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Abstract

Stocks of German renewable energy companies have commonly been regarded as lucrative investment opportunities. Their innovative line of business initially seemed to promise considerable future earnings. As shown by two powerful bubble tests, the positive sentiment for renewable energy stocks even led to explosive price behavior in the mid-2000s. However, intense sector competition and the economic downturn following the global financial crisis erased profit margins to a large extent. As a result, the former fad stocks have recently turned into losers, loading negatively on price momentum and delivering significantly negative Carhart (1997) four-factor alphas. The radical shift in Germany's energy policy following the Fukushima nuclear disaster in Japan could thus only temporarily halt the continuing decline in alternative energy stock prices.

Keywords: Renewable Energy Stocks, Performance Measurement, Speculative Bubbles, Sup ADF Test, Markov Regime-Switching ADF Test

JEL Classification: G10, G11, G12, Q42

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1. Introduction

The rapid expansion of renewable energies in recent years has made the sector one of the most promising industries and has attracted the attention of a growing number of investors. According to Bloomberg New Energy Finance (2011), the global new investment volume in renewable energy reached a new record high of US$211 billion in 2010, an increase of 32% compared to 2009. The growth path was only temporarily interrupted by the global financial and economic crisis. After experiencing double-digit growth rates in the early and mid-2000s, new investments remained practically unchanged in 2009. Despite strong growth in the last years and the adoption of energy policies favoring the use of renewable energy sources in nearly 120 countries, renewable power generation accounted for merely 5.4% of the total global electricity generation in 2010 (Bloomberg New Energy Finance, 2011). Nonetheless, renewable energy sources constituted almost 30% of the increase in global power generation in 2010, reflecting their prominent status in satisfying the world's increasing energy needs.

The further development and promotion of renewable energy technologies is also crucial to dampening the economic effect of dwindling fossil fuel resources and to reducing carbon dioxide emissions that substantially contribute to global warming (Leggett and Ball, 2012). Similarly, renewable energy sources already play a decisive role in achieving the European Union's 2020 climate targets. Among others, the EU-27 member states have committed themselves to raising the share of renewable energy in overall energy consumption to 20% by 2020 (Klessmann et al., 2011; Eskeland et al., 2012).

In view of the sector's growing importance, the primary goal of this paper is to assess the performance of German renewable energy stocks during the time period from 2004 to 2011. Germany provides an interesting and unique setting to analyze the return behavior of companies in the alternative energy sector. The German Federal Government undertook a variety of energy policy changes that have paved the way for a transition to a sustainable energy supply. Such measures include the adoption of the Renewable Energy Sources Act in 2000, which aims to encourage the deployment of renewable energy technologies through the use of feed-in tariffs, as well as the accelerated nuclear power phase-out.

Following the Fukushima nuclear accident in March 2011, Germany decided to permanently shut down eight of its oldest nuclear power plants, while the remaining nine reactors will go offline by 2022 at the latest. The unprecedented decision to accelerate the nuclear power phase-out in Germany was entirely unexpected because in October 2010, the German Federal Government successfully passed an amendment to the Atomic Energy Act that even delayed the original phase-out strategy of June 2000. The amendment extended the lifetimes of the country's nuclear power plants for another eight to fourteen years (Betzer et al., 2011; BMU, 2011; Nestle, 2012), but was repealed again in light of the Fukushima nuclear disaster.

Given the increased public awareness of the potential risks of nuclear energy and climate change, Germany set ambitious goals to foster the development of a sustainable energy system. In 2010, the share of renewable energy sources in total energy consumption amounted to 11.3%, whereas the contribution to electricity generation was slightly higher at around 17.1% (BMU, 2011). By 2050, the German Federal Government even intends to cover at least 60% of total energy consumption and at least 80% of electricity consumption through the use of renewable energy sources (BMU, 2011). As a result, the growth prospects for German alternative energy companies may appear bright at first glance. However, fierce competition from Chinese manufacturers has increased the pressure on the industry, in particular on solar companies. The excess supply of solar panels from China, overcapacity and declining module prices have taken their toll on the solar industry's profitability. The strong decline in solar module prices began in the third quarter of 2008, amidst the global financial and economic crisis. According to Bloomberg New Energy Finance, a research provider that regularly collects market data from a variety of sources, prices for crystalline silicon modules ranged from US$3 to US$4.13 per watt of generating capacity between 2000 and mid-2008.[1] Since then, prices have fallen below US$1 per watt, which is even less than the production costs for many Western manufacturers. In 2011, the price drop of nearly 52% from US$2.01 to US$0.97 per watt was particularly severe and exacerbated the German solar industry's struggle to survive. As a result, a number of once pioneering German solar companies had to file for insolvency in late 2011 and early 2012.

The empirical findings of this paper are in line with the ambiguity concerning the current economic conditions for renewable energy stocks. We first analyze the multi-factor performance of two German stock indices – the ÖkoDAX and the DAXsubsector Renewable Energies. These alternative energy indices earned substantial positive returns from 2004 until 2007, even after controlling for exposures to the Carhart (1997) four-factor model. Most interestingly, the index constituents loaded positively on the price momentum factor, suggesting that they were perceived as winner stocks. However, the favorable risk-adjusted performance entirely reversed between 2008 and 2011, when the German renewable energy sector was severely hit by the global recession and the growing competition from East Asia. As a result, German renewable energy companies have recently turned into loser stocks and have delivered significantly negative Carhart alphas.

