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What impacts wind and solar stock prices? Evidence before and after the financial crisis of 2008

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Table of Contents

Abstract

This thesis investigates the value drivers of wind and solar energy stocks. Through a lag-augmented vector autoregressive model, we test the impact of shocks to interest rates, oil prices and technology stocks on the stock performance of the two renewable energies. The study uses Granger causality tests, impulse response functions and variance decomposition in order to determine the relationships. The study is conducted before and after the Great Recession. The results show differences from the first period to the second, indicating that increases in technology stocks lead to increases in wind and solar stock prices in the pre-crisis period. This relationship is almost absent in the post-crisis period. Oil prices proves only to be weakly significant in the period after the crisis, and changes in interest rates are, surprisingly, not significant to the performance of the renewables in neither of the two periods. Our study presents findings on wind and solar energy stock prices, which contrast from previous research that investigated characteristics of renewable energy stock prices as a whole.

1. Introduction

1.1. Problem description

The development of innovative and sustainable ways of meeting the world's increasing energy needs gives rise to a global energy transition. In recent years, the shift from fossil fuels towards renewable energy sources has accelerated worldwide. Climate concerns, advancements in renewable energy technologies followed by their rapidly falling costs are paving the way for this transition. New markets are created, billions of dollars are invested into renewables and policy makers are encouraging and facilitating the transition. There is nearly a global-consensus that the renewable energy sector will strengthen its position in the world economy in the coming decades, becoming one of the most important drivers of sustained economic growth and development (IRENA, 2017). Understanding the economic and financial mechanisms in this sector is thus of high importance.

A handful of studies have addressed the question of what variables affect the stock prices of alternative energy companies. Inspired by these studies, we dig deeper into the world of renewables and seek to find what drives the stock prices of companies operating in the two sectors of the most rapid growing energy sources among them: the wind and solar energies. The rationale of stripping down the renewable energy stocks into wind and solar stocks is easy: The two energy sources have played minor roles in the upcoming of the renewable energy era (early on dominated by hydro and bioenergy), but are now becoming the main drivers of renewable energy growth (Frankfurt & School-UNEP, 2017). How these stocks perform and what drives their performance is yet to be investigated in the research literature of renewable energy stocks. We want to fill this gap through a vector autoregressive (VAR) model, where we aim to detect causal relationships between the stock prices of wind and solar companies, and some hypothesized variables. More specifically we want to answer the question:

What are the impacts of changes in oil prices, interest rates and technology stock prices to the stock prices of companies operating in the wind and solar sectors?

In order to address the research question, we will outline theory and previous studies that have been conducted on the performance of alternative energy companies. Our thesis will hopefully contribute to a better understanding of the price dynamics in the wind and solar sectors. This information is important to investors holding wind and solar stocks in their portfolios, or for those who want to invest in these companies. Policy makers also need to be aware of what factors influence the wind and solar stocks, so that they can implement effective instruments in order to stimulate the transition from fossil fuels to alternative energy sources. Furthermore, it could be of high interest to policy makers to know whether they should treat the different renewables all in the same way or not.

1.2. Motivation

According to a wide variety of measures, as for instance growth in new added capacity and growth in investments, renewable energy has become the fastest growing energy source. Especially in the electric power industry, renewables are growing at high rates outperforming the conventional energy sources. A report written by the International Renewable Energy Agency (IRENA, 2017) shows that the current share of renewable energy in final energy consumption[1] stands at 18.3%. It is estimated that in the most optimistic scenario this share will increase to 36% by 2030, while the most pessimistic scenario shows a share of 21% by the same year.

As argued above, the growth in renewables is especially prevalent in wind and solar power. International Energy Agency (IEA, 2017a) estimates that wind and solar together will represent more than 80% of global renewable energy capacity growth the next five years. These are by far the two most popular renewable energy sources among investors and in 2015, 90% of all investments in renewable energy were in wind and solar power (IRENA, 2017). Technological advancements have led to decreased production costs. The decline in costs has especially been large and rapid for solar photovoltaic (PV) and onshore wind energy. Since 2010, the solar PV costs have halved (IRENA, 2017), whereas the costs of generating power from onshore wind have fallen by around a quarter

[1] Final energy consumption can be defined as the total energy consumed by end users. It is the energy, which reaches the final consumer's door including all energy users such as industry, transport, agriculture and households. It excludes the energy used by the energy sector itself.

(IRENA, 2018a). This has led to the two energy sources becoming competitive with conventional technologies in power markets in several countries.

Solar power is defined as the conversion of energy from sunlight into electricity. Broadly spoken, there exist two main solar power technologies: photovoltaic (PV) and concentrated solar power (CSP). The former is by far the largest representing more than 98% of all solar power in the world (IEA, 2017c). The majority of companies in the solar index we investigate in this thesis operate within the PV market. In 2016, solar PV additions rose faster than any other fuel for the first time. The expansions accounted for a 50% increase from the previous year (IEA, 2017b), and were mainly led by Chinese companies. The IEA (2017b) expects solar PV to represent the largest annual energy capacity additions the next five years, reaching a total installed capacity of 740 GW by 2022. As a comparison, this is more than the combined total power capacities of India and Japan today. China will continue to lead future solar growth accompanied by the US and India.

Wind power, which is the conversion of airflow through wind turbines into electric power, can also be divided into two main technologies: onshore- and offshore wind energy. While the former is a more mature technology than the latter, both technologies will strengthen their positions in the world's energy mix. According to the IEA (2017d), onshore wind electricity generation will increase by 80% during 2017-2022. As for the offshore wind, which has been less developed and more difficult to construct and maintain, the technological advancements accompanied by cost reductions will lead to more than a doubling from today's levels by 2022 (IEA, 2017b). In the wind power sector, China and the European Union are expected to lead the growth in the coming years.

As the growth in wind and solar energy increases, the sectors will become more dependent on private investors (Wüstenhagen & Menichetti, 2011). For several years, the sectors received large amounts of governmental subsidies such as feed-in-tariffs[2], and green certificates[3]. However, as argued in UNEP (2009),

[2] A feed-in-tariff is an economic policy created to promote and accelerate active investment in renewable energy. Feed-in-tariffs usually include three key provisions. First is guaranteed grid access. Second, they offer long-term contracts, typically 15-25 years. Third, they offer cost-based purchase prices meaning that energy producers are paid in proportion to the resources and capital expended in order to produce the energy.
[3] A green certificate is a tradable commodity proving that certain electricity is generated using renewable sources. The certificates are issued and traded mainly because of governmental policies, which require

unsubsidized wind and solar power can now provide the lowest costs of electrical power in an increasing number of countries. Increased popularity and developments in "green investing" is helping this change to take place. Green investing includes investments that focus on environmentally conscious business practices, hereunder investments in alternative energy sources. As argued in the Financial Times (Tett, 2018), green investing has for a long time been associated with a "moral glow" yielding low returns. Consensus in the financial world today is that the previous associations now are changing, as green investing starts to produce commercially acceptable returns. This highlights the importance of understanding the financial aspects of the renewable energy markets, a motivating factor for our research.

1.3. Contribution to the literature

While there has been conducted some research on what drives the value of alternative energy companies in general, there is a lack of research that decomposes the alternative energy into the different energy sources and discusses differences among them. This research will try to fill this gap by exclusively focusing on wind and solar power. Given the clear trends described above, we find such a decomposition both relevant and interesting.

Henriques and Sadorsky (2008) and Kumar, Shunsuke and Akimi (2012) found that there is causality between prices of technology stocks and prices of alternative energy stocks. The latter study found a more significant evidence of causality between oil prices and alternative energy stock prices than the former. Bondia, Ghosh and Kanjilal (2016) found that oil prices, technology stocks and interest rates impact the alternative energy stock prices in the short run. They found that the causalities were absent in the long run. We will apply the methodology of Henriques and Sadorsky (2008) to find whether the interest rates, oil prices and technology stock prices cause changes to the stock prices of wind and solar companies. In addition, we will use newer data, and we will estimate the model before the financial crisis of 2008 and after the crisis. This will allow us to see if the relationships have changed from one period to another.

suppliers to have a certain percentage of renewable production in their energy mix. The certificates provide the renewable energy technologies with additional income to the market revenue.

The rest of this thesis is structured as follows. In section 2, we review existing literature and theory in our research area followed by a description of the methodology used in section 3. Section 4 consists of data description, and in section 5, we state our hypotheses. In section 6, we discuss the model. Finally, we discuss the results in section 7, followed by our conclusion in section 8. Bibliography and appendices are in section 9 and 10, respectively.

2. Literature Review

There exists numerous papers studying the casual drivers of oil prices and oil price companies; see for example Hamilton (1996), Papapetrou (2001) or Kilian (2009). Henriques and Sadorsky (2008) acknowledged the extensive research related to oil, and identified a literature gap in terms of renewable energy stock prices. Their paper sparked an interest for research related to clean energy stock prices, and there have since been several important contributions to the literature. In this section, we will discuss the most important ones where we empathize the papers that are most closely related to our research objective.

Henriques and Sadorsky (2008) study data from 2001 to 2007 of alternative energy companies, interest rates, stock prices of technology companies and oil prices in a lag augmented vector autoregressive (LA-VAR) model. They find that oil prices, technology stock prices and interest rates each individually Granger cause the stock prices of alternative energy companies. They find that a shock to technology stock prices has a larger impact than a shock to oil prices. Based on their findings, they argue that oil price movements are less important than hypothesized because investors seem to view alternative energy companies, as more similar to other high technology companies rather than categorizing them as energy companies.

Kumar et al. (2012) do a similar study as the one of Henriques and Sadorsky (2008), where they use a VAR model to evaluate potential causality. They look at data from 2005 to 2008 of three different clean energy indices, carbon permit prices, oil prices, technology stock prices and US interest rates. Their findings indicate that the carbon permit prices do not affect the stock prices of the clean energy firms. They find evidence of oil prices, technology stock prices and interest rates influencing renewable energy stock prices. Their findings are very similar to Henriques and Sadorsky (2008).

Building on the work of the above-mentioned studies, Managi and Okimoto (2013) extend the studies into the Markow-switching vector autoregressive (MSVAR) framework. They argue that because there are possible structural changes and asymmetric effects in the economic system that is analysed, a MSVAR model should be used. The results indicate a structural change in late 2007, a period in which there was a significant increase in the price of oil. Before the structural change, the results comply with those of Henriques and Sadorsky (2008). After the structural change, they find that oil prices have positively affected clean energy stock prices.

Bondia et al. (2016) criticizes the study of Managi and Okimoto (2013) for using the Johansen-Juselius cointegration methodologies, which assumes that the cointegrating relationship *does not* change over the entire period of the empirical study. Bondia et al. (2016) argue that this assumption is too unrealistic, especially when the time series is long. Their study uses threshold cointegration tests of Gregory and Hansen and Hatemi-J in order to detect cointegration relationship of stock prices of alternative energy companies with oil prices, technology stock prices and interest rates. Doing so, they are able to investigate long run relationship in the presence of possible regime shifts of underlying variables. The threshold cointegration tests of Bondia et al. (2016) show that there is cointegration among the variables with two endogenous structural breaks. Furthermore, the study finds that alternative energy stock prices are influenced by technology stock prices, oil prices and interest rates in the short run, but *not* in the long run.

There has been some research with volatility approaches to the clean energy markets as well. Sadorsky (2012) utilizes a series of autoregressive conditional heteroscedasticity (GARCH) model in a volatility spillover framework. He finds that clean energy stocks correlate more with technology stocks than with oil prices. Reboredo (2014) uses copulas to determine the dependence-structure between oil prices and different subsectors of renewable energy, as well as conditional value-at-risk measurements. His results indicate that the solar index behaves differently than its peers, showing asymmetry in its response to oil price shocks.

Other papers have focused on abnormal profits, as for instance Ortas and Moneva (2013) who find that clean tech indices outperform the market in terms of return, but that this is mainly due to higher risk. Inchauspe, Ripple and Trück (2015) find that the MSCI World Index and technology stock prices influence clean energy stocks, but that the latter has underperformed since 2009. Henriques and Sadorsky (2017) find that divesting from fossil fuels in favour of clean energy actually yields a positive risk/return trade-off.

