy companies comparing to technological stocks, and that changes in oil prices are not as important as once thought. Kumar et. al. (2012) conclude otherwise. They use the same method as Henrique et. al, but find a positive relationship between the clean energy stock price and oil price, which can indicate that a rise in oil price will give higher demand of clean energy. They also conclude that carbon price return is not a significant factor for the share price movement for clean energy companies. These two articles use a similar LA-VAR approach, but the differences between them is the time period they use. Henrique et.al. (2008) is using a data sample period right before the financial crisis started, while Kumar et. al. has taken the crisis into consideration. Therefore, we believe that the difference in result could be a result of the different time points they are using.

Managi & Okimoto (2013) use a Markov-switching vector autoregressive models (MSVAR) framework. This model is an extension from the two previous papers. They use this method to find the probability for structural change by analyzing smoothed probabilities. Their result indicates a structural change in late 2007 i.e., a period where there was a significant increase in the oil price. Furthermore, they find a positive relationship between clean energy prices and oil prices after 2007. Later, Bondia et. al.(2016) criticize Managi & Okimoto for ignoring structural breaks in such a long time series of data, which can produce misleading results. The results from Bondia et al. (2016) co-integration test suggest a longstanding relationship between alternative stock prices, oil prices, technology stock prices and interest rate for one or two endogenous break points.

Sadorsky (2012) use a multivariate GARCH model to look at conditional correlations and to analyze the volatility spillover between oil prices and the stock prices of clean energy companies and technology companies. By using four different methods he find that stock prices of clean energy companies correlate more highly with technology stock prices than with oil prices. Reboredo (2015) also use a volatility approach. He uses copulas to look at the dependence structure between oil prices and global and subsectors of renewable energy, as well as conditional value-at-risk measurements. His study find that around 30 percent of the downside and upside risk of renewable energy companies has been significantly influenced by the oil price.

Recently, Pham (2019) investigate whether there is a homogeneous relationship between oil prices and cross sub-sectors of the clean energy stock market, and its implication for portfolio diversification and clean energy finance policy. He find that the relationship between oil price and clean energy stocks vary significantly over time and across different sub-sectors of the clean energy market. This implies that the cost and effectiveness of hedging clean energy depend on the type clean energy stock included in the portfolio.

2.1 Crude oil and oil prices

Oil is an important commodity in our global economy. Previous studies clearly show that changes in oil supply has a significant and negative effect on the economy (Arezki et al., 2016). Not only is oil used for fuel, transportation and power, but for production of other consumer goods as well. Therefore, changes in oil price have an impact on several industries. Supply and demand have a significant impact on the prices of oil. Production of crude oil does not seem to slow down, on the contrary the world production of oil has been relatively steady, with a small increase over the last decade (OECD, 2020).

The buildup of oil reserves also contribute to influence oil prices. When the supply of oil is low, oil reserves will be released that will reduce the demand for oil from the refineries, subsequently dampening the increase of the oil price. On the other hand, if supply is high, oil reserves may build up causing the overall oil price to increase, making this strategy a tool to influence oil prices. Demand is also significantly affected by currency value of the US dollar exchange rate, seeing how oil is traded in US dollar globally. Earlier research shows how an appreciation of US dollar leads to a decline in oil demand for a sample of 65 oil-importing countries (De Schryder & Peersman, 2015).

Looking at the supply of oil, OPEC (Organization of the Petroleum Exporting Countries) can be considered the most important supplier, seeing how they stood for around 40 percent of global crude oil production in 2017. In addition, they held about 80 percent of the global oil reserves (OPEC, 2018). The organization was created with a mission to coordinate and unify the petroleum policies of its member countries. They work together to ensure stable oil prices, secure fair returns to producing countries and investors in the oil industry, and provide a steady petroleum supply to consumers (OPEC, 2012). Observing their share of the global oil production and oil reserves, OPEC is an important part of the global oil supply. If OPEC reduces the supply, they can contribute to an increase in the oil price, thus using their supply as a tool to affect the price.

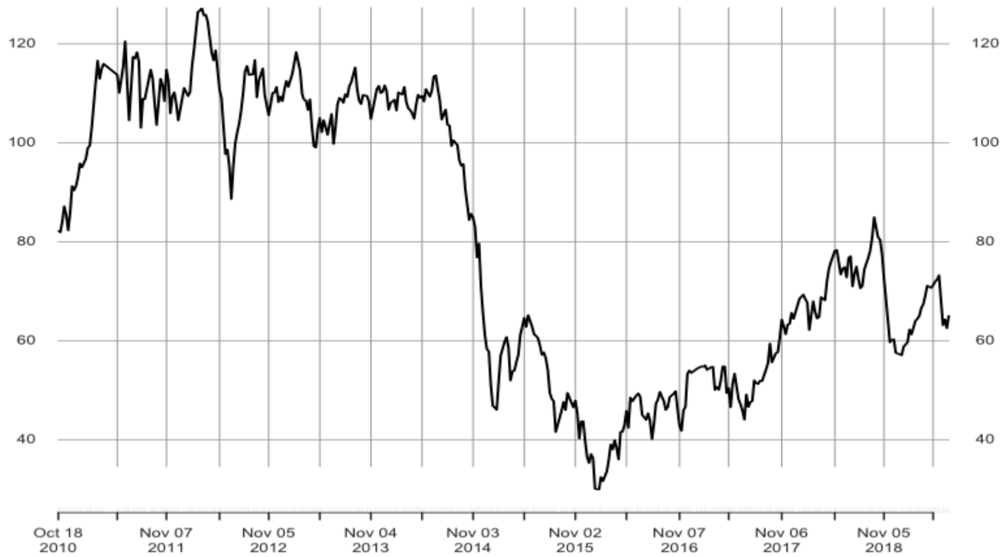

Figure 1: Brent Crude spot price development between 2010 and 2019

In March 2012 was a peak in the oil price when the Brent spot price peaked at above $120, slowly declining before the oil crisis occurred in 2014. Then, it was a deep decline in oil prices, which left the price per barrel at under $30 at the end of January 2016. The reasons for this drop in the oil price, was the decrease in oil demand by large economies like China, along with an increase in oil production from North American countries (Rogoff, 2016). This demonstrates that large economies and large producers of oil have a great impact on the development in oil prices.

2.2 Renewable Energy

Renewable energy is defined as energy derived from sources that can be replenished (Eckley Selin, 2020a). Wind, solar, biofuels, hydro and tidal power are some of the most used renewable energy sources. Hydropower was the leading source of renewable energy in 2015, and it supplied 71 percent of all renewable electricity globally at the end of the year. The second greatest source was wind power, followed by solar power as the third largest (World Energy Council, 2016). Figure 2 reveal that wind and solar energy have had significant growth in capacity during 2018. Observing this, the future of both solar and wind energy look promising.

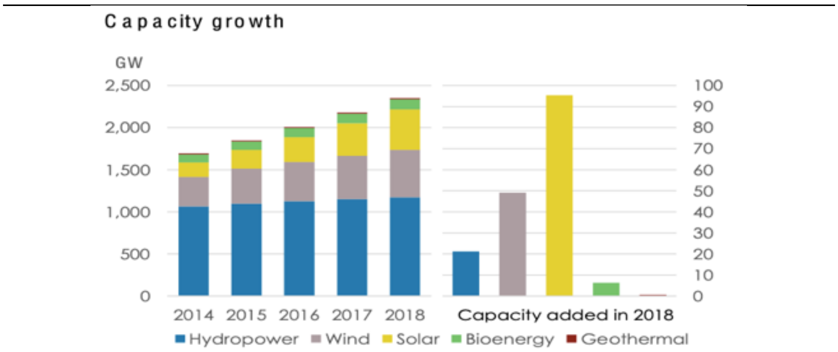

Figure 2: Renewable capacity growth and capacity added

(Source: International Renewable Energy Agency, 2019)

Wind power is a form of energy conversion where turbines convert the kinetic energy of wind into mechanical and electrical energy that can be used for power, constituting a renewable source of energy (Eckley Selin, 2020b). Solar power can be turned into electricity, by photovoltaic cells which converts the energy from solar radiations into electricity. It is considered a clean, rich and unlimited source of energy (Statkraft, n.d.). Both of these sources of renewable energy have faced a substantial drop in costs over the years caused by modern technology, as well as an increase in demand for renewable energy (International Renewable Energy Agency, 2018). Supporting policies and frameworks are currently giving the renewable energy sector a strong push financially. IEA (2017) estimates that during the decade before 2017, $750 billion was spent towards such policies. Cost reductions for wind and solar energy on their own, are still not enough to deliver the decarbonization of the power sector (Cozzi et al., 2017). Policies will be essential in making these sectors profitable as well as reaching governments renewable energy targets. Looking at the current position these sources of renewable energy have globally, it seems like they are likely to be a big part of our future, even though supporting polices will be crucial onwards.

2.3 Focus on transition from fossil energy to renewable energy

Inspired by the focus on a green shift in our society and encouragement towards choosing sustainable solutions, we want to do research related to the transition towards renewable energy sources. Over time, it has become increasingly difficult for most companies to remain unaffected by the transition into sustainable solutions. Several countries have carbon prices to encourage polluters to reduce the amount of greenhouse gases. This is a widely accepted method for effective reduction of global warming emissions (Hagmann, Ho, & Loewenstein, 2019). This type of fees and taxes create an incentive for companies to adapt towards a sustainable business model.

Most countries across the world that are seeking to reduce carbon print by reducing the usage of fossil fuels. In 2015, the Paris Agreement was established, which aims to ensure that countries participate in limiting emission rates and subsequent climate change. The points in the agreement urge that every country is commitment to develop appropriate measures to help reduce the climate change. During the second part of this century, we must be climate-neutral according to article 4 in the Paris Agreement (United Nations, 2015).

In addition to charging carbon prices, Norway have established a CO_2-compenastion scheme. Companies are discouraged from moving Norwegian Industry production to other countries without strict climate policy as in Norway. The industry get compensated for continuing power intensive production in Norway, where electricity is derived from sustainable sources, instead of moving production to countries that rely on heavily polluted fossil fuel energy at a low cost (Miljødirektoratet, 2020). Hopefully a scheme like this will inspire other countries to follow and create equivalent schemes. In addition to the government, we see Norwegian companies also shifting towards renewable energy. Equinor is one of Norway's largest companies, which is originally a petroleum energy company. They started a transitioning towards renewable energy after the company got a new CEO in 2014 (Tollaksen, Ryggvik, & Smith-Solbakken, 2020). Statements from large corporations like Equinor can have influence on other companies into prioritizing sustainability as the future. Consumers can also interpret this as a signal that we need to think green energy.

Not only do governments encourage companies to reduce their carbon print ant think towards renewable energy. Some countries also subsidize citizens for choosing cars with low carbon-print, such as electric or hybrid cars. Norway has no taxes on electric cars as well as giving other fiscal benefits such as reduced road tolls and lower public parking charges. Europe has a varying incentive between different countries. France for example has implemented a feebate system where new cars emitting less than 110gCO_2/km receive a subsidy. In the USA, they can apply for a tax credit up to $7500 for new plug-in electric vehicles, where the credit depends on the capacity of the battery (Fridstrøm & Østli, 2017). Countries are not only creating incentives for buying electric vehicles by cutting taxes. In addition, they impose taxes on fossil fuel to make petrol cars less attractive for consumers.