Given the positive market sentiment for renewable energy stocks in the first subperiod from 2004 to 2007, we conjecture that the strong outperformance might have been driven by a speculative bubble. To the best of our knowledge, no study has been conducted so far to test for explosive price behavior in renewable energy stocks in the mid-2000s. The stock

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[1] We thank Martin Simonek, solar analyst at Bloomberg New Energy Finance, for providing us with the relevant data.

market bubble literature has mostly focused on international large-cap stock indices and the dotcom era of the late 1990s. The reader may refer to Gürkaynak (2008) for a comprehensive survey of econometric techniques widely used to detect bubbles in asset prices. One reason for this gap in the literature might be the lack of usable data on fundamental factors, such as regular dividend payments or positive corporate earnings. Researchers interested in testing for speculative bubbles in German renewable energy stocks are therefore confined to econometric methods that are not based on fundamental factors, but rather focus on the time series of stock prices themselves. The main advantage of the latter approach is that it avoids testing a joint hypothesis of the presence of speculative bubbles and of the validity of the model used to determine the stocks' fundamental values.

Modern techniques, which meet this requirement, are the supremum Augmented Dickey-Fuller (sup ADF) test (Phillips et al., 2011, 2012) and the Markov regime-switching ADF test (Funke et al., 1994; Hall et al., 1999). These two powerful unit root tests indeed find explosive behavior in the real price time series of the ÖkoDAX and the DAXsubsector Renewable Energies during the second half of the 2000s and thus corroborate our conjecture.

The paper proceeds as follows. Section 2 provides a short review of the existing literature on renewable energy stocks. In Section 3, we explain the research methodology employed for performance measurement and bubble detection, while Section 4 describes our data. In Section 5, we present our empirical results. Section 6 summarizes our main findings and finishes with concluding remarks.

2. Literature Review

The extant literature on the performance and price behavior of renewable energy stocks is still relatively scant. Henriques and Sadorsky (2008) show that prices of technology stocks and of crude oil each individually Granger cause stock prices of alternative energy companies listed on major U.S. exchanges. The authors emphasize that the return behavior of alternative energy companies is closely related to that of high-tech stocks, whereas oil price shocks only have a limited impact. In a similar vein, Sadorsky (2012a) employs a number of multivariate GARCH models to study the volatility dynamics of alternative energy stocks. In particular, he finds that stock prices of alternative energy companies correlate more closely with technology stock prices than with oil prices. Kumar et al. (2012) confirm these overall findings by showing that clean energy stock prices are influenced by oil prices, interest rates and technology stock prices, but surprisingly not by the prices of carbon allowance futures from the European Union Emissions Trading System.

Moreover, Sadorsky (2012b) studies the determinants of systematic risk for U.S.-listed renewable energy stocks over the time period from 2001 to 2007. He finds that an increase in a company's sales growth reduces the stock's systematic risk, whereas a rise in oil prices tends to have an even greater, yet positive impact on the stock's beta. Interestingly, both Henriques and Sadorsky (2008) and Sadorsky (2012b) document that renewable energy stocks exhibit substantial market risk, as their betas range from 1.4 to even 2.

Bechtel and Füss (2010) examine the redistributive effects of the government's political orientation on economic sectors for the period from 1991 to 2005. The authors find a positive relationship between the electoral prospects of a left-leaning government in Germany and the stock returns of the alternative energy sector. However, the recent turnaround in energy policy adopted by the current conservative-liberal coalition government suggests that Germany's entire political spectrum now supports the development of renewable energy sources.

Two very recent studies investigate the impact of the Fukushima nuclear disaster in Japan on nuclear and alternative energy stocks. Ferstl et al. (2012) conduct an event study for the time of the nuclear accident and find that nuclear energy companies in France, Germany and Japan earn significantly negative cumulative abnormal returns, while alternative energy companies in the same countries show a positive abnormal performance during the event window. With the exception of Japan, the market adjusts rather quickly to the news of the devastating nuclear accident, indicating some degree of market efficiency. By contrast, U.S. nuclear and alternative energy companies do not seem to be significantly affected by the event. Similarly, Betzer et al. (2011) investigate the unique and unexpected reaction of the German Federal Government to the Fukushima nuclear disaster that included the temporary shutdown of almost half of the nation's nuclear power plants. The authors report that German renewable energy stocks gained nearly 18% on a beta-adjusted basis over the first 20 trading days after the incident, while the German nuclear and conventional energy sector lost about 3.5% over the same period.