Few are the papers that look at the climate changes' direct impact on stock prices. An exception is the paper by Hong, Li and Su (2016) where they forecast profit growth for food companies in 31 countries based on their long-term trends towards drought. Taking into account the climate risks' effect on market efficiency, they provide an interesting approach to the climate question and financial performance among companies. The researchers find that in countries where drought is prevalent (based on long-term drought trends using the Palmer Drought Severity Index) it is forecasted poor profit growths and poor food stock returns for food companies. They conclude that the findings are consistent with food stock prices underreacting to climate change risk.

We use these papers throughout the thesis, either as direct sources or as motivational means. In either way, they have inspired us and provided us with ideas of how to investigate and structure our research topic.

3. Methodology

As we are interested in casual relationships between multivariate time series, we find a VAR-methodology to be most suitable for our needs. A VAR model will also allow us to run Granger causality tests, impulse response functions and variance decompositions, which we will utilize in explaining the relationships between our variables of interest. The VAR model is a generalization of the univariate autoregressive model, which allows us to estimate coefficients and standard errors between our variables of interest. The VAR approach treats all variables as endogenous, where the value of a variable will depend on its own lags, and the lags of all the other variables in the model. The model is arranged such that we have no contemporaneous terms, and it can therefore be estimated by simple OLS. The model was introduced by Sims in 1980, and has later received enormous attention. An example of a VAR(p) model with two variables is shown below.

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

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

The VAR approach assumes certain properties, including stationarity, normality, stability and zero autocorrelation of the residuals. Another assumption is that the variables are not cointegrated, which occurs when the variables have a common trend. The conventional approach when one discovers cointegration is to use a vector error correction model (VECM).

Instead of using a standard VAR approach, we intend to use the lag augmented VAR (LA-VAR, also known as the TY procedure) as proposed by Toda and Yamamoto (1994). A LA-VAR model is invariant to the order of integration in the variables, to cointegration, and it is a robust tool against pre-test bias rising from unit root tests and cointegration tests. We evaluate this methodology as most suitable for the purpose of this thesis as we want to avoid pre-test bias, and because a potentially cointegrated relationship is of no importance to our hypothesis. We do however intend to report Granger causality coefficients from standard VAR and VECM models to serve as a robustness test, complementing our main LA-VAR model. We also want to stress that when one is testing for cointegration and finds evidence that it exists in the data, there is some discrepancy in terms of whether one should use LA-VAR or a VECM. Toda and Yamamoto (1998) concluded that the choice between LA-VAR and VECM is a choice between size and power. LA-VAR performs better in terms of size, which means that it has a lower probability of committing a type 1 error (rejecting a true null hypothesis). VECM, on the other hand, performs better in terms of not committing a type 2 error (not rejecting a false null hypothesis). Clarke and Mirza (2006) revise the findings in Toda and Yamamoto (1998), and reach the same conclusion. We would rather be conservative in our estimates, as we are looking for casual relationships in our study. Therefore, we evaluate LA-VAR as superior to VECM for the purpose of our research question (independent of whether there exists a cointegrated relationship or not).

The steps for constructing a LA-VAR model consist of first estimating a VAR(p) model, by choosing the optimal number of lags (p) through different selection criteria. Next, we identify the maximum order of integration (d) through unit root tests, and we can then estimate a VAR(p+d) model in levels. The model has to have stable coefficients, and finally we run a modified Wald (MWald) statistics test on the first (p) parameters, treating the remaining (d) lags as exogenous. An example of the LA-VAR model with two variables is shown below:

$$Y_{1,t} = \beta_{1,0} + \beta_{1,1}Y_{1,t-1} + \cdots + \beta_{1,p}Y_{1,t-p} + + \beta_{1,p+d}Y_{1,t-p-d}$$

$$+ \alpha_{1,1}Y_{2,t-1} + \cdots + \alpha_{1,p}Y_{2,t-p} + \alpha_{1,p+d}Y_{2,t-p-d} + u_{1,t}$$

$$Y_{2,t} = \beta_{2,0} + \beta_{2,1}Y_{2,t-1} + \cdots + \beta_{2,p}Y_{2,t-p} + \beta_{2,p+d}Y_{2,t-p-d}$$

$$+\alpha_{2,1}Y_{1,t-1} + \cdots + \alpha_{2,p}Y_{1,t-p} + \alpha_{2,p+d}Y_{1,t-p-d} + u_{2,t}$$

As the coefficients themselves are of little interest to our hypotheses, we will focus on the results from the MWald tests, and we will investigate the relationships further with impulse response functions and forecast-error variance decompositions. The impulse response functions will show us whether the variables have a significant positive or negative impact on each other, and it reveals how long a shock will persist. The variance decompositions show the contribution of each shock to variation of each variable. This thesis will employ the generalized impulse response function (GIRF) and generalized variance decompositions proposed (GVD) by Pesaran and Shin (1998) which builds on Koop, Pesaran and Potter (1996). The alternative is the orthogonalized approach following Sims (1980) which is dependent on the ordering of the variables. The latter approach is problematic because different ordering may yield different results, and the correct ordering of the variables is often unclear and prone to discussion. The generalized methodology, on the other hand, is invariant to the ordering of the variables, and provides us with contemporaneous reactions, making it robust and more suitable for our thesis.

4. Data

Most of the previous studies related to alternative energy stock prices, evaluated in section 2, have used the Wilder Hill clean energy index to measure the performance of alternative energy stocks. The index, consisting of approximately 86 stocks, was the first index composed of only clean energy stocks. The companies in the index operate in the whole range of renewable energies including everything from biomass heat to hydropower. It also includes companies operating in the wind and solar sectors. As previously discussed, we will replace the Wilder Hill clean energy index with indices that exclusively consists of wind and solar stocks. Except of this, we will use the same variables as Henriques and Sadorsky (2008) and Managi and Okimoto (2013) as regressors in our model.

The period we focus on stretches from December 21st 2005 to December 31st 2017, as the data for the wind stocks is only available from December 2005. However, we divide the sample into two subsamples to avoid the disturbance caused by the financial crisis of 2008. As argued by Lütkepohl (2005), a method to adjust for potential structural breaks in the VAR model is to estimate the parameters before and after the breakpoints. The Financial Crisis Inquiry Commission (FCIC) argues that the primary features of the 2008 crisis were a financial shock starting in September 2008 followed by financial panic the preceding months (FCIC, 2011). Further, they set the end of the financial crisis to the first half of 2009. We exclude the data between September 2008 to June 2009 and estimate two periods, hereafter named pre- and post-crisis. In figure 1, we have plotted the cumulative returns for the variables of interest. As shown in the figure, there seems to be a break in the variables by the beginning/middle of 2008. We see that, especially the wind and solar stocks are very volatile up to year 2008, before rapidly falling by March/April 2008. The oil prices seem to have reached a peak by 2008 before declining until the end of 2008. As for the technology stocks and S&P 500, they start to fall by April 2008 and reach bottom levels late 2008. All of the variables, except the wind and solar stocks, have started to increase again by mid-2009. In addition to avoiding the financial turmoil present during the crisis, we divide the sample to observe potential changes from one period to another.

Similarly to previous studies, we use weekly data containing Wednesday closing prices, because there are fewer holidays on Wednesdays relative to Fridays. When the Wednesday prices are missing, we use prices of the closest trading day. The data in our models include: a stock index of solar energy companies (hereafter named SUN), a stock index of wind energy companies (WIND) an index of technology stocks (TECH), oil prices (OIL) and US interest rates (TBILL). We also use the S&P 500 index as a benchmark in the descriptive part of our analysis. The stock and oil prices are gathered from Datastream, while the interest rates are retrieved from www.treasury.gov.

4.1. Solar energy stocks: SUN

In order to measure the performance of the solar energy stocks, we use the MAC Global Solar Energy stock index (ticker symbol: SUNIDX). The index consists of 23 solar stocks listed on exchanges in different countries. The majority of the stocks, 56%, are listed on US stock exchanges, 22% are listed in Europe and the remaining 22% are listed on Asian stock exchanges. The companies in the index include all major solar technologies such as crystalline and thin-film PV[4] as well as solar thermal[5]. Furthermore, it covers the entire value chain of solar energy, including everything from raw materials, manufacturers, and installers to solar plant operators. Some of the companies in the index also operate in the markets of solar equipment such as inverters and trackers. The index has a modified market cap weighting, meaning that it is dividing the index weighting of stocks that have solar revenues between 1/3 and 2/3 of total revenues by half. Such companies are named Medium-Play stocks. Pure-play solar stocks, on the other hand, are solar companies with solar revenues above 2/3 of total income. These stocks have an exposure factor of 1.

[4] Thin-film PV is a different kind of solar panel than the standard mono- or polycrystalline PV cells. It is made of light absorbing layers which are about 350 times smaller that that of the standard panels. Thin film solar cells are the lightest PV cells and are commercially used in several technologies including Cadmimum Telloride (CdTe), Amorphous silicon (A-si) and Copper indium Gallium Selenide (CIGS).

[5] Solar thermal is an alternative technology to solar photovoltaic (PV) systems. Rather than generating electricity as the PV systems, solar thermal creates heat through warming up water or other fluids.

4.2. Wind Energy stocks: WIND

The ISE Clean Edge Global Wind Energy Index (ticker symbol: GWE) serves as the reference index for wind energy stocks. It is a float-adjusted modified market capitalization-weighted index designed to track the performance of public companies that are primarily engaged in the wind energy industry (Clean & Inc, 2018). To what degree the companies are involved in wind energy, and thus whether they should be included in the index, is based on analysis of their products and services performed by Clean Edge Incorporation. Similarly to the solar index, the companies in the GWE index operate in the whole range of the wind energy value chain. Furthermore, the index includes companies listed on exchanges in different countries, making it global and suitable for our research.

4.3. Technology stocks: TECH

The Arca Tech 100 index (ticker symbol: PSE) is modelled as a multi-industry technology index. It is a price-weighted index composed of 100 common stocks and American depository receipts of technology-related companies. The companies in the index are all listed on US stock exchanges. The index provides as a benchmark for measuring the performance of companies using technology innovation across a broad spectrum of industries and markets. As Henriques and Sadorsky (2008) pointed out "it may be the case that investors view alternative energy companies as similar to other technology companies". Furthermore, as discussed in section 2, all of the previous studies have found positive significant relationships between technology stock prices and the stock prices of alternative energy companies. Having in mind that wind and solar energy technologies have been heavily reliant on technology development (IRENA, 2017), we will expect a significant relationship between the technology stocks and wind and solar stocks.

4.4. Oil prices: OIL

Because we want to test whether there is a positive relationship between stock prices of renewable energy companies and oil prices, we need to include oil prices in our model. The oil prices will be measured using the average of weekly closing futures prices of West Texas Intermediate (WTI). The commodity is traded on the New York Mercantile (NYMEX) and is, alongside with Brent Crude from the North Sea, a common reference and benchmark of oil prices (Bern, 2011).

4.5. Interest rates: TBILL

As argued by Henriques and Sadorsky (2008) and Bondia et al (2015), previous research shows significant relationships between interest rates and stock price movements. In line with the previous studies, we will use the yield on a 3-month U.S T bill to reflect the interest rate in our study.

4.6. The market benchmark: S&P 500

The Standard and Poor 500 (S&P 500) is used as a benchmark index for the stock market. It is based on the market capitalizations of 500 large companies listed on US stock exchanges. We use the S&P 500 primarily to compare returns of the energy stocks with the market.

4.7. Descriptive analysis

Table 1 and 2 summarize the descriptive statistics of the data. There are a total of 141 weekly observations in the pre-crisis sample and 444 observations in the post-crisis sample. We have compounded the annual average returns by multiplying the average weekly continuously compounded returns with a factor of 52.

