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Time-varying Risk Factor Models for Renewable Stocks

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Problem Description

Climate concerns, advances in technology, reduced costs, improved efficiency and the increased demand for energy have contributed to the extensive growth of the renewable energy sector over the last decade. As this sector will be highly dependent on private investments in the future, more knowledge about the return characteristics of renewable energy stocks is crucial in order to increase the attractiveness of investing in renewable energy.

The purpose of this thesis is to identify and analyze the fundamental factors driving the return of the WilderHill New Energy Global Innovation Index (NEX) and the Ardour Solar Energy Index (SOLRX). Furthermore, return dynamics of the NEX and the SOLRX are compared over the time period 2005 to 2017. A state-space approach is used to estimate the alpha and the beta coefficients for the potential drivers of return of both the NEX and the SOLRX.

Our thesis will contribute to a better understanding of the renewable energy sector, the solar sector, and the relationship between the two. By examining the return dynamics of the renewable sector and the solar sector, in addition to their drivers of return, market participants are given insight on how different factors have influenced these sectors since 2005. Furthermore, trends and developments over recent years are highlighted. Thus, investors and policy makers will be better equipped to make optimal decisions.

Preface

This master's thesis is the result of a collaboration between two fifth year students enrolled in the Industrial Economics and Technology Management program at the Norwegian University of Science and Technology (NTNU), specializing in Financial Engineering and Managerial Economics and Operations Research. The thesis is the final work of a Master of Science degree in Industrial Economics and Technology Management at NTNU, completed the spring of 2017.

We would like to thank our supervisor, Professor Sjur Westgaard, at the Department of Industrial Economics and Technology Management at NTNU for excellent guidance and valuable feedback throughout the process.

Trondheim, June 2, 2017

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Abstract

Despite the considerable growth in the renewable energy market during recent years, many investors believe they face a trade-off between financial profitability and sustainability when investing in renewable energy. Furthermore, some argue that there is higher risk related to investing in the solar sector than investing in other alternative energy sectors. More knowledge about potential drivers of return of renewable energy stocks is therefore crucial in order to give investors a better understanding of the risks related to investing in renewables, and ultimately in order to increase the attractiveness of investing in renewables.

With that as a starting point, this study examines potential factors driving the returns of the WilderHill New Energy Global Innovation Index and the Ardour Solar Energy Index, namely the global stock market, technology stocks, oil prices and the stock market volatility. The alpha of each index is also investigated. Moreover, this study compares return dynamics of the renewable energy sector as a whole and the solar sector in the time period from 2005 to 2017. We analyze the evolution of the estimated alphas and the estimated beta coefficients and compare this evolution for both the renewable sector and the solar sector. In order to do this, a state-space approach is used. The analysis is based on a multi-factor asset pricing model with time-varying coefficients for both the renewable sector as a whole and the solar sector.

The results suggest a strong influence of the global stock market and technology stocks on both renewable stocks and solar stocks throughout the considered sample period. The influence of oil prices is significantly lower and has decreased since 2008. Furthermore, both the renewable sector as a whole and the solar sector have underperformed relative to the considered drivers of returns in latest years. Finally, the results suggest that the global stock market and technology stocks affect the solar sector to a greater extent than the renewable sector as a whole.

Sammendrag

Til tross for den betydelige veksten i markedet for fornybar energi de siste årene, tror mange investorer at de må velge mellom økonomisk lønnsomhet og bærekraft når de investerer i fornybar energi. Videre hevder enkelte at det er høyere risiko knyttet til å investere i solsektoren sammenlignet med å investere i andre alternative energisektorer. Ytterligere kunnskap om potensielle drivere bak avkastningen til fornybar energi er derfor avgjørende for å gi investorer en bedre forståelse av risikoen knyttet til å investere i fornybar energi, og til syvende og sist for å øke attraktiviteten knyttet til å investere i fornybar energi.

Med dette som utgangspunkt undersøker denne studien potensielle drivere bak avkastningen til WilderHill New Energy Global Innovation Index og Ardor Solar Energy Index, nærmere bestemt det globale aksjemarkedet, teknologiaksjer, oljepriser og volatiliteten i aksjemarkedet. Indeksenes tilhørende alfa undersøkes også. Videre sammenlignes avkastningsdynamikken til fornybarsektoren og solsektoren i tidsperioden 2005 til 2017. Vi analyserer utviklingen til de estimerte alfaene og de estimerte betakoeffisientene, og sammenligner denne utviklingen for både fornybarsektoren og solsektoren. For å kunne gjøre dette benyttes en tilstandsromrepresentasjon. Analysen er basert på en multifaktormodell med tidsvarierende koeffisienter for både fornybarsektoren og solsektoren.

Resultatene antyder en sterk innflytelse fra det globale aksjemarkedet og teknologiaksjer på både fornybar- og solaksjer gjennom hele tidsperioden. Oljeprisens innflytelse er betydelig lavere og har avtatt siden 2008. Videre har både fornybarsektoren og solsektoren underprestert i forhold til de potensielle driverne de siste årene. Resultatene tyder på at det globale aksjemarkedet og teknologiaksjer påvirker solsektoren i større grad enn fornybarsektoren.

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Chapter 1

Introduction

The renewable energy market has experienced considerable growth over recent years. The market expanded at its fastest-ever rate in 2015, increasing the total capacity and production of renewable energy by 8.7% (IRENA, 2016b). This is the largest global capacity extension seen to date. Furthermore, global investment in renewable energy reached a record level of 286 billion USD in 2015, exceeding the previous record of 278 billion USD achieved in 2011 by 8 billion USD (REN21, 2016). While the global new investment in the solar and wind sector increased with 12% and 4%, respectively, all other technologies experienced a reduction in investments in 2015 compared to 2014 (REN21, 2016). The solar sector is thus the fastest growing renewable energy sector. In addition to growth in both the renewable energy market and in renewable energy investments, renewable energy technologies has continued to advance (REN21, 2016).

As the interest in the renewable energy field has increased over recent years, several studies have explored the pricing dynamics of renewable energy stocks. Existing literature argues that there is a relationship between the prices of renewable energy stocks and the global stock market (Inchauspe et al., 2015, Bohl et al., 2015), technology stocks (Henriques and Sadorsky, 2008, Sadorsky, 2012, Kumar et al., 2012) and the oil price (Henriques and Sadorsky, 2008, Schmitz, 2009, Kumar et al., 2012, Sadorsky, 2012, Managi and Okimoto, 2013, Reboredo, 2015). However, the results of these studies are rather ambiguous in terms of the magnitude of the influence of especially the oil price to renewable energy stock prices.

Following the existing literature, we wish to investigate the impact of fundamental factors such as the global stock market, technology stocks, the oil price and the stock market volatility on renewable energy stocks. We believe that the influence of these factors will vary over time. Moreover, we want to examine whether the impact of energy prices and stock market indices vary across subsectors, and compare the impact on the renewable sector as a whole to that of the solar sector.

In order to examine the potential drivers of renewable energy returns and solar returns, a multi-factor asset pricing model with time-varying factors is developed. We solve the model by using a state-space approach, which is a widely recognized approach that is often applied to time series models (Koopman et al., 1999, Tsay, 2005, Commandeur and Koopman, 2007, Durbin and Koopman, 2012). As opposed to a static approach, the state-space approach provides information about the time-varying influence of the factors included in the model. This approach also offers insights into the dynamic relationship between the variables.

The applied state-space model is inspired by the work of Inchauspe et al. (2015), and includes the following factors: the global stock market, technology stocks, oil prices and stock market volatility. The volatility factor is added to the model to compensate for potential volatility clusters. Similar to Inchauspe et al. (2015), the applied state-space model allows for an analysis of the performance of the renewable energy sector and the solar sector relative to their identified drivers, illustrated by their respective alphas. This study does, however, differ from the one of Inchauspe et al. (2015) by analyzing both the renewable energy sector as a whole and the solar sector. In that way, it is possible to compare the evolution of the factors for both renewable and solar stocks. In addition, this study extends the time period considered in previous studies by using a data sample from 2005 up to 2017.

The Wilderhill New Energy Global Innovation Index (NEX) is used to represent the renewable energy sector, while the Ardour Solar Energy Index (SOLRX) is used to represent the solar sector. The MSCI World Index (MSCI), West Texas Intermediate Oil Price (WTI), NYSE Arca Tech 100 Index (PSE) and the CBOE Volatility Index (VIX) is used to represent the stock market, the oil price, technology stocks and the stock market volatility, respectively. The monthly U.S. Treasury Bill interest rate is used to calculate monthly excess returns for all indices. Datastream is used to collect the historical data.

The following chapters aim to give the reader a more thorough understanding of the drivers of renewable energy returns. Some general background information about the trends and recent developments within the renewable energy sector is presented in chapter 2. Readers with an extensive knowledge of the renewable energy sector may skip this chapter. Chapter 3 provides an overview of existing literature on the renewable energy field, including factors that may influence the returns of the renewable energy sector. The characteristics of the data sample used in the empirical analysis of this study are explored in chapter 4, while the methodology used is presented in chapter 5. Here, the state-space model is explained in detail. The results of the study are interpreted and discussed in chapter 6. In addition to providing our interpretation of the results, the results are compared to the findings of other relevant studies. Lastly, concluding remarks, limitations and recommendations for further research are presented in chapter 7.

Chapter 2

Trends and Developments in the Renewable Energy Sector

Renewables are currently establishing as mainstream sources of energy around the world. The renewable energy sector has grown markedly over the last decade, and is expected to continue its growth in the years to come. Several factors have contributed to the increase in renewable energy production, including climate concerns, advances in technology, improved cost-competitiveness of renewable technologies, dedicated policy initiatives and the growing demand for energy in developing and emerging economies. Along with the increased demand for renewable energy, there has been a significant amount of financing and investing in the renewable energy sector.

Despite the plunge in the oil price, the strength of the U.S. dollar and the continued weakness of the European economy, global investment in renewable power and fuels reached a record level of USD 286 billion in 2015 (REN21, 2016). Several developments in the last years, such as the extreme decline in global fossil fuel prices and the Paris agreement, have contributed to this large-scale investment. As illustrated in Figure 2.1, global investment in renewable energy in 2015 exceeded the previous record of USD 278 billion achieved in 2011 by USD 8 billion, amounting to a percentage increase of 3%. Developing countries[1], including China, India and Brazil, invested a total of USD 156 billion in renewable energy in 2015, which equals an increase of 19% relative to 2014. The developed countries, on the other hand, invested USD 130 billion, investing 8% less than in 2014.

