Table of contents

Abstract

This thesis investigates the relationship between some hypothesised variables and the stock prices of solar companies. Through a lag augmented vector autoregressive (LA-VAR) model we analyse whether oil prices, technology stock prices and interest rates influence the stock prices of solar companies.

1. Introduction

1.1 Problem description

Innovative and more sustainable ways of meeting our energy needs are leading to a global energy transition. In recent years the world has seen a shift from fossil fuels towards renewable energy sources. Climate concerns, rapidly falling costs and advancements in technology are paving the way for this transition. New markets are created, billions of dollars are invested into renewables and policy makers are encouraging the transition. It is clear that the world will have to deal with renewable energy companies in the coming decades, and understanding the economic and financial mechanisms behind them is of high importance.

A handful of studies have addressed the question of what influences the stock prices of alternative energy companies. Inspired by these studies, we seek to find what influences the stock prices of the most rapid growing energy source among them: the solar energy. More specifically we will 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 solar sector?*

In order to address the research question, we will outline theory and previous studies that have been conducted on alternative energy stock prices. Our thesis will hopefully contribute to a better understanding of the pricing dynamics in the solar sector. This information is important for investors holding solar energy stocks in their portfolios. By evaluating the different factors impacting the stock prices of the solar energy companies, investors become more equipped to optimize their portfolios. Policy makers also need to be aware of what factors impact the solar energy stocks, so that they can implement more effective instruments in order to promote the transition from fossil fuels to solar energy.

1.2 Motivation

According to nearly every measure, renewable energy has become the fastest growing energy source. Especially in the power sector, renewables are growing at high rates outperforming the growth of conventional technologies. A report written by the International Renewable Energy Agency (IRENA, 2017) shows that the current share of renewable energy in final energy consumption stands at 18,3%. 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. Policy and regulatory incentives, increasing energy demand, climate concerns, advancements in technology and reductions in production costs are the main drivers of the growth.

Among the renewables, solar photovoltaic (PV) is the fastest growing in terms of output and in terms of new added capacity. In 2016 the growth of new PV capacity was of 50% reaching over 74 GW, mainly led by Chinese expansions (IEA, 2017). As a result, solar PV additions rose faster than any other fuel for the first time. The IEA (2017) expects that solar PV will represent the largest annual capacity additions for 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.

Most of the overall PV capacity has been installed in the years leading up to 2017. The exceptional growth in the PV market was initiated by Germany, which in year 2000 introduced feed-in tariffs as a policy mechanism to stimulate installations of PV systems. Growth in influential markets such as Japan, the UK, Italy and China lagged some years, but in 2015 China surpassed Germany as the global leader of installed PV capacity. China will continue to drive the growth in the future together with the US and India. According to Frankfurt School-UNEP Centre (2017), there will be a massive spending on new solar installs of $3,7 trillion through 2040. Furthermore, they estimate that the levelized cost of electricity from solar will drop by 66% to 2040. Estimations done by IRENA (2017) show that by 2030 solar PV will account for 7% of the world's global power generation, a six-fold increase from today. Solar energy will hence strengthen its share of the world's energy mix - 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, there is a lack of research that focuses on the solar sector exclusively. Given the rapid growth in the solar sector and the huge investments we see today, we find it highly interesting to dig deeper into what really impacts the stock prices of solar companies. Henriques and Sardosky (2008) and Kumar, Shunsuke and Akimi (2012) found that there is causality between prices of technology stocks and the 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 stock prices and interest rates impact the alternative energy stock prices in the short run. They found that the causalities are *absent* in the long run. By solely focusing on the solar sector, we will add new literature into this field of research. We will apply the methodology of Henriques and Sardosky (2008) to find whether the interest rates, oil prices and technology stock prices influence the stock prices of solar energy companies or not. In addition, we consider adding a new variable: the prices of mono- and polycrystalline silicon. These are the most prevalent materials used for producing solar cells. Furthermore, we will use new and more recent data than the previous studies. We will use weekly stock prices, interest rates and oil prices in the time period from 2009 to 2017.