3. Methodology

3.1 Multi-factor performance measurement

The aforementioned literature identified some variables that influence the returns of renewable energy stocks. However, the performance has not yet been studied extensively from an investor's perspective by attributing the returns to commonly used benchmark factors. We therefore employ Carhart's (1997) four-factor model to adjust monthly excess returns for exposures to the market, size, book-to-market and momentum factor. The performance attribution allows us to investigate whether the return behavior of renewable energy stocks resembles that of known factor-mimicking portfolios and whether renewable energy stocks earn significant abnormal returns. The Carhart (1997) four-factor model is estimated via ordinary least squares (OLS) and reads as follows:

$$R_t - r_{f,t} = \alpha + \beta_1 Market_t + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 PR1YR_t + \varepsilon_t \,. \tag{1}$$

$R_t - r_{f,t}$ is the index excess return over the risk-free rate in month *t*. The unconditional Carhart alpha α represents the return in excess of the reward for the exposure to the four factors. *Market* denotes the value-weighted market portfolio return of month *t* in excess of the risk-free rate. The return difference between small-cap stocks and large-cap stocks is denoted by *SMB*, while *HML* represents the return difference between high book-to-market equity stocks and low book-to-market equity stocks. The prior one-year price momentum factor *PR1YR* captures the return spread between a portfolio of past winner stocks and a portfolio of past loser stocks. The error term is denoted by $\varepsilon_t \sim N(0, \sigma_\varepsilon^2)$.

Given the rather risky and uncertain nature of the renewable energy business, it is not unlikely that factor exposures may change over time instead of being constant throughout the sample period. We address this issue by allowing for time-variation in the Carhart alpha and beta coefficients. We therefore express the Carhart (1997) four-factor model in state-space form and apply the Kalman filter to estimate time-varying coefficients:

$$R_t - r_{f,t} = \alpha_t + \sum_{k=1}^{4} \beta_{k,t} F_{k,t} + \varepsilon_t \,, \tag{2}$$

$$\alpha_t = \alpha_{t-1} + \nu_t \,, \;\; \nu_t \sim N(0, \sigma_\nu^2) \,, \tag{3}$$

$$\beta_{k,t} = \beta_{k,t-1} + \eta_t \,, \;\; \eta_t \sim N(\bar{0}, Q) \,. \tag{4}$$

The time-varying coefficients are assumed to evolve according to a pure random walk and are denoted by α_t and $\beta_{k,t}$ with k = 1, …, 4. $F_{k,t}$ represents the four factors of equation (1).

The normally distributed error terms ε_t, ν_t and η_t are serially uncorrelated with zero mean, variance σ_ε^2, σ_ν^2 and diagonal covariance matrix Q, respectively.

Equation (2) is called the measurement equation, while equations (3) and (4) represent the transition equations, which describe the evolution of the unobserved state variables. The Kalman filter is a recursive algorithm for computing the optimal estimates of the state variables for each period *t*, conditional on the information set available at time *t* (Kim and Nelson, 1999; Durbin and Koopman, 2001). This technique is applied to calculate maximum likelihood estimates of the model parameters σ_ε^2, σ_ν^2 as well as Q and to derive the filtered values of the state variables α_t and $\beta_{k,t}$. To start the algorithm, we set the initial one-step-ahead predicted values of the state variables equal to the OLS estimates obtained from the static model in equation (1) by using only the observations from the first 36 months. Empirical applications of the Kalman filter in multi-factor performance models can be found, amongst others, in Swinkels and van der Sluis (2006), Mamaysky et al. (2008) and Bauer et al. (2009).

3.2 Sup ADF test

Our bubble detection tests are based on methods that only require price time series. We employ two powerful variants of the commonly known ADF test, which examine a possible regime switch from a random walk to an explosive autoregressive process.

The first of these unit root tests, the sup ADF test, was originally proposed by Phillips et al. (2011) and recently extended by Phillips et al. (2012) to account for the case of multiple collapsing bubble episodes. Extensive simulations conducted by Phillips et al. (2011, 2012) as well as Homm and Breitung (2012) indicate that the sup ADF test has substantial power to detect speculative bubbles. Despite its very recent introduction, economic applications of the sup ADF test are not limited to bubble phenomena on stock exchanges, but also cover price booms in commodity and housing markets (Phillips and Yu, 2011; Homm and Breitung, 2012).

Stock market prices are commonly assumed to follow a random walk. As a result, prices usually contain a unit root, except during times when they deviate substantially from their fundamental values. A period of soaring prices might be characterized by explosive behavior or a speculative bubble, which is exactly what we would like to test for by using the sup ADF test. This technique can be regarded as a sequence of ADF test statistics under the null hypothesis of a unit root in the price time series of the renewable energy stock index x_t against the alternative of a mildly explosive root. The sup ADF test estimates the conventional ADF model repeatedly on a forward expanding sample sequence and conducts a right-tailed hypothesis test based on the supremum value of the corresponding sequence of ADF statistics. These forward recursive OLS regressions are performed by using subsets of the total sample incremented by one observation at each pass. More specifically, we estimate the following ADF equation:

$$\Delta x_t = \omega + \delta x_{t-1} + \sum_{p=1}^{P} \phi_p \Delta x_{t-p} + \varepsilon_t \,, \quad \varepsilon_t \sim N(0, \sigma_\varepsilon^2) \,, \tag{5}$$

where Δ stands for the first difference operator, ω, δ and ϕ_p with $p = 1, \ldots, P$ denote the regression coefficients and ε_t represents the normally distributed error term.[2] The initial regression involves $\tau_0 = [Tr_0]$ observations, for some initial fraction r_0 of the total sample length T. Subsequent recursive regressions employ the initial dataset supplemented by successive observations, thus yielding a respective sample of size $\tau = [Tr]$ for $r \in (r_0, 1)$ at each step. Note that if $r = 1$, the conventional ADF test is nested in the sup ADF procedure.

