The Dynamics of Returns on Renewable Energy Companies: A State-Space Approach

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Abstract

The renewable energy sector has accomplished remarkable growth rates over the last decade. This paper examines the dynamics of excess returns for the WilderHill New Energy Global Innovation index, which lists firms in the renewable energy sector and is used as a global benchmark. We propose a multi-factor asset pricing model with time-varying coefficients to study the role of energy prices and stock market indices as explanatory factors. Our results suggest a strong influence of the MSCI World index and technology stocks throughout the sample period. The influence of changes in the oil price is significantly lower, although oil has become more influential from 2007 onwards. We also find evidence for underperformance of the renewable energy sector relative to the considered pricing factors after the financial crisis.

Keywords: Renewable Energy, Oil Price, State-Space Models, CAPM, WilderHill New Energy Index

JEL Classification: Q42, Q43, G12

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#This work was supported by funds from the Australian Research Council through grant no. DP1096326.

Electronic copy available at: https://ssrn.com/abstract=2889891

1. Introduction

The renewable energy sector has accomplished substantial overall growth in the global economy during the last decade. Estimates by the International Energy Agency (IEA) suggest that renewable energy will be the fastest growing component of global energy demand with an annual growth rate of more than 7% within the next two decades (International Energy Agency, 2009). Some of this development may be attributable to the conjunction of government policies, rising oil prices and evolving stock market liquidity for investments in renewable energy companies. Several renewable or clean energy stock indices have been created, including, for example, the WilderHill New Energy Global Innovation Index (NEX), the WilderHill Clean Energy Index (ECO) or the S&P Global Clean Energy Index (SPGCE).

There has also been an increased interest in examining returns of renewable energy companies, as well as in identifying potential drivers of these returns, see, e.g., Henriques and Sadorsky (2008), Kumar et al. (2012), Sadorsky (2012), Bohl et al. (2013), Managi and Okimoto (2013). These studies typically focus on the relationship between renewable energy stocks, changes in the oil price, other equity indices and carbon prices. The authors typically find evidence for the impact of several of these variables on renewable energy stock prices. In particular, returns of high technology and renewable energy stocks seem to be highly correlated. On the other hand, results are not that clear-cut for the influence of changes in the oil price. While Henriques and Sadorsky (2008) suggest that changes in oil prices have only limited impact on returns from investment in renewable energy stocks, Kumar et al. (2012), Sadorsky (2012) and Managi and Okimoto (2013) find some evidence for a significant relationship between these variables.

In this paper we contribute to this stream of literature by proposing a state-space multi-factor asset pricing model to study the impact of explanatory variables such as oil prices, technology stocks and the MSCI World stock market index on renewable energy stocks. The novelty of our approach is the use of time-varying beta-factors which provide insightful information about the dynamic influence for each of the considered explanatory factors. Our approach also allows us to evaluate the performance of the renewables sector through time in relation to the applied pricing factors.

We believe that results on the impact and significance of the considered pricing factors will not be constant through time. Asset pricing models with time-varying factors in a state-space econometric framework have been successfully applied in previous studies, see e.g. Bollerslev et al. (1988), Jagannathan and Wang (1996), Berglund and Knif (1999), Tsay (2005), Koopman et al. (2008), van Geloven and Koopman (2009). In comparison to a static approach, these models offer additional insights into the dynamic relationship between the variables, as well as information on the time-varying influence of the pricing factors. Compared to approaches based on structural changes or regime switching, our approach benefits from extracting information about smooth changes in the relationship under study. For our analysis of the renewables sector, we would expect significant variation in the estimated coefficients and the relative performance of renewable energy stocks, for instance, during periods of substantial changes in the oil price or a financial crisis.

The second motivating idea stems from the observed significant relationship between financial returns of renewable energy companies and those of oil, equity indices and

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technological shares, as they have been reported in various studies. To examine this relationship, the most commonly-used methodologies are CAPM-type, multiple regression or vector-autoregressive models (Faff and Brailsford, 1999; Sadorsky, 2001; Boyer and Filion, 2007; Henriques and Sadorsky, 2008; Kumar et al., 2012). More recently, also the use of multivariate GARCH, dynamic conditional correlation models (Sadorsky, 2012) and Markov-Switching models (Managi and Okimoto, 2013) has been suggested.

Our investigation complements this line of research, while employing a different model with time-varying coefficients. Combining the idea of time-varying coefficients with previously identified explanatory factors, in this study we apply a *state-space multi-factor asset pricing model*. Such an approach will also allow us to study *active* or *abnormal returns* of renewable energy companies, i.e., we can evaluate the performance of the renewables sector through time, relative to the identified pricing instruments. To the best of our knowledge no such approach has been applied previously to the dynamics of the global renewable energy sector that is represented in our study by the WilderHill New Energy Global Innovation Index (NEX). The index has become a major international benchmark index with a market capitalization of over $250 billion [1] that includes worldwide active companies specializing in renewable energy, clean power and energy efficiency.

The use of time-varying beta-factors provides insightful information on the dynamic influence of each explanatory factor. In particular, our results suggest that the impact of the considered variables changes during different regimes, such as: (i) the substantial increase in the oil price from 2001-2008, (ii) the period of the global financial crisis (GFC), and, (iii) the period of recovery in stock markets, which was also characterized by reduced expectations of government subsidies to the renewable energy sector. Our results also complement the findings of Bohl et al. (2013), a study highly related to ours, where the authors apply a four-factor asset pricing model to renewable energy stocks in Germany. Their results suggest that while renewable energy stocks earned considerable risk-adjusted returns between 2004 and 2007, the performance has deteriorated significantly, delivering negative returns since 2008. We argue that a state-space model provides a more appropriate approach than a standard static CAPM-type or multifactor model to investigate the driving factors of renewable energy stocks. The applied approach might also be superior to a vector-autoregressive model as it is implemented in Henriques and Sadorsky (2008) or Kumar et al. (2012), since these models do not allow for time-varying coefficients. The time-varying nature of the relationship between oil prices and renewable energy stocks is also evidenced by the observed structural change in late 2007 (Managi and Okimoto, 2013) or the time-varying correlation structure as suggested by Sadorsky (2012).

Importantly, our applied multi-factor framework also allows for an analysis of *abnormal* or *active return* of renewable energy companies, i.e. the performance of the renewable sector relative to its identified pricing factors. The techniques applied in previous studies such as (Henriques and Sadorsky, 2008; Kumar et al., 2012; Sadorsky, 2012; or Managi and Okimoto, 2013) only allow for a limited interpretation with respect to the important issue of the performance of the renewables sector relative to other equity markets. Note that Bohl et al. (2013) also apply a multi-factor asset pricing model with time-varying coefficients to returns of renewable energy stocks. However, the study focuses on the German market only and the authors restrict themselves to applying typical pricing factors in financial markets such as factor-mimicking portfolios for size, value and price

[1] Source: www.nexindex.com. Accessed: September 2013.

momentum, see e.g. Fama and French (1993) or Carhart (1997). Also, unlike our analysis, the study does not include variables such as energy prices or returns from technology stocks.

Finally, we also significantly extend the time period considered in previous studies (Henriques and Sadorsky, 2008; Kumar et al., 2012; Sadorsky, 2012; Bohl et al., 2013; Managi and Okimoto, 2013) by using a data set up to 2014 that includes observations for the period of the global financial crisis and beyond.

The remainder of the paper is organized as follows. Section 2 provides a brief review of recent developments and trends in the renewable energy sector and the WilderHill New Energy Global Innovation Index. It also provides a motivation for the suggested framework and explores the data used in the empirical analysis. Section 3 deals with the implementation and estimation of the applied multi-factor model with time-varying coefficients. Section 4 provides our interpretation of the results and compares our findings to other major studies in the field. Conclusions and suggestions for future work are presented in Section 5.