[1] Developing countries are distinguished from industrialized and already developed countries by a less developed industrial base and a low Human Development Index

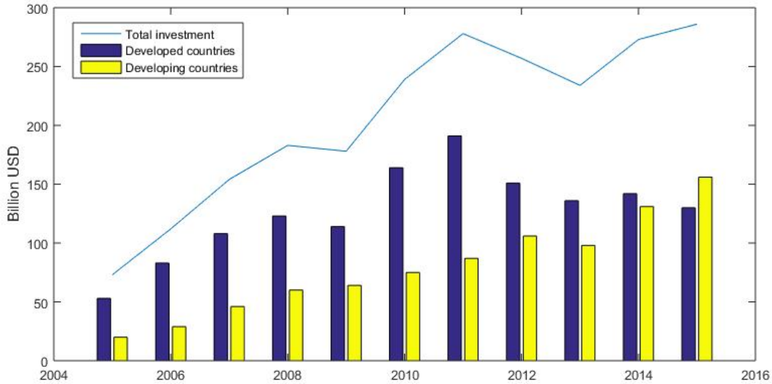


Figure 2.1: Global new investment in renewable power and fuels for developed and developing countries in the period 2005-2015

Source: Global status report 2016, REN21

The biggest decrease in renewable energy investments was seen in Europe, which invested USD 48.8 billion in 2015, representing a 21% decrease compared to 2014. Investments in Europe declined to the lowest figure since 2006 in 2015 (Frankfurt School-UNEP Collaborating Centre for Climate & Sustainable Energy Finance, 2016). Investments in renewable energy power and fuels were in 2015 dominated by five countries, namely China, United States, Japan, United Kingdom and India. The next five countries were Germany, Brazil, South Africa, Mexico and Chile. In general, investments increased in China, India, Africa and the Middle East, and the United States, while it decreased in Canada and Europe. Asset financing of utility-scale projects accounted for the majority of the investments in the top ten investing countries. The investments in the United States were, however, characterized by small-scale distributed capacity and public markets as well, while investments from Japan came mainly from small-scale distributed capacity. (REN21, 2016)

According to Norges Bank Investment Management (2015), private investors have replaced governments as the most important source of capital for renewable energy projects over the past decade. Norges Bank Investment Management identifies two factors causing this development, namely technological improvements and renewable energy policies. Technological improvements have led to increased reliability and declining costs, while renewable energy policies have created new market opportunities that have encouraged private sector investments. Several countries have adopted a variety of mechanisms to produce the policy mix best tailored to their economical situation. Historically, government support for renewable energy has been split between tariff based instruments like feed-in tariffs (FITs) and quantity-based instruments like tendering schemes. As costs are expected to decline further, Norges Bank Investment Management argues that supportive policies are likely to be replaced by competitive market-based tenders going forward.

The majority of renewable energy technologies continue to grow, in terms of both capacity and output. According to IRENA (2017), the total amount of electricity generated from renewables amounted to 5660 TWh in 2015, which is 23.5% of all electricity generated. Hydropower accounted for 58% of the total capacity, while solar PV [2] and wind power accounted for 23% and 12% respectively. The contribution of all renewables to the global energy mix grew significantly in 2015, particularly in the electricity sector. Renewable power generation capacity grew by 154 GW over 2014, representing an increase of 9.3%. The greatest additions were in wind, solar PV and hydropower (IRENA, 2017). Traditionally, hydropower has accounted for the greatest additions in capacity. In 2015, for the first time ever, additions of both wind and solar PV exceeded those of hydropower. Norges Bank Investment Management (2015) argues that onshore wind and solar PV are the technologies closest to being competitive with other sources of energy without subsidies.

During the last couple of years, the solar sector has become predominant in the renewable energy sector. Several factors have contributed to this development, including improvements in energy storage systems, increased efficiency and improved cost-competitiveness. The solar sector was the leading sector in terms of money devoted during 2015, and accounted for more than 56% of total new investment in renewable power and fuels. Solar power is the fastest growing renewable energy technology, with a 12% increase in the global new investment in 2015 compared to 2014. The wind sector experienced a modest growth of 4%, while all other renewable technologies experienced a reduction in investments in 2015 compared to 2014. The most significant reduction was seen in the biomass and waste-to-energy sector and the wave and tidal sector, which both declined by 42% (REN21, 2016).

China, Japan and the United States accounted for the majority of the capacity added in the solar PV market in 2015, with emerging markets on all continents contributing significantly to global growth. According to IRENA (2017), the global PV capacity escalated from 40 GW in 2010 to 219 GW in 2015. IRENA (2016a) estimates that the capacity of solar PV power generation can grow from 230 GW at the end of 2015 to between 1600 GW and 2000 GW by 2030, representing a sevenfold increase. Solar PV will account for as much as 7% of global power generation by 2030, which is six times as much as today (IRENA, 2017). The increased production capacity is driven mainly by improved economics. Solar PV is now competitive with conventional sources of electricity, as costs have reduced significantly over the last years. The solar PV costs is now half of what they were in 2010. Moreover, the cost of solar PV modules has fallen by 80% since 2009. IRENA (2017) estimates that solar PV costs could fall by another 60% over the next decade. According to (IRENA, 2017), ongoing technological innovations, continuing economies of scale, additional automation in production and economic pressures will push costs down even further. The solar CSP market experienced a shift from traditional CSP markets such as Spain and the United States to developing regions (REN21, 2016). In 2015, Morocco, South Africa and the United States were the biggest contributors.

Norges Bank Investment Management (2015) states that renewables will play a growing role in the global power mix in the years to come. By 2027, wind and solar will get cheaper than running existing coal and gas generators. According to Bloomberg New Energy Finance (2016), this tipping point will result in rapid and widespread developments

[2] The two most widely recognized ways of converting solar energy into electricity are photovoltaics (PV) and concentrated solar power (CSP), hereby referred to as solar PV and solar CSP

within the renewable energy sector. Bloomberg New Energy Finance (2016) estimates that zero-emission energy sources will make up 60% of the installed capacity by 2040. The Asia-Pacific region will experience the largest growth in new power generation capacity, with renewables accounting for nearly two-thirds of the additions. The Middle East and Africa will experience an eightfold increase in renewables over the next 25 years. Solar and wind will account for around 60% of total additions, the majority of which being utility-scale solar PV. Renewables will rise to 70% of generation in Europe in 2040, with solar making up almost half of all new capacity. Overall, non-OECD countries will see the majority of new capacity, with China and India leading the way. Although coal will continue to be important, renewables will make up 61% of deployment in the non-OECD economies. The growing electricity demand in the OECD does, on the other hand, continue to look weak. Even though these projections provide valuable insight into the renewable energy trends going forward, it is important to stress that projections of this time horizon are associated with considerable uncertainty.

Chapter 3

Literature Review

In line with the increased growth of the renewable energy sector over the last decade, there has been a significant increase in the number of studies investigating the performance and price behavior of renewable energy stocks, indices and companies (Henriques and Sadorsky, 2008, Schmitz, 2009, Inchauspe, 2011, Sadorsky, 2012, Kumar et al., 2012, Managi and Okimoto, 2013, Ortas and Moneva, 2013, Reboredo, 2015, Inchauspe et al., 2015, Bohl et al., 2015). Although the interest has increased, the number of studies investigating renewable energy investments is relatively small. In particular, there are few studies conducted before 2000. This makes it hard to investigate the time evolution of renewable energy stocks. Additionally, almost no studies compare the performance of different sectors within renewables. The literature presented in this chapter is therefore mainly revolved around recent studies of the renewable sector as a whole.

Henriques and Sadorsky (2008) use a four-variable vector autoregression model to investigate the empirical relationship between alternative energy stock prices, technology stock prices, oil prices and interest rates. The paper states that the overall impact of rising oil prices on the stock prices of alternative energy companies should be positive, as rising oil prices encourage substitution towards other energy sources. The authors do, nevertheless, find that shocks to oil prices have little significant impact on the stock prices of alternative energy companies. In fact, Henriques and Sadorsky find that a shock to technology stock prices has a larger impact on alternative energy stock prices than a shock to oil prices.

Schmitz (2009) uses a CAPM-GARCH multi-factor market model to investigate the relationship between returns on oil and alternative energy stocks. The results indicate that an increase in oil prices and the market in general have a significant positive impact on alternative energy stocks. Furthermore, estimation of the alternative energy index indicated presence of abnormal returns, which were generated from a different sectoral component than the solar sector. This result differs from that of Henriques and Sadorsky (2008), which concluded that virtually no abnormal returns were generated from alternative energy companies.

Inchauspe (2011) uses a state-space methodology for modelling excess returns for the Wilderhill New Energy index. The first part of the paper uses a Kalman-filter multi-factor model that allows for time-varying beta factors, while the second part uses a Markov-switching autoregressive distributed lag model. None of the models provides evidence of excess returns on oil prices being a significant contributor to the NEX excess returns. The latter suggests that both Amex Oil and NASDAQ returns contribute significantly to the NEX returns.

Sadorsky (2012) uses four different multivariate GARCH models to examine volatility spillovers between oil prices and stock prices of clean energy and technology companies. The study finds evidence that the stock prices of clean energy companies correlate more highly with technology stock prices than with oil prices, supporting the findings of Henriques and Sadorsky (2008).

Kumar et al. (2012) extend the work of Henriques and Sadorsky (2008) by also considering carbon market data before and after oil price peaks. The results show that past movements in oil prices, stock prices of high technology firms and interest rates explain the variation in the indices of clean energy stocks. Carbon price returns, on the other hand, are not significant for the stock price movements of clean energy firms. The study also finds that investors view the stocks of clean energy companies as they view the stocks of high technology firms, supporting the results of Henriques and Sadorsky (2008) and Sadorsky (2012).

Managi and Okimoto (2013) investigate the relationship between oil prices, clean energy stocks and technology stock prices. The authors extend previous work by lengthening the data period up to 2010. In addition, Markov-switching vector autoregressive (MSVAR) models are applied to the economic system consisting of oil prices, clean energy and technology stock prices, and interest rates. Managi and Okimoto find that oil prices have positively affected clean energy stock prices after the structural break in late 2007, suggesting a movement from conventional to clean energy. This result is in contrast to the results of Henriques and Sadorsky (2008).

Ortas and Moneva (2013) use a modified state-space market model to recursively estimate the risk and return performance of 21 primary Clean Techs (CT) equity indices. The main findings of the study indicate that Clean Techs indices outperform the benchmarks in terms of returns during periods of market stability. Moreover, CT indices are more volatile during the financial crisis than in periods of market stability.

Reboredo (2015) uses copulas and the conditional value at risk measure to study systematic risk and dependence between oil and renewable energy markets. The results indicate that oil price dynamics significantly contribute around 30% to upside and downside risk of renewable energy companies. Furthermore, Reboredo finds significant time-varying average and symmetric tail dependence between oil returns and several global and sectoral renewable energy indices.

Inchauspe et al. (2015) examine the dynamics of excess return for the Wilderhill New Energy Global Innovation index by using a multi-factor asset pricing model with time-varying coefficients. The results suggest a strong influence of the MSCI World index and technology stocks. Even though oil has become more influential from 2007 onwards, the influence of changes in the oil price is significantly lower than the influence of the MSCI World index and technology stocks. Moreover, the authors find evidence for underperformance of the renewable energy sector after the financial crisis.

Bohl et al. (2015) examine the return behavior of German renewable energy stocks in the period between 2004 and 2011 by using Carhart four-factor model in the state-space form and bubble detection tests. The authors find that German renewable energy stocks earned considerable risk-adjusted returns between 2004 and 2007, while the performance completely reversed between 2008 and 2011. Recent risk and return characteristics therefore indicate that investors should be cautious when holding German alternative energy stocks in their portfolio, as these could damage the overall performance.

This study contributes to the stream of existing literature by studying the impact of the global stock market, oil prices, technology stocks and the stock market volatility on both renewable energy stocks and solar stocks. As pointed out by Bohl et al. (2015), risk and return behavior might vary across subsectors, making it interesting to examine the performance of the biggest subsector within the renewable energy sector. Moreover, Schmitz (2009) argues that it is more risky to invest in the solar sector than to invest in other alternative energy sectors. This is yet another motivating factor for this study.

Chapter 4

Data

This chapter presents the data used in the analysis of this study. First, descriptive statistics for all sample data are presented, before more accurate descriptions of each index are presented. In the last section, the results of the Chow test are explored.

4.1 Data description

This study analyzes five equity indices and one commodity, namely the Wilderhill New Energy Global Innovation Index (NEX), the Ardour Solar Energy Index (SOLRX), the MSCI World Index (MSCI), the NYSE Aca Tech 100 Index (PSE), the CBOE Volatility Index (VIX) and the West Texas Intermediate (WTI). All data is gathered from Datastream for the time period from 01.02.2005 to 01.02.2017.

For all data series, monthly market data is used in order to calculate the continuously compounded returns over the risk-free asset, given by the following equation:

$$r_{i,t} = ln(p_{i,t}) - ln(p_{i,t-1}) - r_t^l \tag{4.1}$$

where $p_{i,t}$ is the monthly closing price of the stock index or the commodity, *i*, in month t, ln is the natural logarithm and r_t^l is the return of the risk-free asset on day t.