[2] In order to ensure that the error terms ε_t are serially uncorrelated, we apply the general-to-specific approach (Campbell and Perron, 1991). The optimal lag length P is determined by starting with the integer part of $P_{max} = T^{1/4}$ and then reducing the model until the last lagged difference term has a statistically significant influence at the 5% level in each recursive regression.

For the unit root test under the null hypothesis H_0: $\delta = 0$ against the right-tailed alternative H_1: $\delta > 0$, we denote the corresponding t-statistic by ADF_r.

In order to locate the origination and termination of explosive price behavior, we compare the time series of the recursive test statistic ADF_r with the right-tailed critical values of the asymptotic distribution of the conventional Dickey-Fuller t-statistic. In particular, if $\hat{\tau}_e = [T\hat{r}_e]$ corresponds to the origination date and $\hat{\tau}_f = [T\hat{r}_f]$ to the collapse date of explosive price behavior, we compute estimates of these dates as in Phillips et al. (2011):

$$\hat{r}_e = \inf_{s \geq r_0}\{s: ADF_s > cv(s)\}, \quad \hat{r}_f = \inf_{s \geq \hat{r}_e}\{s: ADF_s < cv(s)\}, \tag{6}$$

where $cv(s) = \log(\log(Ts))/100$ with $s \in (r_0, 1)$ is the right-tailed critical value of ADF_s and corresponds to a significance level of slightly less than 5%. The sup ADF test is applied to the daily and weekly price time series of the renewable energy stock indices, deflated by the German Consumer Price Index (CPI).[3] The inflation adjustment is carried out to remove the effect of changes in consumer prices on stock price levels.

3.3 Markov regime-switching ADF test

The aforementioned sup ADF test is related to the similarly powerful Markov regime-switching ADF test, which was originally proposed by Funke et al. (1994) and Hall et al. (1999). While the sup ADF procedure allows calculating the origination and conclusion dates of explosive price behavior, the Markov regime-switching ADF approach leads to probabilities of being in the possible bubble and non-bubble regime, respectively. Put differently, if speculative bubbles exist, the Markov regime-switching ADF test should be

[3] As the CPI data are only available at monthly frequency, we assume that inflation remains constant throughout the entire month. We deflate the nominal time series by multiplying the stock index by the consumer price index of the last sample month, December 2011, and dividing it by the consumer price index of the respective month. The data points for December 2011 are thus identical in both nominal and real terms.

able to distinguish between a moderately evolving regime on the one hand and an explosive and subsequently collapsing regime on the other hand. An important difference between the two techniques is that the sup ADF test does not specify the mechanism for switching to explosiveness, whereas the Markov regime-switching ADF test selects the regime at date *t* with a transition probability that depends on the regime the process was in at date *t*-1. According to Phillips et al. (2011), it is reasonable to believe that the *p*-value of the right-tailed sup ADF test is negatively related to the probability of being in the possible bubble regime in the Markov regime-switching ADF model.

The first-order Markov regime-switching ADF equation reads as follows:

$$\Delta x_t = \omega_{S_t} + \delta_{S_t} x_{t-1} + \sum_{p=1}^{P} \varphi_{p,S_t} \Delta x_{t-p} + \upsilon_{S_t}\,, \quad \upsilon_{S_t} \sim N\left(0, \sigma_{S_t}^2\right) \tag{7}$$

where S_t = (0, 1) is the unobserved stochastic regime variable that follows a first-order Markov process with constant transition probabilities, $\psi \equiv (\omega_{S_t}, \delta_{S_t}, \varphi_{p,S_t})$ with p = 1, …, P are the regression coefficients, and υ_{S_t} represents the normally distributed error term.[4] If we are able to distinguish between a bubble and a non-bubble regime, we will obtain one δ_{S_t}, which is statistically significantly greater than zero (i.e., this regime is explosive and then collapsing), and another δ_{S_t}, which is not significantly greater than zero (i.e., this regime is either stationary or contains a unit root). Since the probability of regime S_t depends on the past only through the value of the most recent regime S_{t-1}, the transition probabilities are defined as p_{00}= Prob(S_t = 0 | S_{t-1} = 0) and p_{11}= Prob(S_t = 1 | S_{t-1} = 1). Finally, we collect all unknown parameters in the vector $\theta \equiv (\psi, \sigma_{S_t}^2, p_{S_t,S_t})$ and estimate θ via the expectation-maximization (EM) algorithm (Hamilton, 1994; Kim and Nelson, 1999).

[4] As before, the optimal lag length P is determined by starting with the integer part of P_{max} = $T^{1/4}$ and then reducing the model until the last lagged difference term has a statistically significant influence at the 5% level in at least one regime.

4. Data and Descriptive Statistics

Our sample is based on two widely followed German renewable energy stock indices, the ÖkoDAX and the DAXsubsector Renewable Energies. The equal-weighted ÖkoDAX comprises the ten largest German companies from the solar, wind, hydropower and bioenergy sector, whereas the free float-weighted DAXsubsector Renewable Energies is a broader index consisting of 23 companies as of December 2011. Our period of investigation covers eight years between January 2004 and December 2011.[5] Daily and weekly price index data for the bubble detection tests as well as monthly total return index data for the performance measurement are taken from Thomson Reuters Datastream. The CPI data are obtained from the Federal Statistical Office of Germany.