2. Background Information and Data

2.1. Trends and Recent Development of Renewable Energy Markets

Renewable energy has experienced an impressive overall development in the last decade. Global investment has risen from \$46 billion in 2004 to over \$160 billion in 2009, as is summarized in Table 1. As a result, renewables accounted for 7% of global power capacity in 2009, up from 4% in 2004 (excluding large hydropower, UNEP 2010, p.12)[2].

This increase was also facilitated by expansionary fiscal policies and government established long-term targets for renewable energy, which made private investments into the sector more attractive (REN21, 2010; UNEP, 2010; Justice, 2009). The global recession led some of the world's major governments to implement expansionary stimulus packages, with significant funds going to the renewables sector. It has been estimated that about \$188 billion from these packages has been allocated to renewable energy and energy efficiency in 2008; the greater part of these stimuli was expected to be spent in the 2010-2011 period[3]. In addition, most governments in the world have adopted ambitious renewable energy targets for the next fifteen years. According to statistics elaborated by REN21 (Renewable Energy Policy Network for the 21st Century), by early 2010 more than 100 countries had renewable energy target policies; this figure compares to 55 countries in 2004. Some of these targets are remarkable. For example, renewable energy targets

[2] The UNEP (2010, p.12) 'narrow' definition of renewable energy includes production from industrial plants. Using an alternative 'broad' definition, REN21 (2010, p.15) suggests that nearly 19% of global final energy consumption in 2009 was provided by renewable energy. This 'broad' definition includes traditional biomass which accounts for 13% of the supplied figure. 'Traditional biomass' refers to resources used mostly in development countries that require no or little industrial value added (for example, burning wood for cooking and heating purposes). The definitions of renewable energy investment in Table 1 exclude traditional biomass which is irrelevant for our purposes.

[3] Source: REN21 (2010, p.27). The combined \$188-billion stimulus packages referred to is expected to be spent progressively over the period 2010-11. This is due partly to government's administrative barriers and partly to the research that needs to be done before investing in new renewable energy plants (for instance, the optimal location and operational timing of a new energy plant that connects to an existing electricity network requires careful study).

have been set by the European Union (20% of final energy consumption by 2020), Brazil (75% of electricity by 2030), China (15% of final energy by 2020), and India (20 GW of solar energy by 2022)[4]. Overall, the expansion has occurred not only in traditional markets such as North America or Europe (Table 1), but also in developing countries which now account for more than half of the existing renewable energy capacity. For instance, the combined investment on renewable energy from China and Brazil accounted for 25.5% of the $162 billion global investment in 2009 (UNEP, 2010, p.13).

Table 1: Renewable energy: Detailed disaggregation of global investment (private and public, in billion $) and power capabilities (as % of global power aggregates).

Renewable Energy at a Glance

	2004	2005	2006	2007	2008	2009	2010	2011	Compound Annual Growth Rate
Total New Investment on Renewable Energy (billion $)[a]	39.5	60.8	96.5	132.8	166.6	160.9	219.8	257.5	31%
Disclosure[b]									
New financial investment (NFI)	23.8	45.5	84.3	114.2	138.5	122.2	149.5	173.4	33%
R&D activities and small projects	15.6	15.3	12.2	18.5	28.1	38.7	70.3	84.1	27%
NFI by Technology[c]									
Wind	13.3	22.9	32.0	51.1	67.7	74.6	95.5	83.8	30%
Solar	13.8	16.4	19.5	37.7	57.4	58.0	96.9	147.4	40%
Biofuels	3.5	8.2	26.6	24.5	19.2	9.1	8.5	6.8	10%
Biomass and Waste	6.1	7.8	10.8	11.8	13.6	12.2	12.0	10.6	8%
Small Hydro	1.4	4.4	5.4	5.5	6.6	4.7	3.6	5.8	22%
Geothermal	1.4	1.0	1.4	1.4	1.9	2.0	3.1	2.9	12%
Marine	0.0	0.0	0.9	0.9	0.2	0.3	0.3	0.2	30%
NFI by Region[d]									
Europe	18.6	27.7	37.4	57.8	67.1	67.9	92.3	101.0	27%
US	7.4	11.2	27.2	28.5	37.7	22.5	32.5	50.8	32%
Brazil	0.4	1.9	4.3	9.3	12.7	7.3	6.9	7.5	51%
Americas (excluding US and Brazil)	1.3	3.3	3.3	4.7	5.4	6.4	11.0	7.0	27%
China	2.2	5.4	10.0	14.9	24.3	37.4	44.5	52.2	57%
India	2.0	2.9	4.7	5.6	4.7	4.2	7.6	12.3	29%
Asia and Oceania (excluding China and India)	7.2	8.0	8.0	10.1	11.0	12.1	18.4	21.1	17%
Middle East and Africa	0.3	0.4	1.6	1.9	3.7	3.1	6.7	5.5	50%
Power Supply Capabilities[e]									
Power capacity (as % of global)	3.6%	4.6%	5.0%	5.4%	6.1%	6.9%	7.9%	9.2%	-
Power generation (as % of global)	3.5%	3.5%	3.6%	3.8%	4.0%	4.5%	5.1%	6.0%	-
Capacity of Selected Technologies (Gigawatts)[f]									
Wind Power	47.9	59.4	74.3	94.0	122.2	160.1	-	-	-
Geothermal	8.9	9.1	9.5	9.9	10.3	10.7	-	-	-
Solar	3.8	5.3	6.8	9.2	15.6	22.9	-	-	-
Ethanol (annual production, million tonnes of oil equivalent)	14.9	16.9	21.1	26.9	35.6	38.4	-	-	-

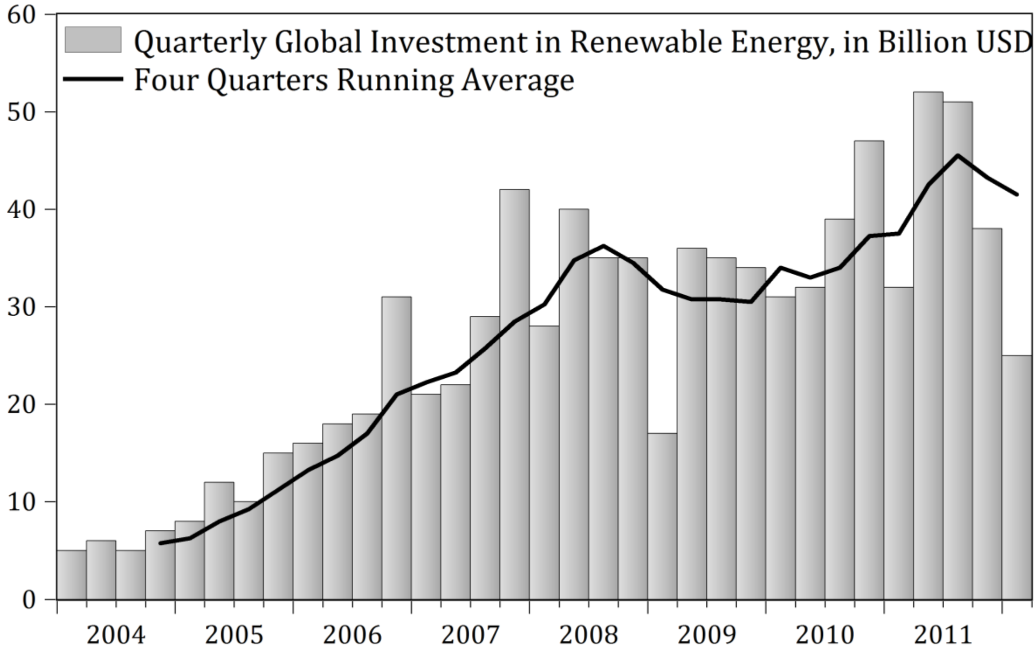
Notes: ([a,b,c,d]) provided by UNEP, 2012, p.15; ([e]) provided by UNEP, 2012, p.31; ([f]) provided by BP, 2010. ([a]) excludes re-invested equity, includes estimates for undisclosed deals and does not account for merger and acquisitions, and ([e]) excludes hydropower.