Many countries economy is still relatively dependent on revenues from the petroleum industry (Hutt, 2016). We are interested in seeing how oil price volatility affects stock prices of the renewable energy companies in different sectors. According to a report by the International Renewable Energy Agency (IRENA), unsubsidized renewable energy is now most frequently the cheapest source of energy generation. They also state that cost and maintenance of renewables are becoming lower over timer, which earlier has been a barrier for mass adoption (IRENA, 2018).

3 Methodology

3.1 Stationarity

Determining whether a time series is stationary or not is important, since it can strongly influence the time series behavior and properties. Stationarity occur when a time series probability distribution does not change over time. We can separate stationarity into two parts, weak and strict stationarity. A time series is strictly stationary if the entire distribution is constant over time. If the time series is weak it has a constant mean, constant variance and constant autocovariance for each lag (Brooks, 2014). A time series can be considered stationary if the data can satisfy the following relationships:

$$E(y_t) = \mu \tag{1}$$

$$E(y_t - \mu)(y_t - \mu) = \sigma^2 < \infty \tag{2}$$

$$E\left(y_{t_1} - \mu\right)\left(y_{t_2} - \mu\right) = \gamma_{t_2 - t_1} \ \forall_{t_1, t_2} \tag{3}$$

Equation 1 and 2 require a constant mean and variance, while in equation 3 the autocovariance depend on the distance in time between the two observations (Dougherty, 2016). Random walk is a term where the current value of a variable is disrupted by the previous value in a time series (Brooks, 2014). To find out if our time series is stationary, we can apply a unit root test. Most financial data become stationary after the first difference (Brooks, 2014). There are different types of unit root tests, for example Augmented Dickey- Fuller test (ADF), Kwiatkowski-Phillips-Schmidt-Shin tests (KPSS) and Phillips-Peron tests (PP) for stationarity. If the data is not stationary, we have to differentiate it until it is stationary.

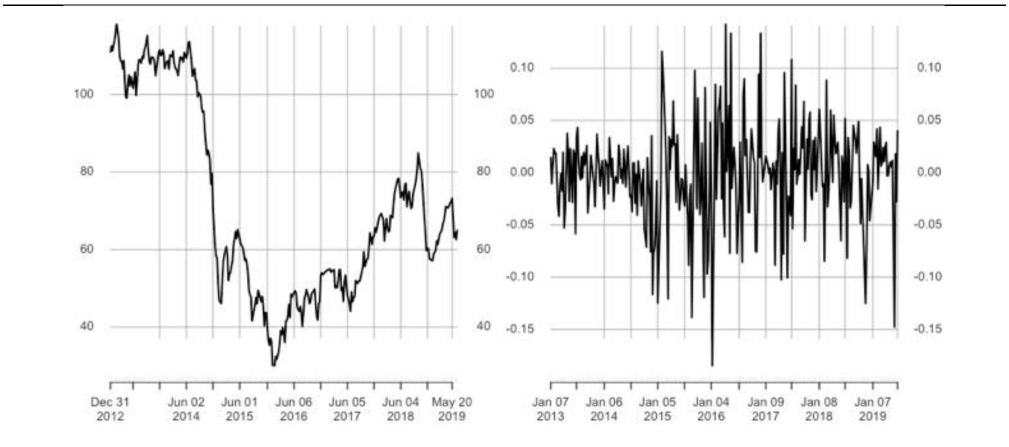

Figure 3: Plot of a stationary and non-stationary time series

Figure 2 show both stationarity and non-stationarity. The left plot represents a non-stationary time series, where we can see a clear trend. By differentiate the data, we can make the data stationary, and this is shown in the right plot.

3.2 Autocorrelation

In time series data, a common problem is that the value of Y in one period correlates with its own value in the next period. When the value in a time series correlate with its previous lag, we call it autocorrelation, and it is also known as serial correlation. To explain this further, it is the current value of a time series and how it is related to its own previous value (Dougherty, 2016). The first autocorrelation is the correlation between Y_t and Y_{t-1}, the second autocorrelation is between Y_t and Y_{t-2}, up until the j^{th} autocorrelation, which is between Y_t and Y_{t-j} (Stock & Watson, 2015).

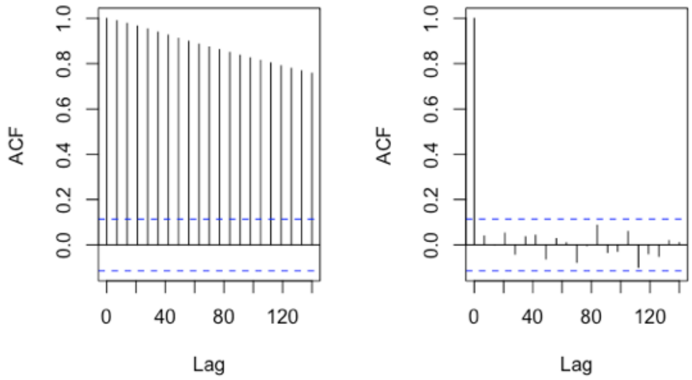

Figure 4: Autocorrelation plot

In figure 3 we illustrate both a plot with and without autocorrelation. In the left plot we can see a clear trend from one lag to the next, and that the values are dependent on the previous values. This is called random walk. In the right plot we can see a that the data is unrelated to its previous values, and therefore without autocorrelation, which also includes white noise. This indicates that the variables have the same variance and zero correlation (Brooks, 2014). In the plot it is shown by the different lag values does not cross the blue dotted line.

3.3 Vector Autoregression

We conclude that using a VAR-methodology would be suitable to test the relationship between our multivariate time series. VAR is short for Vector Autoregression, which is a generalization of the univariate autoregressive model. This model allows us to estimate coefficients and standard error between our variables. Each value will depend on its own lag and the lags of the other variables of interest. Sims (1980) think it is better to start with the assumption that all variables are endogenous (Brooks, 2019). It is normal to use this model to estimate the linear cointegration among these endogenous variables and estimates a regression for each variable. By determining the number of lags for each variable along with the exogenous variables can provide better estimates for Y_t, if there is autocorrelation or delay between endogenous variables.

$$Y_{1,t} = \beta_{1,0} + \beta_{1,1}Y_{1,t-1} + \cdots + \beta_{1,p}Y_{1,t-p} + \alpha_{1,1}Y_{2,t-1} + \cdots + \alpha_{1,p}Y_{2,t-p} + u_{1,t} \quad (4)$$

$$Y_{2,t} = \beta_{2,0} + \beta_{2,1}Y_{2,t-1} + \cdots + \beta_{2,p}Y_{2,t-p} + \alpha_{2,1}Y_{1,t-1} + \cdots + \alpha_{2,p}Y_{1,t-p} + u_{2,t} \quad (5)$$

The dependent variables are $Y_{1,t}$ and $Y_{2,t}$ and moving along the time series where $t = 1, 2, \ldots, T$. The VAR(p) model allow interpretation of the interaction of the explanatory variables, $Y_{1,t-1}$ and $Y_{2,t-1}$, but cannot conclude if there are causal relationship between the endogenous variables.

The model can include components such as constant term, trend or seasonality, and test whether these deterministic factors are significant. If the time series are not stationary, it is important differentiate the data until it achieves stationarity. For a system where all the series are non-stationary in their levels but there is cointegration in it, one should apply a vector error correction model (VECM). This model is a type of VAR model, but with additional error correction term. This model can also capture both long and short-run dynamics between the variables in the system. VECM can be presented as (Bönner, 2009):

$$\Delta Y_t = \delta + \lambda Y_{t-1} + \sum_{i=1}^{p-1} A_i \Delta Y_{t-i} + E_t \quad (6)$$

We can further investigate the relationships of our VAR-model through granger causality test and an impulse response function.

3.4 Granger causality

It is normal to use Granger causality test for testing whether current and lagged values of one time series can help predict the future values of another time series (Stock & Watson, 2015). We can test a VAR model using a granger causality test. This test can determine if one time series is useful in forecasting another, i.e. the lags of one variable explain the current value of some other variable, and to describe the dynamics of the data (Brooks, 2019).

3.5 Impulse Response Function

The Impulse Response Function represent how a shock affects one variable on the current and the future value of another variable. If there is serial correlation in the error term in the VAR model, there will be correlations in the impulse responses. This effect makes it difficult to interpret the results. To solve this problem, it is possible to use orthogonalized impulse-response function. This method assigns a synchronic correlation to specific series, and it presents the results in an impulse response function plot (hereby called irf-plot). So, the shock from different variables will not affect the first variable, but shocks to the first variable will affect the other variables, and so on. By applying shock to the impulse function, it is possible to see how this shock affects the response function in period t. The impulse responses only depend on time s, and that is the time from the shock occurred (ε_t) until we observe the shock in the future (y_{t+s}). The plots from IRF will summarize how the shock to the impulse function at time t will influence the y vector at time t + s (Brooks, 2014).

3.6 Lag length selection

Determining the lag length is important when estimating a VAR model. If the lag length is to short it could cause autocorrelation in the error term, and with a too long lag length, the last parameter will be insignificant. The results will suppress degree of freedom, provide too large standard errors and widening the confidence intervals for model coefficients (Brooks, 2019). There are two different method of selecting the lag length of a VAR model, cross-equation restriction and information criteria. A common way to select the lag length is through the use of information criteria, which is the method we use. The most common information criteria's are Akaike (AIC), Swartz-Bayesian (BIC) and Hannan- Quinn (HQ):

$$AIC(p) = \ln\left|\tilde{\sum}(p)\right| + \frac{2}{T}\,pn^2 \tag{7}$$

$$BIC(p) = \ln\,\left|\tilde{\sum}(p)\right| + \frac{lnT}{T}pn^2 \tag{8}$$

$$HQ(p) = \ln |\tilde{\sum}(p)| + \frac{2\ln \ \ln T}{T} pn^2 \qquad (9)$$

These three criteria are estimators of the optimal lag length p. BIC has the largest penalty term, and therefore select fewest lags. AIC have the smallest penalty term and therefore select higher lag length then BIC. HQ will select a lag length between BIC and AIC. We will use AIC to decide the lag length.

4 Data description

To perform the analysis, we have been using R and applied a sample period from 2010 until mid 2019 using weekly data. Due to limitations, we chose to cap our data collection in mid 2019. This was limited by some of the variables that had no historical data later than June 2019 available for the public. Additionally, we did not have access to any financial data vendors, which might have eased the process of data collection.

4.1 WilderHill

The WilderHill New Energy Global Innovation Index has since 2006 been the first and best-known index for new energy. It captures solutions to climate change and is composed of 87 companies, that are mostly from outside the U.S., whose innovative technologies focus on clean energy, low CO2 renewables. It is mainly comprised of companies in wind, solar, biomass, biofuels, small-scale hydro, geothermal, marine and other relevant energy businesses (WilderHill, 2019). The index does not aim at beating the market, they are robustly reviewing clean energy broadly conceived and consider stocks and sectors on technological, environmental and relevance-to-the-sector criteria. They are judging the performance based on how well the index can track movements of global clean energy and expect significant volatility.

4.2 S&P Global Clean Energy

In addition to looking at the WilderHill Index, we look into Standard & Poor’s Global Clean Energy Index, which is an index created in 2007 exposed to 30 companies around the world that are involved in clean energy business. The index compromises a diversified mix of clean energy production and clean energy equipment & technology companies. Companies must have a market capitalization greater or equal to $300 million and a float-adjusted market cap greater or equal to $100 million (S&P, 2020).