Panel A of Figures 1 and 2 depicts the performance of the two renewable energy stock indices. The graphs show the inflation-adjusted price data, which we later use for our bubble detection tests. Both indices rose steadily until January 2006 when renewable energy stock prices virtually skyrocketed until May 2006. After a short correction phase, stock prices began to climb up again in late 2006, reaching another peak at the end of 2007. The subsequent eruption of the global financial and economic crisis in 2008 sent renewable energy stock prices into a tailspin, from which they have not recovered yet. Moreover, as can be seen by the little spike around March 2011, the Fukushima nuclear disaster in Japan and the subsequent radical shift in Germany's energy policy could only temporarily counteract the continuing decline in renewable energy stock prices (see also Betzer et al., 2011; Ferstl et al., 2012). As of December 31, 2011, the aggregate market capitalization of the ÖkoDAX amounted to €3.3 billion, while that of the broader DAXsubsector Renewable Energies stood at €4.3 billion. Market values have shrunk substantially compared to their

[5] We start on January 1, 2004, as this is the first date for which Thomson Reuters Datastream provides data on the DAXsubsector Renewable Energies.

all-time highs of €17.8 billion and €23.1 billion in 2007, respectively, turning German renewable energy companies into small and micro-cap stocks.

[*Figures 1* and *2* about here]

For the monthly market return in the Carhart (1997) four-factor model, we use the value-weighted CDAX, which is a total return index covering the broad German equity market. The risk-free rate is proxied by the one-month EURIBOR. We calculate the monthly factor-mimicking portfolios *SMB*, *HML* and *PR1YR* by using all active and dead German stocks listed on the Frankfurt Stock Exchange during the sample period, provided that return and balance sheet data are available on Thomson Reuters Datastream and Worldscope. The factors are constructed as described in Fama and French (1993) and Carhart (1997).[6]

Table I presents mean returns and the correlation matrix of the four factor-mimicking portfolios for the sample period from January 2004 to December 2011. Not surprisingly, the market excess return *Market* is only positive and significant for the first subperiod until December 2007, before it turns negative in the wake of the global financial and economic crisis of the late 2000s. The size factor *SMB* is negative for both subperiods, whereas the value factor *HML* delivers positive returns throughout the entire sample period. The momentum factor *PR1YR* is most pronounced with a positive and significant mean return of 0.92% per month. Overall, our results are similar to those reported in Artmann et al. (2012), who investigate the German stock market for a much longer time period from 1962 to 2006.

[*Table I* about here]

[6] We closely follow the screening procedures suggested by Schmidt et al. (2011) to ensure data quality.

5. Empirical Results

5.1 Performance analysis

We investigate the multi-factor performance of the two renewable energy stock indices for both the full sample period from 2004 to 2011 and two subperiods of equal length. Table II reports the regression results of the Carhart (1997) four-factor model in equation (1). For the full sample period in Panel A, the ÖkoDAX earns a negative mean excess return over the one-month interbank rate, whereas the DAXsubsector Renewable Energies delivers a slightly positive mean excess return. However, since both excess returns are statistically insignificant, investors would not have been much worse off if they had simply invested in the money market. Similarly, the Carhart alphas are also statistically indistinguishable from zero, indicating that the two renewable energy stock indices were not able to generate abnormal returns in excess of the returns earned by the systematic benchmark factors.

Consistent with prior literature on U.S. alternative energy stocks (Henriques and Sadorsky, 2008; Sadorsky, 2012b), the German counterparts also have market betas of about two and are thus twice as risky as the general market. Besides, they load heavily on the size factor *SMB*, which reflects their relatively small firm size in terms of market capitalization. Given the negative size premium earned in Germany during the sample period (see Table I), this pronounced sensitivity contributes negatively to the systematic excess return component. The latter is negative, albeit not significant, for both stock indices. Not surprisingly, the coefficient on the value factor *HML* is negative, indicating that the returns of renewable energy stocks have more in common with the returns of growth stocks. In addition, renewable energy stocks appear to be unexposed to the price momentum factor *PR1YR*, at least on average for the entire sample period. It is worth mentioning that the return behavior of renewable energy stocks contains a substantial idiosyncratic component, since the four-factor model explains no more than 50% of the return variation, as indicated by the adjusted R^2.

[*Table II* about here]

When splitting the full sample into two subperiods of equal length from 2004 to 2007 and from 2008 to 2011, respectively, some interesting patterns emerge. For the first subperiod, the mean excess returns and the four-factor alphas are considerably positive and mostly significant, reflecting the remarkable outperformance of renewable energy stocks during that period of time. As also reflected in the price charts in Panel A of Figures 1 and 2, the mean excess and the mean risk-adjusted return are considerably higher for the broader DAXsubsector Renewable Energies than for the ÖkoDAX. The positive loadings on the price momentum factor *PR1YR* are also substantial and contribute positively to the systematic excess returns. German renewable energy stocks could thus be regarded as winner stocks in the mid-2000s. However, they became loser stocks in the second subperiod from 2008 to 2011, when their exposure to *PR1YR* turned negative. Overall, the prior outperformance turned into a pronounced underperformance. The negative and significant Carhart alphas reveal that the two indices lost on average more than 2% per month on a risk-adjusted basis.