The risk-free rate represents the minimum return an investor would expect for any investment. For this study, the monthly U.S. Treasury Bill is used to represent the risk-free asset. As U.S. Treasury Bills are backed by the credit of the U.S. Government, T-bills are commonly used as risk-free rates as the market considers it to be highly unlikely that the government will default on its obligations. Additionally, U.S.-based investors often use U.S. T-bills as the risk-free rate in order to avoid being subject to currency risk. Since all index prices for this study are denominated in U.S. dollars, it is natural to use the monthly T-Bill to represent the risk-free rate.

Figure 4.1 and Figure 4.2 exhibit the performance of the sample data, while Table 4.1 gives an overview of the descriptive statistics for the monthly sample data. In order to compare the price evolution for the data series in Figure 4.1, each series is set equal to a base value of 100 at the beginning of the sample period. Both the NEX and the SOLRX exhibit negative monthly average returns of -0.15% and -0.89%, respectively.

The median, however, is positive for the NEX. The MSCI, the PSE and the WTI provide positive average monthly returns and positive monthly medians. The SOLRX has the second highest standard deviation, which is almost twice as high as for the NEX. The VIX offers the greatest standard deviation for sample period, but this result is somewhat expected as the index captures market insecurity. The Jarque-Bera test shows that none of the data series in the sample are normally distributed. The direct beta, which is given as the beta coefficient for the returns of the sample data against the MSCI index, is 1.5 for the NEX and 2.3 for the SOLRX. Thus, both the NEX and the SOLRX are subject to high systematic risk and have greater standard deviations than the market.

As exhibited in Table 4.2, the returns of the NEX have a high correlation with the returns of the MSCI and the PSE, and a significant correlation with the returns of the WTI. Table 4.3 illustrates that the same correlations are found between the SOLRX and the MSCI, the PSE and the WTI, although to a lesser extent. The correlation coefficient for the returns of the VIX is negative for both the returns of the NEX and for the returns of the SOLRX. Figure 4.2 shows the yearly correlation coefficients between the NEX and the MSCI, the PSE, the VIX and the WTI, and Figure 4.3b shows the yearly correlation between the SOLRX and the MSCI, the PSE, the VIX and the WTI. The correlation between the NEX and the MSCI and between the NEX and the PSE is rather stable during the sample period. The correlation coefficients between the NEX and the WTI and between the NEX and the VIX, on the other hand, vary greatly over time. The correlations between the SOLRX and the MSCI, the PSE, the VIX and the WTI exhibit the same patterns as the NEX. However, the correlations between the SOLRX and the MSCI and the PSE are more unstable than those of the NEX, especially after 2009. For both the NEX and the SOLRX, the correlation coefficients with the WTI were almost zero in 2013.

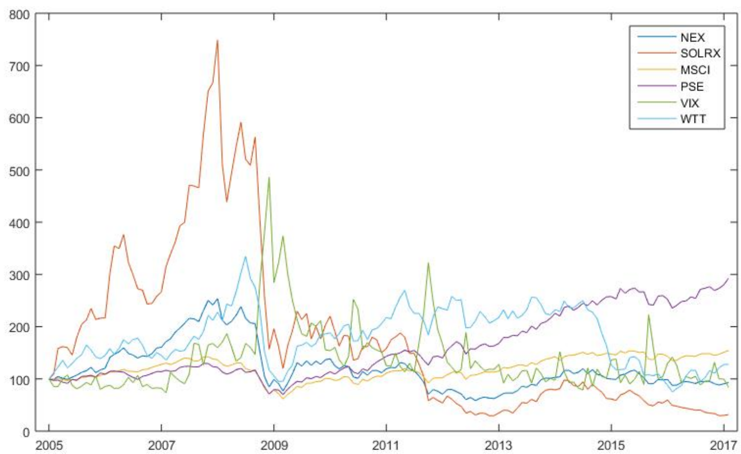
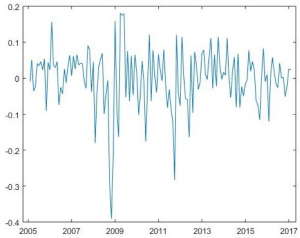
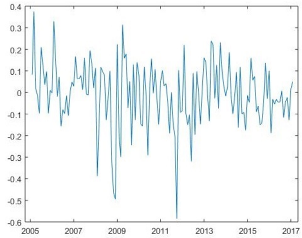


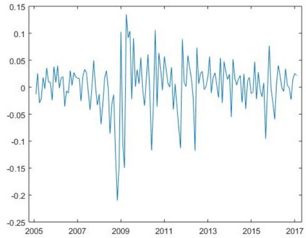
Figure 4.1: Stock price for the NEX, the PSE, the MSCI, the VIX, the SOLRX and the WTI for the time period 01.02.2005-01.02.2017



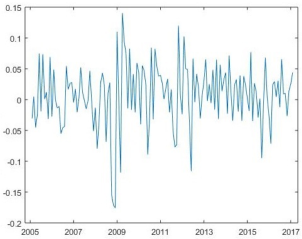
(a) Returns for the NEX



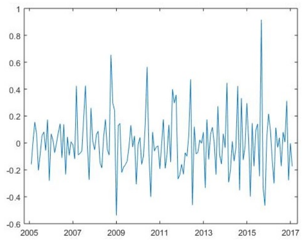
(b) Returns for the SOLRX



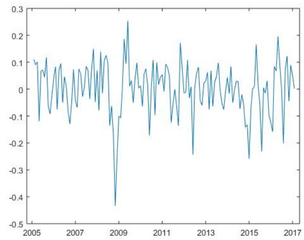
(c) Returns for the MSCI



(d) Returns for the PSE



(e) Returns for the VIX



(f) Returns for the WTI

Figure 4.2: Excess stock returns for the NEX, the SOLRX, the MSCI, the PSE, the VIX and the WTI for the time period 01.02.2005-01.02.2017

Table 4.1: Descriptive statistics for monthly excess returns

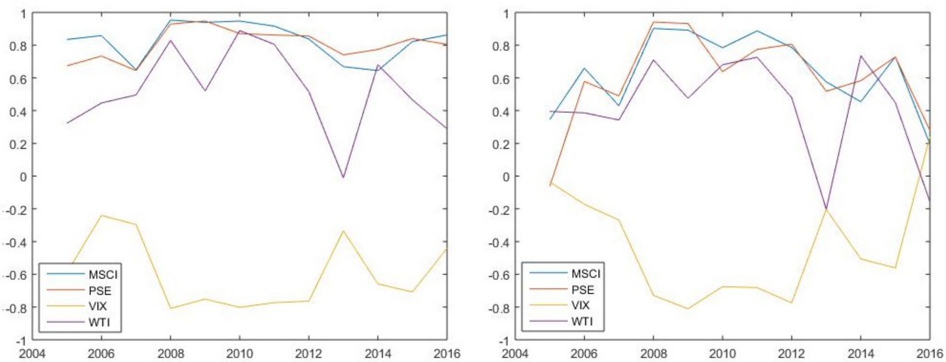
	NEX	**SOLRX**	**MSCI**	**PSE**	**VIX**	**WTI**
Maximum	**18.11 %**	**37.51 %**	13.55 %	14.03 %	91.63 %	25.38 %
Minimum	**-39.06 %**	**-58.50 %**	-20.98 %	-17.59 %	-53.83 %	-43.42 %
Range	**57.17 %**	**96.01 %**	34.52 %	31.62 %	145.45 %	68.80 %
Mean	**-0.15 %**	**-0.89 %**	0.20 %	0.64 %	-0.22 %	0.07 %
Median	**0.67 %**	**-0.37 %**	0.61 %	0.99 %	-1.28 %	0.87 %
St.Dev.	**8.55 %**	**15.31 %**	5.01 %	5.23 %	22.13 %	9.96 %
Variance	**0.0073**	**0.0235**	0.0025	0.0027	0.0490	0.0099
Skewness	**-1.1570**	**-0.6841**	-0.9566	-0.6734	0.7304	-0.8542
Kurtosis	**6.4625**	**4.5500**	5.8307	4.5246	4.8115	5.0318
Jarque-Bera	**0.3674**	**0.1426**	0.2705	0.1391	0.1644	0.2063
Normal dist.	**No**	**No**	No	No	No	No
Direct beta	**1.5009**	**2.2529**	1.0000	0.9530	-3.1787	1.0761

Table 4.2: Correlation matrix for monthly excess returns for the NEX

	NEX	MSCI	PSE	VIX	WTI
NEX	1				
MSCI	0.8790	1			
PSE	0.8430	0.9121	1		
VIX	-0.5964	-0.7191	-0.7055 1		
WTI	0.5940	0.5411	0.4667	-0.2824	1

Table 4.3: Correlation matrix for monthly excess returns for the SOLRX

	SOLRX	MSCI	PSE	VIX	WTI
SOLRX	1				
MSCI	0.7367	1			
PSE	0.6927	0.9121	1		
VIX	-0.4707	-0.7191	-0.7055	1	
WTI	0.4854	0.5411	0.4667	-0.2824	1

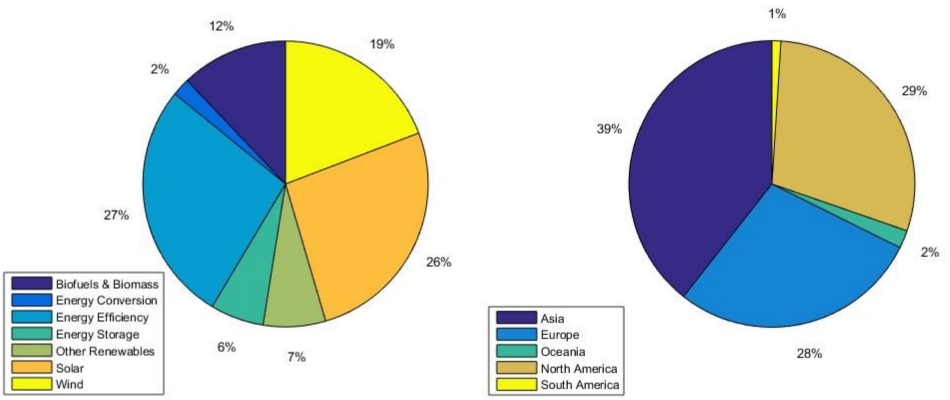


(a) Correlation with the NEX **(b)** Correlation with the SOLRX

Figure 4.3: Yearly correlation coefficients between the NEX and the SOLRX and the MSCI, the PSE, the VIX and the WTI

4.1.1 The WilderHill New Energy Global Innovation Index (NEX)

The NEX is a major international renewables benchmark with a market capitalization of USD \$252 billion as of September 30th 2016. The index is composed of 99 companies in 26 different markets. As exhibited in Figure 4.4a, the NEX is mainly comprised of companies with operations within energy efficiency, solar, wind and biomass & biofuels. Figure 4.4b illustrates that most of the companies included in the index are located in North America, Asia and Europe. The index components are chosen based on technological, environmental, and relevance-to-the-sector criteria – rather than a risk-averse portfolio strategy. Thus, the NEX captures both downward and upward movements of global clean energy and may therefore appear as more volatile compared to other global renewable indices (WHNEF, 2016). Although some studies have used the WilderHill Clean Energy Index (ECO) in their analyses (Henriques and Sadorsky, 2008, Sadorsky, 2012, Kumar et al., 2012, Managi and Okimoto, 2013), more recent studies (Kumar et al., 2012, Inchauspe et al., 2015) have chosen the NEX over the ECO. The global reach of the NEX and its direct focus on production of renewable energy, are the main reasons for choosing the NEX over the ECO.