The rest of this preliminary thesis is structured in the following way. In the next section we review existing literature on what influences the stock prices of alternative energy companies. This is followed by our hypothesises in the third section. An explanation of the methodology to be used in our research is provided in the fourth section. In the fifth section we give a description of the data to be used, followed by a progression plan in the sixth and last section.

2. Literature Review

There have been 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 Sardosky (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 data related to clean energy stock prices, and there has 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 Sardosky (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 both oil prices and technology stock prices each individually Granger causes the stock price of alternative energy. However, they find that a shock to technology stock prices has a larger impact than a shock to the oil prices, which has little significant impact. 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 energy companies.

Kumar et al. (2012) do a similar study as the one of Henriques and Sardosky (2008), where they use a VAR model to evaluate potential causality. They look at data from 2005 to 2008 of three different clean energy indexes, 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 do however find evidence of oil prices and technology stock prices influencing renewable energy stock prices.

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, the 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 Sardosky (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 volatility approaches to the clean energy markets as well. Sardosky (2012) utilizes a series of autoregressive conditional heteroscedasticity (GARCH) models 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 Ortas and Moneva (2013) who find that clean tech indexes 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 Sardosky (2017) find, however, that divesting from fossil fuels in favour of clean energy actually yields a positive risk/return trade-off.

3. Hypothesis

The objective of our thesis is to evaluate what impacts the stock prices of solar energy companies. Because the solar energy companies fall under the umbrella of alternative energy companies, we expect our results to be similar to the findings of the aforementioned studies on what impacts the value of alternative energy companies. As the development of solar energy is dependent on advancements in technology, we hypothesize that **an increase in the technology stock prices will lead to an increase in the solar energy stock prices.**

Following previous research showing a positive relationship between alternative energy stock prices and oil prices, we believe that **the prices of solar energy stocks will increase when the oil price increases.** This is based on the assumption that solar energy is a substitute to energy from fossil fuels. We believe that, due to the improved competitiveness of the solar energy, **our study will find even stronger evidence of a substitution effect than the previous studies have been able to.**

Finally, as has been proved in the previous studies, we expect that **a rise in the interest rates will be followed by a decrease in the prices of the solar energy stocks.**

4. Methodology

As we are interested in casual relationships between univariate time series, we find a VAR-methodology to be most suitable for our needs. 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 lag, and the lags of all the other variables we choose. 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, which should be controlled for. Another assumption is that the variables are not cointegrated, which occurs when the variables co-move within a long run relationship. The conventional approach, when one discovers cointegration, is to use an error correction model (ECM).

Instead of using a standard VAR approach however, we intend to use the lag augmented VAR (LA-VAR, also known as the TY procedure) as proposed by Toda and Yamamoto (1994). This is partly because a potential cointegrated relationship is of no importance to our hypothesis, and partly because Bondia, Ghosh and Kanjilal (2016) found evidence of cointegration between clean energy stocks and several of the variables we intend to use. We could test for cointegration ourselves, but the methods used in Bondia et al. (2016) are outside the scope of our thesis. Furthermore, if we do test for cointegration and find evidence that it exists in the data, there is some discrepancy in terms of whether one should use LA-VAR or ECM. Toda and Yamamoto (1998) concluded that the choice between LA-VAR and ECM 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). ECM on the other hand performs better in terms of not committing a type 2 error (not rejecting a false null hypothesis). Clarke and Mirza (2004) revise the findings in Toda and Yamamoto (1998), where they reach the same conclusion. We would rather be conservative in our estimates, as we are looking for casual relationships in our thesis, and we therefore evaluate LA-VAR as superior to ECM for the purpose of our thesis.