The performance reversal suggests some time-variation in the coefficients of the Carhart (1997) four-factor model. We therefore compute time-varying alphas and factor exposures using the Kalman filter and display them in Figures 3 and 4.[7] The graphs illustrate both the reversal of the momentum exposure and the deterioration in risk-adjusted returns of the two stock indices. While the market beta and the sensitivity to the value factor *HML* remain largely constant over time, the exposure to the size factor *SMB* tends to decrease somewhat

[7] Recursive and rolling window regressions yield similar results for the time-varying coefficients of the Carhart (1997) four-factor model.

until the middle of the second subperiod. This decline might be due to the increased market capitalization of German renewable energy stocks after the sharp rise in stock prices in the first subperiod.

[*Figures 3* and *4* about here]

5.2 Sup ADF test

The multi-factor performance analysis reveals a remarkable outperformance of German renewable energy stocks between 2004 and 2007. We next investigate whether the price run-ups during that period of time were affected by speculative bubbles and perform the sup ADF test as outlined in Section 3.2. Following Phillips et al. (2011), we set r_0, which is the fraction of the total sample size used to determine the initial window length, equal to 0.10. Using the recursive regression approach, the first row in Panel A of Table III reports the results for the real price indices of the ÖkoDAX and the DAXsubsector Renewable Energies. The supremum of the recursive ADF test statistics, which is used to evaluate the null hypothesis of a unit root against the alternative of an explosive root, is highly statistically significant for both daily and weekly data. Thus, we conclude that speculative bubbles were indeed present in German renewable energy stocks during the sample period between 2004 and 2011.

[*Table III* about here]

In order to locate the origination and termination of exuberance, we compare the time series of the recursive test statistics ADF_r, which are displayed in Panel B of Figures 1 and 2, with the right-tailed critical values at the 5% significance level. The first row in Panel B of Table III summarizes the bubble episodes identified by the recursive sup ADF test for daily and weekly real price data of the ÖkoDAX and the DAXsubsector Renewable Energies, respectively. Using daily real data of the ÖkoDAX, for example, speculative bubbles can be detected in September and October 2005, from January to May 2006, and again in February 2007. Relating this evidence to the price time series from Panel A of Figure 1, we see that the inflation-adjusted ÖkoDAX indeed skyrocketed by up to 130 percent during the first months of 2006.

As a robustness check, we repeat the sup ADF procedure based on rolling regressions. Hence, we do no longer extend the initial subsample by one observation at each pass, but hold the length of the regression window constant and roll it through the entire sample. Following Phillips et al. (2011), we set $r = 0.20$, so that the rolling window has 408 daily and 83 weekly observations, respectively. The second row in Panel A of Table III presents the results for the real price indices of the ÖkoDAX and the DAXsubsector Renewable Energies, respectively. The maximum value of the rolling ADF test statistics is again highly statistically significant for both data frequencies employed. The corresponding bubble episodes identified by the rolling sup ADF test are reported in the second row in Panel B of Table III and are qualitatively similar to those reported for the recursive approach.

Finally, we also run the generalized sup ADF test, as proposed by Phillips et al. (2012). While the forward recursive approach fixes the starting points of the subsamples on the first observation of the total sample, the generalized sup ADF procedure extends the subsample sequence by changing both the starting points and the end points of the subsamples over a feasible range of flexible windows. This modified test procedure may benefit from its higher power compared to the conventional sup ADF test, once multiple collapsing bubble episodes are present. As indicated by the third row in Panels A and B of Table III, the generalized sup ADF test corroborates our overall findings.

5.3 Markov regime-switching ADF test

Finally, we turn to our second bubble detection approach, namely the Markov regime-switching ADF test. Phillips et al. (2012) point out that Markov regime-switching models are not always able to distinguish periods that exhibit genuine explosive price behavior from periods of spurious explosiveness caused by a high regime-dependent error variance. As a result, they may erroneously identify different regimes, even though there are no structural breaks in the data. To test for the stability of the ADF coefficient over time, we first apply the Quandt-Andrews unknown breakpoint test to the real price data of the two renewable energy stock indices. Results are reported in Table IV and show that all test statistics are highly statistically significant for both daily and weekly data, indicating the presence of at least one structural break in the ADF coefficient. This finding is not surprising given the evidence for the sup ADF test in the previous subsection.

[*Table IV* about here]

The presence of structural breaks allows us to run the Markov regime-switching ADF test as described in Section 3.3. Table V presents the results for the real price data of the two renewable energy stock indices. Irrespective of the data frequency, some characteristics appear to be robust for both stock indices. First, regime 0, which turns out to be the unit root regime, is in all cases more volatile and slightly less persistent than the explosive regime 1 (i.e., $\sigma_0 > \sigma_1$, $p_{00} < p_{11}$). Second and most important, the ADF coefficient in regime 1 is always significantly greater than zero, indicating explosive price behavior. By contrast, the ADF coefficient in regime 0 is not significantly smaller than zero and thus suggests a unit root process.