4.3 Solar

To track the performance of the solar energy sector, we look at the Ardour Solar Energy Index. It is an index that measures the performance of the solar energy stocks, focusing on renewable solar energy. The index is based on public companies worldwide, that gain at least 66% of their revenues from solar power. Further requirements are that the companies must have a minimum market capitalization of $100 million, $50 million in shares publicly traded and a minimum daily trading volume of $1 million.

The index requires that companies have a minimum market capitalization of $100 million, minimum $50 million in shares publicly traded, and a minimum daily trading volume of $1 million. In addition, the companies must be traded on a recognized stock exchange to be qualified. The majority of the companies in the index originates from the United States and China, who respectively counts for 28% and 18%. European companies count for only a total of 15%, where 10% is originating from Spain, while 5% originates from Germany (Ardour Global, 2018). Based on this methodology of the index, we think it gives a good representation of the performance of the solar energy sub-sector.

4.4 Wind

To track wind energy, we use the ISE Global Wind Energy Index as a benchmark. It is designed to track public companies that are active in the wind energy industry based on analysis of the products and services offered by those companies. To be included in the index, securities are required to be primarily engaged and involved actively in some aspect of the wind energy industry. In addition to being engaged in wind power, they must be listed on an index-eligible global stock exchange, have a minimum free float of 25% and must have a market capitalization of minimum $100 million (Clean Edge, 2019).

4.5 Fuel Cell

A fuel cell is a device that can resemble a battery in many respects, but it supplies electrical energy over a much longer period of time by continuously being supplied with hydrogen and air/oxygen from an external source (Schumm, 2020). To track the performance of fuel cells, we have decided to use The Nasdaq OMX Fuel Cell Index, which is a sub-sector index of the Nasdaq OMX Green Economy Index that was created in 2010 and is designed to track companies that produce energy through fuel cells. For a company to be eligible in the Green Economy Index, it must be within one of many sectors, where one of them is Renewable Energy Generation. The Fuel Cell Index consist of the companies within the Renewable Energy Index that are operating within the Fuel Cells sub-sector (Nasdaq, 2015).

4.6 Oil

We choose to use the spot price of Brent Crude as a benchmark for oil. Brent Blend oil is a combination from 15 different oil fields in the North Sea. Its API Gravity is 38,3, which defines it as a light oil (Dept, 2009). The historical date of Brent spot price is retrieved from the website of EIA (Energy Information Administration). We include the 2014 price drop period in our analysis, as we are interested in seeing how the renewable energy sector reacts to this type of shock. In addition, we wish to see how the relationship is before and after the shock.

4.7 Interest Rate

Schmidt et al. (2019) states that low interest rate increase the profitability for renewable energy companies. Renewable energy sources are more capital-intensive than the fossil energy sources. This can therefore make renewables less competitive against the fossil fuel energies if the interest rate rises. Furthermore, it has been stated that an increased interest rate can give a rise in expenses with 11 per cents for solar plants, and 25 per cents for wind power plants (Schmidt et al., 2019). With this research in mind, it will be interesting to see whether a rise in interest rate give this negative effect to our renewable indexes, and vice versa. In previous studies, such Kumar et al. (2012) interest rate is used as a variable for analysis. Kumar et al. (2012) refer that previous research show a significant relationship between stock price movements and change in interest rate. To represent the interest rate, we use a 3-month US Treasury bill.

4.8 Carbon Price

There is more focus on reducing carbon footprint, and that companies must choose more clean energy solutions than fossil fuel. We think that carbon prices encourage companies to choose renewable energy sources over fossil ones. When carbon price rise, it creates incentives to choose renewable energies. This will make renewable energy companies more profitable and the stock prices would increase. A price on carbon will make fossil-fuel alternative more expensive, and therefore it can make a positive impact on the renewable energy stock prices (Best & Burke, 2018).

Kumar et al. (2012) investigate if carbon prices have led to investments in clean energy companies. They are using futures contract prices for carbon, which we have decided to include in our analysis. Kumar et al. (2012) do not find an effect on clean energy firms by the change in carbon prices. However, this research was done several years ago, and it would therefore be interesting to see if this has an effect today.

4.9 Historical development

In figure 4 we present the cumulative return of the oil price and the different indexes. By looking at cumulative returns, we can easier compare the performance of each index to the oil price, and to each other. From October 2010 to the middle of 2014 the oil price has a relatively stable cumulative return, with around 0,4 return in the period. The indexes we look at are more volatile during the period. While the oil cumulative return is very flat at the beginning, the different indexes had a negative return. The index with the worst performance, is the Solar index. The solar index is presented by the red line and had a deep decline during the period. Comparing the index to the other renewable indexes, solar had the same pattern as the other indexes, but the decline is higher than the other.

Figure 5: Cumulative returns of assets between October 2010 and June 2019

From the middle of 2014, when the oil crisis occurs, it is possible to see that the returns for both the solar index and fuel cells index decline. If we look at similarities between the oil price, represented by the black line, and the indexes represented in the plot, we notice that the fuel cell index and solar index have a similar path. These indexes decrease in the same period as the oil crisis occur. They do not experience a dramatic decline as the oil price, but they decline over a longer period of time. This can indicate that the oil price has an impact on the fuel cells companies, which is represented by the orange line. When the oil prices increase at the end of 2015, we see the fuel cells index has a lagged effect. Wind index, represented by the light blue line, has a stable increase the whole period. Looking strictly at this plot, wind does not seem affected by the changes in oil price. This can also be said about the WilderHill and S&P clean energy indexes, represented by green and dark blue respectively in the plot. Their graphs indicate a similar performance, with WilderHill having a slightly higher return than S&P Clean Energy index.

Looking at previous studies related to oil price shocks and its relationship with the clean energy market, a lot of studies use indexes to serve as a benchmark for the renewable energy sector. We choose to look at indexes with a focus on renewable energy. In addition, we are looking at sub-sector specific indexes. We exclude looking at mutual funds for tracking performance. By looking at indexes to track the sector performance, we can get a better understanding of how these sectors perform in the market, as their aim is to track actual sector performance, oppose to mutual funds who often seek to beat a benchmark.

5 Model

5.1 Descriptive Analysis

Table 1: Descriptive Statistic

	WilderHill Index	S&P Clean Energy	Solar Index	Wind Index	Fuel Cell	Oil Price	Interest Rate	Carbon Price
Minimum	-0,176	-0,183	-0,228	-0,134	-0,226	-0,169	-0,857	-0,303
Maximum	0,116	0,131	0,190	0,103	0,576	0,153	3,000	0,207
Mean	0,000	-0,001	-0,002	0,001	0,001	0,000	0,051	0,003
Median	0,001	0,001	-0,002	0,001	-0,005	0,002	0,000	0,005
Variance	0,001	0,001	0,004	0,001	0,006	0,002	0,123	0,004
Std. Dev.	0,032	0,035	0,060	0,029	0,077	0,046	0,350	0,062
Skewness	-0,599	-0,419	0,014	-0,319	1,519	-0,097	3,813	-0,390
Kurtosis	3,247	2,626	0,996	1,765	9,493	1,174	26,687	2,856
Observations	385	385	385	385	385	385	385	385

Table 1 summarize the descriptive statistic of the data. There is a total of 385 weekly observation in the table and summarize the weekly return in the period. Solar and Nasdaq Fuel Cell return is volatile. They respectively have a minimum of -0.228 and -0.226 and maximum of 0.19 and 0.576 weekly return for the period, which is high. This is confirmed also by a higher standard deviation than other indexes and can therefore make them riskier than the other indexes. The most stable indexes are the wind and the WilderHill index, which respectively have a weekly return of minimum of -0.103 and -0.123, and a maximum of 0.077 and 0.076 in the period. They also have the smallest standard deviation.

By analyzing skewness and kurtosis, we can consider the extremes of the data set. Skewness defines the shape of the distribution (Brooks, 2019). There are three indexes which have negative skewness, and WilderHill and S&P clean energy has the highest negative value. This tells us that these indexes have a large number of negative returns comparing to positive returns, also called fat left tail. Solar and Nasdaq fuel cell has positive skewness and therefore has a large number of positive returns. This mean that the two indexes have a fat right tale. Kurtosis measures the fatness of the tail and how peaked at the mean the series is (Brooks, 2019). All the indexes have a higher value of the kurtosis than the mean return.

5.2 Correlation

Table 2 show the correlation coefficient and we can see how they correlate to each other. Some of the variables are heavily correlated, and some does not correlate as much as anticipated.

Table 2:Correlation

	WilderHill Index	S&P Clean Energy	Solar Index	Wind Index	Nasdaq Fuel Cell	Oil Price	Interest rate	Carbon price
WilderHill	1							
S&P Clean Energy	0,71	1						
Solar Index	0,52	0,94	1					
Wind Index	0,73	0,13	-0,14	1				
Nasdaq Fuel Cell	0,48	0,65	0,75	-0,11	1			
Oil Price	-0,23	0,18	0,39	-0,62	0,53	1		
Interest Rate	0,24	-0,19	-0,40	0,63	-0,38	-0,35	1	
Carbon Price	0,29	0,29	0,13	0,30	-0,03	-0,03	0,73	1

Interpreting the results in the table, we can first see that the WilderHill index show a positive relationship towards every variable. The exception is the negative correlation between oil prices and the WilderHill index. Since we hope that an increase in oil prices would have a positive effect towards renewable energy, we find the negative relationship between these variables surprising. Additionally, the wind index also shows an even more negative correlation towards oil price changes.

Interestingly we also see that the interest rate shows a strong positive effect on the wind index. Seeing how previous research show that an increased interest rate would increase expenses for wind power plants, we would expect a negative effect for the wind index. An increase in expenses for wind power companies, would result in a lower profit margin and affect stock prices negatively.

5.3 Unit root test

By applying the natural logarithm to all our variables, we reduce unwanted variability in the data. To run the Unit root test, we are using Augmented Dickey- Fuller test (ADF), Kwiatkowski-Phillips-Schmidt-Shin tests (KPSS) and Phillips-Peron tests (PP). The goal of these tests is to achieve stationarity. The first three columns presented in table 3 show the p-values before differentiating is made, and the next three is after differentiating in the first order. Looking at the results in the first three columns, ADF and PP tests have a high p-value, which indicate non-stationarity. By differentiating in the first order, the the p-value is now of 1%, and we can conclude that the data is stationary. In the table, KPSS test provide evidence against stationary in the first difference. By doing the KPSS test the data is stationary before differentiating the data.

Table 3: Unit Root Test (P-values)

	Levels			First difference		
	ADF Test	KPSS Test	PP Test	ADF Test	KPSS Test	PP Test
WilderHill Index	0,51	0,01	0,57	0,01	0,10	0,01
S&P Clean Energy Index	0,39	0,01	0,60	0,01	0,10	0,01
Solar Index	0,69	0,01	0,76	0,01	0,10	0,01
Wind Index	0,46	0,01	0,68	0,01	0,10	0,01
Nasdaq Fuel Cell Index	0,94	0,01	0,95	0,01	0,10	0,01
Oil Price	0,42	0,01	0,62	0,01	0,10	0,01
Interest Rate	0,46	0,01	0,54	0,01	0,10	0,01
Carbon Price	0,38	0,01	0,32	0,01	0,10	0,01

5.4 VAR models

Before conducting a VAR model, we need to determine the lag length of the variables. By using information criterion like Akaike Information criterion (AIC), Hannan- Quinn criterion (HQ) and Schwartz Information criterion (SC), we determine the optimal lag length for our variables and models. To see if the variables have an effect on the different indexes, we have made five different models. Every model has one index as the dependent variable, and the oil price, interest rate and carbon price as independent variables. Furthermore, we have partitioned the data into three periods. The first period is before the oil crisis, which is from 18.10.2010 to 18.08.2014. Second period is from 01.06.2015 to 24.06.2019 and marks the end of the oil crisis and onwards. The last period is the whole time series and stretches from 18.10.2010 to 24.06.2019. This is done to see if the oil price and the other variables have an impact on the indexes in the different periods. Hereby we will refer to these periods as «pre-crisis», and «post-crisis» and “whole period”.