Despite all the long-run government targets, investment on renewable energy suffered a significant drop during the period 2008-2009. Figure 1 plots the quarterly frequency of global financial investment in renewable energy: it can be observed that the 4-quarter moving average peaked in the middle of 2008 and declined until the beginning of 2009 suggesting that renewable energy investment cycles may be related to oil prices. Exploring the data in Table 1 suggests that the decline in renewable energy investment occurred mostly in North America and Europe, while the Asia and Oceania region saw an increase in investment during the period 2008-2009. A key difference between these markets is that the US and Europe tend to use more market friendly policies and seek private participation in mixed (public and private investment) projects, whereas in China renewable energy projects tend to be much more controlled by central or provincial government funding.

[4] Source: REN21 (2010, p. 57-61).

Overall, we would expect a significant impact of government policies on investment in the renewable energy sector and, therefore, also on stock prices of companies related to the sector. As suggested by Wüstenhagen (2009), in particular experienced investors consider supportive policy environments as an important way to encourage investment in clean energy technologies

Figure 1: Global financial investment in renewable energy, quarterly data, in billion US dollars. Source: UNEP, 2012, p.19.



2.2. The WilderHill New Energy Global Innovation Index (NEX)

The WilderHill New Energy Global Innovation Index can be considered as the first and leading global stock market index for renewable, clean and alternative energy stocks (http://www.wildershares.com/stock.php). The index focuses on the generation and use of renewable energy, and the efficiency, conservation and advancement in renewable energy in general[5]. The index is composed of 106 companies in 25 countries (the largest company accounts for 1.95% and the top 10 holdings account for 16.7% of total NEX investment). The index has a total market capitalization of over $250 billion; comparing this figure to the data in Table 1 gives an account of the importance of the NEX as a major trading instrument in the global market for renewable energy.

The NEX portfolio is well-diversified across renewable energy sub-sectors and as of September 2013 NEX investment was composed of: solar energy (20.6%), wind energy (15.1%), biofuel and biomass (13.9%), renewable energy efficiency (34.8%), energy storage and conversion (3.4%) and projects related to renewable energy other than the

[5] Source: www.nexindex.com. Accessed: October 2014.

above (12.2%). The investments are distributed by regions with weights of 43.8% for the Americas, 29.1% for Asia and Oceania and 27.1% for Europe, the Middle East and Africa[6].

Given previous work on the related WilderHill ECO index employed by Henriques and Sadorsky (2008) Kumar et al. (2012) and Sadorsky (2012), it is worth commenting on the differences between the two indices. First, while stocks of firms producing renewable energy constitute a relatively small component of the ECO index, the NEX has a more direct focus on production of solar, wind, biomass and other renewable energy. Instead, the ECO index focuses more on power supplies, power transportation, electricity storage and cleaner fuels companies. Second, the NEX is globally diversified across different countries while the ECO index tends to focus more on North American firms. Also, the ECO index is listed in the US only, while the NEX is listed in many global markets and several currencies. Finally, the NEX also has a significantly higher capitalization than the ECO index. Overall, we believe that the NEX provides very suitable characteristics for analysing investment and the performance of renewable energy stocks at a global scale.

2.3 Modeling Strategy and Data Definitions

The proposed model and set of variables are motivated by a number of previous studies investigating the effects of energy and stock market prices on the renewable sector (Faff and Brailsford, 1999; Sadorsky, 2001; Boyer and Filion, 2007; Henriques and Sadorsky, 2008; Kumar et al., 2012; Sadorsky, 2012; Managi and Okimoto, 2013).

Faff and Brailsford (1999) examine the relationship between oil prices and stock market indices of various industries in Australia. They find significant effects of oil prices on equity returns, in particular for the oil, gas, resource and building industry stocks. Sadorsky (2001) finds positive effects of an increasing oil price on Canadian oil and gas stocks. The results are confirmed by Boyer and Filion (2007) who find evidence of a significant relationship between oil, respectively, natural gas prices and stock returns of Canadian oil and gas companies.

Henriques and Sadorsky (2008) consider the relationship between returns in equity investments and oil prices. The authors use a four-variable vector-autoregressive model including returns on renewable energy stocks, technology stocks, crude oil price and interest rates. Conducting Granger causality tests, they find that movements in technology stock prices, oil prices and interest rates each have some impact on the movements of the stock price of renewable energy companies. However, their study also shows that while shocks to technology stock prices have a large impact on prices of renewable energy companies, shocks to the oil price seem to have only little and no significant impact on renewables.

Kumar et al. (2012) also examine the relationship between alternate energy prices, oil prices, technology stocks and interest rates, but extend the analysis by also including carbon prices. Similar to Henriques and Sadorsky (2008), they also apply a vector-autoregressive model to study the relationship between the variables. Their results suggest that both the oil price and technology stock prices separately affect stock prices of clean energy firms. However, the authors do not find a significant relationship between carbon prices and renewable energy stocks.

[6] Source: www.nexindex.com. Accessed: September 2013.

Sadorsky (2012) applies multivariate GARCH and dynamic conditional correlation models to examine volatility spillover effects between oil prices, technology stocks and clean energy companies. The results of this study suggest that returns from clean energy companies correlate highly with returns from technology stocks and less so with changes in the oil price. The results also have significant impact on hedging the risk of price movements of renewable energy companies: technology stocks cannot be considered a good hedge, while due to significantly lower correlations oil provides a more useful hedge for clean energy stocks.

Finally, Managi and Okimoto (2013) also analyse the relationship between oil prices, clean energy stocks and technology stock prices. They extend previous work by analysing data up to 2010 and apply Markov-switching vector autoregressive models to detect possible structural changes in the examined relationship. They find evidence of a structural change occurring in late 2007, a period where a significant increase in the price of oil coincides with the U.S. economy entering into a recession. In contrast to Henriques and Sadorsky (2008), the authors find a positive relationship between oil prices and clean energy prices after the structural break, suggesting a movement from conventional energy to clean energy. They also suggest that there is a strong similarity between the market response of clean energy and technology stock prices to oil price shocks, which can be explained by both types of companies benefiting from government policies.

We approach the data from an investment viewpoint to try to obtain information about the determinants of NEX excess returns. We argue that NEX excess returns cannot be adequately modeled by a simple linear capital asset pricing model (CAPM) specification against a world equity index such as the MSCI World index. One reason for this is that, in reality, beta-factors are not constant over time. If the time-varying effects are significant, it is more appropriately to model the relationship by a state-space multi-factor asset pricing model which uses time-varying beta coefficients (van Geloven and Koopman, 2009; Tsay 2005, p.577; Bollerslev et al, 1988). In a state-space specification, the variation in the beta coefficient could be interpreted as a summary of how different factors –such as oil prices and technology stock returns- affect the relationship between NEX and MSCI World excess returns. However, we believe that it is more appropriate to incorporate these additional explanatory factors into our model directly, forming a multi-factor asset price model. It is our goal to study whether estimated beta factors in this more broadly-defined model can become time-varying, and, if this is the case, analyze their evolution through time.

We now proceed to the selection of additional factors to be included in our model. Based on our earlier discussions, it may be reasonable to consider at least two additional factors in the analysis. First, we believe that oil prices play an important role for observed returns of renewable energy companies. Generally, the literature suggests a negative relationship between rising oil prices and stock prices, see e.g. Huang and Masulis (1996), Sadorsky (1999, 2001), Park and Ratti (2008), Kilian and Park (2009). However, this might not be necessarily true for the renewables sector, since increasing oil prices may enhance the interest and investment in alternative energy sources, potentially causing a rise of clean or renewable energy stocks. Figure 1 suggests that the annual investment in renewable energy reached a peak in 2008[7]. This corresponds to a period when also oil prices reached a record high over $140/barrel in July 2008, after a steady climb over several years.