[*Table V* about here]

In order to locate the origination and termination of the periods of explosive price behavior, we finally turn to the filter and smoothed probabilities of being in the bubble regime 1. Panel C of Figures 1 and 2 shows these probabilities for the less noisy weekly real price data of the ÖkoDAX and the DAXsubsector Renewable Energies, respectively. In contrast to the relatively short bubble episodes identified by the sup ADF test, the Markov regime-switching model identifies explosive price behavior for a much longer time period beginning in 2006 and ending in early 2009. Apart from a few exceptions, the price indices mostly stayed in the bubble regime during that period of time. Taken as a whole, the Markov regime-switching ADF test strengthens our earlier empirical findings, but does not switch back to the unit root regime as quickly as the sup ADF test does. More precisely, the sup ADF test only detects explosive behavior, but does not incorporate sideways price movements after a sharp price increase has occurred. By contrast, the Markov regime-switching ADF test accounts for the prolonged period of time during which stocks trade at higher price levels.

6. Summary and Conclusions

The rapidly growing renewable energy sector has attracted the attention of numerous stock market investors over the last decade. To arrive at a fair valuation of renewable energy stocks, it is of utmost importance to have a good understanding of the associated risk and return properties, which substantially deviate from those of conventional large-cap stocks.

The goal of this paper was therefore to analyze the common risk factors that drove the performance of German renewable energy stocks over the period from 2004 to 2011. We focus on Germany as this country provides an interesting setting for two reasons. Both the accelerated nuclear phase-out by 2022 and the ongoing efforts to encourage the transition to a sustainable energy system make German alternative energy stocks appear lucrative at first glance. However, increasing global competition and the current overcapacity in the solar sector weigh heavily on the profitability of the renewable energy industry.

Our empirical results for the two German stock indices ÖkoDAX and DAXsubsector Renewable Energies mirror the ambiguity concerning the industry's future economic outlook. We find that German renewable energy stocks earned considerable risk-adjusted returns during the first subperiod between 2004 and 2007. They also loaded positively on the price momentum factor, indicating that they belonged to the group of winner stocks. The strong outperformance, however, completely reversed during the 2008 to 2011 period, when renewable energy stocks delivered significantly negative Carhart alphas and showed a negative loading on price momentum. Moreover, German renewable energy stocks exhibited substantial systematic risk, given their market beta of nearly two and a strongly positive sensitivity to the size factor, which has delivered negative returns in recent years. Altogether, the recent risk and return characteristics suggest that investors should be cautious when holding German alternative energy stocks in their portfolios, as these could prove detrimental to their overall performance.

It is interesting to note that German renewable energy stocks have turned into loser stocks after being perceived as fad stocks during the mid-2000s. In fact, we find that the outperformance for the years until 2008 was driven by explosive price behavior. Two powerful variants of the ADF test detect the presence of speculative bubbles in German renewable energy stocks before the global financial and European sovereign debt crises erupted in the late 2000s. This evidence for the existence of a price bubble also attests to the notion that positive investor sentiment for certain stock market sectors can easily trigger sharp upward deviations from fundamental value, similar to those observed in the period of irrational exuberance during the dotcom era of the late 1990s. However, we do not examine in detail the potential sources of the identified explosive price behavior, which could have resulted from the presence of a rational bubble, investors' herding behavior, changing economic fundamentals or time-variation in the discount rate used in present value models.

The explosive price behavior could also be attributed to a concept known as the “peso problem”. Investors might have perceived a small probability of an event – such as a further increase in government support or seminal advances in technology – that would have exerted a positive effect on the future profitability of renewable energy stocks. Apparently, the stocks fell short of these high expectations market participants once placed upon them, leading to a reassessment of their artificially inflated prices.

We suggest several avenues for future research. First, it would be interesting to see if U.S. and Chinese alternative energy stocks exhibit a somewhat different price pattern, as they might be more capable of withstanding the fierce competition. Besides, their governments might follow a slightly different approach to supporting the deployment of clean energy technologies and to ensuring the domestic sector’s global competitiveness. Second, this paper focuses solely on the German renewable energy sector as a whole. However, the bubble and return behavior might vary across subsectors, such as solar, wind or biomass. It is also worthwhile to take a closer look at the impact which the various government-funded support schemes have had on the emergence of alternative energy stock price bubbles and their subsequent bursts.

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***Table I.* Mean returns and correlations for factor-mimicking portfolios**

Factor Portfolio	01/2004 – 12/2011	01/2004 – 12/2007	01/2008 – 12/2011	Correlation Matrix			
				Market	*SMB*	*HML*	*PR1YR*
Market	0.24% (0.41)	1.29%*** (2.85)	-0.82% (-0.77)	1			
SMB	-0.46% (-1.38)	-0.57% (-1.53)	-0.36% (-0.64)	-0.63	1		
HML	0.37%* (1.87)	0.18% (0.62)	0.55%** (2.14)	0.23	-0.19	1	
PR1YR	0.92%*** (3.07)	0.96%*** (4.14)	0.87% (1.58)	-0.36	0.19	-0.03	1

This table shows mean returns of the Fama-French (1993) and Carhart (1997) factor-mimicking portfolios for the full sample period from January 2004 to December 2011 as well as for two subperiods of equal length. The *t*-statistics are reported in parentheses. *Market* is the market excess return over the one-month interbank rate, *SMB* and *HML* are proxies for the size and value effect, and *PR1YR* is a zero-investment portfolio capturing prior one-year price momentum. Pearson correlation coefficients are calculated for the full sample period from January 2004 to December 2011. *, ** and *** denote statistical significance at the 10%, 5% and 1% level, respectively.