Prior to the financial crisis of 2008, the wind and solar stocks outperformed both TECH and the S&P 500 in terms of annual risk-adjusted average return (measured by the Sharp ratio). Table 1 shows that even though SUN and WIND have higher standard deviations, they have high ex-post Sharpe ratios, 0.127 and 0.172 respectively, due to their great yearly average returns of 38.9% and 45.5%. TECH and the S&P 500, on the other hand, have yearly Sharpe ratios of –0.037 and –0.012. The reason why we see these negative Sharpe ratios is that the markets started to decline prior to the financial crisis (remembering that we only have 141 observations prior to the crisis). As can be seen in table 2, this completely changes after the financial crisis. SUN obtains an annual Sharpe ratio of –0.381, while WIND obtains a slightly positive ratio of 0.007. Compared to the performance of TECH (Sharpe ratio of 0.143) and the S&P 500 (Sharpe ratio of 0.125), the two renewable energy indices are doing much worse in terms of risk-adjusted return in the post-crisis period.

We have set the price series to 100 from the start of the sample periods to better illustrate the development of the series relative to one another (Figure 1). The

	SUN	WIND	TECH	S&P500	OIL	TBILL
Mean	0.455	0.389	0.026	0.006	0.261	0.039
Median	0.446	0.524	0.132	0.054	0.424	0.047
Maximum	8.104	6.122	2.677	2.079	5.666	0.052
Minimum	-10.634	-7.974	-2.659	-3.252	-4.242	0.006
Std. Dev.	3.284	2.052	1.054	0.911	2.164	0.013
Skewness	-0.682	-0.811	-0.394	-0.631	-0.066	-0.927
Kurtosis	4.404	5.171	3.058	4.135	2.308	2.294
Sharpe	0.127	0.172	-0.012	-0.037	0.103	na
Observations	140	140	140	140	140	140

Table 1. Descriptive statistics for the pre-crisis period.

figure illustrate a more volatile performance of SUN and WIND compared to TECH and the S&P 500. The volatility pattern is especially clear in the pre-crisis period. Furthermore, we see that despite growth opportunities in both the wind and solar sectors, the stocks perform poorly in the post-crisis period. There are numerous factors contributing to the weak financial performance in the second period. Firstly, in several countries, there have been cuts in governmental subsidies negatively affecting the company performances (research, 2018). Secondly, in the post- crisis period the competition in the sectors has intensified leading to sharp drops in material and components prices. Especially in the US and Germany overcapacity in wind and solar manufacturing has resulted in company failures and even factory closures during the post-crisis years (Reuters, 2012). Chinese companies producing at low-costs have helped trigger the increased competition (Bloomberg, 2018b). Thirdly, as described in UNEPs post crisis report (2009) on renewable energy finance (2009), fear and risk-aversion after the financial crisis have made investors underprioritize the renewables. The increased risk-aversion has led to increased capital costs, which combined with lower prospected earnings, can help explain the poor performance of the wind and solar stocks in the post-crisis period.

	SUN	WIND	TECH	S&P500	OIL	TBILL
Mean	-0.152	0.004	0.163	0.128	-0.017	0.002
Median	0.023	0.108	0.278	0.195	0.092	0.001
Maximum	8.354	5.136	3.371	3.679	10.194	0.014
Minimum	-9.685	-7.000	-6.248	-6.103	-8.428	0.000
Std. Dev.	2.917	1.470	1.131	1.009	2.277	0.003
Skewness	-0.115	-0.388	-0.817	-0.812	0.152	2.292
Kurtosis	3.646	4.277	5.934	7.245	4.907	7.379
Sharpe	-0.053	0.001	0.143	0.125	-0.008	na
Observations	444	444	444	444	444	444

Table 2. Descriptive statistics for the post-crisis period.

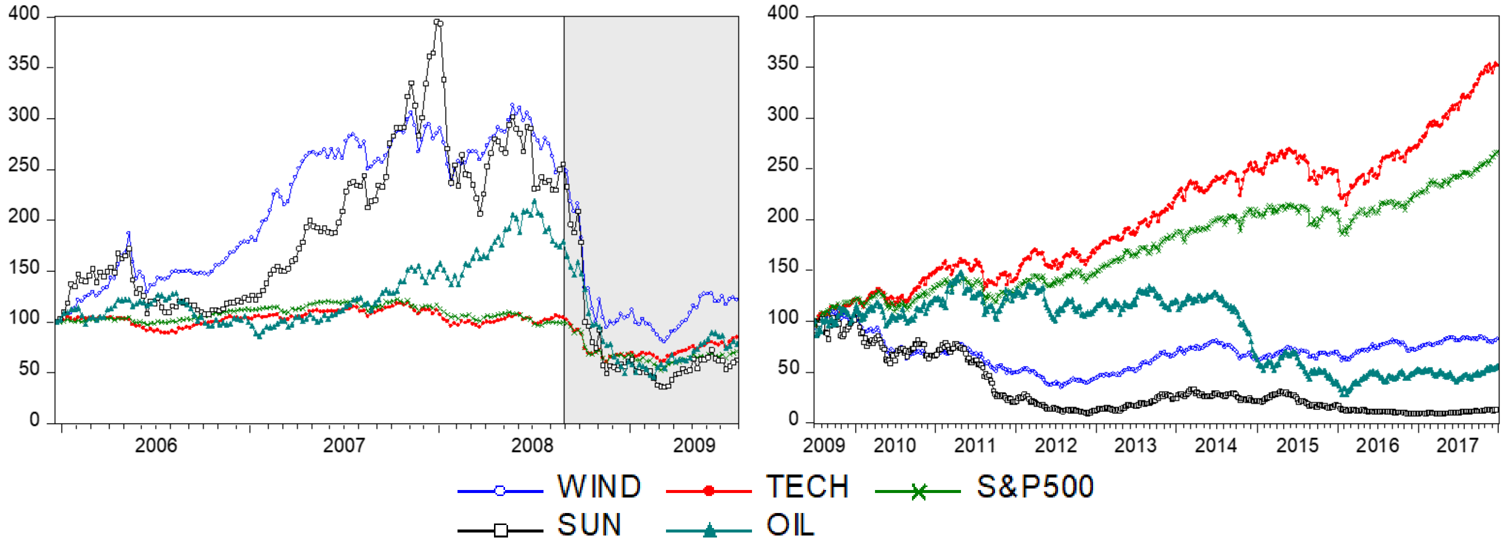

Figure 1. Cumulative returns for all variables in both periods. The grey area represents the financial crisis, which is left out of our estimations.

As for the oil prices, they are relatively volatile both before and after the financial crisis with standard deviations of 2.164 and 2.277 respectively (Table 1 and 2). Moreover, we observe in figure 1 a sharp drop in the oil prices in the middle of 2014. Among the most important reasons to the 2014-drop is the decrease in oil demand by large economies such as China (Forum, 2016). A second reason is related to the North-American countries, the US and Canada, which increased their oil-production resulting in decreased oil imports from these countries (reduced North-American demand). This further pressured the oil prices down.

Finally, because Saudi-Arabia, the world's largest oil exporter (OPEC, 2018), could withstand the low oil prices, they decided to not cut the oil production in order to pressure prices upwards. Saudi-Arabia has the world's second largest oil reserves (about 22% of the proven reserves in the world). Mainly due to their onshore reserves which require less capital spending and production cost, Saudi-Arabia can produce oil at very low costs relative to other oil producers such as for instance North American shale oil extraction or Norwegian offshore production. Due to this they could maintain their high production levels, supporting the low oil prices we saw in the wake of the 2014 oil crisis.

4.8. Correlations

Table 3 and 4 report the correlation coefficients among the variables in our model in the pre- and post-crisis periods respectively. We have also included the S&P

	SUN	WIND	TECH	SP500	OIL	TBILL
SUN	1.000					
WIND	0.892	1.000				
TECH	0.581	0.605	1.000			
SP500	0.414	0.612	0.824	1.000		
OIL	0.803	0.644	0.113	-0.115	1.000	
TBILL	-0.685	-0.546	-0.024	0.188	-0.876	1.000

Table 3. Correlations in the pre-crisis period.

500 in the correlation matrix. As expected, there is a strong positive correlation between the two renewable energy indices and TECH prior to the crisis. The correlations dramatically change after the crisis and the correlation between SUN and TECH becomes strongly negative (-0.607), whereas the correlation between WIND and TECH halves down to 0.293. This is surprising, but could be explained by the weak performances of the wind and solar stocks in the post-crisis period discussed in section 4.7. Nevertheless, this is important information for investors because they can no longer assume the two renewables to move in the same direction as the technology stocks. This finding is going to be tested more formally later on.

Another interesting change in correlation regards OIL and the renewables. Prior to the crisis both SUN and WIND correlated positively with OIL (0.803 and 0.644), but again, the correlations changed significantly after the great recession. In the post-crisis period SUN and OIL obtain a correlation coefficient of 0.309 and OIL and WIND a coefficient of -0.457.

The correlation between TBILL and the renewables is negative (-0.685 for sun and -0.546 for wind) prior to the crisis. After the crisis only SUN has a negative correlation coefficient (-0.325) with TBILL. WIND has now a positive correlation with the interest rates (0.347). We find no rationale for this, as we would assume the correlations to remain negative because higher capital costs make investments in renewable energy more expensive (and thus affect the renewable stocks negatively), regardless of time period. Finally, we observe that the strong correlation between SUN and WIND in the pre-crisis period (0.892) is reduced to 0.376 in the post-crisis period. This could be explained by better post-crisis performance among the wind stocks relative to the solar stocks.

	SUN	WIND	TECH	SP500	OIL	TBILL
SUN	1.000					
WIND	0.376	1.000				
TECH	-0.607	0.293	1.000			
SP500	-0.595	0.332	0.996	1.000		
OIL	0.309	-0.457	-0.548	-0.575	1.000	
TBILL	-0.325	0.347	0.311	0.323	-0.518	1.000

Table 4. Correlations in the post-crisis period.

Clearly, it has been harder to make profits on solar energy in the years after the crisis compared to wind energy. This might, to some degree, be explained by higher costs of PV projects. Even though the costs are rapidly declining (as discussed in section 1), the global weighted average levelised cost of electricity (LCOE) of utility-scale solar projects was 0.10 USD per kilowatt-hour (kWh) in 2017 (IRENA, 2018b). Compared to a LCOE of 0.06 USD per kWh for onshore wind, we see that there still is a remarkable cost difference among the two power sources. It will be interesting to see how further technology improvements can push the costs of PV projects the coming years, and how this will affect the profitability of solar energy companies.

4.9. Financial structure

As we shall test whether the interest rates influence the stock performances of the companies in the renewable energy indices, we want to look at how the renewable energy companies are financed. Our initial assumption was that the renewable energy companies are largely financed by debt. After investigating some of the key leverage ratios of all companies in the indices, we find evidence that this assumption holds. As can be seen in appendix 12, the companies in the solar energy index had an average yearly debt/equity ratio of 2.25 from 2014-2017. The companies in the wind index seem to be less leveraged with a yearly average debt to equity ratio of 1.31 the same period. The debt to equity ratio indicates whether the companies use debt or equity to finance their assets.

Because the companies in the two indices operate in different parts of the wind and solar power value chains (some are manufacturers, some are system integrators etc.), and because the company sizes differ, it is not straightforward to tell whether these ratios are high or low. As with most ratios, it is important to consider comparable companies when evaluating the ratios. According to data from Bloomberg (2016), the S&P 500 had an average debt to equity ratio of 1.1 in

2016. We hence see that the debt ratios of the solar companies, on average, are relatively much higher, whereas the wind companies have a slightly higher ratio.

We thus have reasons to believe that the wind and solar companies we investigate have important debt levels, and that the interest expenses could be important parts of the companies' costs.

5. Hypotheses

The main objective of this thesis is to determine the drivers of wind and solar stock performance. Because these stocks are alternative energy stocks, we expect our results to be similar to the findings of the research discussed in section 2. However, as we shall describe in detail below, we expect to find some differences. Further, we explore how potential causal relationships change over time by investigating whether there are differences in the pre- and post-crisis periods. Based on outlined theory and existing literature, we have formulated five hypotheses to be investigated.