(a) Sector distribution for the NEX **(b)** Location distribution for the NEX

Figure 4.4: Sector and location distribution for the NEX as of Q2 2017

4.1.2 The Ardour Solar Energy Index (SOLRX)

The SOLRX is a global index composed of solar companies exclusively, which serves as one out of two main global solar indices. The index consists of 15 companies, covers seven markets and covers two technologies of solar energy, namely solar PV and solar CSP. As exhibited in Figure 4.5, almost two-third of the companies included in the SOLRX are located in Asia, while the remaining companies are located in North America and Europe. The index provides exposure to publicly traded companies that derive at least 66% of their revenues from solar power and related products and services. On a weighted basis, the index derives 90% of its revenues from the solar industry exclusively. About one third of the solar companies included in the NEX are represented in the SOLRX, accounting for 8% of the companies included in the NEX on a weighted basis. The SOLRX has been used in several recent studies that analyze the performance of the solar sector (Ortas and Moneva, 2013, Chan and Walter, 2014).

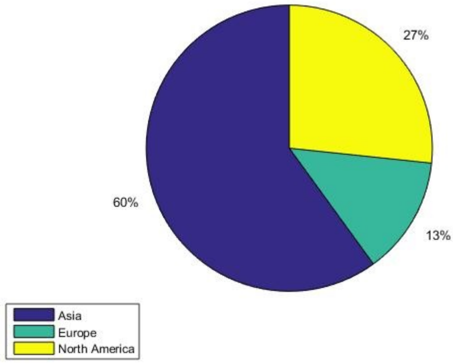


Figure 4.5: Location distribution for the SOLRX as of March 17th 2017

4.1.3 The MSCI World Index (MSCI)

The MSCI is a broad global equity benchmark that represents large and mid-cap equity performance across 23 developed countries. The index covers approximately 85% of the free-float adjusted market capitalization in each country. The index is composed of 1.652 stocks and has been calculated since 1969 (INC., 2017). As opposed to the S&P500 Index, the MSCI is a purely cap-determined index that includes components from all over the world. The MSCI is therefore considered a better option for this study, as both the NEX and the SOLRX cover markets in several countries.

4.1.4 The NYSE Arca Tech 100 Index (PSE)

The PSE provides a benchmark for measuring the performance of technology-utilizing companies operating across a broad spectrum of industries. The index has been tracked since 1982, and is modeled as a multi-industry innovative technologies index (Wikipedia, 2015). The PSE has been used in several studies over the last couple of years, including Kumar et al. (2012), Sadorsky (2012) and Inchauspe et al. (2015).

4.1.5 The Western Texas Intermediate (WTI)

The WTI is one out of three primary oil benchmarks, and refers to oil extracted from wells in the U.S. The WTI continues to be the main benchmark for oil consumed in the United States (Kurt, 2015). The WTI is one of the most commonly used oil benchmarks in the literature (Henriques and Sadorsky, 2008, Sadorsky, 2012).

4.1.6 The CBOE Volatility Index (VIX)

The VIX is a measure of the implied volatility of the S&P 500 index, calculated by the Chicago Board Options Exchange. To date, the index is regarded the premier barometer of investor sentiment and market volatility. The index represents the market's expectation of stock market volatility over the next 30-day period (CBOE, 2017). Although some studies have assessed the influence of the VIX on stock returns (Giot, 2005, Ang et al., 2006), the influence on renewable energy stock returns is, to our knowledge, yet to be evaluated. Hence, including the VIX in the analysis might lead to additional insights into renewable energy stock returns.

4.2 Testing for time-varying betas

For the proposed multi-factor model, all alphas and betas are allowed to be time-varying. For such a model to be appropriate, the factors should indeed exhibit substantial variation through time. In order to prove – or disprove – such a variation, the Chow test is performed. The Chow test aims to test equality of sets of coefficients in two or more regressions, and follows the F distribution with k and $N_1 + N_2 + ... + N_i - 2k$ degrees of freedom. The null hypothesis of the test claims that there is no break point, meaning that the data set can be represented with a single regression line. This null hypothesis is rejected if the F Chow value falls into the rejection region, i.e. below the F critical value.

The following regression model is considered: $y_t = a+\beta x_{1t}+cx_{2t}+\varepsilon$. For one single breakpoint, the data can be split into the following two groups: (1) $y_t = a_1 + \beta_1 x_{1t} + c_1 x_{2t} + \varepsilon$ and (2) $y_t = a_2 + \beta_2 x_{1t} + c_2 x_{2t} + \varepsilon$. The null hypothesis of the Chow test asserts that $a_1 = a_2$, $b_1 = b_2$ and $c_1 = c_2$. The model errors, ε, are identically distributed from a normal distribution with unknown variance.

The F Chow value for one single breakpoint is given as:

$$\frac{RSS_p - (RSS_1 + RSS_2)/k}{(RSS_1 + RSS_2)/(N_1 + N_2 - 2k)} \tag{4.2}$$

where RSS_p is the residual sum of squares for the combined regression line, RSS_1 is the regression line before the break, RSS_2 is the regression line after the break, N_1 is the number of observations before the break, N_2 is the number of observations after the break and k is the number of parameters. The formula can easily be extended to more than one breakpoint.

The Chow test for monthly data is performed with 22 and 121 degrees of freedom and $\alpha = 0.05$ on all factors, so that $X \sim F_{(0.05,22,121)}$. The test is performed with yearly breakpoints. The results, exhibited in Table 4.4 for regressions against the NEX and in Table 4.5 for regressions against the SOLRX, show that the null hypothesis is rejected for all data series. Thus, the regression coefficients are different for the split data sets. In conclusion, the beta coefficients are considered to be time-varying and a state-space model with time-varying coefficients is deemed appropriate for this study. This is also supported by the time-varying correlations illustrated in Figure 4.3.

Table 4.4: Chow test results for the NEX with yearly breakpoints

Index	Chow value	F critical value	Time varying
MSCI	2.0682	1.6310	Yes
PSE	2.6661	1.6310	Yes
VIX	3.6687	1.6310	Yes
WTI	2.1223	1.6310	Yes

Table 4.5: Chow test results for the SOLRX with yearly breakpoints

Index	Chow value	F critical value	Time varying
MSCI	1.9044	1.6310	Yes
PSE	2.5638	1.6310	Yes
VIX	2.8924	1.6310	Yes
WTI	1.7575	1.6310	Yes

Chapter 5

Methodology

The following chapter presents the methodology used in the study. First, the state-space multi-factor asset pricing model is introduced. Then, the model selection is explored. Lastly, the test for residual heteroscedasticity is presented.

5.1 State-space model

There exists a number of different techniques by which one can model and estimate time-varying beta values, with some of the most common being different versions of GARCH models, Markov switching models and the state-space approach. Several studies argue in favor of using state-space approaches (Bollerslev et al., 1988, Jagannathan and Wang, 1996, Brooks et al., 1998, Berglund and Knif, 1999, Koopman et al., 1999, Faff et al., 2000, Tsay, 2005, Mergner and Bulla, 2008, Choudhry and Wu, 2009, van Geloven and Koopman, 2009), as this method enables one to analyze variables through time as well as the dynamic relationship between them. For this study, a state-space model is deemed appropriate, as the approach will allow one to closely investigate the dynamics of the drivers behind renewable energy returns. Additionally, both the renewable energy sector and the solar sector are emerging markets. Moonis and Shah (2003) and Holmes and Faff (2008) point out that emerging markets are particularly volatile, making time variation in risk levels natural.

In order to estimate the time-varying coefficients, a four-factor state-space model is formulated and the Kalman filter is applied. Applying the Kalman filter allows one to solve the linear state-space equation to optimality, and the technique is successfully applied in previous studies (Koopman et al., 1999, Tsay, 2005, Commandeur and Koopman, 2007, Durbin and Koopman, 2012, Inchauspe et al., 2015). The Kalman filter assumes that the market model residual is Gaussian and homoscedastic (Moonis and Shah, 2003). The time-varying coefficients in the state-space are assumed to follow a pure random walk, as supported by Faff et al. (2000). The analysis is run in EViews.

The proposed model is formulated as a state-space multi-factor model with five time-varying coefficients, namely α_t, $\beta_{MSCI,t}$, $\beta_{PSE,t}$, $\beta_{VIX,t}$ and $\beta_{WTI,t}$. The analysis is run on both the NEX and the SOLRX where $r_{renewable,t}$ denotes the monthly excess returns at time t of either the NEX or the SOLRX, depending on the respective analysis. The monthly excess returns of the MSCI, the PSE, the VIX and the WTI at time t are represented as $r_{MSCI,t}$, $r_{PSE,t}$, $r_{VIX,t}$ and $r_{WTI,t}$, respectively.

The model is given as:

$$r_{renewable,t} = \alpha_t + \beta_{MSCI,t} r_{MSCI,t} + \beta_{PSE,t} r_{PSE,t} + \beta_{VIX,t} r_{VIX,t} + \beta_{WTI,t} r_{WTI,t} + \varepsilon_t, \quad \varepsilon_t \sim nid(0, \sigma_\varepsilon^2) \tag{5.1}$$

$$\alpha_{t+1} = \alpha_t + \tau_{\alpha,t}, \quad \tau_{\alpha,t} \sim iid(0, \sigma_{\tau_\alpha}^2) \tag{5.2}$$

$$\beta_{MSCI,t+1} = \beta_{MSCI,t} + \tau_{MSCI,t}, \quad \tau_{MSCI,t} \sim iid(0, \sigma_{\tau_{MSCI}}^2) \tag{5.3}$$

$$\beta_{PSE,t+1} = \beta_{PSE,t} + \tau_{PSE,t}, \quad \tau_{PSE,t} \sim iid(0, \sigma_{\tau_{PSE}}^2) \tag{5.4}$$

$$\beta_{VIX,t+1} = \beta_{VIX,t} + \tau_{VIX,t}, \quad \tau_{VIX,t} \sim iid(0, \sigma_{\tau_{VIX}}^2) \tag{5.5}$$

$$\beta_{WTI,t+1} = \beta_{WTI,t} + \tau_{WTI,t}, \quad \tau_{WTI,t} \sim iid(0, \sigma_{\tau_{WTI}}^2) \tag{5.6}$$

The state-space matrix representation is formulated as:

$$\begin{pmatrix} B_{t+1} \\ r_{renewable,t} \end{pmatrix} = \phi_t B_t + u_t \tag{5.7}$$

where the state equation is given as:

$$B_{t+1} = F B_t + v_t, \quad v_t \sim N(0, Q_t) \tag{5.8}$$

and the measurement equation is given as:

$$r_{renewable,t} = H_t B_t + \varepsilon_t, \quad \varepsilon_t \sim nid(0, \sigma_{\varepsilon,t}) \tag{5.9}$$

where

$$H_t = [1 \; r_{MSCI,t} \; r_{PSE,t} \; r_{VIX,t} \; r_{WTI,t}],$$

$$B_t = [\alpha_t \; \beta_{MSCI,t} \; \beta_{PSE,t} \; \beta_{VIX,t} \; \beta_{WTI,t}]',$$

$$F = I_5,$$

$$v_t = I_5[\tau_{a,t} \; \tau_{MSCI,t} \; \tau_{PSE,t} \; \tau_{VIX,t} \; \tau_{WTI,t}],$$

$$Q_t = [\sigma_{\tau\alpha,t} \; \sigma_{\tau MSCI,t} \; \sigma_{\tau PSE,t} \; \sigma_{\tau VIX,t} \; \sigma_{\tau WTI,t} \;],$$

$$\phi_t = [T_t H_t]$$

$$u_T = [Q_t \varepsilon_t]$$

The model is inspired by previous applications of state-space models, particularly the three-factor state-space model proposed by Inchauspe et al. (2015). The model in this study is, however, extended by taking account for the market's expectation of stock market volatility by including the returns over the VIX index. In addition, the model is run for both the NEX and the SOLRX, not only the NEX, which provides a basis for comparison between the sector as a whole and the solar sector.