[7] The annual average of global investment in renewable energy peaks in the year 2008. Examining quarterly data suggests that the mode is found in the fourth quarter of 2007, although the annual average for 2007 is below the level in 2008.

Similarly, the NEX index also peaks in 2008. There are good reasons to think that high oil prices provide strong incentive to both governments and private investors to seek an acceleration of the development of alternative energy to reduce dependence on oil and fossil fuels over the long run (Bleischwitz and Fuhrmann, 2006; McDowall and Eames, 2006; Financial Times, 2006). As high oil prices are typically associated with recessions, expanding the share of the energy mix attributable to alternative energy should reduce the exposure of economies to oil price shocks. In line with this argument, high oil prices coupled with uncertainty about their future movement may have been one of the reasons why governments introduced the aforementioned long-run targets. There is also the possibility that private investors may use current oil prices as a proxy for the level of commitment by governments to support renewable energy programs.

Table 2: Descriptive Statistics for excess returns of the considered variables for the period September 2001 to February 2014 .

	Excess Returns			
	WilderHill NEX Index	**Pacific Stock Technology (PSE) Index**	**WTI Crude Oil Price**	**MSCI World Index (MSCI)**
Number of Observations	150	150	150	150
Mean	0.0043	0.0042	0.0125	0.0029
Median	0.0114	0.0063	0.0186	0.0146
Minimum Value	-0.3145	-0.2253	-0.2817	-0.2230
Maximum Value	0.2428	0.1970	0.2436	0.1457
Standard Deviation	0.07842	0.0692	0.1003	0.0480
Skewness	-0.7459	-0.3032	-0.2398	-0.7868
Excess Kurtosis	5.0905	3.3535	3.0523	5.9815
Sharpe Ratio	0.0543	0.0608	0.1242	0.0613
Correlation Structure				
NEX ER	1	-	-	-
PSE ER	0.7380	1	-	-
WTI Oil Price ER	0.3130	0.1514	1	-
MSCI ER	0.8741	0.7580	0.2494	1

The second additional factor that we incorporate relates to excess returns of high-technology stocks. The main reason for including this variable is based on previous work by Henriques and Sadorsky (2008), Kumar et al. (2012), Sadorsky (2012), Managi and Okimoto (2013), suggesting that investors might view renewable and alternative energy companies as representing an asset class similar to high technology stocks. As in these studies, we use the Pacific Stock Exchange Technology Index (PSE, also known as Arca Technology Index from 2006 onwards) as a benchmark, measuring the performance of pure technology stocks. The objective of the index '*is to provide a benchmark for measuring the performance of technology related companies across a broad spectrum of industries.*'[8] Also, unlike the Nasdaq, the PSE includes over-the-counter transactions, which may provide for a broader coverage. Note, however, that despite its broad focus, the PSE does not contain any firms being listed in the NEX.

In our multi-factor framework, it will be appealing to study the time-varying influence for each of these factors on NEX excess returns. Typically, multi-factor asset pricing models are concerned with excess returns of an asset or index over the risk-free rate, see, for example, Roll and Ross (1980), Fama and French (1993), Engle et al (1992), Carhart (1997), just to mention a few. This approach has also been implemented in the study of pricing factors for energy and gas companies (Boyer and Filion, 2007) or renewable energy

[8] Source: http://www.nyse.com/pdfs/NYSEEuronext_ArcaTech100.pdf

companies (Bohl et al., 2013). Therefore, using the monthly US treasury bill interest rate as a proxy for the risk-free rate, we calculate excess returns for the NEX, the MSCI World index, the WTI Crude Oil price and the PSE. Time series for the considered data are obtained from DataStream®:

NEX: New Energy Global Innovation Index.
MSCI: MSCI World Index.
OIL: WTI Crude Oil Price.
PSE: Pacific Stock Exchange Technology Index.
I: 4-Week US Treasury Bill Interest Rate (monthly rate, proxy to riskless investment).

$r_{NEX.t} = \frac{NEX_t - NEX_{t-1}}{NEX_{t-1}} - I_t$: Month t excess returns on *NEX*.
$r_{MSCI.t} = \frac{MSCI - MSCI_{t-1}}{MSCI_{t-1}} - I_t$: Month t excess returns on *MSCI*.
$r_{PSE.t} = \frac{PSE_t - PSE_{t-1}}{PSE_{t-1}} - I_t$: Month t excess returns on *PSE*.
$r_{OIL.t} = \frac{OIL_t - OIL_{t-1}}{OIL_{t-1}} - I_t$: Month t excess returns on *OIL*.

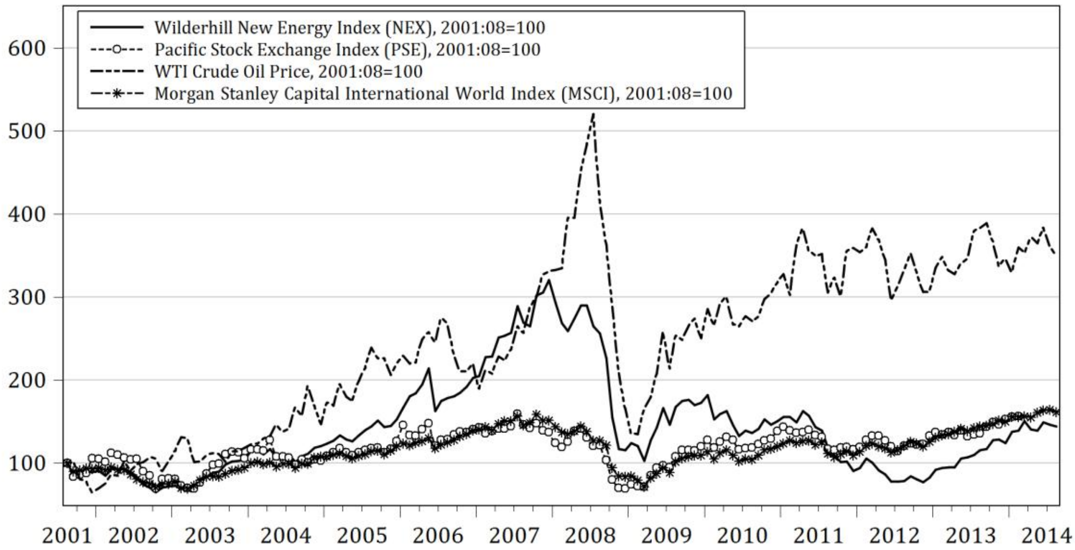
Our sample includes monthly observations for the indices from August 2001 to February 2014[9]. Table 2 provides descriptive statistics as well as Sharpe ratios for the excess returns of the variables. We find that mean monthly excess returns for the NEX, PSE and MSCI are close to zero during the time period, ranging from 0.29% for the MSCI up to 0.43% for the NEX. On the other hand, the WTI yields an average monthly return of 1.25% during the same time period. The WTI series is also the most volatile, and has a standard deviation of monthly returns of 10.03%, while the other variables yield standard deviations between 4.80% (MSCI) and 7.84% (NEX). The highest negative returns are observed for the NEX, which lost more than 31% over one month during the GFC period. With respect to measuring risk-adjusted performance, the WTI clearly yields the highest monthly Sharpe ratio of 0.1242, while comparable numbers are 0.0543 for the NEX, 0.0608 for the PSE and 0.0613 for the MSCI. Overall, the MSCI has the lowest performance with respect to mean excess returns, while the NEX yields the lowest risk-to-reward measured by the Sharpe ratio. Table 2 also illustrates the high correlation between excess returns of the NEX and the considered equity indices. We find a correlation coefficient of ρ=0.8741 for NEX and MSCI World returns, ρ=0.7380 for NEX and PSE returns, while correlations between the NEX and returns on the oil price are significantly lower (ρ=0.3130).