The relationship between interest rates and stock market is a widely discussed topic in financial settings. Common beliefs suggest that an increase in interest rates should be followed by a decrease in stock prices. The main argument for such thinking says that higher rates make borrowing more expensive, making it more difficult for companies to invest into new projects. We suggest that this reasoning is especially true in the wind and solar sectors because as we discussed in section 4.9, the sectors are very capital intensive. Capital costs are the most important costs of wind and solar energy, and financing becomes more expensive when interest rates increase. This will affect the performance of the companies negatively. We anticipate that:

H1) *An increase in interest rates will have a negative effect on wind and solar energy stock prices.*

As argued by Henriques and Sadorsky (2008): despite the alternative energy production and usage being small compared to petroleum-based energy, the alternative energy sources might benefit from increased oil prices. The authors argue that rising oil prices provide a strong stimulus for investors, consumers, governments and other industries to seek for alternative energy sources. They emphasize that a substitution-effect is more realistic for the industry in the long run, but they stress that it is important to understand the relationships in the short run. Henriques and Sadorsky (2008), as well as Managi and Okimoto (2013), discover that increases in oil prices influence the performance of alternative energy companies positively. As we have seen, both wind and solar energy have increased their importance in the world's energy mix the recent years as well as their competitiveness, becoming direct competitors to the fossil fuels in many countries. In line with the previous findings on alternative energy companies, we suggest that:

H2) *An increase in oil prices will lead to increased wind and solar stock prices.*

However, due to the recent increase in competitiveness of wind and solar companies, we believe the substitution-effect from oil to wind and solar energy to be more significant in the post-crisis period than in the pre-crisis period. We hypothesize that:

H3) *After the financial crisis of 2008, increases in oil prices have more significant impact on prices in wind and solar energy stocks than prior to the crisis.*

Furthermore, Henriques and Sadorsky (2008) write that investors seem to categorize alternative energy stocks as technology stocks. They find that movements in technology stock prices can explain the movements of alternative energy stock prices. Their findings are supported by Managi and Okimoto (2013) who, in addition, suggest that alternative energy becomes cheaper via technology improvement. Consensus in renewable energy clusters is that both wind and solar energy are highly dependent on technology development. We believe that:

H4) *An increase in technology stock prices will be followed by an increase in wind and solar stock prices.*

Nevertheless, as with the oil prices, we expect different significance of causality between technology stock prices and wind and solar stock prices in the pre- and post crisis periods. This time we expect the opposite of what we expected for the oil prices. Particularly, we expect a more significant relationship between technology stock prices *before* the 2008-crisis than after, because in the post-crisis period the renewables might have established themselves in the energy markets becoming direct competitors to the conventional energy sources. Rather than being strongly impacted by technology stocks, we hypothesize that:

H5) *After the financial crisis of 2008, increases in technology stock prices have less significant impact on prices in wind and solar energy stocks than prior to the crisis.*

6. Model

As discussed in section 4, we have five variables that we wish to investigate, and we will do so before and after the financial crisis. We have no interest in the relationship between SUN and WIND, so they will be divided into separate equations (see table 5). To mitigate heteroscedasticity (which may potentially invalidate the coefficients), we have taken the natural logarithm of all five variables (which reduces extreme values), hereafter; LSUN, LWIND, LTECH, LOIL and LTBILL.

Model	Variables		Period
(1)	LSUN	LTECH, LOIL, LTBILL	Pre crisis
(2)	LWIND	LTECH, LOIL, LTBILL	Pre crisis
(3)	LSUN	LTECH, LOIL, LTBILL	Post crisis
(4)	LWIND	LTECH, LOIL, LTBILL	Post crisis

Table 5. Description of the four models.

We will in this section present the model choices for all four models, and we will begin with the first period.

6.1. Pre-crisis

For the first step in the LA-VAR framework, we determine the order of integration for all variables. The unit root tests are conducted using the Augmented Dickey Fuller-test, Phillips and Perron tests and the Kwiatkowski–Phillips–Schmidt–Shin tests. Appendix 1 shows that all variables are integrated of order one, except LWIND that has two unit roots. For the model with LWIND, we therefore have to add two lags, while it is sufficient to add one lag for the LSUN model. Next, we need to determine the lag length of the models, which we have assessed using Akaike Information Criterion (AIC), Hannan-Quinn criterion (HQ), Schwarz Information Criterion (SC) and the Likelihood Ratio test (LR), appendix 2. Where the criteria suggests different lag lengths, we choose the model that is most stable, determined through autocorrelation (of residuals) and with

(1)	LSUN	LTECH	LWTI	LTBILL
Adj. R-squared	0.979	0.902	0.977	0.946
S.E. equation	0.060	0.021	0.040	0.110
F-statistic	198.068	39.145	178.552	72.829
(2)	LWIND	LTECH	LWTI	LTBILL
Adj. R-squared	0.987	0.913	0.975	0.941
S.E. equation	0.038	0.019	0.041	0.113
F-statistic	663.484	90.485	337.346	137.678

Table 6. VAR model fit for model (1) and (2).

assessment of the unit root properties of the residuals. It is worth noting that dynamic stability is not a necessary assumption for the TY-approach to yield reliable MWald statistics, but it is a crucial part for estimating impulse response functions. This approach gives us a recommended seven lags for the LSUN(1) model (based on LR recommendation being the most stable) and two lags for the LWIND(2) model (supported by the most stable properties from LR and AIC), yielding a $VAR_{(1)}$(7+1) and a $VAR_{(2)}$(2+2) model.

Testing for autocorrelated residuals with a Lagrange multiplier test (10 lags), displays no problems with serial correlation in either of the models. The results are reported in appendix 3, where the null hypothesis (zero autocorrelation) is not rejected for any lags at the 5% level, and it is robust at the 10% level for most lags. Furthermore, none of the roots (28 for model (1) and 8 for model (2)) lie outside the unit root circle (appendix 4).

Table 6 shows the VAR model fit. The two models display very similar properties, with all the adjusted R-squared values being above 0.9, which is very high and indicates a good fitting model, even for equations estimated in levels. The standard error of the equation measures the dispersion between the predicted and actual values of the dependent variable. These numbers are also low and display good fitting models. The standard error of the LWIND equation in model (2) is lower than what we see from LSUN in model (1). The standard error is relatively high in both equations where LTBILL is the depend variable, which should convey caution when interpreting the corresponding results. The F-statistics shows that all independent variables are collectively significant at the 1% level for all equations. Overall, the properties are satisfactory and we have a good fitting model that is viable for further investigation.

6.2. Post-Crisis

In this section we will follow the exact same procedure as above, but this time for the post-crisis models: LSUN(3) and LWIND(4). Similar to the pre-crisis estimates, we observe that all variables have one unit root, except LWIND, which has two (appendix 1). Next, we assess the appropriate lag length (reported in appendix 2). In model (3) we see that LR and AIC suggests a lag length of two, which is more stable than the lag length suggested by the other criteria. For model (4), the appropriate lag length is six, decided by the LR criteria. These specifications results in a $VAR_{(3)}$(2+1) and a $VAR_{(4)}$(6+2) model. We found no evidence of autocorrelation in the residuals in either of the models (appendix 3), and none of the roots lie outside the unit root circle (appendix 4).

The model fit properties are displayed in table 7. The adjusted R-squared values are very high for all equations, indicating a high explanatory power. The standard error of each equation is very low and satisfactory, expect for the equations with LTBILL as the dependent variable in model (3) and (4). These high standard errors for the LTBILL equations indicate unreliable results when interpreting the corresponding coefficients. The F-statistics display the importance of the explanatory variables, showing that they are all collectively significant at the 1% level. Overall, the model fit properties are satisfactory for moving on to the next steps.

(3)	LSUN	LTECH	LWTI	LTBILL
Adj. R-squared	0.991	0.996	0.984	0.934
S.E. equation	0.056	0.021	0.043	0.320
F-statistic	3756.857	9728.798	2165.095	511.268
(4)	LWIND	LTECH	LWTI	LTBILL
Adj. R-squared	0.987	0.996	0.984	0.937
S.E. equation	0.027	0.021	0.042	0.312
F-statistic	1021.973	3661.921	822.987	195.103

Table 7. VAR model fit for model (3) and (4).

7. Results and discussion

With the assertion of the most suitable models, we will here present the output from the MWALD statistics, the impulse response functions (IRFs) and the variance decompositions from the corresponding VARs. We also present results from equations serving as a robustness test. The section ends with a discussion on the results related to the stated hypotheses.

7.1. Granger causality

	Dependent variable			
(1)	LSUN	LTECH	LOIL	LTBILL
LSUN	-	3.099	9.400	7.754
LTECH	16.199**	-	6.777	5.071
LOIL	2.127	3.094	-	9.310
LTBILL	8.647	4.642	4.261	-
(2)	LWIND	LTECH	LOIL	LTBILL
LWIND	-	5.498*	1.064	0.599
LTECH	6.532**	-	1.071	7.428**
LOIL	3.252	0.428	-	0.799
LTBILL	2.905	4.938	0.731	-

*Table 8. Toda and Yamamoto modified Wald statistics. ***, ** and * denotes statistically significance at the 1%, 5% and 10% level. Model (1) has 7 degrees of freedom for each independent variable, and model (2) has 2.*

Table 8 reports the MWALD statistics for model (1) and (2), displaying the Granger causality for LSUN and LWIND in the pre-crisis period. Surprisingly, model (1) shows no sign of causality between any variables, besides technology stock prices influencing LSUN. Model (2) shows bidirectional granger causality between LTECH and LWIND, and indicates a unidirectional relationship running from LTECH to LTBILL. These results are contradicting previous literature that has found causality running from oil prices and interest rates to renewable energy stock prices, which we will discuss later.

The MWALD output for the second period is reported in table 9. Interestingly, we see no Granger causality running from any of the variables to either LSUN or LWIND. Model (3) does show that past movements in LTBILL influence both LTECH and LOIL, but no other relationships are revealed. Model (4) shows a unidirectional relationship between LTECH and LOIL, as well as for LTECH and LTBILL. In addition, we see that LWIND help to explain movements in LTECH.

	Dependent variable			
(3)	LSUN	LTECH	LOIL	LTBILL
LSUN	-	1.167	1.183	1.306
LTECH	2.044	-	0.329	1.105
LOIL	0.414	0.024	-	2.659
LTBILL	1.198	6.704**	4.816*	-
(4)	LWIND	LTECH	LOIL	LTBILL
LWIND	-	14.906**	8.417	6.673
LTECH	6.684	-	11.369*	14.432**
LOIL	10.219	10.752*	-	7.800
LTBILL	3.208	18.510***	9.114	-

*Table 9. Toda and Yamamoto (1995) modified Wald statistics. ***, ** and * denotes statistically significance at the 1%, 5% and 10% level. Model (3) has 2 degrees of freedom for each independent variable, and model (4) has 6.*

7.2. Generalized impulse response functions

Figure 2 presents the output from the generalized impulse response functions, where we see how the variables react in the next ten weeks to a one standard deviation shock to one of the other variables. The solid lines are the responses, and the dotted lines show two analytically calculated standard errors in each direction for each response. If both the response and the standard errors are above or below zero, the response is interpreted as positively or negatively significant. The figure shows the responses to LSUN and LWIND both before and after the financial crisis. For the remaining impulse response functions with the remaining variables as the dependent one, see appendix 5 to 8.

Figure 2 shows the response of LSUN and LWIND to the other three variables, in all four models. In model (1) we observe that the solar index has a significant impact on itself for the first six weeks, which is gradually declining thereafter.