The procedure steps for constructing a LA-VAR model consist of first estimating a VAR(p) model by choosing the optimal p through different selection criteria. Then, we identify the maximum order of integration (d) through unit root tests, and we can then estimate a VAR(p+d) model. The properties have to be controlled with a battery of diagnostic tests, and finally we run a Wald test on the first p parameters. An example of the LA-VAR model with two variables is shown below.

$$\begin{aligned}
Y_{1,t} = {} & \beta_{1,0} + \beta_{1,1}Y_{1,t-1} + \cdots + \beta_{1,p}Y_{1,t-p} + + \beta_{1,p+d}Y_{1,t-p-d} \\
& + \alpha_{1,1}Y_{2,t-1} + \cdots + \alpha_{1,p}Y_{2,t-p} + \alpha_{1,p+d}Y_{2,t-p-d} + u_{1,t} \\
Y_{2,t} = {} & \beta_{2,0} + \beta_{2,1}Y_{2,t-1} + \cdots + \beta_{2,p}Y_{2,t-p} + \beta_{2,p+d}Y_{2,t-p-d} \\
& + \alpha_{2,1}Y_{1,t-1} + \cdots + \alpha_{2,p}Y_{1,t-p} + \alpha_{2,p+d}Y_{1,t-p-d} + u_{2,t}
\end{aligned}$$

We will investigate the potential causality between the variables of interest through utilization of the Granger causality tests. The coefficients themselves are of little interest to our hypothesizes, but we will supplement with impulse response functions (IRF) to visualize the relationships. The IRFs will show us whether the variables have a positive or negative impact on each other, and it reveals how long a shock will persist.

5. Data

Most of the previous studies on the drivers of alternative energy stock prices, evaluated in section 2, have used the Wilder Hill clean energy index to measure the performance of alternative energy stocks. This index, consisting of around 86 stocks, was the first index for tracking the stock prices of clean energy companies. The companies in the index operate in the whole range of renewable energies, including everything from biomass heat to hydropower. For our purpose, we will replace the Wilder Hill clean energy index with an index that tracks solar energy stocks solely. Tentatively, we will also include the prices of mono- and polycrystalline, as these are the basic commodities for producing solar cells. Except of this, we will use the same data sources as Henriques and Sardosky (2008) and Managi and Okimoto (2013). However, our sample period will be more recent, ranging from 2009 to 2017 containing only weekly data. We start from 2009 in order to avoid the turmoil in 2008. Similarly to the previous studies, we will use Wednesday closing prices, as there are fewer holidays on Wednesdays relative to Fridays. The data to be used include: the stock index of solar energy companies, the index of the prices of technology stocks, oil prices and US interest rates.

5.1 Solar energy stocks

In order to measure the performance of the solar energy stocks, we will use the MAC Global Solar Energy stock index. This index consists of 23 qualified solar stocks listed on exchanges in different countries. The majority, 56%, of the stocks 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 as well as solar thermal. Furthermore, it includes the entire value chain of solar energy, stretching from raw materials, manufacturers, installers, and solar plant operators to financing, as well as related solar equipment, such as inverters and trackers. The index has a modified market cap weighting. It is modified in the way that it is cutting the index weighting of stocks that have solar revenue between 1/3 and 2/3 by half (named Medium-Play stocks). Pure-play solar stocks, on the other hand, are the solar stocks with solar revenue above 2/3. These stocks have an exposure factor of 1.

5.2 Technology stocks

The Arca Tech 100 index 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 objective of the index is to provide a benchmark for measuring the performance of companies using technology innovation across a broad spectrum of industries. As Henriques and Sardosky (2008) pointed out "it may be the case that investors view alternative energy companies as similar to other technology companies". As discussed in section 2, all of the previous studies have found a significant relationship between this variable and the stock prices of alternative energy companies. We will hence expect this to be the case for the solar energy stocks as well.

5.3 Oil prices

As we want to test whether there is a positive relationship between stock prices of renewable energy companies and oil prices due to substitution of energy source, we need to include oil prices in our model. The oil prices will be measured by 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 the most traded physical commodity in the world.