Figure 2 provides a time series of the values for the equity indices and the WTI for the considered time period from August 2001 to February 2014. To make it easier to compare the performance of the indices, each series is set equal to a base value of 100 at the start of the sample period in August 2001. The figure illustrates that all price series exhibited strong growth rates between August 2001 and the first half of 2007 and then dropped significantly during the GFC period. The slowest initial growth is observed for the MSCI, while the WTI Crude Oil price showed the most substantial growth rates that are also evidenced by the highest excess returns in Table 2. We observe that between 2001 and 2007 also the NEX provided growth rates that were substantially higher than for the PSE and MSCI World index. However, the graph also illustrates that after the GFC period, the PSE, WTI and MSCI recovered much faster from the extreme drop than the NEX. The NEX displays another significant drop in value during the period April 2011 to November 2012. Overall, Figure 2 suggests that after a comparatively strong performance of the

[9] Our monthly dataset corresponds to the value of the variables on the second Friday of each month, based on the considered sample we calculate excess returns for the period September 2001 to February 2014.

index between 2001 and 2007, after the financial crisis it seems like the NEX has underperformed in comparison to the other indices.

Figure 2: Index values for the NEX, WTI Crude Oil Price, MSCI World and PSE Index for the considered time period August 2001 – February 2014.



3. A Multi-Factor Asset Pricing Model with Time-Varying Coefficients

3.1. Model Setup

We now proceed to define the state-space multi-factor model with time-varying coefficients to be used in our empirical analysis. This specification can be seen as an extension of a CAPM in which additional explanatory variables are introduced and coefficients are allowed to change over time. The model can be written as

$$r_{NEX.t} = \alpha_t + \beta_{SP.t} r_{SP.t} + \beta_{PSE.t} r_{PSE.t} + \beta_{OIL.t} r_{OIL.t} + \varepsilon_t \,, \quad \varepsilon_t \sim nid(0, \sigma_\varepsilon^2), \tag{1}$$
$$\alpha_{t+1} = \alpha_t + \tau_{\alpha.t}, \quad \tau_{\alpha.t} \sim iid(0, \sigma_{\tau\alpha}^2), \tag{2}$$
$$\beta_{MSCI.t+1} = \beta_{MSCI.t} + \tau_{MSCI.t}, \quad \tau_{SP.t} \sim iid(0, \sigma_{\tau MSCI}^2)\,, \tag{3}$$
$$\beta_{PSE.t+1} = \beta_{PES.t} + \tau_{PSE.t}, \quad \tau_{PSE.t} \sim iid(0, \sigma_{\tau PES}^2)\,, \tag{4}$$
$$\beta_{OIL.t+1} = \beta_{OIL.t} + \tau_{OIL.t}, \quad \tau_{OIL.t} \sim iid(0, \sigma_{\tau OIL}^2)\,. \tag{5}$$

This model is similar to applications of state-space models in van Geloven and Koopman (2009), Tsay (2005), Koopman et al. (2008), Kim and Nelson (1999) and Bollerslev et al. (1988), although none of these authors applied this method to equity returns of energy companies. The novel aspect of the proposed model is the introduction of time-varying coefficients $\alpha, \beta_{MSCI}, \beta_{PSE}$ and β_{OIL}. To estimate these coefficients, we follow the procedures and notation in Koopman et al. (2008). In its state-space matrix representation, the model can be denoted the following way:

Measurement equation: $r_{NEX.t} = H_t B_t + \varepsilon_t \,, \ \varepsilon_t \sim nid(0, \sigma_{\varepsilon.t}),$

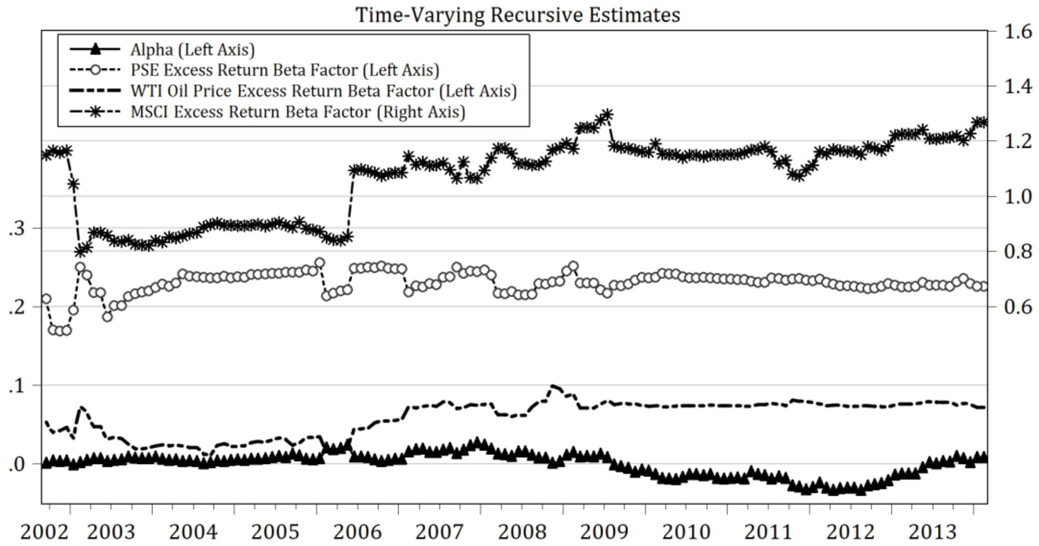
State equation: $B_{t+1} = F B_t + v_t \,, v_t \sim N(0, Q_t),$

State-space form: $\begin{pmatrix} B_{t+1} \\ r_{NEX.t} \end{pmatrix} = \phi_t B_t + u_t,$

where: $H_t = [1\ r_{MSCI.t}\ r_{PSE.t}\ r_{OIL.t}\ ]$, $B_t = [\alpha_t\ \beta_{MSCI.t}\ \beta_{PSE.t}\ \beta_{OIL.t}]'$, $F = \mathrm{I}_{4\times4}$, $v_t = \mathrm{I}_{4\times4}[\tau_{\alpha.t}\ \tau_{MSCI.t}\ \tau_{PSE.t}\ \tau_{OIL.t}]$, $Q_t = [\sigma_{\tau\alpha.t}\ \sigma_{\tau MSCI.t}\ \sigma_{\tau PSE.t}\ \sigma_{\tau OIL.t}]$, $\phi_t = [T_t\ H_t]'$, $u_t = [Q_t\ \varepsilon_t]'$.

The coefficients of the model can be estimated by a recursive maximum likelihood algorithm. In a first step the Kalman filter is used to obtain filtered estimates of the coefficients. Then, in a second step, smoothed coefficient estimates are obtained using the information from the whole sample. For a full description of the estimation procedure we refer, for instance, to Kim and Nelson (1999), Koopman et al. (2008), Durbin and Koopman (2001), and Commandeur and Koopman (2007). Note that as the number of observation increases, the distribution of the elements in v_t approaches normality.

Figure 3: Time-varying recursive estimates for $\hat{\alpha}_t, \hat{\beta}_{MSCI.t}, \hat{\beta}_{PSE.t}$ and $\hat{\beta}_{OIL.t}$.



3.2. *Estimation Output*

The results from our estimations are summarized in Table 3 and Figure 3. Table 3 provides information about the estimation results for equations (1)-(5), as well as for the smoothed time-varying estimates ($\hat{\alpha}_t, \hat{\beta}_{MSCI.t}$, $\hat{\beta}_{PSE.t}$, $\hat{\beta}_{OIL.t}$). The most relevant information for our analysis is provided by the smoothed time-varying coefficients displayed in Figure 3. One particular advantage of estimating a state-space model is that information about the dynamic nature of the factors influencing NEX returns can be extracted by examining the time-varying coefficients. Therefore, in the following we provide a detailed analysis of these results as well as tests investigating whether or not the estimated beta factors should be allowed to change over time.