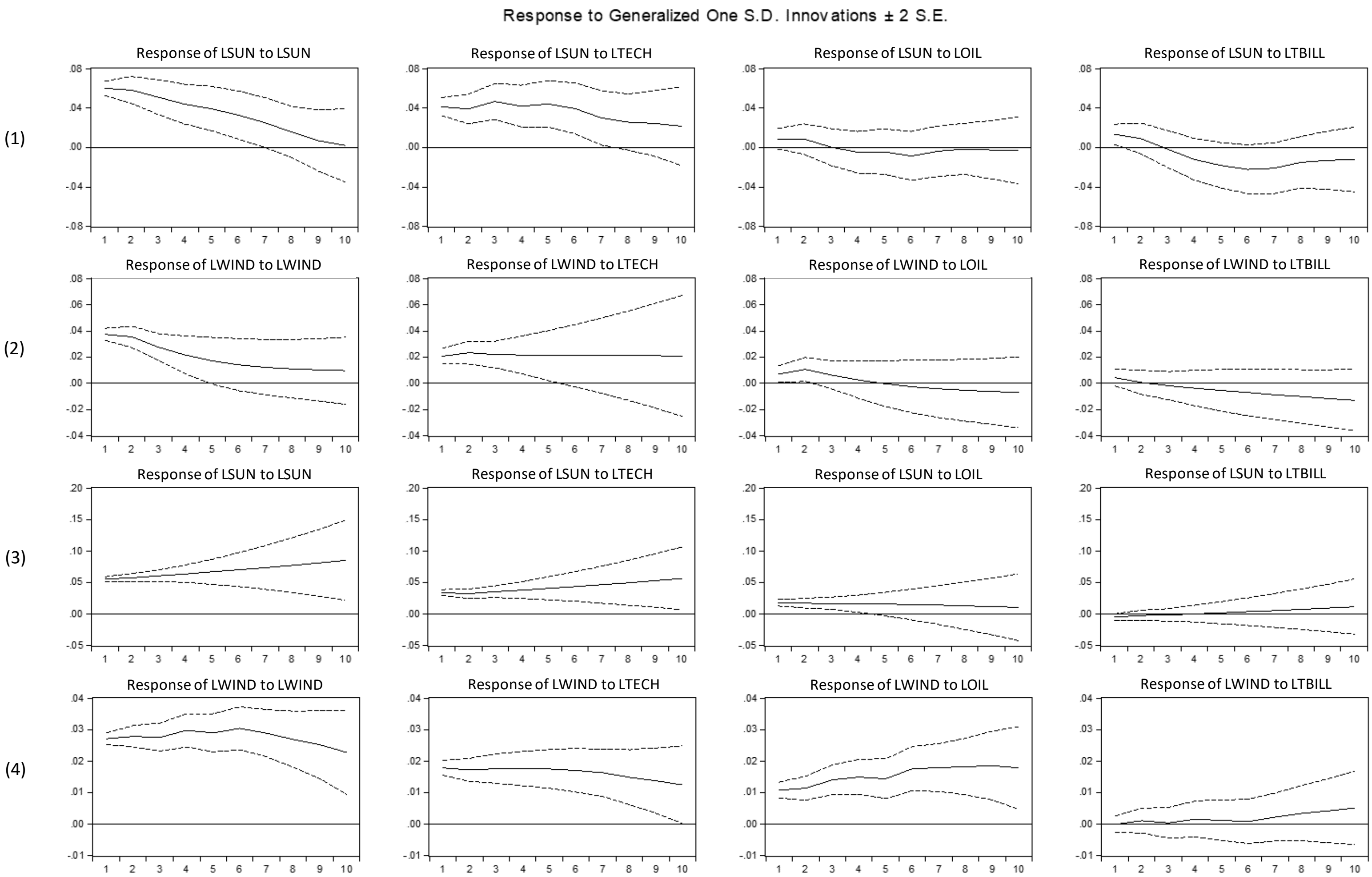

Figure 2. Generalized impulse response functions with LSUN and LWIND as dependent variables, in all four models.

A shock to LTECH will significantly increase LSUN for the next seven weeks, a result that is in line with the MWALD statistics. We find no signs of oil prices affecting LSUN, but the interest rate has a positive significant increase on the stock prices of solar companies in the first week. Model (2) displays similar properties, with LWIND and LTECH having a positive significant impact initially, which gradually diminishes with increasing standard errors. A one standard deviation shock to LWTI has a small and short-lived impact on LWIND, and we reveal no relationship between the stock prices of wind and the interest rates in the first period. Overall, the results from the generalized impulse response functions are very similar to what we discovered in the previous section. The relationship between our selected renewables and technology stock prices is in line with previous research, while it is still very surprising that we reveal no large significant impact from neither LOIL nor LTBILL.

In model (3) and (4), the most dramatic response to LSUN and LWIND comes from their own innovations, with a significant increase for at least ten weeks into the future. Surprisingly, we observe that technology stock prices are also positively significant to both LSUN and LWIND for ten weeks into the future. These results are in direct contradiction to the results obtained within the MWald methodology, making the true relationship between these variables unclear in the second period. Another observation is the ten weeks significant reactions to LWIND from a one standard deviation shock to LOIL. The response is positive and increasing, displaying a strong reaction. Oil does also have a positive impact on the solar index, though this effect is just significant for the first four weeks. Interest rates have no significant effect on neither LSUN nor LWIND in the second period, consistent with the MWALD statistics.

7.3. Generalized forecast-error variance decompositions

In this section, we look at the generalized forecast-error variance decompositions. Table 10 shows how the variance of LSUN and LWIND is affected by all variables in the system, where we report the contemporaneous reaction, and the reaction for every other week up to week number ten. For the variance decomposition of the remaining variables, see appendix 9 and 10. Note that when using the generalized methodology, the sum of each row does not necessarily sum up to one, as opposed to the orthogonalized calculations.

As expected, the variation of each variable does mainly come from its own innovations. Looking at the first period, we can see that variations in the two indices of interest are highly influenced by LTECH, where more than 50% of their variation after ten weeks is due to previous shocks in LTECH. These findings are in line with the MWALD statistics, and the initial reaction shown in the impulse response functions. Furthermore, we observe that LOIL does not seem to have a large impact on either LSUN or LWIND, as expected by the results reported in section 7.1 and 7.2. The interest rates do seem to cause some amount of variation in the two renewable indices, with 8-9% after 10 weeks.

Do note that we cannot compare the results related to the variance decomposition analysis to any previous research, as neither Sadorsky and Henriques (2008), Kumar et al. (2012) nor Managi and Okimoto (2013) use variance decompositions in their papers.

Next, we look at the second period, where it is interesting to see that LTECH is responsible for 30-40% of all variation in both LSUN and LWIND. These results contradict the granger-statistics in section 7.1, but they correspond well to the results of the impulse response functions. The real relationship running from LTECH to the indices of sun and wind is therefore somewhat unclear. There still seems to be a connection there, though the relationship is weaker than it was before the financial crisis of 2008. Besides technology stock prices, LSUN is mostly under influence by itself in terms of variance. LWIND however has a strong and increasing influence from LOIL, with 32% after 10 weeks. This relationship is consisten with the GIRF estimates, though it was not revealed

Pre-crisis										
(1)	Horizon	LSUN	LTECH	LOIL	LTBILL	(2)	LWIND	LTECH	LOIL	LTBILL
LSUN	0	1.000	0.478	0.022	0.051	LWIND	1.000	0.306	0.035	0.014
	2	0.950	0.538	0.015	0.027		0.941	0.402	0.056	0.006
	4	0.822	0.575	0.012	0.046		0.846	0.481	0.043	0.013
	6	0.725	0.569	0.014	0.080		0.730	0.525	0.038	0.030
	8	0.665	0.567	0.012	0.089		0.620	0.540	0.039	0.055
	10	0.610	0.555	0.012	0.090		0.529	0.537	0.043	0.084
Post-crisis										
(3)	Horizon	LSUN	LTECH	LOIL	LTBILL	(4)	LWIND	LTECH	LOIL	LTBILL
LSUN	0	1.000	0.371	0.106	0.009	LWIND	1.000	0.433	0.162	0.002
	2	0.996	0.334	0.089	0.005		0.993	0.391	0.185	0.001
	4	0.992	0.346	0.078	0.003		0.987	0.368	0.204	0.001
	6	0.984	0.361	0.067	0.002		0.968	0.342	0.245	0.001
	8	0.973	0.376	0.057	0.003		0.942	0.318	0.283	0.001
	10	0.959	0.389	0.047	0.004		0.912	0.297	0.316	0.003

Table 10. Generalized forecast-error variance decompositions for all four models.

Within the MWALD framework.

7.4. Robustness testing

In this section we will run Granger causality tests through VECM or standard VAR (depending on results from cointegration tests) to see if we get similar results as the aforementioned LA-VAR statistics.

In table 11 we report the results from Johansen cointegration tests, where we use number of lags according to the findings in section 6. The variables are all I(1) going into the Johansen tests; LSUN, d(LWIND) (LWIND differentiated one time), LTECH, LOIL, LTBILL (see section 6 for unit root tests). Table 11 reveals a possible cointegrated relationship in model (1), while the tests discover no evidence of cointegration for the remaining models. Accordingly, we will run a VECM for model (1), and standard VAR for the three remaining models.

Table 12 shows the test statistics from the Granger causality tests, on the first two models. Model (1) is run as a VECM with all variables differentiated one time in order to become stationary, the order of cointegration is set as two, and with 7 lags (these specifications are discussed in section 6). The results are similar to the MWALD statistics, with technology stock prices influencing the solar index, and no causality is found running from oil prices or interest rates towards LSUN. The VECM displays Granger causality running form LSUN and LTBILL towards oil prices, contradicting the LA-VAR results regarding that equation. In model (2) we have to differentiate LWIND twice (d2(LWIND)) to make it stationary, while the remaining variables are differentiated once. In model (2) we run a standard VAR, as we found no proof of cointegration, and we run the information criteria anew since we have differentiated the variables (differentiating is not necessary in the

	(1)	(2)	(3)	(4)
None	59.826***	99.933***	24.515	84.765***
At most 1	35.093**	17.578	10.385	14.028
At most 2	13.6967*	5.359	4.473	4.652
At most 3	1.644	0.007	1.007	0.076

*Table 11. Trace statistics from Johansen cointegration tests. ***, ** and * denotes statistically significance at the 1%, 5% and 10% level.*

Dependent variable				
(1)	d(LSUN)	d(LTECH)	d(LOIL)	d(LTBILL)
d(LSUN)	-	4.101	13.097*	7.349
d(LTECH)	12.074*	-	6.959	5.142
d(LOIL)	3.162	3.005	-	10.002
d(LTBILL)	5.621	1.830	12.610*	-
(2)	d2(LWIND)	d(LTECH)	d(LOIL)	d(LTBILL)
d2(LWIND)	-	4.602	2.335	1.213
d(LTECH)	8.991*	-	2.784	10.138**
d(LOIL)	2.599	5.840	-	1.762
d(LTBILL)	3.428	2.359	1.701	-

*Table 12. Granger causality tests. ***, ** and * denotes statistically significance at the 1%, 5% and 10% level.*

LA-VAR framework). The results from the lag selection criteria are reported in appendix 11 for all four models. The criteria suggests 2 and 3 lags for model (2), but these specifications perform very poorly in terms on autocorrelated residuals, so we run the model with 4 lags. The Granger causality for model (2) still shows that past movements of LTECH influence LWIND, though the relationship is not bidirectional as it was in the LA-VAR framework. Furthermore, it shows LTECH influencing LTBILL, consistent with the results in section 7.1.

Table 13 shows the results from the Granger causality tests for model (3) and (4). Model (3) is calculated with 1 lag, consistent with the lag selection recommendation, and with no problems regarding autocorrelated residuals. The results are very similar to the LA-VAR results, with the sole exception of no Granger causality running from TBILL to OIL. In model (4) we use 10 lags as recommended by the LR criteria, while having the most stable residuals. These results differ greatly from the previous evidence reported in section 7.1. Most notably, we see a strong influence from LTECH running to LWIND. This is not revealed with the MWALD statistics within the LA-VAR framework, though we

Dependent variable				
(3)	d(LSUN)	d(LTECH)	d(LOIL)	d(LTBILL)
d(LSUN)	-	0.792	0.288	0.734
d(LTECH)	1.895	-	0.342	1.119
d(LOIL)	0.200	0.016	-	1.691
d(LTBILL)	1.304	5.557**	0.715	-
(4)	d2(LWIND)	d(LTECH)	d(LOIL)	d(LTBILL)
d2(LWIND)	-	12.759	18.444**	6.272
d(LTECH)	30.913***	-	21.244**	11.436
d(LOIL)	9.529	12.402	-	15.133
d(LTBILL)	6.439	18.259*	15.300	-

*Table 13. Granger causality tests. ***, ** and * denotes statistically significance at the 1%, 5% and 10% level.*

suspect that there is a relationship between the variables through the previous GIRF and GVD tests.