Table 4: VAR-models

Models	Variables
Model 1	Solar Index, Oil, Interest Rate, Carbon
Model 2	Wind Index, Oil, Interest Rate, Carbon
Model 3	WilderHill Index, Oil, Interest Rate, Carbon
Model 4	Nasdaq Fuel Cells Index, Oil, Interest Rate, Carbon
Model 5	S&P Clean Energy Index, Oil, Interest Rate, Carbon

From table 14 in Appendix B, we can see the impact oil price, interest rate and carbon price have on the different indexes for the whole period. All the different information criteria decide that one lag for all five models is the best fit for the VAR model. When using lag length of 1, we notice the R-squared value is very low for all the variables, and there is no significant relationship between the indexes and the variables.

The information criteria shown in table 9 in Appendix A choose lag length of 1, as the optimal fit of the different VAR models for the period pre oil crisis. The explanatory factors of the different models and variables are not high and give us approximately the same result as in the whole period.

Table 5: Optimal lag for models post oil crisis

	AIC.n.	HQ.n.	SC.n.
Model 1	2	1	1
Model 2	5	1	1
Model 3	5	1	1
Model 4	1	1	1
Model 5	5	1	1

From table 5 we can see that the different information criteria´s give us a longer optimal lag length for the period post oil crisis. The most interesting VAR models are model 2, 3 and 5. These are the models that gives us the highest R-squared value and lowest p-value. In these three models we can see that the VAR model fit is much higher than in the period before the oil crisis and the period as a whole. Model 2 gives us an r-squared of 0,146. Here, the lagged value of wind index and the different variables that explains the changes in the wind index.

Table 6: VAR Model 2 Post Oil Crisis

	Wind Index	Oil	Interest	Carbon
F-statistic	1,327	1,563	3,117	0,844
R-squared	0,146	0,168	0,287	0,098
Standard Error	0,025	0,052	0,203	0,058

Table 7 shows how WilderHill index is affecting by the lagged value of itself and the different variables. This index has the highest r-squared compared to all the other models.

Table 7: VAR Model 3 Post Oil Crisis

	WilderHill Index	Oil	Interest	Carbon
F-statistic	1,498	1,429	3,647	0,707
R-squared	0,162	0,156	0,320	0,084
Standard Error	0,027	0,052	0,198	0,059

In table 8 you can see that the R-squared value of the S&P clean energy index is almost as high as WilderHill index. This is not surprising, since both indexes seem to have a similar performance based on visual interpretation from a plot of historical performance.

Table 8: VAR Model 5 Post Oil Crisis

	S&P Clean Energy Index	Oil	Interest	Carbon
F-statistic	1,445	1,394	3,232	0,795
R-squared	0,157	0,152	0,294	0,093
Standard Error	0,029	0,052	0,202	0,058

6 Results

6.1 Results from granger causality test

In Appendix F, the granger causality test for the different models and periods. From the lag selection criteria presented in tables in Appendix A, we use 1 lag for both the pre-crisis and whole period models. For the post crisis models we use the optimal lags from table 5 into the different granger tests. The granger tests from the whole period and pre-crisis which are presented in the tables 17 and 18, show us that there is no granger causality running from oil to the indexes. The same is shown from interest rate and carbon price to the indexes.

For the post crisis granger causality tests, which is presented in the table 16, we see that there is no granger causality running from oil and carbon price to any index. But in model 1 we can see granger causality running from the interest rate to the solar index with a significant level of 1%. For model 3 and 5 there is granger causality running from interest rate to WilderHill index and the S&P clean energy index with a significant level of 5%. Model 2 reveal that there is granger causality running from interest rate to wind index with a significant level of 10%.

6.2 Results from impulse response function

Here we present the results from applying shocks to the different variables. In Appendix C to E show the different impulse response functions plots (irf-plots). Here we can see how a shock given to one variable affect another one, and their reaction the next 10 weeks. The hard lines in the plot show their response, while the dotted lines represent the standard error in each direction of the line. The irf-plots in figure 10, express the effect of the oil price, interest rate and carbon price have on the indexes before the oil crisis. By giving a shock to the variables, we can see how the different indexes react to this shock. The shocks given to the variables just mentioned, show no big reaction to any of the indexes. It gives a small negative or positive reaction until week 2 until flattening out. In figure 11we can see that the reaction is more or less the same during the whole period.

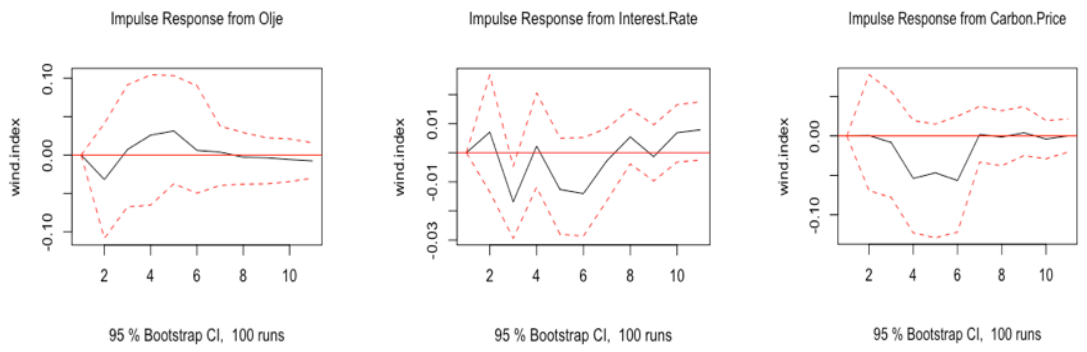

Figure 6: IRF-plot of Wind Index and variables post-crisis

An interesting result was the reactions the indexes have post oil crisis. Especially looking at the wind index, WilderHill index and S&P clean energy index. These indexes seem to have a long-term effect from the shock. Taking a closer look at how the wind index is affected by shocks after the oil crisis, demonstrated by the irf-plots presented in figure 5, reveal the wind index reaction to a shock from oil in the first plot. Here we see a slightly negative shock until week 2, before the effect turns slightly positive until the curve flattens out around week 6. When applying a shock to the interest rate, the wind index seems to have a fluctuating reaction over the next weeks. The wind index has a reaction shaped like a channel, where it has a negative reaction from the first week before increasing in week 6 and flattening out afterwards.

7 Discussion

By using impulse response function, we find no significant effect between the oil price and the different indexes. This applies to all the different periods we looked into, which makes us reject our first hypothesis. We find it interesting to see how this contradicts the finding by Kumar et al., (2012) and Managi & Okimoto (2013). Especially during the whole period, and the pre-crisis period we find no significant result. As observed in the different irf-plots, we see almost no effect from the shock given to the oil price. This could be explained by e.g. the time periods we are looking at and changes in which companies the index is exposed to.

In the pre-crisis period, the result from solar, S&P and the WilderHill show the most interesting results. While not significant, they show a negative effect after week 2. During the whole sample period, none of the indexes show any reaction to the shocks given. The post-crisis period plots express different results than the other periods, but since there is no significant relationship, we cannot confirm an effect in the time period. What all of the indexes have in common is that they show a negative effect at the beginning of the shock, before turning positive.

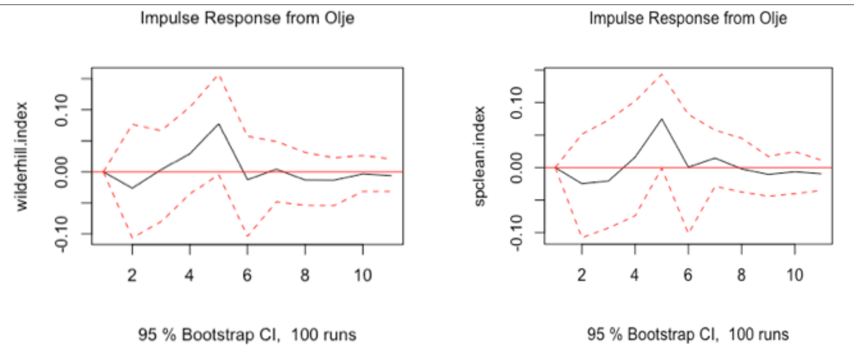

Figure 7: IRF-plots of WilderHill index and the S&P Clean Energy Index post-crisis

We see both WilderHill and the S&P index reaction to an oil shock in figure 7, starting with a negative reaction before increasing after week 2. This we interpret as a short-term growth in the renewable energy sector, following oil price shock. As previously discussed, companies might seek towards renewable energy when oil prices are fluctuating. Still, if this was the case, it should have affected the sub-sector indexes as well, in the same fashion. The response on these sub-sectors is rather small compared to the global indexes. As these models are not significant, there is no evidence to support that these effects are factual. Lack of granger causality also makes it hard for us to know how to interpret these relationships.

We were not able to find significant relations between the interest rate and the different indexes pre-crisis and under the whole period. Our second hypothesis can therefore be rejected for these two periods. This is also contradicting the previous papers discussed in the literature review that find a relationship between the interest rate and the indexes. A reason for this could be that the interest rate has been historically low after 2009. An increase or a decrease of the interest rate, might not be as effective as it has been in earlier research.

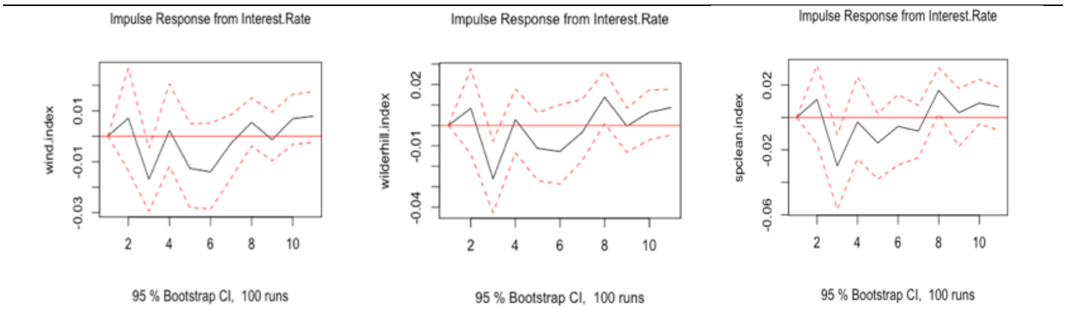

Figure 8: IRF-plot of Wind, WilderHill and the S&P Clean Energy Index post-crisis

Looking at the post-crisis period we find some significant results. Through the VAR model, some lags from the interest rate that show significant results. As we can observe from the irf-plots presented in Figure 7, a shock to the interest rate give a reaction to the wind index, WilderHill index and the S&P Clean energy index. The effect show a fluctuating response to the lags that are significant. The standard error is low as well, in addition to significant granger causality at 5% for S&P and WilderHill, while at 10% for the wind index. According to granger causality, we can accept the second hypothesis, concluding that the interest rate has a negative effect on the three indexes mentioned above. This confirms the previous results by Schmidt et al. (2019), who showed that an increase in the interest rate gave a rise in expenses for solar and wind plants. Increased costs will lead to lower profits, which will decrease renewable energy companies stock prices.