From a first glance at the estimated time-varying coefficients in Figure 3, we find in particular that the returns of the MSCI World index and the PSE seem to impact on NEX returns during the considered time period. This is indicated by coefficients of significantly greater magnitude in the estimated state-space multi-factor model in comparison to the coefficient for WTI crude oil returns. We also observe that the estimated coefficients seem to vary quite substantially during the considered time period from September 2001 to February 2014: estimated beta coefficients for MSCI returns typically have a range between 0.8 and 0.9 for the period 2003 and 2005, while they take on significantly higher values above 1.0 from mid-2006 onwards and even greater than 1.2 from 2013 onwards; coefficients for PSE returns fluctuate between 0.17 and 0.26, while for WTI returns we find coefficients to be much lower, ranging from 0.02 and 0.04 between June 2003 and May 2006, while they are above 0.08 from 2008 onwards. We will more thoroughly examine and interpret the evolution of the coefficients in Section 4. We also find that while the estimates for the variances of $\tau_{PSE.t}$, $\tau_{MSCI.t}$, $\tau_{OIL.t}$ in the state equation are quite small, they are all statistically significant, as is indicated by large z-statistics in Table 3. This can be interpreted as evidence for the appropriateness of a model with time-varying coefficients, which will be further investigated in the next section.

3.3. Tests for Constant versus Time-Varying Coefficients

In the above estimations, all beta-factors as well as the intercept were allowed to vary over time. Such an approach is only appropriate when the estimated model coefficients indeed exhibit substantial variation through time. Therefore, in the following we carry out tests to examine whether the alpha- and beta-factors should be modeled with constant or time-varying coefficients. The testing approach used here is similar to that proposed in Koopman et al. (2008, p. 68) and van Geloven and Koopman (2009). The basic idea behind the test can be explained as follows: the test is applied to smoothed time-varying estimates of the coefficients $\{\hat{B}_t\} = [\hat{\alpha}_t\ \hat{\beta}_{MSCI.t}\ \hat{\beta}_{PSE.t}\ \hat{\beta}_{OIL.t}]_{t=1,..,n}$[10]. A constancy test at time $t = \overline{T}$ for the time-varying estimate $\hat{\beta}_i$ investigates whether its mean in the subsample (1,..., $\overline{T}$) is significantly different from its mean in the complementary subsample ($\overline{T}+1$,...,n). This can be examined using Welch's t test for unequal sample sizes with unequal mean and variances (Welch, 1947). The test is repeated period-by-period for $\overline{T}$=1,2,3,...,n.

More formally, the $\overline{T}$ –period null hypothesis of the test is defined as $\mathrm{E}(\beta_{i.1,...,}\beta_{i.\overline{T}}) = \mathrm{E}(\beta_{i.\overline{T}+1}, \dots, \beta_{i.T})$ and tested against the hypothesis $\mathrm{E}(\beta_{i.1,...,}\beta_{i.\overline{T}}) \neq \mathrm{E}(\beta_{i.\overline{T}+1}, \dots, \beta_{i.T})$. The Welch's t statistic for this test is given by:

$$t = \frac{\bar{b}_{i2} - \bar{b}_{i1}}{S_{\overline{\beta}_{i2}-\overline{\beta}_{i1}}}\ \text{, with}\ S_{\overline{\beta}_{i1}-\overline{\beta}_{i2}} = \sqrt{\frac{s_{i1}^2}{n_1} + \frac{s_{i2}^2}{n_2}}, \tag{6}$$

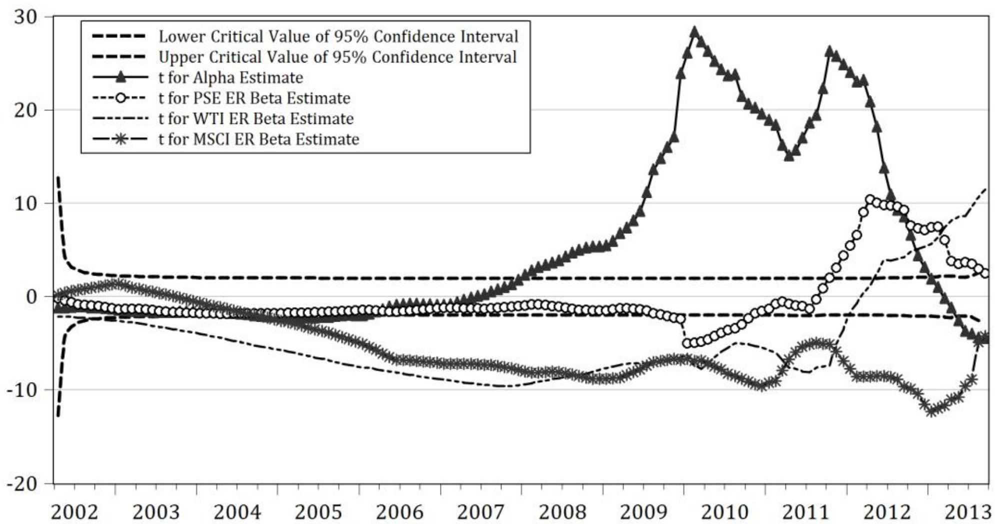
where n_1, $\bar{b}_{i1}$, s_{i1}^2 are the respective size, mean and variance of the first subsample for t = (1,..., $\overline{T}$) and n_2, $\bar{b}_{i2}$, s_{i2}^2 are the size, mean and variance for the second subsample, referring to observations t = ($\overline{T}+1, \dots, T$). The degrees of freedom parameter for the test statistic can then be approximated using the Welch-Satterthwaite equation.

[10] Note that the test could also be conducted using filtered estimates, however, Koopman et al. (2008, p. 68) suggest using smoothed values.

Table 3: Estimation output: summary.

Multi-factor asset pricing model with time-varying coefficients			
Estimation Results			
		Characteristics of Recursive Estimates	
Sample	09:2001 – 02:2014		
Data Frequency			
Observations	Monthly	Time-varying	
Log Likelihood	150	coefficient $\beta_{MSCI.t}$	
AIC	248.6981	Z-Statistic	7.268222
SC	-3.249308	Prob.	0.0000
HQC	-3.148954	Mean	1.071906
Fixed Parameters	-3.208538		
Diffuse Priors	5	Time-varying	
Time-varying	4	coefficient $\beta_{PSE.t}$	
Parameters	4	Z-Statistic	3.598684
		Prob.	0.0003
Fixed Estimates		Mean	0.230237
$\hat{\sigma}^2_{\varepsilon}$ = 0.0011096			
$\hat{\sigma}^2_{\tau\alpha}$ = 0.000014877		Time-varying	
$\hat{\sigma}^2_{\tau PSE}$ = 0.000000		coefficient $\beta_{OIL.t}$	
$\hat{\sigma}^2_{\tau OIL}$ = 0.000000		Z-Statistic	2.436031
$\hat{\sigma}^2_{\tau MSCI}$ = 0.00061251		Prob.	0.0148
		Mean	0.058701
		Time-varying	
		intercept α_t	
		Z-Statistic	0.644525
		Prob.	0.5192
		Mean	-0.00071

Figure 4: Linearity test: Period-by-period Welch's t testing suggests that the constancy of the parameters can be rejected for all variables.



Employing this period-by-period testing methodology for each of the variables in our model, we obtain the results exhibited in Figure 4. To interpret this graph, our criterion is that it is enough for a parameter to exhibit significant rejections of the null over a prolonged period of time to justify its time-varying nature in the setup of the model. We find that test statistics for all coefficients are well outside the specified critical values under the null hypothesis for a significant fraction of the sample period. This is true in particular for the beta-factors for the Crude Oil and the MSCI World index, but also for the majority of subsample choices for the intercept alpha and towards the end of the sample period for the PSE. Using the applied test, we conclude that constancy of each of the coefficients is rejected. Therefore, our time-varying coefficients model is deemed appropriate and is expected to provide us with additional information about the evolution of the included factors through time.