5.2 Model selection

In order to find the best-fitting model, different candidate models are tested and evaluated based on a set of information criteria. The candidate models differ from each other based on whether each factors is kept constant over time or is able to vary. In order to choose among the candidate models, the models' corresponding Akaike information criterion (AIC), Bayesian information criterion (BIC) and Hannan-Quinn criterion (HQ) are considered. The log likelihood function serves as an input for the AIC, the BIC and the HQ, and a high log likelihood value leads to lower values for the AIC, the BIC and the HQ. The log likelihood function is evaluated at the estimated values of the coefficients, assuming normally distributed errors. It is based on the comparison of restricted and unrestricted versions of an equation.

In EViews, the log likelihood is computed as:

$$l = -\frac{T}{2}(1 + log(2\pi) + log(\frac{\hat{\epsilon}'\hat{\epsilon}}{T})) \tag{5.10}$$

where T is the number of observations and $\hat{\epsilon}$ is the residual.

The AIC is a measure of the relative quality of statistical models for a given set of data, and the preferred model is the one with the lowest AIC value.

The AIC is computed as:

$$AIC = -\frac{2l}{T} + \frac{2k}{T} \tag{5.11}$$

where l is the log likelihood and k is the number of estimated parameters in the model.

Bayesian Information Criterion (BIC) is an extension of the AIC that imposes larger penalty for additional coefficients.

The BIC is given as:

$$BIC = -\frac{2l}{T} + \frac{klogT}{T} \tag{5.12}$$

The Hannan-Quinn Criterion (HQ) is an even further extension of the AIC, and employs yet another penalty function.

The HQ is formulated as:

$$HQ = -\frac{2l}{T} + \frac{2klog(log(T))}{T} \tag{5.13}$$

For each of the candidate models, the AIC, the BIC and the HQ are considered, and a lower value indicates a better model fit. As the AIC, BIC and HQ values might favor different candidate models, it is important to compare them in order to find the best possible fit. With regard to this study, the preferred models for both the NEX and for the SOLRX have the lowest AIC, BIC and HQ values.

5.3 Testing for residual heteroscedasticity

A widespread belief in the field of economic theory is that volatility clustering is present only in high-frequency data. The empirical analysis of Jacobsen and Dannenburgb (2003) does, however, show that the homoscedasticity assumption for monthly stock return series can be rejected. The same result is obtained when examining shorter time series for low frequencies. Therefore, in order to avoid volatility clusters in the time series, a stock market volatility index is added to the state-space model. Contrary to Inchauspe (2011), who discards the state-space model due to evidence of volatility clustering, we believe that adding the CBOE Volatility Index (VIX) to the state-space model will allow us to take advantage of the benefits the state-space approach provides, while at the same time avoiding the implications of volatility clustering.

The Kalman filter assumes that the market model residuals are Gaussian and homoscedastic, which means that all random variables have the same finite variance and that no volatility clustering is present. However, there is abundant evidence of unconditional non-normality and heteroscedasticity in financial time series, as suggested by Bollerslev et al. (1988), Schwert and Seguin (1990), Ng (1991) and Moonis and Shah (2003), to mention some. If evidence of non-normality or heteroscedasticity is found, one should model the heteroscedasticity to obtain estimates that are more efficient by using for instance a modified Kalman filter or a GARCH model. One way to test for residual heteroscedasticity is to conduct the Engle's ARCH test for univariate residual series. The null hypothesis of the test is that the series of residuals exhibit no conditional heteroscedasticity (ARCH effects), against the alternative that the series are described by an ARCH model.

The Engle's ARCH test is conducted for both renewable stocks and solar stocks in MATLAB. Five tests, with 1, 2, 3, 4 and 5 lagged terms, are conducted at a 1% and a 5% significance level. As illustrated in Table 7.2 and Table 7.3 in Appendix E, results of the tests indicate failure to reject the null hypothesis for both the NEX and the SOLRX in all cases, meaning that there is no evidence of conditional heteroscedasticity in the return series of the NEX and the SOLRX. A state-space approach using the Kalman filter is therefore considered appropriate for estimating the drivers of renewable returns and solar returns.

Chapter 6

Results

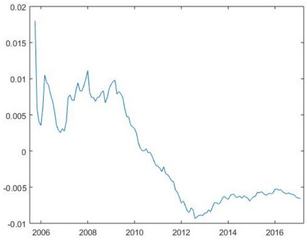
In the following chapter, the results of the study are interpreted and discussed. Model output for the NEX and the SOLRX is presented, before a detailed comparison of the estimated alphas and estimated beta coefficients for each factor for both the NEX and the SOLRX is provided. The model output for both the NEX and the SOLRX exhibits small variances of the estimated coefficients and large Z-statistics, indicating that the state-space model is an appropriate estimation technique and that the model is a good fit. Detailed model output for the analysis for the NEX and for the SOLRX is found in Appendix E.

Note that due to the Kalman filter, it takes a while before the estimated beta coefficients settle. This period of time is referred to as the burning period of the model. Due to significant peaks in the first eight estimations, these results are considered invalid and are ignored in the following analysis.

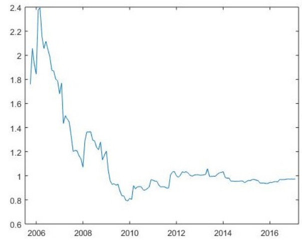
6.1 Overall model output for the NEX and the SOLRX

According to the information criteria, the best-fitting model for the NEX is the one where all factors but the VIX are able to vary. The average mean squared error (MSE) using this model is 8.79E-06, indicating that this model is a very good estimator of the returns of the NEX. However, there is little variation in the values of the information criteria for regressions where none or one factor is kept constant. Keeping more than one variable constant results in very low log likelihood values and very high values for both the AIC, the BIC and the HQ, and thereby a poor estimation.

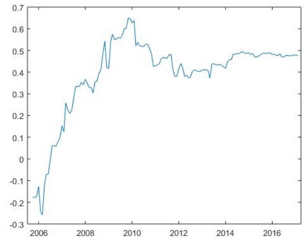
Figure 6.1 exhibits the estimated alpha and the estimated beta coefficients from October 2005 to February 2017 where the VIX coefficient is kept constant, while Table 6.1 exhibits the estimation results for the coefficients.



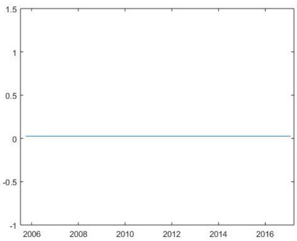
(a) Estimated alpha



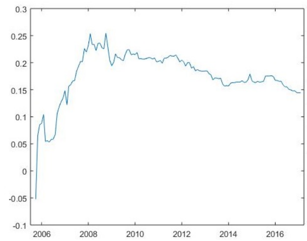
(b) Estimated beta coefficient for the MSCI



(c) Estimated beta coefficient for the PSE



(d) Estimated beta coefficient for the VIX



(e) Estimated beta coefficient for the WTI

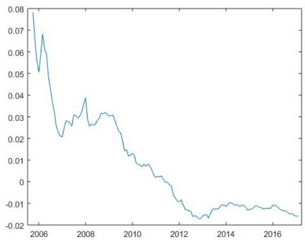
Figure 6.1: Alpha and beta coefficients for the MSCI, the PSE, the VIX and the WTI against the NEX

Table 6.1: Estimation results for the coefficient for the NEX

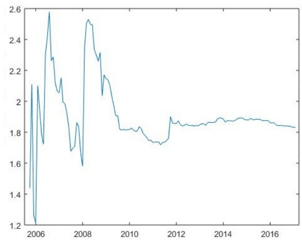
Coefficient	**Mean**	**St.Dev.**
α_t	-0.0007	0.0067
$\beta_{MSCI,t}$	1.1356	0.3510
$\beta_{PSE,t}$	0.3886	0.1873
β_{VIX}	0.0257	-
$\beta_{WTI,t}$	0.1761	0.0461

As illustrated in Figure 6.1, the PSE and the MSCI betas influence the NEX returns to a far greater degree than the VIX and the WTI. Out of the estimated coefficients, the alpha value exhibits the least variation. The PSE and the MSCI coefficients exhibit an almost inversely proportional relationship from year 2009, where the MSCI coefficient increase when the PSE coefficient decrease and vice versa. All coefficients apart from the alpha seem to stabilize somewhat after December 2009. The development of the respective coefficients will be discussed in detail later.

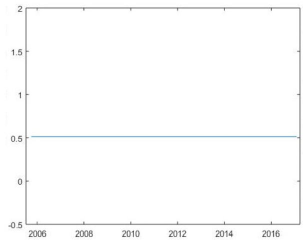
According to the information criteria, the best-fitting model for the SOLRX is the one where both the PSE, the WTI and the VIX is held constant. As opposed to the NEX, there are substantial differences in the values of the information criteria for the various models. In general, holding two or more variables constant results in a high log likelihood value and low criteria values. Thus, keeping several factors constant serves as the best fit for the SOLRX. The average MSE using this model is 6.42E-05, suggesting that the quality of this model is very good. Compared to the average MSE of the best-fitting model for the NEX, the average MSE of the best-fitting model for the SOLRX is closer to zero. The model for the SOLRX is thus more accurate than that of the NEX.



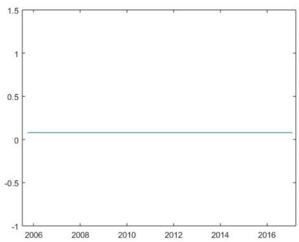
(a) Estimated alpha



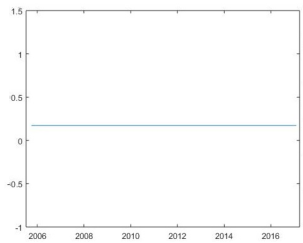
(b) Estimated beta coefficient for the MSCI



(c) Estimated beta coefficient for the PSE



(d) Estimated beta coefficient for the VIX



(e) Estimated beta coefficient for the WTI

Figure 6.2: Alpha and beta coefficients for the MSCI, the PSE, the VIX and the WTI against the SOLRX

Figure 6.2 exhibits the estimated alpha and the estimated beta coefficients from October 2005 to February 2017 where the coefficient of the PSE, the VIX and the WTI is kept constant. Similar to the NEX, the MSCI influences the SOLRX returns significantly. After December 2009, the value of the MSCI stabilize somewhat. The alpha value, on the other hand, face a decreasing trend until 2012, before it stabilizes at a negative value of approximately -0.01. The evolution of the time-varying coefficients will be more thoroughly examined in the following sections.

Table 6.2: Estimation results for the coefficients for the SOLRX

Coefficient	Mean	St.Dev.
α_t	0.0072	0.0229
$\beta_{MSCI,t}$	1.9052	0.2099
β_{PSE}	0.5136	-
β_{VIX}	0.0800	-
β_{WTI}	0.1721	-

6.2 Dependence structure between the NEX, the SOLRX and the global stock market (MSCI)

With $\bar{\beta}_{MSCI,t} = 1.14$ and $Corr(r_{NEX}, r_{MSCI}) = 0.88$, the MSCI World Index serves as the most influential out of the factors that affect the NEX. This is in line with the findings of Inchauspe et al. (2015), where it is argued that the MSCI coefficient is the most vital among the beta coefficients. The average impact of the MSCI on the NEX is found by multiplying the mean beta coefficient by the standard deviation of the MSCI, which is $\bar{\beta}_{MSCI} * \sigma_{MSCI} = 5.44\%$. On average, this means that a positive return on the MSCI index with the magnitude of one standard deviation, or 5.01%, will lead to an expected 5.44% increase on the NEX. The MSCI beta is most influential in the period from early 2006 to mid 2007, where the monthly betas all range over 1.45, with a maximum value of 2.39 in March 2006. The beta has, however, faced an overall decrease for the total sample period. After the peak in the beginning of 2006, the beta declines to a value of 1.00 in early 2009. The beta stays around this value until 2017. While Inchauspe et al. (2015) argue that the beta coefficient increases from late 2006 to 2014, the findings of this study suggest that the value of beta decreases over the same period. In fact, the estimated beta coefficient of the MSCI decreases over the entire time period from 2005 to 2017.