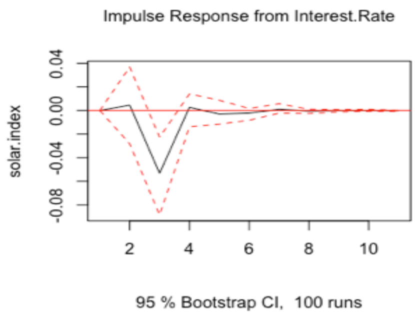

Figure 9: IRF-plot of Solar Index post-crisis

Solar index is the most significant model, shown in Figure 8, which we find significant granger causality at 1% level. This is the index best explained by changes to the interest rate. The irf-plot for this index presents a negative effect from the shock in interest rate. For the rest of the indexes, we must reject the second hypothesis in the post-crisis period. The high standard errors in the different models and no granger causality relationship, could contribute to make the results unreliable.

From the impulse response function at post-crisis, as well as the whole period, we see that the effect from the shocks to the carbon price does not significantly impact the different indexes. We can confirm this based on results of granger causality models. They show no significant results for none of the indexes, independent of the period. There is moreover just a small effect from the shocks. On this basis we reject the third hypothesis. This contradicts our assumption that increased carbon prices would lead toward investments in renewable energy. Previous research by Kumar et al. (2012) had similar results, but we proposed that the increased importance of sustainability and focus on climate changes, would have turned carbon prices to significantly impact the renewable sector positively. In the results from post-crisis we can see a negative effect from the shocks given. But here the standard errors from the shock is very high and will therefore not be as reliable. This result causes us to reject the third hypothesis for post-crisis too.

8 Summary and limitations

To summarize, we can partly confirm one of our hypotheses, but we also get results that contradict earlier research. This is regarding the relationship between oil and the renewable indexes. We believe that this can be explained by the data sample period, as well as seeing an increased performance in later years within ESG assets (Benhamou, Chasan, & Kishan, 2020). Policies and incentives supporting the shift towards renewable energy has also increased over the years, making us believe that the renewable energy companies could be more robust towards changes in oil price now than previously. Furthermore, we analyze both overall sector indexes as well as specialized sub-sector indexes, in attempt to get more narrow results, looking at which sub-sector has most effect from these changes. Unfortunately, most models show no significant results, with the exception of some models from the post-crisis period using interest rate.

In relation to limitations, we acknowledge that some additional variables would be interesting to include, that was left out by limitations in gathering data material. One of the variables excluded is polysilicon prices. Polysilicon prices are highly relevant for the solar energy industry, seeing how some types solar panels are made from this material. In addition, we wanted to look at electricity prices, which were left out seeing how there is a high variation of the prices between countries and no obvious benchmark for us to use. There can also be directed some criticism towards the vector autoregressive models we use. Other papers are using other, more advanced versions of VAR, like a lagged augmented VAR, and some studies also use Markov-switching VAR models. Other research also use different version of GARCH etc., which might give us different results.

9 Conclusion

The United Nations sustainable development goals, as well as the Paris Agreement, are putting focus on working towards a sustainable future. This is making the transition from fossil fuel to more sustainable sources of energy utterly important for the next decade. How renewable energy assets are affected by oil prices are interesting both from a financial standpoint, as well as an environmental. Analyzing this relationship using vector autoregressive models, our findings indicate no relationship between any renewable index and crude oil prices or carbon prices. Interest rate indicate a significant effect on some of the renewable energy indexes, during the post oil crisis period. More specifically, we see that the S&P Global Clean energy, WilderHill New Energy Global Innovation Index, ISE Global Wind Energy and Ardour Solar Energy are the indexes that show a significant reaction. Based on the VAR-methodology we use in this thesis; it is hard for us to draw a conclusion that represent the whole renewable energy sector. Examining the result, we can answer to our problem statement; changes in crude oil prices, do not seem to affect renewable energy assets.

Building upon previous research, we hope to contribute with a more modern view on this matter. When conducting future research, we would recommend try finding other economic factors that can have more impact on the renewable companies. This can be electricity prices, polysilicon prices etc. Furthermore, this is a very exciting area where the future technological development can be massive, and important for the future environmental sustainability. Replicating this study, a year from now, can be exiting. In the middle of writing this thesis, we encountered a pandemic caused by the coronavirus. The economy and oil prices showed a steep drop in March 2020 because of this. Seeing how well renewable energy companies are performing during this challenging period, indicate that renewables have become more robust in the market (A. Solheimsnes, 2020).

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11 Appendix

Appendix A: Optimal lag

These tables show us the optimal lags for all five models before and through the whole period.

Table 9: Optimal lag for VAR models

Pre-crisis	AIC.n.	HQ.n.	SC.n.
Model 1	1	1	1
Model 2	1	1	1
Model 3	1	1	1
Model 4	1	1	1
Model 5	1	1	1
Whole period	AIC.n.	HQ.n.	SC.n.
Model 1	1	1	1
Model 2	1	1	1
Model 3	1	1	1
Model 4	1	1	1
Model 5	1	1	1

Table 10: Lag selection model, post-crisis

Model 1	1	2	3	4	5	6	7	8	9	10
AIC(n)	-20,531	-20,569	-20,513	-20,388	-20,542	-20,511	-20,444	-20,421	-20,415	-20,502
HQ(n)	-20,382	-20,300	-20,125	-19,881	-19,916	-19,765	-19,579	-19,437	-19,311	-19,279
SC(n)	-20,164	-19,907	-19,557	-19,138	-18,999	-18,673	-18,313	-17,996	-17,696	-17,489
Model 2	1	2	3	4	5	6	7	8	9	10
AIC(n)	-22,031	-22,026	-21,973	-21,889	-22,066	-21,982	-21,895	-21,870	-21,799	-21,862
HQ(n)	-21,882	-21,758	-21,586	-21,382	-21,440	-21,237	-21,030	-20,886	-20,695	-20,639
SC(n)	-21,663	-21,365	-21,018	-20,639	-20,523	-20,145	-19,764	-19,445	-19,080	-18,849
Model 3	1	2	3	4	5	6	7	8	9	10
AIC(n)	-21,901	-21,919	-21,895	-21,821	-21,986	-21,872	-21,802	-21,793	-21,724	-21,772
HQ(n)	-21,752	-21,651	-21,508	-21,314	-21,360	-21,126	-20,937	-20,809	-20,620	-20,549
SC(n)	-21,534	-21,258	-20,940	-20,572	-20,443	-20,035	-19,671	-19,368	-19,004	-18,759
Model 4	1	2	3	4	5	6	7	8	9	10
AIC(n)	-20,131	-20,082	-19,992	-19,884	-20,037	-19,920	-19,848	-19,772	-19,653	-19,672
HQ(n)	-19,982	-19,814	-19,605	-19,377	-19,411	-19,175	-18,983	-18,788	-18,550	-18,450
SC(n)	-19,764	-19,421	-19,037	-18,635	-18,494	-18,083	-17,717	-17,347	-16,934	-16,659
Model 5	1	2	3	4	5	6	7	8	9	10
AIC(n)	-21,689	-21,728	-21,705	-21,587	-21,739	-21,634	-21,553	-21,533	-21,466	-21,515
HQ(n)	-21,540	-21,460	-21,318	-21,081	-21,113	-20,888	-20,689	-20,549	-20,363	-20,292
SC(n)	-21,322	-21,067	-20,750	-20,338	-20,196	-19,797	-19,422	-19,108	-18,747	-18,502

Table 11: Lag selection model, pre-crisis

Model 1	1	2	3	4	5	6	7	8	9	10
AIC(n)	-19,377	-19,289	-19,228	-19,348	-19,205	-19,083	-19,004	-18,882	18,836	-18,719
HQ(n)	-19,219	-19,005	-18,817	-18,811	-18,541	-18,292	-18,087	-17,838	-17,666	-17,422
SC(n)	-18,987	-18,588	-18,215	-18,025	-17,570	-17,136	-16,746	-16,312	-15,955	-15,526
Model 2	1	2	3	4	5	6	7	8	9	10
AIC(n)	-20,821	-20,747	-20,707	-20,684	-20,604	-20,478	-20,371	-20,233	-20,184	-20,147
HQ(n)	-20,663	-20,462	-20,296	-20,147	-19,940	-19,688	-19,454	-19,190	-19,014	-18,851
SC(n)	-20,432	-20,046	-19,695	-19,360	-18,969	-18,532	-18,113	-17,664	-17,303	-16,955
Model 3	1	2	3	4	5	6	7	8	9	10
AIC(n)	-20,658	-20,580	-20,527	-20,591	-20,475	-20,371	-20,282	-20,148	-20,110	-20,062
HQ(n)	-20,500	-20,295	-20,116	-20,054	-19,811	-19,581	-19,365	-19,105	-18,940	-18,766
SC(n)	-20,269	-19,879	-19,515	-19,268	-18,840	-18,425	-18,024	-17,579	-17,229	-16,870
Model 4	1	2	3	4	5	6	7	8	9	10
AIC(n)	-18,922	-18,884	-18,872	-18,821	-18,691	-18,586	-18,494	-18,341	-18,324	-18,188
HQ(n)	-18,764	-18,599	-18,461	-18,284	-18,027	-17,795	-17,577	-17,297	-17,154	-16,892
SC(n)	-18,533	-18,183	-17,860	-17,498	-17,056	-16,639	-16,236	-15,771	-15,443	-14,996
Model 5	1	2	3	4	5	6	7	8	9	10
AIC(n)	-20,426	-20,334	-20,305	-20,375	-20,270	-20,17	-20,076	-19,928	-19,848	-19,735
HQ(n)	-20,268	-20,049	-19,894	-19,837	-19,606	-19,380	-19,159	-18,885	-18,678	-18,438
SC(n)	-20,036	-19,633	-19,292	-19,051	-18,635	-18,223	-17,818	-17,359	-16,967	-16,542