4. Interpretation of Results

Our estimation results –in particular for the time-varying beta-factors displayed in Figure 3- allow us to extract insightful information about the determinants of NEX excess returns as well as for active returns, i.e. the performance of the renewables sector relative to its identified pricing factors, throughout the considered time period. In the following we discuss the results separately for each variable as well as for the intercept alpha. We also relate our findings to previous studies on the relationship between prices of renewable energy stocks, energy prices and equity indices.

Influence of the MSCI World index. This factor is the most influential of the three, and the high correlation between MSCI and NEX returns is evidenced by Table 2. Considering that the whole-sample mean of the time-varying beta factor is $\bar{\beta}_{MSCI} = 1.07$, we can estimate the average impact of a change in the MSCI by one standard deviation on NEX excess returns at $\bar{\beta}_{MSCI} \times \sigma_{MSCI} = 0.051$. Therefore, one may say, that, on average, during the considered sample period a positive return in the MSCI index with the magnitude of one standard deviation, or 4.8%, could be expected to lead to a 5.1% increase in the NEX. This figure compares to $\bar{\beta}_{PSE} \times \sigma_{PSE} = 0.016$ and $\bar{\beta}_{OIL} \times \sigma_{OIL} = 0.006$. Overall, we find that a world equity index such as the MSCI can be considered as a key pricing factor for renewable energy stocks.

We also find that for the considered sample period, estimated beta coefficients for the MSCI have increased significantly between 2003 and 2014. While estimated coefficients typically are between 0.8 and 0.9 for the period 2003 and 2005, they take on significantly higher values in later periods. From late 2006 onwards estimated coefficients are above 1.0, while they even take on values greater than 1.2 in 2013 and 2014. The results also illustrate the additional benefit of applying a model with time-varying coefficients over a model with constant beta factors. The latter could not have detected the increasing influence of returns from a global equity index such as the MSCI World on returns from renewable energy companies.

There is also evidence of a structural change in the relationship between NEX and MSCI returns in mid-2006, when $\bar{\beta}_{MSCI}$ jumps from 0.85 to 1.09. This change is rather abrupt rather than smooth and we interpret it as a revision of the pricing strategy of the renewable sector with respect to a major world equity index. Risk re-assessments leading to abrupt changes are not uncommon in stock markets. A benefit of applying a multifactor asset pricing model with time-varying coefficients is also the distinction between abrupt and smooth changes.

Influence of Pacific Stock Technology (PSE) Index. This factor is the second most influential of the three, and Table 2 also indicates high correlations between PSE and NEX returns. The whole-sample mean of the time-varying beta factor is $\bar{\beta}_{PSE} = 0.23$, indicating a significant impact of changes in the PSE index on NEX excess returns, although it is weaker than the impact of the MSCI. However, our results in Table 3 and Figure 3 indicate that the PSE is highly significant as a pricing factor for renewable energy stocks. Despite some fluctuations through time and an initial increase of the estimated beta-factor during the beginning of the sample period, we observe that the coefficients for the PSE remain relatively stable, between 0.17 and 0.26, throughout the entire time period. Therefore, our findings suggest that returns on technology stocks provide supplementary information for investors in the renewable sector, in addition to a general global equity index such as the MSCI World. Technology stocks should be considered as an important additional pricing factor for the performance of renewable energy companies in global equity markets.

Our results regarding the influence of PSE returns on NEX returns are in line with Henriques and Sadorsky (2008), Kumar et al. (2012), Sadorsky (2012) and Managi and Okimoto (2013). These authors also suggest that investors might see renewable energy stocks as similar to high technology stocks such that the performance of a technology stock index like the PSE yields important pricing signals also for the renewable sector. A possible explanation for this phenomenon is that high technology and renewable energy companies often compete for the same inputs. These resources might include highly-qualified engineers and researchers, research facilities, semi-conductors, integrated circuits and thermoelectric materials, among others.

Influence of Oil Prices. The contribution of oil as a pricing factor is less clear-cut. Estimated time-varying beta-factors for changes in the oil price range between 0.01 and 0.10, indicating that oil is significantly less influential than the MSCI and the PSE. The estimated beta-factor for oil was close to zero in the period up to 2005, but then experienced rapid growth between late 2005 and 2007 (Figure 3). The influence of this beta factor was reinforced by further increases in oil prices. As the WTI crude oil price increased from \$134.84/b in June 2008 to \$144.96/b in July, our estimate $\hat{\beta}_{OIL}$ grows to approximately 0.10, meaning that an increase in oil price of 10% (about \$14/b) would have led to an increase of approximately 1% in monthly NEX returns at the time. Remarkably, the beta-factor remained approximately at the same level after the oil price peak in July 2008 until the end of the sample period. Additional conducted tests also indicate that if we split the entire period into two subperiods, e.g. before and after mid-2005, we find that oil becomes more significant in later subperiods. Recall that conducted tests on the time-varying nature of estimated coefficients clearly indicate that $\hat{\beta}_{OIL.t}$ should not be assumed as constant. The overall conclusion we draw from these results is that the crude oil price has been gaining influence as a pricing factor for NEX returns over the period of study.

Our results also explain the somehow contradictory findings in previous studies: while Henriques and Sadorsky (2008), using data up to 2007, only find a small or insignificant effect of oil prices on renewable energy stocks, later studies such as Kumar et al. (2012) and Managi and Okimoto (2013) suggest a positive relationship between oil and stock returns of alternative energy companies. Our state-space model with time-varying coefficients illustrates the changing nature of the relationship between the variables and the increased influence of WTI Crude Oil on NEX returns. From 2007 onwards, investors may have concluded that oil prices are an important factor shaping the renewable energy investment environment and government decisions. We link this to the various policy measures that governments have been introducing since 2005. As explained earlier, it is possible to argue that governments may see peaking or spiking prices for oil as a sign of strong recessionary pressure, which gives them incentive to promote alternative energy.

As pointed out previously, often renewable markets' profitability relies heavily on the role of governments to subsidize or support their activities.

Alpha (Intercept). Typically, in a CAPM or multifactor model, the intercept alpha measures an asset's return in excess of the compensation for the risk borne by the asset. This is often also referred to as the *abnormal* or *active return* of an asset. For our state-space model, the estimated $\hat{\alpha}_t$ varies through time and takes values between approximately -0.033 and 0.026. As indicated by Figure 4, the conducted constancy tests also suggest that alpha should be modeled as a time-varying coefficient.

Regarding the time-varying estimates of active returns, we find that during the first eight years of the sample period until mid-2009, the estimated $\hat{\alpha}_t$ are positive, indicating that investments in the NEX provided returns in excess of its expected risk-adjusted return. The highest abnormal returns can be observed towards the end of 2007, where estimates for active monthly returns are highly positive and take on a maximum value of $\hat{\alpha}_t = 0.026$ in November 2007. Interestingly, starting from this point in time, we observe that estimated $\hat{\alpha}_t$ exhibit a downward trend until the end of 2012. Investments in the NEX provided negative abnormal returns for the entire August 2009 to May 2013 period. During 2010 until the third quarter of 2011, $\hat{\alpha}_t$ is estimated between -0.013 and -0.020, while for the period October 2011 to December 2012 the underperformance of renewable energy stocks is even more pronounced with values of alpha below -0.028. These results are also in line with Figure 2 where the price levels of the indices as well as the oil price are displayed: the plot illustrates that unlike the PSE, MSCI and the WTI Oil price, the NEX did not offer a recovery of the same magnitude from the losses that occurred during the financial crisis in subsequent years. In particular from 2011 until the end of 2012 the NEX index exhibits another significant drop in value, while the other equity indices MSCI World and PSE are relatively stable and the WTI oil price even slightly increases. Only towards the end of the sample period the NEX shows another significant increase and provides higher returns, yielding also positive estimates of $\hat{\alpha}_t$ from the second half of 2013 onwards.