As for the NEX, the MSCI has the largest impact on the returns of the SOLRX out of all the factors in the model. The high correlation between the MSCI and the SOLRX is illustrated in Table 4.3, with $Corr(r_{SOLRX}, r_{MSCI}) = 0.74$. The whole-sample mean of the time-varying beta factor is $\bar{\beta}_{MSCI,t} = 1.91$. The beta coefficient of the MSCI varies between 2.58 and 1.21, implying that it is impacting the SOLRX to a large extent over the entire sample period. The average impact of a change in the MSCI is given as $\bar{\beta}_{MSCI,t} * \sigma_{MSCI} = 9.99\%$. A global stock market index such as the MSCI can therefore be considered a key pricing factor for solar stocks. Aside from a peak in late 2006 and early 2008, the estimated beta coefficient is relatively stable in the considered sample period. In late 2006 the beta coefficient reached a peak of 2.58, before it declined to 1.58 during the following year. This observation is in line with the findings of Inchauspe et al. (2015), which consider the decline as a result of a revision of the pricing strategy of the renewable energy sector with respect to a major world equity index. The solar sector does, in this case, seem to follow the general movements of the renewable energy sector. The estimated beta coefficient experienced a relatively abrupt increase during the first months of 2008, implying a structural change following the financial crisis. Since mid 2009 the estimated beta coefficient has been rather stable around 1.80.

The estimated beta coefficient of both the NEX and the SOLRX reached a peak in 2006, with the NEX reaching its maximum value of 2.39 in March 2006 and the SOLRX reaching its maximum value of 2.58 in August 2006. In the following months, both beta coefficients decreased, before they both experienced a new high in April 2008. Here, the beta coefficient for the SOLRX reached a value of 2.53, while the beta coefficient for the NEX reached a value of 1.36. Both beta coefficients have been relatively stable since mid 2009. The estimated beta coefficient for the SOLRX stabilizes around 1.80 and the estimated beta coefficients for the NEX stabilizes around 1.00. Accordingly, both the NEX and the SOLRX are subject to a significant systematic risk for the sample period. However, the value of the estimated beta coefficient is generally greater for the SOLRX than for the NEX, indicating that the MSCI influence the SOLRX to a larger extent than it influences the NEX. This observation is supported by the average impact of the MSCI on the two indices, which is 5.44% for the NEX and 9.99% for the SOLRX. A return on the MSCI with the magnitude of one standard deviation will thus lead to a twice as big change in the SOLRX as in the NEX. This finding may be explained by the stock pricing for the NEX and the SOLRX throughout the sample period. Although the price evolution for both the NEX and the SOLRX follow the same pattern, the SOLRX has generated returns of a much greater magnitude than the NEX has during the sample period. This is illustrated by the squared mean return for both the NEX and the SOLRX throughout the sample period, which is 0.73% and 2.34%, respectively. As an example, solar stocks were affected by the global financial crisis in 2007-2008 to a much larger extent than renewable stocks. The SOLRX experienced a price decrease of 61 percentage points from January 2008 to December 2008, compared to the NEX which experienced a decrease of 26 percentage points. During the considered time period, the solar sector has been subject to several smaller price bubbles, and several solar companies have in turn gone bankrupt (Wesoff, 2013, Ogg, 2013). One possible reason for this relatively high market sensitivity is that solar companies rely more on government subsidies than the renewable sector as a whole does. This was illustrated by changes in government energy policy in the UK in 2016, which led to the loss of more than half of all jobs in the UK solar industry (Macalister, 2016). On the other hand, the NEX includes companies that are less dependent on natural resources and government subsidies, for instance Tesla (Pressman, 2016).

6.3 Dependence structure between the NEX, the SOLRX and technology stocks (PSE)

The PSE coefficient is the second most influential out of the factors that affect the NEX. The average beta coefficient of the PSE is $\bar{\beta}_{PSE,t} = 0.39$ during the sample period. Thus, an average shift of the PSE return would cause a $\bar{\beta}_{PSE,t} * \sigma_{PSE} = 2.29\%$ shift in the NEX value, about half of the impact a shift in the MSCI return would cause. The PSE coefficient is negative from October 2005 to July 2006, but face a solid increase starting in the beginning of 2006. The estimated beta coefficient increases until late 2009, where it reaches a maximum value of 0.65. The beta coefficient faces a downward trend in the following years, and ultimately stabilizes at a value of approximately 0.50 from 2014. The correlation coefficient between the returns of the NEX and the PSE is $Corrr_{NEX}, r_{PSE} = 0.84$. This is in line with the findings of Henriques and Sadorsky (2008), Kumar et al. (2012), Sadorsky (2012) and Inchauspe et al. (2015), who argue that there exists a strong correlation between the price of renewable energy stocks and technology stocks. Inchauspe et al. (2015) suggest that this might be caused by competition for the same inputs between technology and renewable energy companies.

There is a notable correlation between the monthly returns of the SOLRX and the PSE, as $Corr(r_{SOLRX}, r_{PSE}) = 0.69$. In the best-fitting model for the SOLRX, the estimated beta coefficient of the PSE is constant at $\beta_{PSE} = 0.51$, indicating a considerable impact on the SOLRX excess returns. The impact of a 5.23% change in the PSE is a 2.69% change in the SOLRX. Thus, a change of 5.23% in the PSE leads to a half as big change in the SOLRX. In comparison, a change of 5.01% in the MSCI leads to a twice as big change in the SOLRX. Even though the PSE affects the returns of the SOLRX, it is to a smaller degree than the MSCI. Overall, the PSE is the second most influential factor out of all the factors that affect the SOLRX. When running the state-space model for the SOLRX with all factors being time-varying and following a random walk, the estimated beta coefficient varies to a certain degree. The estimated beta coefficient was negative until mid 2008. Technology stocks did, in other words, underperform relative to solar stocks before the financial crisis. The estimated beta coefficient started increasing in mid 2008, and has since the end of 2008 been positive and stable between 0.4 and 1. Thus, it has been appropriate to view the estimated beta coefficient of the PSE as constant since late 2008.

Technology stocks serve as the second most influential driver of both renewable stocks and solar stocks. The average impact of a change in the PSE is of approximately the same magnitude for both the NEX and the SOLRX. In the state-space model for the NEX, the beta coefficient of the PSE is allowed to vary over time and takes an average value of 0.39. In the state-space model for the SOLRX, the beta coefficient is constant at 0.51. In conclusion, the PSE has a significant influence on the returns of both renewable stocks and solar stocks. When allowing the beta coefficient of the PSE to vary in the model for the SOLRX, the beta coefficient of the PSE is negative until mid 2008. The estimated beta coefficient of the PSE is negative also for the NEX, although only until mid 2006. The negative beta coefficients in the beginning of the sample period might be explained by a challenging market after the bursting of the technology stock market bubble in 2001. It does, however, seem like the renewable energy sector was able to turn the negative trend faster than the solar sector. The development of the time-varying estimated beta coefficient of the PSE is quite similar for both the NEX and the SOLRX, despite the fact that the value of the beta is higher for the SOLRX than for the NEX. Consequently, solar stocks are more volatile than renewable stocks relative to technology stocks, which might explain why the renewable energy sector was able to turn the negative trend following the dot-com bubble burst in 2001 faster than the solar sector. This is not a surprising result, as one may expect the solar sector to be less stable than the older and more established renewable sector.

6.4 Dependence structure between the NEX, the SOLRX and the stock market volatility (VIX)

The estimated beta coefficient of the VIX is constant at $\beta_{VIX} = 0.03$, indicating a minor impact on the returns of the NEX, especially compared to that of the MSCI and the PSE. On average, the result of a 22.13% change in the VIX will lead to a $\beta_{VIX} * \sigma_{VIX} = 0.57\%$ change in the NEX. This, in addition to the low value of beta, suggests that the VIX has little or no influence on the NEX. There is a negative correlation between the returns of the NEX and the VIX, where $Corr(r_{NEX}, r_{VIX}) = -0.60$. Thus, an increase in the VIX is associated with a decrease in the NEX. When allowing all of the factors to be time-varying and follow a random walk, the estimated beta coefficient of the VIX varies considerably. Then, the whole-sample mean is $\bar{\beta}_{VIX,t} = -0.0008$. The beta coefficient was negative until late 2006, following an upward trend from early 2007. The highest value of $\beta_{VIX,t}$ was observed in May 2008, with the maximum value being 0.06. In mid 2008, the estimated beta coefficient started decreasing, and provided negative beta values for the period February 2009 to May 2013. From mid 2014, the beta value has been positive and slightly increasing, at around 0.02.

There is a notable negative correlation between the SOLRX and the VIX, illustrated in the correlation matrix as $Corr(r_{SOLRX}, r_{VIX}) = -0.47$. The estimated beta coefficient of the VIX is constant at $\beta_{VIX} = 0.08$, indicating little or no impact on the SOLRX. The result of a 22.13% change in the VIX is a $\beta_{VIX} * \sigma_{VIX} = 1.77\%$ change in the SOLRX. When all factors are time-varying and follow a random walk, the estimated beta coefficient of the VIX varies between -0.15 and 0.20. The beta coefficient was negative until late 2005. The estimated beta faced an upward trend from mid 2006 until early 2008, reaching its maximum value of 0.20 in March 2008. The beta coefficient decreased in the following months until late 2009, before it started increasing. During the period late 2009 to early 2013, the VIX provided some negative beta returns, indicating underperformance relative to the other factors included in the model. In February 2013, the beta started increasing, and has faced an increasing trend since then. The whole-sample mean of the time-varying beta coefficient is $\bar{\beta}_{VIX,t} = 0.05$.

Out of all the factors included in the model, the VIX is the least influential. The NEX and the SOLRX have significant negative correlations with the VIX. The correlation between the NEX and the VIX is somewhat stronger than between the SOLRX and the VIX. The beta coefficient of the VIX is constant both for the NEX and for the SOLRX, suggesting that no volatility clustering is present in the returns of the NEX and of the SOLRX. This is not a surprising result, as one would expect sufficient flexibility to achieve well-distributed residuals with no volatility clusters when using time-varying coefficients. The beta coefficient of the VIX is greater for the SOLRX than for the NEX. Furthermore, the average impact of the VIX leads to a 0.57% change in the NEX and a 1.77% change in the SOLRX, demonstrating that the VIX has a larger impact on the SOLRX than the NEX, although the impact is of little significance for both renewable stocks and solar stocks. When the VIX is allowed to vary over time, the estimated beta coefficient for the NEX and the SOLRX follow the same movements. Overall, the beta coefficient of the VIX is higher during volatile periods, such as the financial crisis in 2008 and the oil price collapse in 2014. Given that the VIX tracks the stock market volatility, this is not a surprising finding.