In summary, this section shows results that are very similar to the findings in section 7.1. We find no evidence of oil price movements or interest rates influencing neither sun nor wind stock prices, and we still find that technology stock prices seem to influence the renewables prior to the financial crisis. The biggest difference between the MWALD-statistics and these results is that tech prices have a significant impact on the wind index after the financial crisis within the standard VAR framework, a relationship we did not discover in the LA-VAR framework.

7.5. Discussion

H1

Neither by using MWALD tests, IRFs nor variance decomposition, we find any evidence that interest rates influence the performance of wind or solar stocks. This goes for both the pre- and post-crisis periods. Our first hypothesis (H1) can thus be rejected. This is a surprising result, and contradicts the findings of Henrqiues and Sadorsky (2008), as well as the other papers discussed in section 2 that found granger causality running from interest rates to the alternative energy stocks.

A reason to the non-existing relationships, at least for the post-crisis period, could be that the interest rates have been historically low after 2009. A model-specific reason to the absent causalities could be related to the findings in section 7 where we saw that the equations with LTBILL as dependent variable displayed high standard errors, which may make the corresponding results somewhat unreliable.

Nevertheless, the importance of interest rates and capital costs should not be neglected when discussing wind and solar valuations. As argued in Greentechmedia (2011) and supported by Best (Best, 2017), the cost of capital can have a much greater impact on solar project value than other costs. They argue that for solar projects (mostly financed by debt), there are two primary factors that contribute to the cost of capital: the long-term interest rates and the premium that must be paid above the interest rates. The second factor was in the wake of the crisis very high as investors were unsecure about investments in renewables. This has changed lately, and investors' confidence in the renewables seem to have increased, causing debt costs to fall despite rising treasury yields (Bloomberg, 2018a). It will be interesting to see how further increases in interest rates will impact the performance of the two renewables in the coming period.

H2 and H3

Only in the second period do we find some evidence, through the IRF-tests, that an increase in oil prices leads to increased wind and solar stock prices. The relationships in the post-crisis period are further confirmed by the GVD-tests where we see that the variation in the stocks can be explained by the variation in oil prices. These results are much stronger for the wind stocks than for the solar stocks. It is clear that the relationships between the renewable stocks and oil prices have changed from period 1 to period 2, indicating some evidence for H3, claiming that increases in oil prices have more significant impact on wind and solar stock performance *after* the crisis. The lack of granger causality, however, makes us unsure of how to interpret the relationships, and makes it difficult to reach a clear conclusion regarding H2.

Our findings differ from the research papers discussed in section 2, where all, expect of Henriques and Sadorsky (2008), found very significant relationships between oil prices and alternative energy stocks. This could be an indication that wind and solar stocks, in isolation, do not react to the same variables as the renewables in the alternative energy stocks used in the previous research (remembering that these stocks included all kinds of alternative energy). Worth noticing is that our time period before the crisis does not exactly match other papers' time periods, as our data only is available from 2005. This could, to some extent, help explain the difference in results.

There are also other possible reasons to the absence in significant relationships between oil prices and wind and solar stock performance. One is related to the markets in which oil, wind and solar compete. Oil is mostly used for transportation and petrochemicals (Statista, 2018). Wind and solar energies are mostly used to create electricity. One could argue that it would be better to use natural gas prices in the model, because gas is to a larger degree used to generate electricity than oil (IEA, 2018). Unfortunately, finding an appropriate proxy for natural gas prices proved difficult because these prices are highly dependent on local supplies. As most economic theory suggests (Villar & Joutz, 2006), natural gas prices are linked to oil prices, which is not locally dependent and thus a better variable for our purposes. To conclude this argument: the non-perfect link in the usage of oil and wind and solar energy, could help explain our findings of a reduced relationship between oil prices and wind and solar stock performance.

Another explanation is the limitations of where wind and solar energy can be produced and used. Obviously, wind and solar energy can only be well utilized in locations around the globe where there is frequent wind and sunlight for long periods. Oil, on the other hand, can easily be transported and compete in more markets. As a result, the energy sources are only direct competitors in certain markets where the nature permits it.

Finally, it could simply be that because the wind and solar energies are only (as per today) competitive with the fossil fuels in some markets, we don’t have enough evidence to prove a substitution-effect from fossil fuels to the two renewables when the prices of the former rise.

H4 and H5

In the pre-crisis period, all of the three methodologies provide us with strong evidence of causality running from LTECH to both LSUN and LWIND. Looking at the IRFs, it is fair to say that an increase in technology stock prices will be followed by an increase in wind and solar stock prices, and we can confirm H4 for the first period. The relationships are absent in the post-crisis period indicating that H5 holds. It might be that investors do not treat wind and solar stocks as technology stocks anymore. As we suggested in H5, this could be due to the increased competitiveness of the wind and solar energies in the power markets making the two renewables more comparable to other energy stocks. An extension of this argument can be related to the increased knowledge investors have gained of the renewable stocks the recent years. Because both wind and solar stocks were relatively new before 2008, investors might not have known where to "place them" and as a result, categorized them in the same group as pure technology stocks due to their similarities. As the wind and solar technologies have become more common, it might be that investors today are more able to understand the behavior of wind and solar stocks.

7.6. Summary and limitations

To sum up, we have found results confirming some of our hypothesis, but we also found some surprising results contradicting what was initially hypothesized and what other research on alternative energy stock performance has found. The differences can potentially be explained by the unique art of wind and solar stocks, and/or by limitations in our model.

We have deliberately chosen to focus on three explanatory variables to make our LA-VAR model comparable to previous studies. Nevertheless, we accept that other variations of the model could have been conducted. First and foremost, it should be mentioned that a lot of variables were left out during the preparation of the model. The most important ones are polysilicon prices[6], US-Yuan exchange rates and electricity prices. Especially the latter would potentially be an important factor, but is left out due to the high variation in electricity prices across borders.

It should also be stressed that regulatory issues play important roles in renewable stock performance. Examples of influencing factors are governmental subsidies, global political issues such as trade barriers or political crisis, and local matters such as access to electricity grids. Factors like these are difficult to implement in a model used to test empirics in a global scope, but are important in a discussion.

Some critique may also be directed at our choice of literature, as none of the papers used as primary inspiration are published in what may be considered as top journals within the field of finance (with the exception of Toda and Yamamoto (1995)). We have however chosen to use these particular papers in our thesis as they are the only ones treating the topic of interest. We find their theme and methodology interesting, and most suitable for answering our research question.

8. Conclusion

The rise of renewable energy will influence energy markets worldwide in the upcoming decades. Especially wind and solar power will be dominant in what many refer to as the energy transition, moving away from fossil fuels. Different

[6] Polysilicon is the main material used to create solar PV cells. It is a hyper pure form of silicon and is the earth's second most abundant element.

factors are driving the transition and among the most important we find climate concerns, technology advancements and cost reductions.

The understanding of the renewable energy markets becomes more and more important. This study takes a financial approach to understanding the wind and solar energy sectors. The study investigates the relationships among wind and solar stock prices, interest rates, oil prices and technology stock prices. Through a four-variable lag-augmented vector autoregressive model it investigates the relationships in two different time periods, the years before the financial crisis of 2008, and the years after the crisis. It discovers that the behaviours of the indices change after the financial crisis. Comparing the wind stocks to the solar stocks, the study finds a close resemblance in how the two energy sources react to changes in the variables of interest.

According to Granger causality tests, technology stock prices influence the stock prices of wind and solar stocks in the pre-crisis period, while interest rates and oil prices have no significant impact on the renewables. This finding is further strengthened through the generalized impulse response functions where we find that a positive shock to technology stocks results in increased wind and solar stock prices, while interest rates and oil prices still show no significance. The generalized forecast-error variance decomposition further supports these findings.

The relationships change in the post-crisis period. We see that neither oil prices, interest rates nor technology stock prices Granger cause the wind or solar stock prices. According to the impulse response function, there is evidence that an increase in technology stock prices and in oil prices lead to an increase in wind and solar stock prices. The generalized forecast-error variance decomposition also shows that technology has an impact on the renewables, and shows that the wind stocks are influenced by oil to a larger degree than the solar stocks. The interest rates show no importance in any of the models. In summary, we see that technology still impacts the indices of interest, though to a smaller degree that in the pre-crisis period, while oil plays a bigger part than before the financial crisis. Due to the lack of significant Granger causality, it is however difficult to make any clear conclusion regarding technology and oil prices.

As robustness test, we ran the variables anew in a VECM model and in VAR models (not lag-augmented), and we have reported the corresponding Granger causality estimators. The results were very similar to our main model, with the exception of technology prices playing a larger role on the wind index in the post-crisis period.

All over, our results differ from previous research on renewable energy in that we find no big causality running from oil prices and interest rates to the renewable energy stocks. Because the previous studies focus on indices consisting of all kinds of renewable energy companies, our results might indicate that wind and solar stocks, separately, have different characteristics than when investigated in a renewable energy index containing all kinds of renewables. We have also discovered that the relationships have changed in the two periods we looked at, indicating that the indices and their characteristics are changing over time. The latter statement makes sense when considering that the renewable sector is still relatively new, and it is growing at an incredible rate, making it hard to know its drivers and to know what to compare it with. Investors and policy makers should have this in mind when investing or choosing political measures.

We encourage future research to continue investigating the financial characteristics of renewable energy companies, and preferably treat the different energy sources separately, as done in this paper. When investigating wind and solar companies, it could be interesting to also include other factors than the ones in our models, such as silicon prices, political regulations, gas prices and different price estimates of electricity.

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10.Appendix

10.1. Appendix 1 – Unit root testing

	Levels			First differences		
	ADF(lags)	PP(NWBW)	KPSS(NWBW)	ADF(lags)	PP(NWBW)	KPSS(NWBW)
				First period		
LSUN	-1.333(0)	-1.354(4)	1.224(2)***	-10.573(0)***	-10.555(4)***	0.082(2)
LTECH	-1.896(0)	-1.969(5)	0.499(9)**	-13.390(0)***	-13.285(4)***	0.064(4)
LOIL	-0.545(0)	-0.545(0)	1.028(10)***	-12.617(0)***	-12.619(1)***	0.127(1)
LTBILL	-0.541(1)	-0.545(5)	1.050(9)***	-15.454(0)***	-15.883(7)***	0.214(9)
LWIND	-2.453(0)	-2.436(4)	1.268(10)***	-10.986(0)***	-10.997(5)***	0.381(5)*
				Second period		
LSUN	-1.675(0)	-1.694(2)	1.310(16)***	-20.358(0)***	-20.360(1)***	0.1855(2)
LTECH	-1.270(1)	-1.025(13)	2.636(16)***	-24.257(0)***	-24.432(10)***	0.082(14)
LOIL	-1.315(0)	-1.349(6)	1.550(16)***	-21.604(0)***	-21.590(7)***	0.123(6)
LTBILL	-1.343(1)	-1.806(8)	0.800(16)***	-26.780(0)***	-28.630(9)***	0.220(18)
LWIND	-1.258(0)	-1.328(6)	0.691(16)**	-21.225(0)***	-21.248(6)***	0.361(6)*

*Unit root tests using Augmented Dickey Fuller-test (ADF), Phillips and Perron (PP) tests and the Kwiatkowski–Phillips–Schmidt–Shin tests (KPSS). Parenthesis shows selected lags using Schwarz information criteria for the ADF tests, and the Newey-West bandwidth using Bartell Kernel for the PP and KPSS tests. . ***, ** and * denotes statistically significance at the 1%, 5% and 10% level.*

10.2. Appendix 2 – Lag length criteria

(1)