Overall, the index provides significantly lower returns during and after the GFC period than what would be suggested based on expected risk-adjusted returns from the applied multi-factor pricing model. In other words, the index clearly underperforms relative to the included pricing factors in our model for the period August 2009 until the end of 2012. Our findings also confirm and complement results of a recent study by Bohl et al (2013) who apply a four-factor asset pricing model to renewable energy stocks in Germany. The authors suggest that while renewable energy stocks earned considerable risk-adjusted returns between 2004 and 2007, the performance has deteriorated significantly since 2008 until the end of 2011. The authors argue that the initial outperformance of German renewable energy stocks until 2008 was driven by explosive price behaviour that created a price bubble. Reasons for such a bubble may also have been expectations about a further increase in government support or seminal advances in technology for renewables. Clearly, both developments would have had a significantly positive effect on the future profitability of renewable energy companies in Germany. Interestingly, we find a very similar pattern for the performance of a global index such as the NEX that includes worldwide active companies specializing in renewable energy, clean power and energy efficiency. Similar to Bohl et al (2013), we argue that when the stocks fell short of these high expectations, market participants reassessed their evaluation leading to a significant underperformance of the renewable sector from 2009 onwards.

There are also several additional reasons for the underperformance of the NEX in recent years. One explanation for the re-evaluation could be that investors did not believe in a further acceleration of the development of alternative energy after the global financial crisis. The importance of overcoming the gap between innovation, adoption and diffusion of new energy technologies, the so-called 'Valley of Death' is pointed out by Weyant (2011). Through subsidies, taxes, and research and development programs, governments play a significant role in facilitating private investment in this industry. Results of a survey among venture capitalists and private investors by Bürer and Wüstenhagen (2009) suggest that in particular experienced clean energy investors consider supportive policy environments as an important way to encourage investment in renewable energy technologies. However, as pointed out by Radowitz et al. (2010), the financial crisis has forced several governments to cut their subsidies since the costs of these policies is huge and government deficits have become too high. This includes for example a cut in feed-in tariffs in major European economies including Germany, Spain and Italy. Under such a scenario, in combination with a significantly lower oil price after the financial crisis, investors will consider it less likely that significant amounts of funding can be provided by governments for subsidies or tax reductions towards the renewable energy sector. Also, Hofman and Huisman (2012), conducting a follow-up study to Bürer and Wüstenhagen (2009), find that since the financial crisis most of the renewable energy policies have decreased in popularity by venture capital and private equity investors. Such an interpretation of the investment environment is clearly expected to place downward pressure on the value of renewable energy companies relative to other sectors.

Another possible explanation is mentioned by Sadorsky (2012), who states that the high correlation between the stock prices of clean energy companies and technology companies may create a dilemma. Since returns of clean energy companies are highly correlated to returns from technology companies, investors might only be interested in investing in renewable energy stocks if they provide at least a similar return-to-risk trade off as technology stocks. This has not necessarily been the case in the aftermath of the financial crisis, what might have further accelerated the poor performance of the renewable energy sector. Also, the mentioned gap between innovation, adoption and diffusion for renewable energy technologies might make it difficult to compete with technology stocks. The often significantly faster adoption and market acceptance of new technology goods such as, e.g. consumer electronic products, could also make investors prefer high technology over renewable energy companies. This may be true in particular during times of uncertainty about government policies towards creating a strong investment environment for the renewable sector. In summary, these arguments contribute to the explanation of observed negative active returns for the NEX during the 2009-2013 period.

5. Summary and Conclusions

Investments in renewable energy companies have exhibited substantial growth rates in the last decade. This development can be attributed to the conjunction of government policies, rising oil prices and evolving stock market liquidity for investments in renewable energy companies. Equity and venture capital investments in the renewable energy sector have the potential to provide high returns and there has also been an increased interest in the renewable sector at the global level. Several renewable or clean energy stock indices have been created, including the WilderHill New Energy Global Innovation Index

(NEX), the WilderHill Clean Energy Index (ECO) or the S&P Global Clean Energy Index (SPGCE).

In this paper, we examine factors impacting on the WilderHill New Energy (NEX) index, which represents a significant proportion of private investments in the sector. In particular, we propose a state-space multi-factor asset pricing model to study the role of excess returns of oil prices, technology stocks and the MSCI World index as explanatory factors. Our findings provide important insights into the dynamic nature of the determinants of NEX returns.

We find that NEX returns are highly correlated with the MSCI World Index as well as technology stock returns and to some extent also influenced by oil prices. Our results indicate that the MSCI World index plays a key role as pricing factor also for renewable energy companies. We also find that the PSE technology stock index is significant as an additional pricing factor for renewable stocks. Thus, returns on technology stocks provide information in addition to a common benchmark equity index such as the MSCI World. In that respect, our findings are consistent with previous studies in the field such as Henriques and Sadorsky (2008), Kumar et al. (2012) and their suggestion that investors may see renewable energy and high-technology markets as similar asset classes. We argue that the link between these two sectors may be due to the fact that they compete for the same inputs.

The influence of oil prices is relatively weak, although it has become more influential in recent years with a beta-factor that continued to increase after 2005. The application of a model with time-varying coefficients also helps to explain the somehow contradictory findings in previous studies. Earlier studies such as Henriques and Sadorsky (2008) only find a small or insignificant effect of oil prices on renewable energy stocks, while more recently, Kumar et al. (2012) and Managi and Okimoto (2013) suggest a positive relationship between oil and stock returns of alternative energy companies. The applied state-space model with time-varying coefficients clearly illustrates the changing nature of the relationship between the variables and the increased influence of oil prices on NEX returns.

With respect to active or abnormal returns, we find that the NEX initially provided returns in excess of its risk-adjusted premium during the period from 2003-2007, while it yielded negative active returns during the 2009-2013 period. A major reason for this is that the NEX did not recover from the losses experienced during the financial crisis in 2009 by the same magnitude as the other considered pricing factors. We argue that due to the lower oil price and subsidy cuts by governments after the global financial crisis, there was a higher uncertainty among investors towards the profitability of the renewable energy sector. As pointed out by Wüstenhagen (2009), in particular experienced clean energy investors consider supportive policy environments as an important way to encourage investment in the clean energy sector. Also, Hofman and Huisman (2012), suggest that since the financial crisis renewable energy policies have decreased in popularity by venture capital and private equity investors. These factors help to explain the clear underperformance of the renewable energy sector since 2009. Our findings also complement a recent study by Bohl et al. (2013) who examine the performance of renewable energy stocks and Germany. Similar to their results, we find that also the global index provided high risk-adjusted returns until 2007, while the performance has deteriorated significantly since 2008 due to to revised expectations and higher uncertainty among investors with regards to the profitability of the renewable energy sector.

Our study also contributes to demystifying the possibility of structural change. Our approach provides enough flexibility to accommodate both smooth and abrupt changes. We find evidence of an abrupt structural change in the relationship between NEX and MSCI excess returns, occurring in early 2006. Apart from this change, we do not find any evidence of an abrupt regime switch. All other changes affecting NEX returns were rather smooth, as opposed to abrupt. Empirical analysis suggests that the 2006 structural change is better explained as a change in the beta factor for MSCI returns. It means that investors may have changed their pricing strategy with respect to a benchmark stock index, rather than adjusting expectations affecting alpha or the other beta factors. The presence of this abrupt structural change does not affect the growing influence of NEX fundamentals, but rather reinforces the idea that the latter occur smoothly.

Overall, our paper contributes to understanding some important aspects of private investment and the performance of renewable energy companies in the stock market. In that process we can also identify directions for future research. First, it might be worthwhile to examine more deeply the relationship between the inputs in high-technology and renewable-energy industries to better explain common patterns as well as differences in the performance of specific companies in these sectors. Second, further global comparative research on government policies aimed at promoting renewable energy under the influence of oil prices would certainly contribute to the research agenda. We leave these issues for future research.

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