6.5 Dependence structure between the NEX, the SOLRX and oil prices (WTI)

The WTI is the third most influential factor with an average beta of $\bar{\beta}_{WTI,t} = 0.18$ and a correlation coefficient with the NEX of $Corr(r_{NEX}, r_{WTI}) = 0.59$. The average impact of a shift in the WTI would cause a 1.72% shift in the NEX, which is 68% lower than the average impact of a shift in the MSCI and 25% lower than the average impact of a shift in the PSE. As illustrated in Table 4.1, the standard deviation of the WTI is almost twice as large as the standard deviations of the MSCI and the PSE. Even though the WTI seems to have a small impact on the NEX returns based on the average beta, a relatively high standard deviation leads to an average impact of 1.72%. The estimated beta coefficient of the WTI was negative until late 2005, before it faced a steep increase until its maximum value of 0.25 was reached in February and October 2008. After the peak in October 2008, the WTI coefficient was rather stable between 0.19 and 0.24 until late 2011. The beta coefficient then experienced a moderate decrease until February 2017, with a final state value of 0.15. It is worth noticing that the WTI coefficient was more volatile than usual after the oil price plummeted during the financial crisis in 2008, but seemed relatively unaffected by the fall in the oil price in 2014. The development of the WTI coefficient follows the same pattern as described in Inchauspe et al. (2015), but exhibits an overall higher estimated WTI coefficient. However, while Inchauspe et al. (2015) find that the WTI oil price becomes more significant from mid 2005 to 2013 than from 2002 to mid 2005, the findings of this study suggests that the WTI is more significant from 2005 to 2008, and then becomes less significant.

The correlation between the excess returns of the SOLRX and the WTI is $Corr(r_{SOLRX}, r_{WTI}) = 0.49$, which is lower than the correlation with both the MSCI and the PSE. This is in line with the findings of Sadorsky (2012), who finds evidence that renewables correlate more highly with technology stock prices than with oil prices. Similar to the PSE, the estimated beta coefficient of the WTI is constant. The value of the beta coefficient is $\beta_{WTI} = 0.17$, indicating a certain effect of oil prices on solar stocks. When all factors are time-varying and follow a random walk, the value of the estimated beta coefficient of the WTI varies between -0.14 and 0.49. Similar to the estimated beta coefficient of the WTI for the NEX, the time-varying estimated beta coefficient of the WTI for the SOLRX is negative until late 2005. In the following years, the value of the beta coefficient fluctuates before reaching a maximum value of 0.49 in February 2008. The estimated beta coefficient faced a downward trend until February 2014. In the following months the estimated beta coefficient increased, before it started decreasing early 2016. It seems as if the impact of oil prices on solar stocks increased during the oil price collapse in 2014, and decreased when the oil price recovered in early 2016. In February 2017, the value of the estimated beta coefficient was 0.09, almost as low as the minimum value over the entire sample period, which was 0.07. The whole-sample mean of the time-varying beta coefficient is $\bar{\beta}_{WTI,t} = 0.22$.

Even though the WTI beta coefficient is time-varying in the state-space model for the NEX and constant in the model for the SOLRX, the values of the coefficients are approximately the same. Furthermore, the correlation coefficients with both the NEX and the SOLRX are of considerable strength. The WTI oil price is the third most influential driver of the returns of both the NEX and the SOLRX, although the effect of oil prices on renewable stocks and solar stocks is smaller than that of the MSCI and the PSE. The impact of oil prices on solar stocks increased during the oil price collapse in 2014, and decreased when the oil price recovered in 2016. The effect of oil prices on renewable stocks was unchanged during these events. Thus, oil prices seem to have a stronger influence on solar stocks during volatile periods and a weaker influence during strong market periods.

Unlike Inchauspe et al. (2015), the findings of this study suggest that oil prices have a decreasing impact on both renewable and solar stocks. There might be several reasons for this weakening relationship. Energy market dynamics have changed during the 21st century so that oil and renewables no longer compete in the same markets. While oil is predominantly used for transport, renewable energy is used mostly to generate electricity.

As many renewable energy sources cannot be stored, gas may serve as a back-up source of energy and hence can complement renewable energy sources (Nyquist, 2015). However, it has been pointed out that solar prices in emerging markets might be more influenced by oil and gas prices as diesel plays a bigger role in the power supply (Hering, 2014). This might explain why there is a slightly greater dependency between solar stocks and oil prices than between renewable stocks and oil prices. Additionally, the economics of renewables are improving. While most government support schemes remain in place, the capital, operating and financing costs for renewables have fallen dramatically in recent years. The competitiveness of renewables is increasing and the science behind renewable technologies are improving (Nyquist, 2015). These developments have primarily taken place in recent years and might be a part of the reason why renewable stocks and solar stocks seemed rather unaffected by the oil price drop in 2014. In general, the extended time period of this study captures the shift from traditional to alternative energy sources, the reduced oil prices and the investment and production cuts in the oil and gas sector over recent years (Biscardini et al., 2017). These developments have seemingly contributed to the weakening relationship between oil prices and stock returns of the renewable energy sector and the solar sector.

6.6 Dependence structure between the NEX, the SOLRX and the alpha

The alpha is often referred to as the *excess* or *abnormal return* on an asset. Equilibrium models, such as the CAPM and multifactor models, estimate the return of an asset. The abnormal return is the return on the asset in excess of what would be predicted by such equilibrium models. As a result, an alpha value of zero would indicate that the asset performs in line with the benchmark index, meaning that no value is neither lost nor added.

In the state-space model for the NEX, the alpha varies through time and takes values between -0.009 and 0.02. Alpha is positive from late 2005 until mid 2010, indicating returns in excess of the expected return of the NEX the first five years. The maximum values of the alpha are observed in October 2005 and January 2008, with values of 0.02 and 0.01. The estimated alpha is rather stable between 0.006 and 0.01 from early 2008 to early 2009, before it starts decreasing significantly. Since August 2010 investments in the NEX has provided negative abnormal returns, indicating that the renewable energy sector underperformed during this time period. The alpha reached a minimum value of -0.009 in mid 2012, and has been rather stable around -0.006 since then.

Overall, the NEX provides lower abnormal returns after the financial crisis and underperforms in the time period 2010 to 2017. As pointed out by Inchauspe et al. (2015) and Bohl et al. (2015), there might be several reasons for the underperformance of the renewable energy sector during this time period. One of the main reasons for the underperformance is identified as investors reassessing their evaluation of the renewable sector. The financial crisis led to cut in renewable energy subsidies and uncertainty about government policies, which in turn led to concerns regarding further acceleration of the renewable energy sector among investors. As pointed out by Sadorsky (2012), there is a high correlation between the stock prices of renewable energy companies and technology companies. Thus, in the aftermath of the financial crisis investors might have choosen to invest in technology stocks over renewable stocks due to less risk and similar characteristics. Moreover, the gap between innovation, adoption and diffusion of new energy technologies, the so-called ”Valley of Death”, has made it even more difficult for renewables to compete with technology stocks (Weyant, 2011). Additionally, factors that influence renewable energy policy making, like technological innovation, falling prices and increased deployment, have shifted severely in recent years in order to keep pace with changing market conditions. Feed-in tariffs (FITs) have been identified as the main driver of the European success story to promote renewables in the electricity sector. Since 2015, several European countries have implemented a shift from tariff-based instruments like FITs to quantity-based instruments like tendering schemes. With 28% of the components of NEX being located in Europe, this might have contributed to the underperformance of the NEX. Moreover, several countries have started introducing a combination of different policy types (REN21, 2016). This is the case for large parts of Asia and North America, which constitutes 39% and 29% of the components of the NEX, respectively. Thus, the underperformance of the renewable energy sector might also be explained by a shift from conventional to new and possibly inefficient policies.

In the state-space model for the SOLRX, the alpha varies through time and takes values between -0.02 and 0.08. The range for the value of the alpha is thus much larger for the SOLRX than for the NEX. During the first six years of the sample period, the alpha is positive. The alpha started decreasing in early 2006, before stabilizing somewhat between 2007 and 2009. Between the beginning of 2009 and mid 2013, the index faced a downward trend. The presence of abnormal returns in the solar sector contradicts the findings of Schmitz (2009), who finds no abnormal returns in the solar index model. Investments in the SOLRX provided negative abnormal returns from mid 2011 through the rest of the time period in consideration. The negative returns are fairly stable around -0.01.

The financial crisis had an adverse effect on the solar sector, as many solar projects to a large extent are debt financed (Norges Bank Investment Management, 2015). A dramatic reduction in general availability of loans, in addition to cut in subsidies in big markets such as Germany and Italy during the financial crisis, made it hard for the solar sector to compete with cheap and less risky coal-fired power. As a result, the solar sector experienced a global fall in demand. The weakening in demand caused a shakeout where highly leveraged firms came under stress (Hook, 2011), which in turn had a negative effect across the entire sector. Moreover, policies have played an important role in the solar sector over the last decade. Policy makers in China have made considerable efforts to expand the renewable energy sector. This have affected the performance of the SOLRX to a large extent, as China constitutes 27% of the components of the SOLRX. China announced its first nationwide solar FIT in 2011 (Hook, 2011). This was seen as a confirmation of China's intent to support the solar industry, and several Chinese solar developers started projects in anticipation of a good tariff coming through. It is possible that the markets overreacted to this policy development, leading to an all-time low alpha in 2012. The United States Solar Investment Tax Credit, which is one of the most important federal policy mechanisms to support the deployment of solar energy in the U.S., lapsed at the end of 2013 and were reinstated for only two weeks in December 2014 (Bloomberg New Energy Finance, 2016). With the United States making up for 20% of the components of the SOLRX, this might have contributed to the underperformance of the SOLRX. During the last years, trouble at two high-profile solar companies and the U.S. presidential election are pointed out by Trefis Team (2016) as some of the factors contributing to the weak performance of solar stocks.

The abnormal returns of the NEX and the SOLRX has experienced the same development in the time period 2005 to 2017. While the NEX provides positive abnormal returns the first five years, the SOLRX provides positive abnormal returns the first six years. This finding differs from the ones of Henriques and Sadorsky (2008), which concludes that virtually no abnormal returns were generated from alternative energy companies. The alpha is negative from August 2010 for the NEX and from June 2011 for the SOLRX. Compared to the NEX, the negative returns of the SOLRX occurs approximately a year later and are of a greater value. Thus, neither the NEX nor the SOLRX recovered from the losses caused by the financial crisis to the same level as the considered drivers in the model. Furthermore, high abnormal returns were observed between 2007 and 2009 for both the NEX and the SOLRX. Subsequently, the solar sector seem to experience the same development as the renewable energy sector. The abnormal returns of the SOLRX is generally of a greater value than those of the NEX.

Chapter 7

Conclusions, Limitations and Further Research

The following chapter presents concluding remarks based on the key findings, limitations of the study and recommendations for further research.

7.1 Concluding remarks

This study examines four potential drivers of renewable energy returns for the WilderHill New Energy Global Innovation Index (NEX) and for the Ardour Solar Energy Index (SOLRX), namely the global stock market (MSCI), technology stocks (PSE), oil prices (WTI) and the stock market volatility (VIX). In addition, the alpha of the renewable energy sector and solar sector is examined. A comparison between return dynamics of the renewable energy sector as a whole (NEX) and the solar sector (SOLRX) is carried out. Furthermore, this study analyzes the evolution of the estimated alpha and the estimated beta coefficients in the time period from 2005 to 2017.

This study finds that the MSCI serves as the most influential driver of returns of both renewable stocks and solar stocks. The MSCI influences solar stocks to a larger extent than renewable stocks, as a return on the MSCI with the magnitude of one standard deviation leads to a twice as big change in the SOLRX as in the NEX. While the estimated beta coefficient of the MSCI for the SOLRX remains somewhat stable throughout the considered time period, the estimated beta coefficient of the MSCI for the NEX is nearly halved. The evolution of the estimated beta coefficients is similar until early 2008, which is when the beta coefficients of the MSCI for the NEX started decreasing while the beta coefficients of the MSCI for the SOLRX started increasing. We believe that the high market sensitivity for the solar sector might be explained by the fact that the solar sector relies more on government subsidies than the renewable sector as a whole does.

The PSE serves as the second most influential driver of returns of both renewable stocks and solar stocks. The average impact of a change in the PSE is of approximately the same magnitude for the NEX and for the SOLRX, indicating that the influence is of the same extent. Overall, the estimated beta coefficient of the PSE for the SOLRX is higher than the estimated beta coefficients of the NEX. The renewable sector was able to turn the negative trend following the dot-com bubble burst in 2001 faster than the solar sector, indicating that a shock to technology stocks might have a larger impact on solar stocks than renewable stocks.