Lag	LR	AIC	SC	HQ
0	NA	-3.710737	-3.622945	-3.675063
1	1259.139	-13.45963*	-13.02066*	-13.28126*
2	24.06986	-13.41265	-12.62251	-13.09158
3	24.13219	-13.37288	-12.23158	-12.90912
4	9.692517	-13.21363	-11.72116	-12.60717
5	15.23859	-13.10789	-11.26425	-12.35873
6	10.87308	-12.96619	-10.77138	-12.07434
7	27.92178*	-12.99566	-10.44968	-11.96111
8	14.87353	-12.90315	-10.00601	-11.72591
9	15.69970	-12.82589	-9.577580	-11.50596
10	21.46820	-12.82016	-9.220672	-11.35752

(2)

Lag	LR	AIC	SC	HQ
0	NA	-3.601687	-3.513894	-3.566013
1	1344.514	-14.02816	-13.58920*	-13.84979*
2	37.17619*	-14.08860*	-13.29847	-13.76754
3	25.47625	-14.06023	-12.91893	-13.59647
4	8.888370	-13.89392	-12.40145	-13.28747
5	13.84870	-13.77555	-11.93191	-13.02639
6	8.869103	-13.61494	-11.42014	-12.72309
7	21.95457	-13.58591	-11.03993	-12.55136
8	14.90822	-13.49376	-10.59661	-12.31652
9	17.20242	-13.43249	-10.18417	-12.11255
10	23.19157	-13.44590	-9.846413	-11.98327

(3)

Lag	LR	AIC	SC	HQ
0	NA	5.148331	5.187513	5.163832
1	6699.148	-11.31473	-11.11882*	-11.23722*
2	45.79833*	-11.35089*	-10.99825	-11.21138
3	18.14725	-11.31855	-10.80918	-11.11703
4	10.73742	-11.26782	-10.60173	-11.00430
5	25.60173	-11.25559	-10.43277	-10.93006
6	22.02992	-11.23476	-10.25521	-10.84723
7	20.18790	-11.20970	-10.07342	-10.76016
8	21.53840	-11.18878	-9.895774	-10.67723
9	22.59031	-11.17130	-9.721561	-10.59774
10	8.543601	-11.11640	-9.509938	-10.48084

(4)

Lag	LR	AIC	SC	HQ
0	NA	3.676599	3.715781	3.692100
1	6728.186	-12.85816	-12.66225*	-12.78065*
2	48.00165	-12.89981*	-12.54718	-12.76030
3	23.77181	-12.88164	-12.37228	-12.68012
4	17.67269	-12.84856	-12.18247	-12.58504
5	22.63790	-12.82871	-12.00589	-12.50318
6	29.40524*	-12.82704	-11.84749	-12.43950
7	16.22726	-12.79158	-11.65530	-12.34204
8	20.16852	-12.76703	-11.47402	-12.25548
9	21.90549	-12.74771	-11.29797	-12.17416
10	5.303359	-12.68403	-11.07757	-12.04847

Lag length criteria for model 1-4, using Akaike Information Criterion (AIC), Hannan-Quinn criterion (HQ), Schwarz Information Criterion (SC) and the Likelihood Ratio test (LR). The stars indicates the suggested lag length recommended by the different criteria.

10.3. Appendix 3 – Multivariate LM testing

	(1)		(2)		(3)		(4)	
Lags	LM-Stat	Prob	LM-Stat	Prob	LM-Stat	Prob	LM-Stat	Prob
1	5.435	0.993	17.088	0.380	19.044	0.266	16.042	0.450
2	21.080	0.175	22.873	0.117	18.070	0.320	21.343	0.166
3	12.801	0.687	8.409	0.936	9.464	0.893	19.818	0.229
4	19.904	0.225	11.360	0.787	19.105	0.263	18.204	0.312
5	23.856	0.093	12.616	0.701	24.256	0.084	30.018	0.018
6	16.807	0.398	24.733	0.075	11.815	0.757	15.233	0.508
7	13.888	0.607	17.184	0.374	19.380	0.249	20.376	0.204
8	13.135	0.663	7.654	0.959	19.774	0.231	14.010	0.598
9	25.242	0.066	26.013	0.054	10.816	0.821	7.934	0.951
10	24.421	0.081	13.695	0.621	8.903	0.917	26.227	0.051

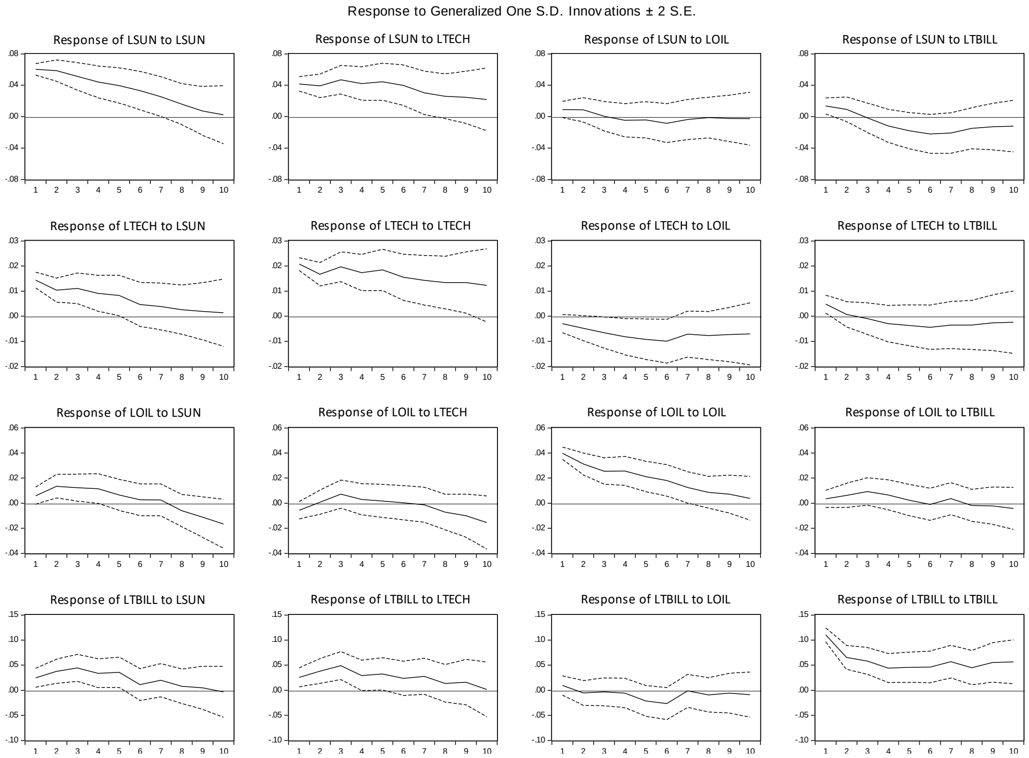
Shows the multivariate LM test statistics for all four models, up to 10 lags. The LM-Stat is calculated using Breusch-Godfrey a test, the Prob shows the significance with null hypothesis of no serial correlation.

10.4. Appendix 4 – Unit root testing

	(1)		(2)		(3)		(4)	
# Root	Root	Modulus	Root	Modulus	Root	Modulus	Root	Modulus
1	0.981	0.981	0.987	0.987	0.997	0.997	1.000	1.000
2	0.981	0.981	0.987	0.987	0.991	0.991	0.983	0.984
3	0.908	0.916	0.897	0.897	0.978	0.979	0.983	0.984
4	0.908	0.916	0.897	0.897	0.978	0.979	0.982	0.982
5	-0.865	0.865	-0.217	0.239	-0.313	0.313	-0.758	0.758
6	0.320	0.861	-0.217	0.239	-0.097	0.097	0.757	0.757
7	0.320	0.861	-0.090	0.090	0.079	0.079	-0.575	0.722
8	-0.543	0.846	-0.047	0.047	0.003	0.003	-0.575	0.722
9	-0.543	0.846					0.473	0.700
10	0.761	0.836					0.473	0.700
11	0.761	0.836					0.245	0.671
12	0.003	0.780					0.245	0.671
13	0.003	0.780					0.566	0.659
14	-0.691	0.778					0.566	0.659
15	-0.691	0.778					-0.355	0.644
16	0.747	0.759					-0.355	0.644
17	0.747	0.759					-0.174	0.624
18	0.563	0.743					-0.174	0.624
19	0.563	0.743					0.139	0.610
20	-0.328	0.723					0.139	0.610
21	-0.328	0.723					-0.506	0.602
22	-0.076	0.697					-0.506	0.602
23	-0.076	0.697					-0.334	0.334
24	-0.565	0.689					0.278	0.278
25	-0.565	0.689						
26	0.266	0.666						
27	0.266	0.666						
28	-0.652	0.652						

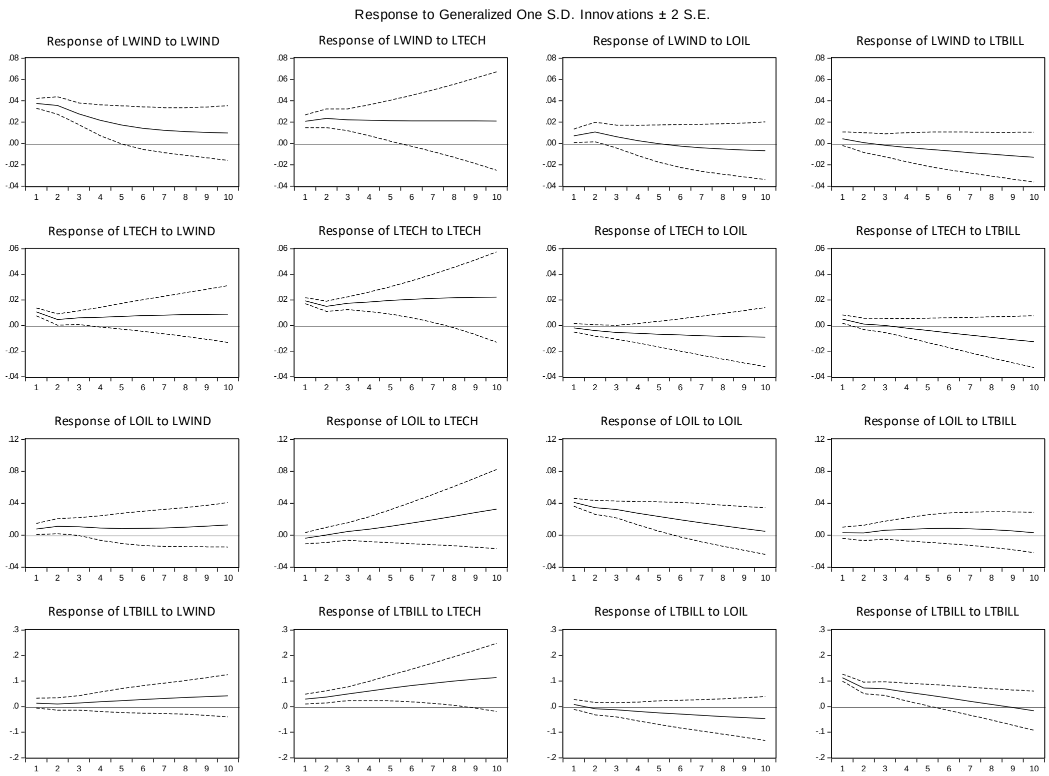
Reports the inverse roots of the characteristic AR polynomial. If the absolute value of the root is less than 1, the root lies inside the unit root circle, and the model can be considered as stable. Number of roots is decided by number of endogenous variables (4 for all four models), times the number of lags; 7, 2, 2 and 6 for model (1), (2), (3) and (4), respectively.