Table 12: Lag selection model, whole period

Model 1	1	2	3	4	5	6	7	8	9	10
AIC(n)	-19,783	-19,730	-19,720	-19,742	-19,702	-19,662	-19,625	-19,570	-19,589	-19,569
HQ(n)	-19,699	-19,580	-19,503	-19,459	-19,352	-19,246	-19,142	-19,020	-18,972	-18,886
SC(n)	-19,573	-19,352	-19,174	-19,028	-18,821	-18,613	-18,408	-18,185	-18,036	-17,849
Model 2	1	2	3	4	5	6	7	8	9	10
AIC(n)	-21,248	-21,209	-21,196	-21,175	-21,151	-21,089	-21,052	-20,988	-20,973	-20,974
HQ(n)	-21,165	-21,059	-20,980	-20,891	-20,801	-20,673	-20,569	-20,438	-20,357	-20,291
SC(n)	-21,038	-20,831	-20,651	-20,461	-20,269	-20,040	-19,835	-19,603	-19,420	-19,253
Model 3	1	2	3	4	5	6	7	8	9	10
AIC(n)	-21,084	-21,034	-21,022	-21,034	-21,004	-20,950	-20,911	-20,845	-20,846	-20,826
HQ(n)	-21,000	-20,884	-20,806	-20,751	-20,654	-20,533	-20,427	-20,295	-20,229	-20,143
SC(n)	-20,874	-20,656	-20,477	-20,321	-20,122	-19,900	-19,693	-19,460	-19,293	-19,105
Model 4	1	2	3	4	5	6	7	8	9	10
AIC(n)	-19,359	-19,336	-19,330	-19,285	-19,245	-19,195	-19,156	-19,098	-19,072	-19,010
HQ(n)	-19,276	-19,186	-19,113	-19,002	-18,895	-18,779	-18,673	-18,548	-18,455	-18,327
SC(n)	-19,150	-18,958	-18,784	-18,571	-18,363	-18,146	-17,939	-17,713	-17,519	-17,290
Model 5	1	2	3	4	5	6	7	8	9	10
AIC(n)	-20,859	-20,808	-20,805	-20,811	-20,778	-20,725	-20,696	-20,635	-20,625	-20,589
HQ(n)	-20,776	-20,658	-20,589	-20,528	-20,428	-20,309	-20,212	-20,086	-20,008	-19,906
SC(n)	-20,649	-20,431	-20,26	-20,097	-19,897	-19,676	-19,479	-19,25	-19,072	-18,868

Appendix B: Vector Autoregressive Models

Table 13: VAR Models pre-crisis

Model 1	Solar Index	Oil	Interest	Carbon
F-statistic	1,578	0,377	0,063	2,065
R-squared	0,038	0,009	0,002	0,049
Standard Error	0,070	0,035	0,327	0,073
Model 2	Wind Index	Oil	Interest	Carbon
F-statistic	0,183	0,442	0,180	2,486
R-squared	0,005	0,011	0,004	0,058
Standard Error	0,035	0,035	0,033	0,072
Model 3	WilderHill Index	Oil	Interest	Carbon
F-statistic	0,489	0,433	0,083	1,921
R-squared	0,012	0,011	0,002	0,046
Standard Error	0,038	0,035	0,327	0,073
Model 4	Fuel Cels Index	Oil	Interest	Carbon
F-statistic	0,152	0,399	0,148	1,910
R-squared	0,004	0,010	0,040	0,045
Standard Error	0,086	0,035	0,327	0,073
Model 5	S&P Clean Energy Index	Oil	Interest	Carbon
F-statistic	0,738	0,478	0,050	1,917
R-squared	0,018	0,012	0,001	0,045
Standard Error	0,042	0,035	0,327	0,073

Table 14: VAR Models for the whole period

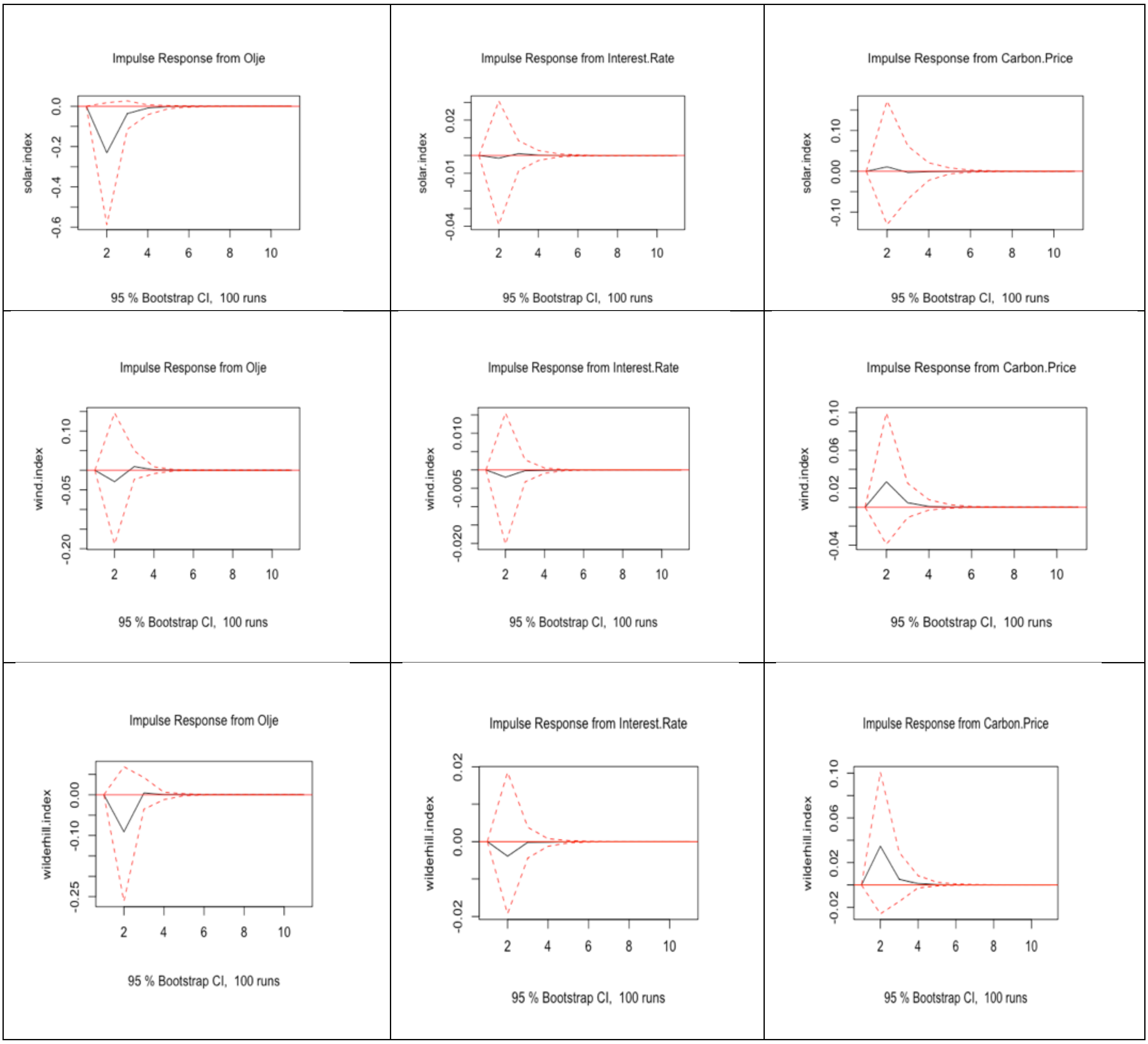
Model 1	Solar Index	Oil	Interest	Carbon
F-statistic	1,116	0,472	0,531	4,517
R-squared	0,012	0,005	0,006	0,046
Standard Error	0,061	0,046	0,292	0,062
Model 2	Wind Index	Oil	Interest	Carbon
F-statistic	0,407	0,483	0,752	4,061
R-squared	0,004	0,005	0,008	0,041
Standard Error	0,030	0,046	0,291	0,062
Model 3	WilderHill Index	Oil	Interest	Carbon
F-statistic	0,322	0,490	0,449	3,761
R-squared	0,004	0,005	0,005	0,038
Standard Error	0,032	0,046	0,291	0,062
Model 4	Fuel Cels Index	Oil	Interest	Carbon
F-statistic	0,322	0,476	0,583	3,634
R-squared	0,003	0,005	0,006	0,037
Standard Error	0,074	0,046	0,291	0,062
Model 5	S&P Clean Energy Index	Oil	Interest	Carbon
F-statistic	0,514	0,636	0,478	3,683
R-squared	0,005	0,007	0,005	0,038
Standard Error	0,036	0,046	0,291	0,062

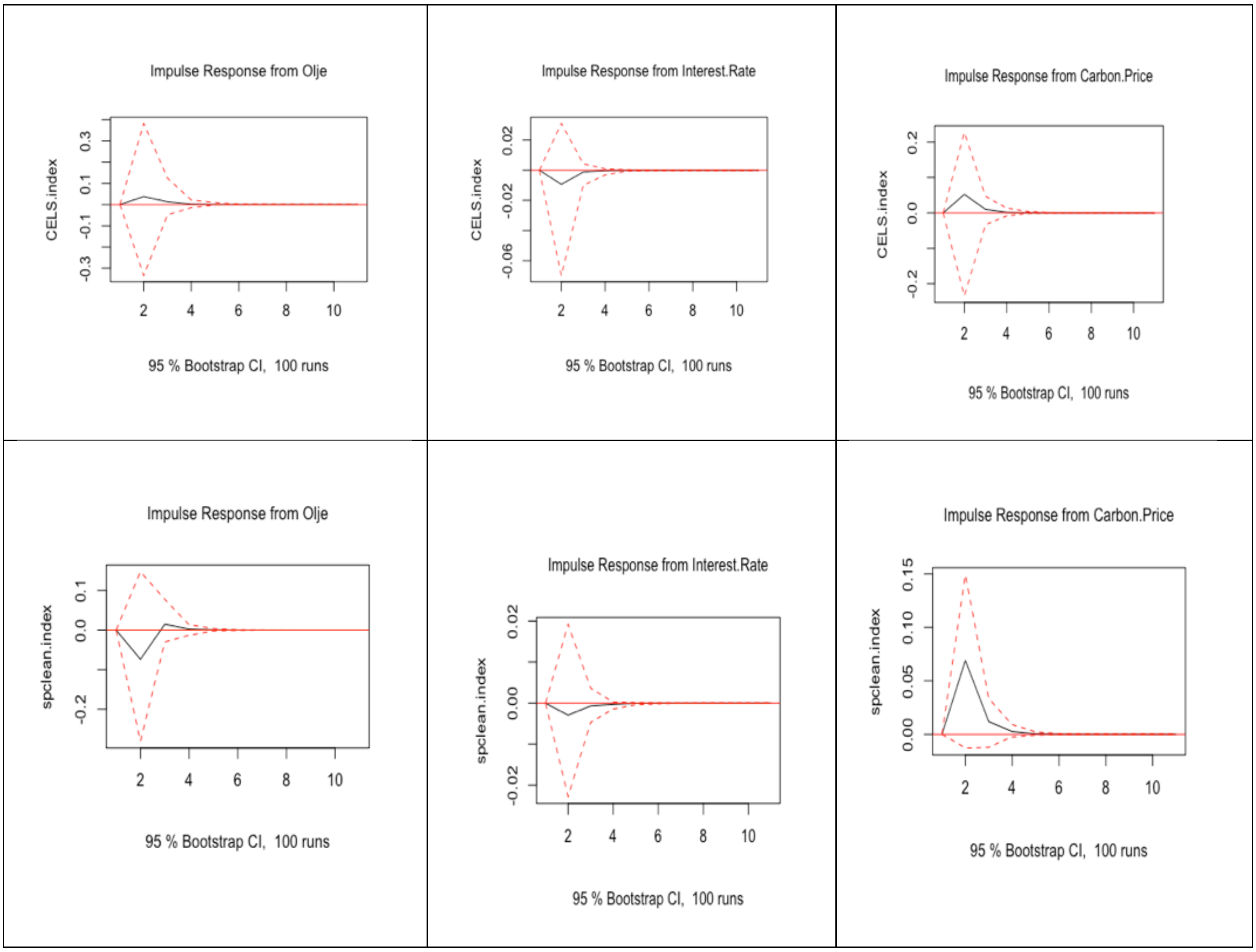
Table 15: VAR Models post-crisis

Model 1	Solar Index	Oil	Interest	Carbon
F-statistic	1,578	0,377	0,063	2,065
R-squared	0,038	0,009	0,002	0,049
Standard Error	0,070	0,035	0,327	0,073
Model 4	Fuel Cels Index	Oil	Interest	Carbon
F-statistic	0,152	0,399	0,148	1,910
R-squared	0,004	0,010	0,040	0,045
Standard Error	0,086	0,035	0,327	0,073