The WTI is the third most influential driver of the returns of renewable stocks and solar stocks. Oil prices have a significant impact of equal magnitude on both renewable and solar stocks, although to a smaller degree than the MSCI and the PSE. Oil prices seem to have a stronger influence on solar stocks during volatile periods, and a weaker influence during strong market periods. The estimated beta coefficient of the WTI follows the same pattern as described in Inchauspe et al. (2015), but exhibits an overall higher value. Unlike Inchauspe et al. (2015), we find that oil prices have had a decreasing impact on both renewable stocks and solar stocks. The fact that oil and renewables no longer compete in the same markets, in addition to increased cost competitiveness of renewables and the ongoing shift from traditional to alternative energy sources, are identified as the main reasons for this development.

The VIX is the least influential driver of renewable returns and solar returns out of all the factors included in the model. The VIX has a larger impact on the SOLRX than on the NEX, although the impact is of little significance for both renewable and solar stocks. The estimated beta coefficient of the VIX is constant both for the NEX and for the SOLRX, suggesting that no volatility clustering is present in the returns of the NEX and of the SOLRX. Overall, the VIX impacts renewable stocks and solar stocks to a larger extent during volatile periods such as the financial crisis in 2008 and the oil price collapse in 2014.

The alpha of the SOLRX is of greater value than that of the NEX throughout the considered time period. Thus, greater value was added by investing in the solar sector from 2005 to 2017 compared to investing in the renewable sector as a whole. The renewable sector has provided negative abnormal returns since mid 2010, while the solar sector has provided negative abnormal returns since mid 2011. Thus, both the renewable sector and the solar sector have underperformed the last years. Cuts in renewable energy subsidies, uncertainty about government policies, strong competition with less insecure technology stocks and a shift from conventional to new and possibly inefficient policies are identified as possible reasons for the underperformance of the renewable energy sector as a whole. The global fall in demand for solar energy in the aftermath of the financial crisis, in addition to policy alterations in big markets such as China and the United States, might explain the underperformance of the solar sector.

In conclusion, systematic risk varies over time in the indices representing the renewable sector and solar sector. Similar to previous studies, findings of this study suggest a strong influence of the global stock market (MSCI) and technology stocks (PSE) on renewable stocks throughout the considered sample period. Contrary to previous literature, we find that the influence of oil prices (WTI) is significantly lower, with its influence on both the renewable sector as a whole and the solar sector decreasing after 2008. The stock market volatility (VIX) has no significant influence on neither renewable stocks nor solar stocks. Furthermore, there is evidence for underperformance of the renewable sector as a whole and the solar sector relative to the considered drivers of returns. Overall, the solar sector seem to follow the same development as the renewable sector as a whole. The solar sector is, however, more strongly affected by the global stock market (MSCI) and technology stocks (PSE) than the renewable sector as a whole.

7.2 Limitations

To date, there is a limited amount of indices comprised of only solar companies. Even though the SOLRX is considered one of the most recognized indices tracking the solar sector, analyzing the SOLRX exposes this study to certain shortcomings. The SOLRX includes only 15 components and two different solar technologies, in comparison to the MAC Global Solar Energy Stock Index (SUNIDX), which consists of 23 components and includes all solar technologies and the entire solar value chain. Both indices are geographically diversified and include components from seven different countries.

The main reason that the SOLRX is chosen over the SUNIDX is that the SOLRX tracks the solar sector back to 2005, while the SUNIDX was incepted in 2008. Thus, we would not have been able to analyze the development in the solar sector both before and after the financial crisis in 2008 when using the SUNIDX. Moreover, it is easier to discover trends and developments if a longer sample period is applied. Another reason for choosing the SOLRX is that the data of the SOLRX is available in Datastream, while the data of the SUNIDX is not. Datastream is one of the most powerful financial time series databases available, and is a widely recognized and trustworthy source of data. As all data is gathered from this database, it is considered appropriate to choose a solar index that is listed in this database as well.

7.3 Further research

A natural extension of this study would be to include other sectors within the renewable energy sector in the analysis. The wind sector would be especially interesting, as wind is the second fastest growing technology within the renewable energy sector (IRENA, 2017). In addition, the wind and solar sector currently hold a leading market share, as they account for about 90% of 2015 investments in renewable energy (IRENA, 2017). Finding the drivers of returns for the wind sector would therefore contribute to a greater understanding of the renewable sector. There is, however, no wind indices with a substantial tracking history available to date.

Previous studies have suggested that political factors might affect the return of renewable energy investments (de Jager and Rathmann, 2008, Bürer and Wüstenhagen, 2009, Couture and Gagnon, 2010, Masini and Menichetti, 2012, Menichetti and Wüstenhagen, 2012, Bohl et al., 2015), mainly because government policies and regulatory frameworks create stable and predictable investment environments. Additionally, several authors argue that successful policies are vital in encouraging investments in renewable energy. Moreover, Norges Bank Investment Management (2015) reveals that policy and overall market framework instability is perceived by financial investors as the main risk in the development phase of renewable energy projects. It would therefore be highly interesting to examine the impact political factors has on renewable energy returns by including a political factor in a multi-factor model. To the best of our knowledge, a model like this does not exist. This might be due to the geographical and sector-wise variations in subsidies, which makes it hard to measure and quantify the impact subsidies and policies has across all levels. One direction for further research would therefore be to examine specific geographical markets, and then expand to a global comparative study.

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Appendix

7.4 Appendix A

The following appendix will explain the value and price calculations applied in Datastream.

Equity indices

Datastream calculates its own aggregate sector and market price indices, together with associated aggregations, such as sector, price/earnings ratio (PE) and dividend yield (DY). *Price Index* is the default datatype for equity indices in Datastream and the index value is calculated as follows:

$$I_0 = \text{index value at base date} = 100 \tag{7.1}$$

$$I_t = I_{t-1} * \frac{\sum_{1}^{n}(P_t * N_t)}{\sum_{1}^{n}(P_{t-1} * N_{t-1} * f)} \tag{7.2}$$

where
I_t = index value at day 1
I_{t-1} = index value on previous working day (of t)
P_t = unadjusted share price on day t
P_{t-1} = unadjusted share price on previous working day (of t)
N_t = number of shares in isssue on day t
f = adjustment factor for a capital action occuring on day t
n = number of constituents in index

Commodities

Datastream obtains its commodity price by using the *Price (adjusted)*. This is the price issued by an exchange or a third party.

Interest rates

The Total Return Index is the chosen method of calculating interest rates. The Total Return Index is the return on investment, including interest payments, as well as appreciation or depreciation in the price of the bond and is calculated as follows:

$$RI_t = RI_{t-1} * \frac{P_t + A_t + NC_t + CP_t}{P_{t-1} + A_{t-1} + NC_{t-1}} \tag{7.3}$$

where
RI_t = return for index on day t
RI_{t-1} = return for index on day $t-1$
P_t = unadjusted share price on day t
P_{t-1} = unadjusted share price on previous working day (of t)
A_t = appreciation on day t
A_{t-1} = appreciation on previous working day (of t)
NC_t = depreciation on day t
NC_{t-1} = depreciation on previous working day (of t)
CP_t = coupon price on day t

7.5 Appendix B

The formula used to calculate the annual percentage yield, which in turn is used to calculate monthly excess return, is presented in the following appendix. In addition, the formula used to calculate the direct beta is given.

Annual percentage yield

The annualized yields for T-bills are converted to monthly yield by using the annual percentage yield (APY) formula:

$$APY = (1 + periodic\ rate)^{\#periods} - 1 \tag{7.4}$$

Direct beta

The beta value of a stock is given as:

$$\beta = Corr(r_m, r_i) * \frac{\sigma_i}{\sigma_m} \tag{7.5}$$

where
$Corr(r_m, r_i)$ = the correlation between the market, m, and the investment, i
σ_i = is the standard deviation of the returns of i
σ_m = is the standard deviation of the returns of m

This value is referred to as the *direct beta* in Table 4.1.

7.6 Appendix C

The results for the Chow tests are presented below. All tests are run with yearly breakpoints (11 breakpoints in total).

Table 7.1: Chow F values for monthly data

	Chow value, NEX	Chow value, SOLRX
MSCI	2.068203	1.904375
PSE	2.666055	2.563796
VIX	3.668723	2.892417
WTI	2.12233	1.757508

7.7 Appendix D

The following appendix presents the results from the Engle's ARCH test conducted in MATLAB.

Table 7.2: Results from the Engle's ARCH test for the NEX

# Lags	**1**	**2**	**3**	**4**	**5**
α = 0.01					
h	0	0	0	0	0
p-value	0.9287	0.9918	0.9837	0.5509	0.1862
Test statistics	0.008	0.0164	0.1607	3.0414	7.4979
Critical value	6.6349	9.2103	11.3449	13.2767	15.0863
α = 0.05					
h	0	0	0	0	0
p-value	0.9287	0.9918	0.9837	0.5509	0.1862
Test statistics	0.008	0.0164	0.1607	3.0414	7.4979
Critical value	3.8415	5.9915	7.8147	9.4877	11.0705

Table 7.3: Results from the Engle's ARCH test for the SOLRX

# Lags	**1**	**2**	**3**	**4**	**5**
α = 0.01					
h	0	0	0	0	0
p-value	0.4402	0.3787	0.2989	0.4359	0.3443
Test statistics	0.5958	1.9421	3.6735	3.7849	5.6261
Critical value	6.6349	9.2103	11.3449	13.2767	15.0863
α = 0.05					
h	0	0	0	0	0
p-value	0.4402	0.3787	0.2989	0.4359	0.3443
Test statistics	0.5958	1.9421	3.6735	3.7849	5.6261
Critical value	3.8415	5.9915	7.8147	9.4877	11.0705

7.8 Appendix E

The following appendix presents the model output for the state-space model.

Table 7.4: Estimation results for the time-varying coefficients for the NEX

Variable	Final State	Z-statistic	Probability
α_t	-0.0066	-2.0342	0.0419
$\beta_{MSCI,t}$	0.9731	5.9869	0.0000
$\beta_{PSE,t}$	0.4766	3.2223	0.0013
$\beta_{WTI,t}$	0.1445	3.8140	0.0001

Table 7.5: Estimation results for the time-varying coefficients for the SOLRX

Variable	Final State	Z-statistic	Probability
α_t	-0.0158	-1.8762	0.0606
$\beta_{MSCI,t}$	1.8324	10.8372	0.0000

Table 7.6: Variances for fixed estimates for the NEX

Variance	Value
$\hat{\sigma}^2_{\epsilon}$	0.0014
$\hat{\sigma}^2_{\tau\alpha}$	0.0000
$\hat{\sigma}^2_{\tau PSE}$	5.87E-48
$\hat{\sigma}^2_{\tau MSCI}$	4.54E-14
$\hat{\sigma}^2_{\tau WTI}$	3.55E-51

Table 7.7: Variances for fixed estimates for the SOLRX

Variance	Value
$\hat{\sigma}^2_{\epsilon}$	0.0103
$\hat{\sigma}^2_{\tau\alpha}$	2.72E-35
$\hat{\sigma}^2_{\tau MSCI}$	3.1E-255

Table 7.8: Values for the information criteria and for the log likelihood for the NEX when the VIX is constant

Criterion	Value
Log likelihood	229.2508
Akaike info. criterion	-3.079322
Bayesian info. criterion	-3.079322
Hannan-Quinn criterion	-2.956147

Table 7.9: Values for the information criteria and for the log likelihood for the SOLRX when the PSE, the VIX and the WTI are constant

Criterion	**Value**
Log likelihood	106.4604
Akaike info. criterion	-1.385661
Bayesian info. criterion	-1.262485
Hannan-Quinn criterion	-1.33561