10.5. Appendix 5 – Generalized impulse response functions model 1



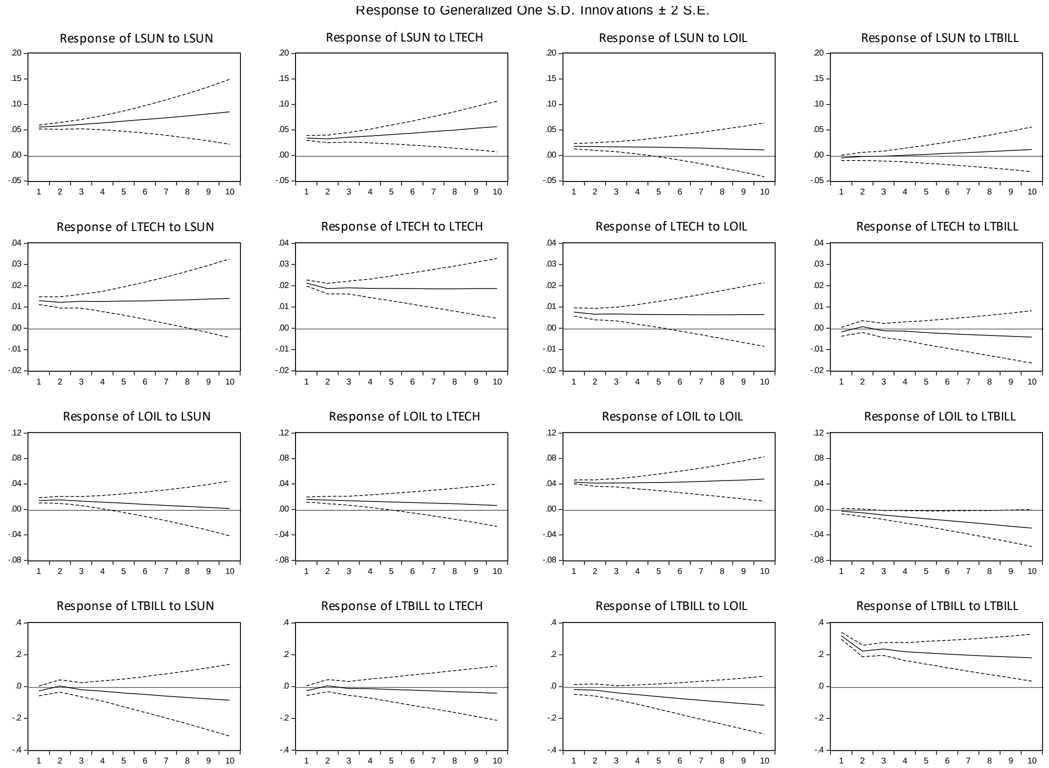
Generalized impulse response functions for all variables in model (1).

10.6. Appendix 6 - Generalized impulse response functions model 2



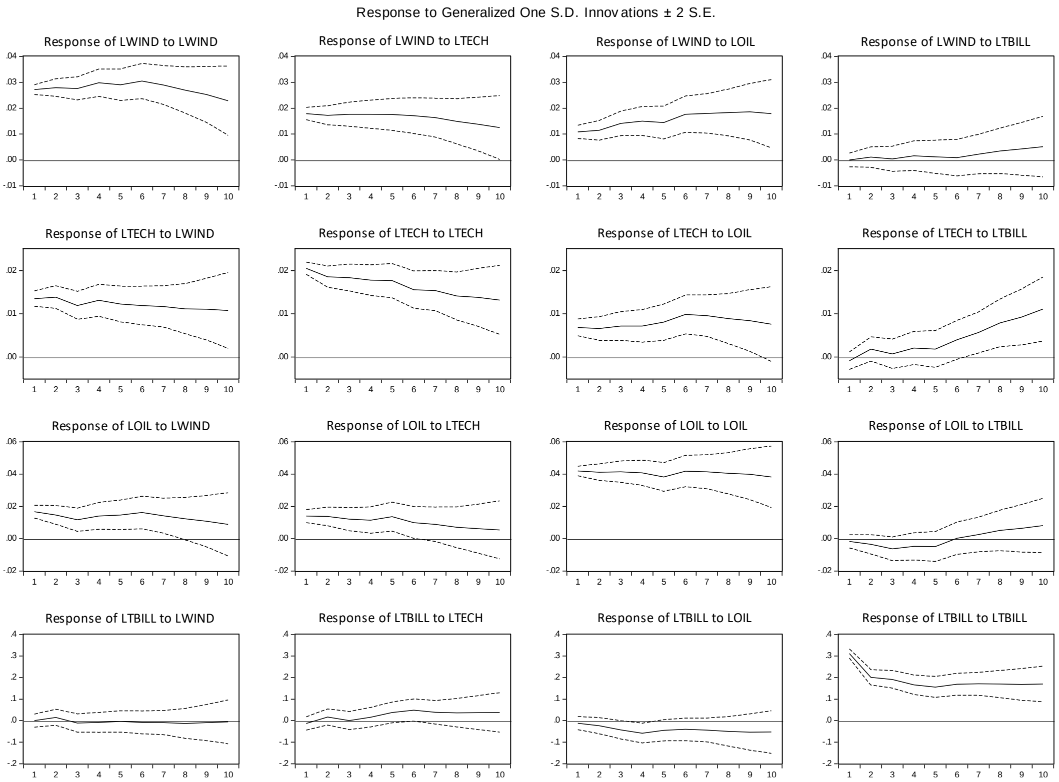
Generalized impulse response functions for all variables in model (2).

10.7. Appendix 7 - Generalized impulse response functions model 3



Generalized impulse response functions for all variables in model (3).

10.8. Appendix 8 - Generalized impulse response functions model 4



Generalized impulse response functions for all variables in model (4).

10.9. *Appendix 9 – Generalized forecast-error variance decompositions for model 1 and 2*

Period 1										
(1)	Horizon	LSUN	LTECH	LOIL	LTBILL	(2)	LWIND	LTECH	LOIL	LTBILL
LSUN	0	1.000	0.478	0.022	0.051	LWIND	1.000	0.306	0.035	0.014
	5	0.761	0.576	0.014	0.065		0.789	0.508	0.039	0.021
	10	0.610	0.555	0.012	0.090		0.529	0.537	0.043	0.084
LTECH	0	0.478	1.000	0.020	0.054	LTECH	0.306	1.000	0.009	0.067
	5	0.256	0.832	0.136	0.028		0.132	0.827	0.075	0.031
	10	0.166	0.741	0.151	0.027		0.107	0.677	0.087	0.107
LOIL	0	0.022	0.020	1.000	0.007	LOIL	0.035	0.009	1.000	0.005
	5	0.111	0.019	0.930	0.037		0.082	0.070	0.883	0.039
	10	0.218	0.126	0.794	0.038		0.102	0.392	0.517	0.034
LTBILL	0	0.051	0.054	0.007	1.000	LTBILL	0.014	0.067	0.005	1.000
	5	0.207	0.221	0.042	0.823		0.048	0.453	0.047	0.651
	10	0.147	0.168	0.032	0.848		0.085	0.671	0.098	0.269

Generalized forecast-error variance decompositions for model (1) and (2), showing lag week 0, 5 and 10 for all five variables.

10.10. *Appendix 10 - Generalized forecast-error variance decompositions for model 3 and 4*

Period 2										
(3)	Horizon	LSUN	LTECH	LOIL	LTBILL	(4)	LWIND	LTECH	LOIL	LTBILL
LSUN	0	1.000	0.371	0.106	0.009	LWIND	1.000	0.433	0.162	0.002
	5	0.988	0.353	0.072	0.002		0.977	0.353	0.226	0.001
	10	0.959	0.389	0.047	0.004		0.912	0.297	0.316	0.003
LTECH	0	0.371	1.000	0.132	0.005	LTECH	0.433	1.000	0.131	0.005
	5	0.380	0.993	0.121	0.015		0.482	0.964	0.179	0.007
	10	0.350	0.969	0.124	0.050		0.431	0.854	0.216	0.080
LOIL	0	0.106	0.132	1.000	0.003	LOIL	0.162	0.131	1.000	0.005
	5	0.067	0.101	0.950	0.057		0.125	0.109	0.984	0.023
	10	0.031	0.058	0.826	0.130		0.084	0.068	0.948	0.013
LTBILL	0	0.009	0.005	0.003	1.000	LTBILL	0.002	0.005	0.005	1.000
	5	0.028	0.011	0.058	0.950		0.003	0.015	0.046	0.915
	10	0.107	0.048	0.186	0.813		0.003	0.020	0.053	0.889

Generalized forecast-error variance decompositions for model (3) and (4), showing lag week 0, 5 and 10 for all five variables.

10.11. Appendix 11 – Lag length selection for robustness testing

(1)

Lag	LR	AIC	SC	HQ
0	NA	-3.710737	-3.622945	-3.675063
1	1259.139	-13.45963*	-13.02066*	-13.28126*
2	24.06986	-13.41265	-12.62251	-13.09158
3	24.13219	-13.37288	-12.23158	-12.90912
4	9.692517	-13.21363	-11.72116	-12.60717
5	15.23859	-13.10789	-11.26425	-12.35873
6	10.87308	-12.96619	-10.77138	-12.07434
7	27.92178*	-12.99566	-10.44968	-11.96111
8	14.87353	-12.90315	-10.00601	-11.72591
9	15.69970	-12.82589	-9.577580	-11.50596
10	21.46820	-12.82016	-9.220672	-11.35752

(2)

Lag	LR	AIC	SC	HQ
0	NA	-13.23476	-13.14609*	-13.19873
1	42.04308	-13.32576	-12.88237	-13.1456
2	63.81816	-13.60951*	-12.81143	-13.28523*
3	27.75114*	-13.60068	-12.44789	-13.13228
4	19.67807	-13.52832	-12.02082	-12.91579
5	13.57447	-13.40595	-11.54374	-12.6493
6	16.16257	-13.31329	-11.09639	-12.41252
7	12.0778	-13.18601	-10.6144	-12.14111
8	15.70353	-13.10153	-10.17521	-11.9125
9	23.51381	-13.10905	-9.828025	-11.7759
10	22.06695	-13.11175	-9.476018	-11.63448

(3)

Lag	LR	AIC	SC	HQ
0	NA	-11.32498	-11.28559*	-11.30939*
1	49.27657*	-11.36894*	-11.17195	-11.29098
2	18.58629	-11.33701	-10.98243	-11.19669
3	12.76139	-11.29078	-10.7786	-11.08809
4	23.69363	-11.27291	-10.60313	-11.00785
5	21.19296	-11.24919	-10.42182	-10.92176
6	20.07466	-11.22312	-10.23815	-10.83332
7	20.35889	-11.19835	-10.05579	-10.74619
8	22.68276	-11.18038	-9.88022	-10.66585
9	7.669481	-11.12248	-9.664729	-10.54559
10	11.95843	-11.07653	-9.461184	-10.43727

(4)

Lag	LR	AIC	SC	HQ
0	NA	-11.89715	-11.85768	-11.88153
1	259.3621	-12.46512	-12.26777*	-12.38701
2	82.19593	-12.59335	-12.23811	-12.45275*
3	46.25433	-12.63223	-12.1191	-12.42914
4	49.12204	-12.67969*	-12.00867	-12.41411
5	26.69689	-12.67021	-11.84131	-12.34215
6	14.99057	-12.63074	-11.64395	-12.24019
7	36.49102	-12.64871	-11.50404	-12.19568
8	27.04354	-12.6424	-11.33984	-12.12687
9	13.47602	-12.6001	-11.13966	-12.02209
10	29.01420*	-12.60077	-10.98244	-11.96027

Lag length criteria for model 1-4, using Akaike Information Criterion (AIC), Hannan-Quinn criterion (HQ), Schwarz Information Criterion (SC) and the Likelihood Ratio test (LR). The stars indicates the suggested lag length recommended by the different criteria.

10.12. Appendix 12 – Leverage ratios

Leverage ratios	Solar index	Wind index
Assets/Equity	5.8932	4.0523
Debt/Equity	2.2473	1.3087
Long Term Debt to Total Capital	0.3955	0.3610
(Total Debt - Cash) / EBITDA	7.9240	3.6492

Yearly average of each leverage ratio for all companies in the wind and solar indices from year 2014-2017. The averages have been calculated by taking the average of each company´s yearly average in the time span. Because the indices consist of different companies each year, the averages are of the companies presented in the MAC Global Solar Energy stock index and in the ISE Global Wind Energy index as of year 2018. Due to limitations in the data set, the time period for this calculation starts in year 2014. The debt/equity, which is the ratio referred to in the text, is calculated by dividing total debt by shareholders equity.