Appendix C: Impulse response function pre oil crisis

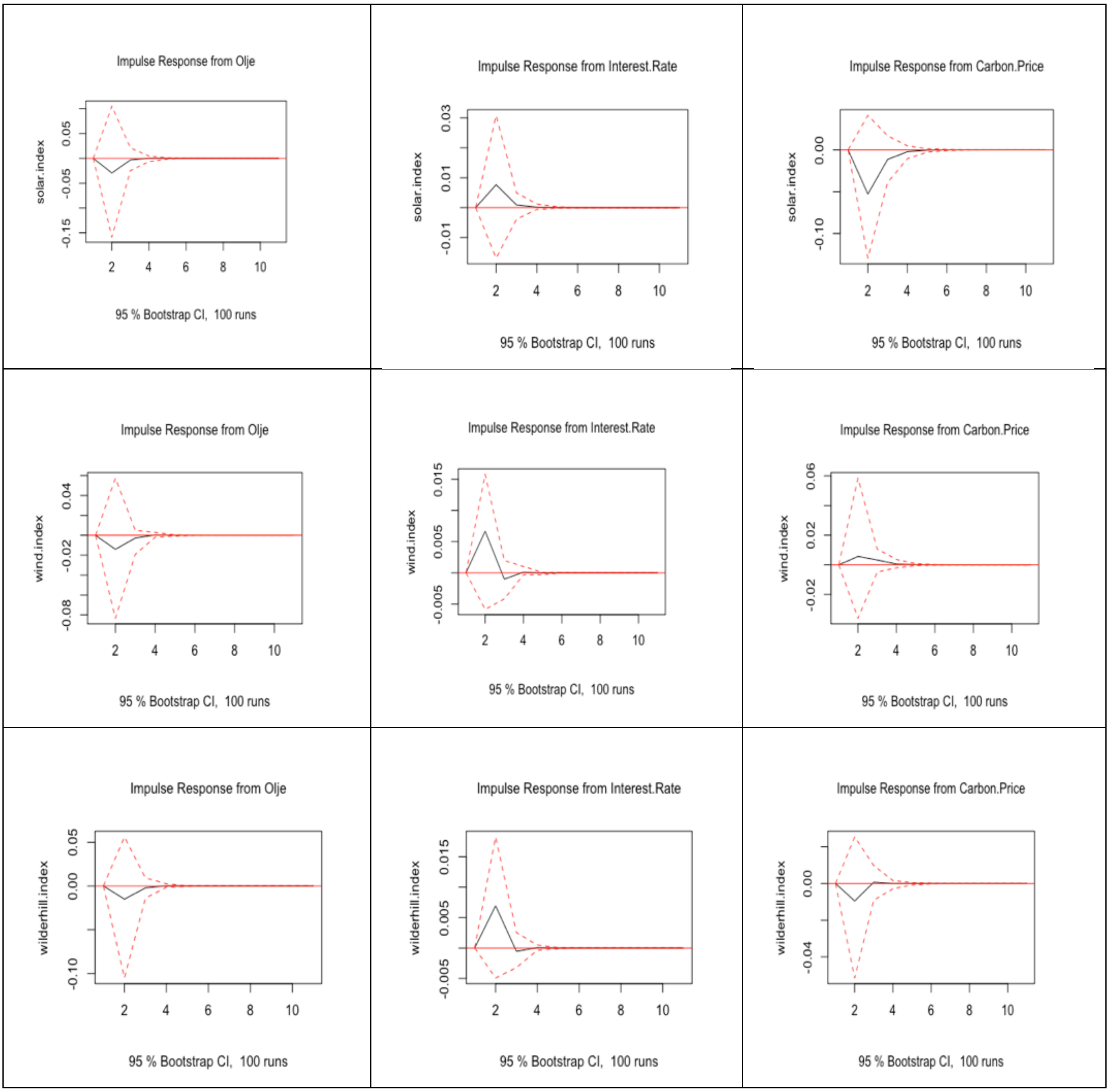
Figure 10: Impulse response function, pre-crisis

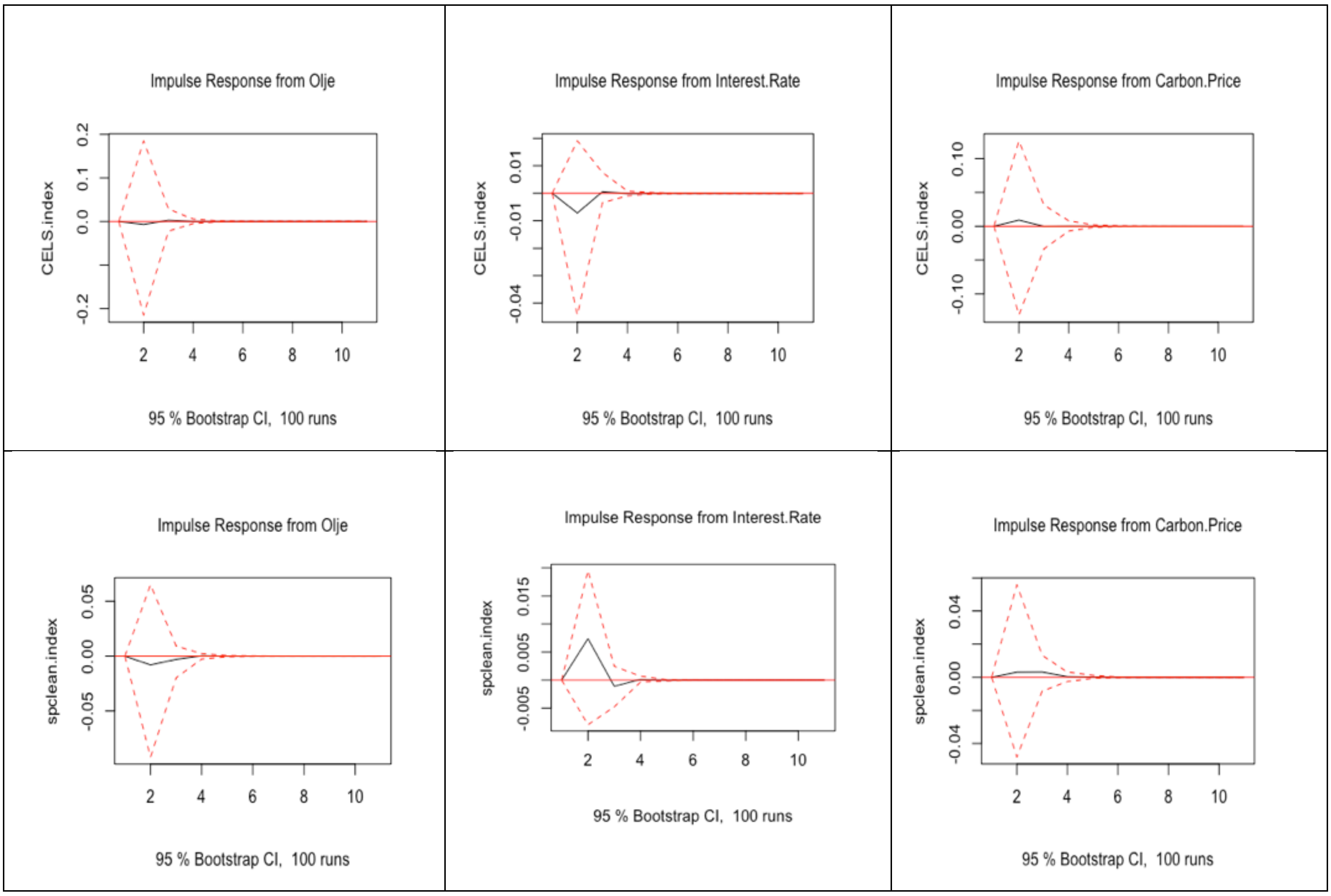



Impulse Response from Olje
CELS.index
95 % Bootstrap CI, 100 runs
Impulse Response from Interest.Rate
CELS.index
95 % Bootstrap CI, 100 runs
Impulse Response from Carbon.Price
CELS.index
95 % Bootstrap CI, 100 runs
Impulse Response from Olje
spclean.index
95 % Bootstrap CI, 100 runs
Impulse Response from Interest.Rate
spclean.index
95 % Bootstrap CI, 100 runs
Impulse Response from Carbon.Price
spclean.index
95 % Bootstrap CI, 100 runs

Appendix D: Impulse response function whole period

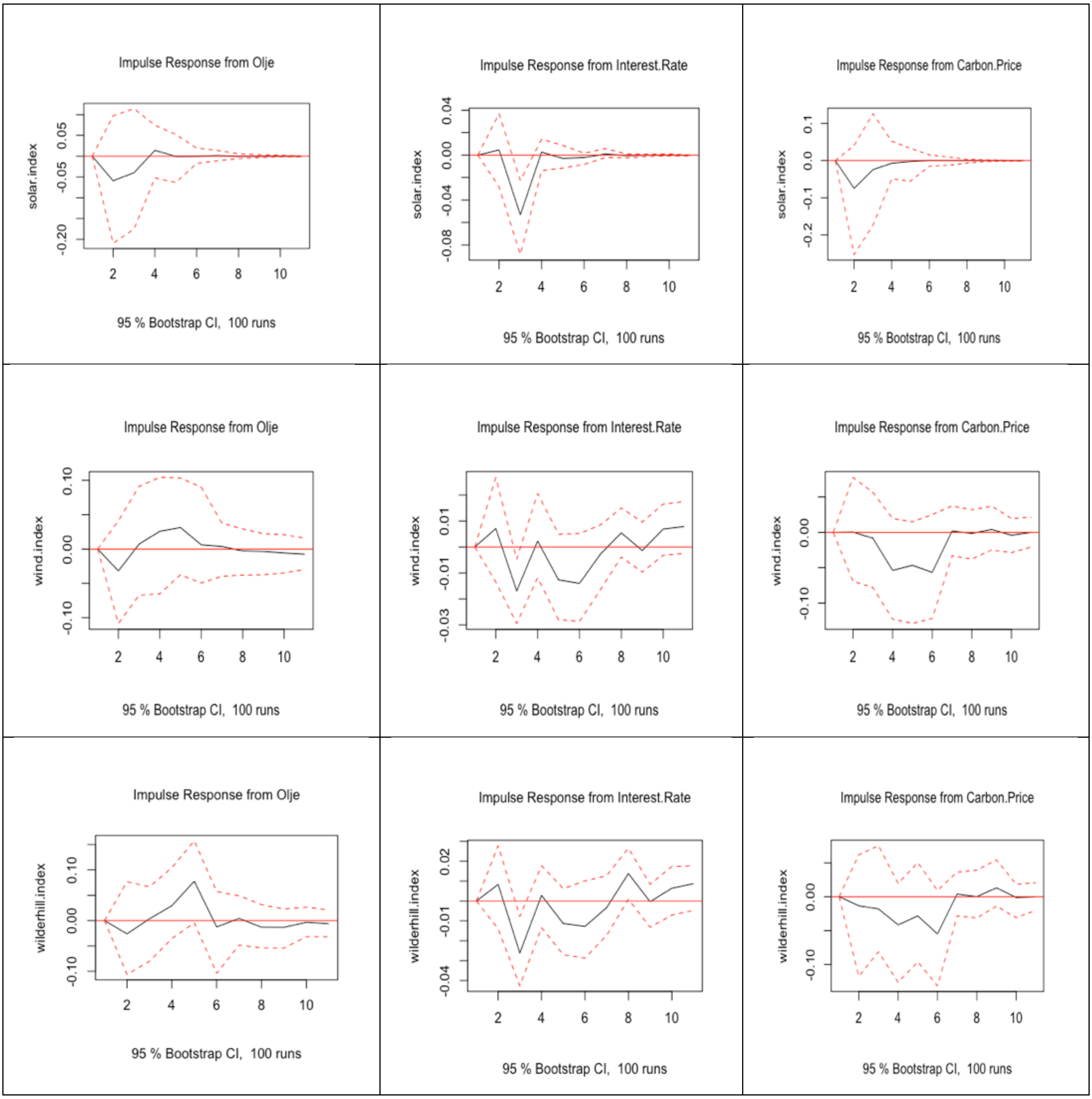
Figure 11: Impulse response function, whole period