5.4 Interest rates

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

6. Progression plan

The first step on our agenda is to collect the data used in Henriques and Sardosky (2008), as we would like to replicate their main findings. We will do this as a tool to control that we have understood the methods, and to see that we are able to apply them. The next step is to collect the data described in this preliminary. We intend to start on the data collection immediately after finishing the preliminary part. After collecting the data, we will prepare the data for testing. The program(s) we intend to use will either be STATA, EViews, R or a combination of these. This will depend on the flexibility of the program with respect to the model we aim to create. We hope to be able to replicate the main results in Henriques and Sardosky (2008) by the end of February, after which we will begin working with the data of interest to our topic. Given that we are able to replicate the paper, we believe that it will be relatively straightforward to apply the same method on our data. We hope to start interpreting the results by early April at the latest. Finalizing the thesis will be time consuming and challenging, but we hope to have ready a draft by the end of May.

7. Bibliography

Bondia, R., Ghosh, S., & Kanjilal, K. (2016). International crude oil prices and the stock prices of clean energy and technology companies: Evidence from non-linear cointegration tests with unknown structural breaks. *Energy*, *101*, 558-565.

Clarke, J. A., & Mirza, S. (2006). A comparison of some common methods for detecting Granger noncausality. *Journal of Statistical Computation and Simulation*, *76*(3), 207-231.

Frankfurt School-UNEP Centre/BNEF. (2017). Global Trends in Renewable Energy Investment 2017. Retrieved from : http://fs-unep-centre.org/sites/default/files/publications/globaltrendsinrenewableenergyinvestment2017.pdf

Hamilton, J. D. (1996). This is what happened to the oil price-macroeconomy relationship. *Journal of Monetary Economics*, *38*(2), 215-220.

Henriques, I., & Sadorsky, P. (2008). Oil prices and the stock prices of alternative energy companies. *Energy Economics*,*30*(3), 998-1010.

Henriques, I., & Sadorsky, P. (2017). Investor implications of divesting from fossil fuels. *Global Finance Journal*.

IEA. (2017). Renewables 2017: analysis and forecasts to 2022. Retrieved from: https://www.iea.org/publications/renewables2017/

Inchauspe, J., Ripple, R. D., & Trück, S. (2015). The dynamics of returns on renewable energy companies: A state-space approach. *Energy Economics*, *48*, 325-335.

IRENA . (2017). REthinking Energy 2017: Accelerating the Global Energy Transformation. Retrieved from: https://www.irena.org/DocumentDownloads/Publications/IRENA_REthinking_Energy_2017.pdf

Kilian, L. (2009). Not all oil price shocks are alike: Disentangling demand and supply shocks in the crude oil market. *American Economic Review*, *99*(3), 1053-69.

Kumar, S., Managi, S., & Matsuda, A. (2012). Stock prices of clean energy firms, oil and carbon markets: A vector autoregressive analysis. *Energy Economics*, *34*(1), 215-226.

Macsolarindex. (2018). Index details. Retrieved from: http://www.macsolarindex.com/index-details/

Managi, S., & Okimoto, T. (2013). Does the price of oil interact with clean energy prices in the stock market?. *Japan and the World Economy*, *27*, 1-9.

Ortas, E., & Moneva, J. M. (2013). The Clean Techs equity indexes at stake: Risk and return dynamics analysis. *Energy*, *57*, 259-269.

Papapetrou, E. (2001). Oil price shocks, stock market, economic activity and employment in Greece. *Energy economics*, *23*(5), 511-532.

Reboredo, J. C. (2015). Is there dependence and systemic risk between oil and renewable energy stock prices?. *Energy Economics*, *48*, 32-45.

Sims, C. A. (1980). Macroeconomics and reality. *Econometrica: Journal of the Econometric Society*, 1-48.

Toda, H. Y., & Yamamoto, T. (1995). Statistical inference in vector autoregressions with possibly integrated processes. *Journal of econometrics*, *66*(1), 225-250.

Yamada, H., & Toda, H. Y. (1998). Inference in possibly integrated vector autoregressive models: Some finite sample evidence. *Journal of Econometrics*, *86*(1), 55-95.

Wikipedia. (2018). NYSE Arca Tech 100 Index. Retrieved from: https://en.wikipedia.org/wiki/NYSE_Arca_Tech_100_Index