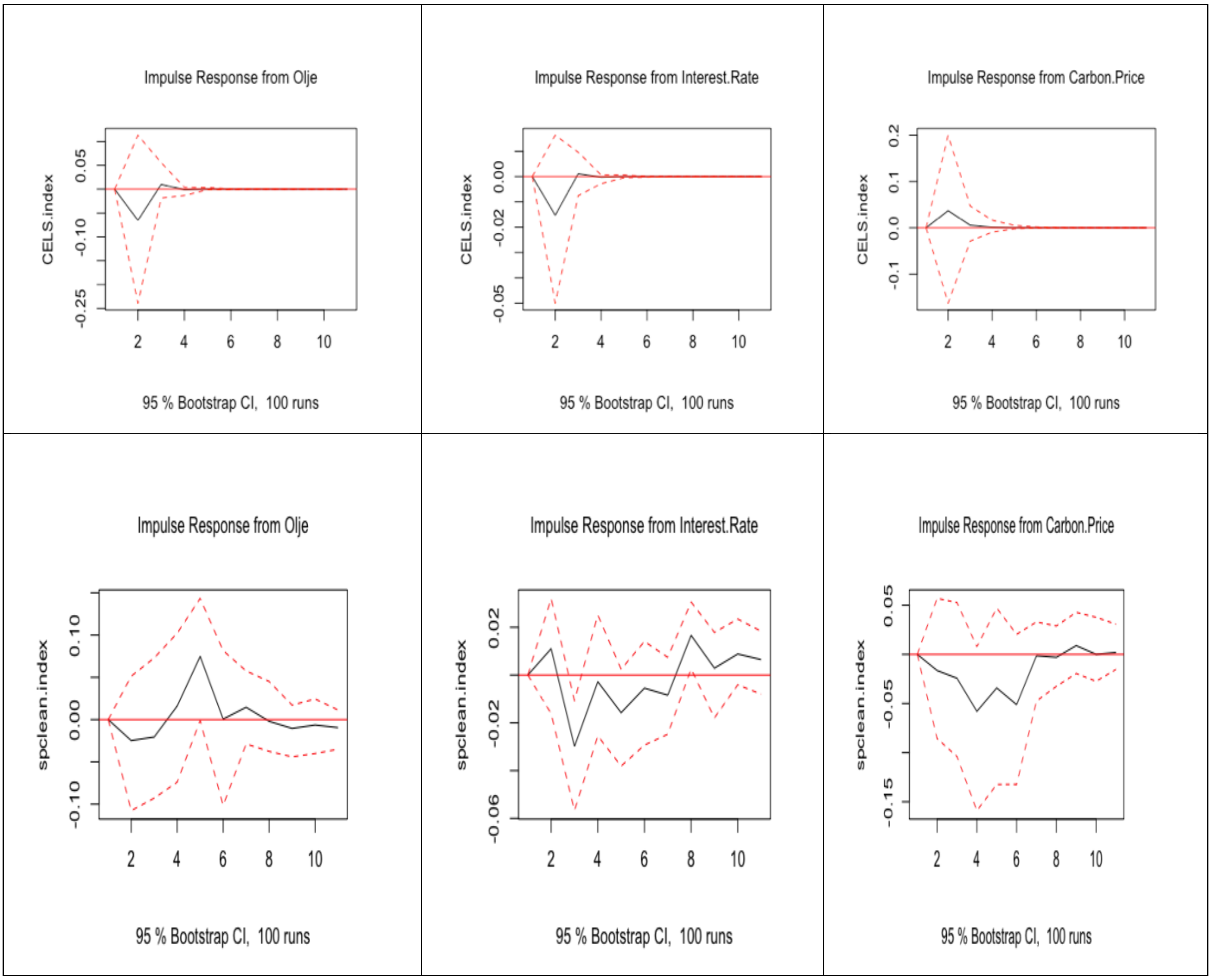



Impulse Response from Olje
CELS.index
95 % Bootstrap CI, 100 runs
Impulse Response from Interest.Rate
CELS.index
95 % Bootstrap CI, 100 runs
Impulse Response from Carbon.Price
CELS.index
95 % Bootstrap CI, 100 runs
Impulse Response from Olje
spclean.index
95 % Bootstrap CI, 100 runs
Impulse Response from Interest.Rate
spclean.index
95 % Bootstrap CI, 100 runs
Impulse Response from Carbon.Price
spclean.index
95 % Bootstrap CI, 100 runs

Appendix E: Impulse response function post oil crisis

Figure 12: Impulse response function, post oil crisis




Impulse Response from Olje
CELS.index
95 % Bootstrap CI, 100 runs
Impulse Response from Interest.Rate
CELS.index
95 % Bootstrap CI, 100 runs
Impulse Response from Carbon.Price
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95 % Bootstrap CI, 100 runs
Impulse Response from Olje
spclean.index
95 % Bootstrap CI, 100 runs
Impulse Response from Interest.Rate
spclean.index
95 % Bootstrap CI, 100 runs
Impulse Response from Carbon.Price
spclean.index
95 % Bootstrap CI, 100 runs

Appendix F: Granger Causality Test

Table 16: Test for granger causality post-crisis

Model 1	Solar Index	Oil Price	Interest Rate	Carbon Price
Solar Index	-	0,2113	5,0382***	0,4149
Oil Price	0,7040	-	5,0908***	0,0773
Interest Rate	3,4837**	0,7907	-	0,1645
Carbon Price	2,3036	0,8523	0,2849	-
Model 2	Wind Index	Oil Price	Interest Rate	Carbon Price
Wind Index	-	0,5771	2,0049*	1,3845
Oil Price	1,6569	-	3,0964**	0,5686
Interest Rate	2,5136**	0,5985	-	0,2045
Carbon Price	1,0185	0,8045	0,2302	-
Model 3	WilderHill Index	Oil Price	Interest Rate	Carbon Price
WilderHill Index	-	1,1346	2,4504**	0,9980
Oil Price	0,6414	-	3,0964**	0,5686
Interest Rate	4,2074***	0,5985	-	0,2045
Carbon Price	0,3301	0,8045	0,2302	-
Model 4	Fuel Cells Index	Oil Price	Interest Rate	Carbon Price
Fuel Cells Index	-	0,3186	0,5116	0,1353
Oil Price	0,1316	-	1,6773	0,0287
Interest Rate	0,9588	1,7196	-	0,0014
Carbon Price	0,1058	0,2649	0,2988	-
Model 5	S&P Clean Energy Index	Oil Price	Interest Rate	Carbon Price
S&P Clean Energy Index	-	0,7144	1,9042**	0,3630
Oil Price	1,0362	-	3,0964**	0,5686
Interest Rate	2,8009**	0,5985	-	0,2045
Carbon Price	0,7402	0,8045	0,2302	-

*Granger Causality test: ***, ** and * denotes statistically significance at the 1%, 5% and 10% level.*

Table 17: Test for granger causality pre-crisis

Model 1	Solar Index	Oil Price	Interest Rate	Carbon Price
Solar Index	-	1,9371	0,0429	0,0051
Oil Price	0,0289	-	0,6798	0,6084
Interest Rate	0,1034	0,1290	-	0,0465
Carbon Price	1,1098	1,3354	0,5275	-
Model 2	Wind Index	Oil Price	Interest Rate	Carbon Price
Wind Index	-	0,1062	0,0712	0,5028
Oil Price	0,2711	-	0,6798	0,6084
Interest Rate	0,3371	0,1290	-	0,0465
Carbon Price	1,1370	1,3354	0,5275	-
Model 3	WilderHill Index	Oil Price	Interest Rate	Carbon Price
WilderHill Index	-	0,9231	0,2594	0,6716
Oil Price	0,2276	-	0,6798	0,6084
Interest Rate	0,0436	0,1290	-	0,0465
Carbon Price	0,4055	1,3354	0,5275	-
Model 4	Fuel Cell Index	Oil Price	Interest Rate	Carbon Price
Fuel Cell Index	-	0,0282	0,1939	0,3414
Oil Price	0,2044	-	0,6798	0,6084
Interest Rate	0,3325	0,1290	-	0,0465
Carbon Price	0,0722	1,3354	0,5275	-
Model 5	S&P Clean Energy Index	Oil Price	Interest Rate	Carbon Price
S&P Clean energy Index	-	0,4288	0,1939	0,3414
Oil Price	0,4517	-	0,6798	0,6084
Interest Rate	0,0222	0,1290	-	0,0465
Carbon Price	0,0405	1,3354	0,5275	-

*Granger Causality test: ***, ** and * denotes statistically significance at the 1%, 5% and 10% level.*

Table 18: Test for granger causality for the whole period

Model 1	Solar Index	Oil Price	Interest Rate	Carbon Price
Solar Index	-	0,3647	0,4662	1,2490
Oil Price	0,0411	-	0,8129	0,0346
Interest Rate	0,8472	0,9705	-	1,6184
Carbon Price	0,3725	0,0012	1,7254	-
Model 2	Wind Index	Oil Price	Interest Rate	Carbon Price
Wind Index	-	0,2666	1,4870	0,0310
Oil Price	0,2798	-	0,8129	0,0346
Interest Rate	0,3494	0,9705	-	1,6184
Carbon Price	1,9630	0,0012	1,7254	-
Model 3	WilderHill Index	Oil Price	Interest Rate	Carbon Price
WilderHill Index	-	0,3044	1,3656	0,1830
Oil Price	0,0294	-	0,8129	0,0346
Interest Rate	0,5355	0,9705	-	1,6184
Carbon Price	0,0074	0,0012	1,7254	-
Model 4	Fuel Cell Index	Oil Price	Interest Rate	Carbon Price
Fuel Cell Index	-	0,0001	0,1689	0,0151
Oil Price	0,0017	-	0,8129	0,0346
Interest Rate	0,0346	0,9705	-	1,6184
Carbon Price	0,2432	0,0012	1,7254	-
Model 5	S&P Clean Energy Index	Oil Price	Interest Rate	Carbon Price
S&P Clean Energy Index	-	0,0843	0,1689	0,0151
Oil Price	0,4888	-	0,8129	0,0346
Interest Rate	0,0003	0,9705	-	1,6184
Carbon Price	0,2806	0,0012	1,7254	-

*Granger Causality test: ***, ** and * denotes statistically significance at the 1%, 5% and 10% level.*