Table II. **Four-factor model performance**

Index	MER	SER	α^{4F}	*Market*	*SMB*	*HML*	*PR1YR*	$R^2_{adj.}$
			Panel A: Full Period 01/2004 – 12/2011					
ÖkoDAX	-0.36% (-0.23)	-0.32% (-0.79)	-0.04% (-0.04)	1.98*** (12.22)	1.53*** (5.19)	-0.33 (-0.73)	0.04 (0.13)	0.49
Renewable Energies	0.21% (0.13)	-0.11% (-0.25)	0.32% (0.32)	2.10*** (11.34)	1.40*** (3.57)	-0.33 (-0.66)	0.17 (0.49)	0.46
			Panel B: Subperiod 01/2004 – 12/2007					
ÖkoDAX	3.47%** (2.32)	2.43%** (2.35)	1.04% (0.99)	1.60*** (6.67)	1.87*** (7.73)	-0.48 (-0.86)	1.58* (1.96)	0.40
Renewable Energies	5.13%*** (3.30)	2.47%* (1.91)	2.66%* (1.88)	1.58*** (5.27)	1.76*** (4.44)	-0.18 (-0.24)	1.52 (1.18)	0.34
			Panel C: Subperiod 01/2008 – 12/2011					
ÖkoDAX	-4.19%* (-1.98)	-2.08%*** (-3.96)	-2.11%* (-1.82)	1.57*** (9.71)	0.90*** (2.86)	-0.23 (-0.34)	-0.39 (-1.25)	0.53
Renewable Energies	-4.70%** (-2.26)	-2.08%*** (-3.64)	-2.62%* (-1.97)	1.65*** (8.39)	0.69** (2.25)	-0.44 (-0.59)	-0.27 (-0.85)	0.51

This table reports the regression results of the Carhart (1997) four-factor model of equation (1) for the full sample period from January 2004 to December 2011 and for two subperiods of equal length. MER denotes the monthly mean excess return of the respective renewable energy stock index over the one-month interbank rate. SER represents the monthly systematic excess return, which is the return component explained by the four benchmark factors, while α^{4F} is the risk-adjusted return component. The monthly index excess returns are regressed on the market excess return (*Market*) as well as factor-mimicking portfolios for size (*SMB*), value (*HML*) and one-year price momentum (*PR1YR*). Heteroskedasticity and autocorrelation consistent standard errors (Newey and West, 1987) are used to compute the *t*-statistics reported in parentheses. *, ** and *** denote statistical significance at the 10%, 5% and 1% level, respectively.

Table III. **Sup ADF test**

	ÖkoDAX		Renewable Energies	
	Daily	Weekly	Daily	Weekly
	Panel A: Sup ADF Test Statistics			
Recursive	3.911***	3.527***	3.180***	3.774***
Rolling	2.713***	2.664***	2.982***	3.400***
Generalized	4.531***	3.564***	4.311***	3.462***
	Panel B: Bubble Periods			
Recursive	09/2005 – 10/2005 01/2006 – 05/2006 02/2007	06/2005 – 07/2006 02/2007 – 07/2007	01/2005 – 06/2006 09/2007 – 11/2007	01/2005 – 06/2006 10/2007 – 11/2007
Rolling	09/2005 – 10/2005 01/2006 – 05/2006	08/2005 – 11/2005 01/2006 – 06/2006	08/2005 – 05/2006	08/2005 – 05/2006
Generalized	09/2005 – 10/2005 01/2006 – 05/2006	01/2006 – 05/2006	02/2005 – 03/2005 09/2005 – 10/2005 01/2006 – 05/2006	09/2005 – 10/2005 01/2006 – 05/2006

This table reports the results of the sup ADF test. In Panel A, the maximum value of the sequence of ADF test statistics, which is used to evaluate the null hypothesis of a unit root against the alternative of an explosive root, is shown for daily and weekly real price indices of the ÖkoDAX and the DAXsubsector Renewable Energies, respectively. In the recursive and generalized sup ADF regressions, r_0 = 0.10, and in the rolling sup ADF regressions, r = 0.20 (Phillips et al., 2011, 2012). The optimal lag length is determined by starting with a maximum lag of $[T^{1/4}]$ and then reducing the model until the last lagged difference term has a statistically significant influence at the 5% level in each regression. *** denotes statistical significance at the 1% level. Critical values for the sup ADF statistics are taken from Phillips et al. (2011, 2012). Panel B shows the start and end dates of the detected bubble periods. The sample period contains 2043 daily and 417 weekly observations from January 2004 to December 2011.

***Table IV*. Stability tests**

	ÖkoDAX			Renewable Energies		
	SupLR	ExpLR	AveLR	SupLR	ExpLR	AveLR
Daily	16.318***	4.204***	3.941**	18.139***	4.788***	3.497**
Weekly	11.780**	2.820**	3.022**	14.649***	3.690***	3.004**

This table shows the results of the Quandt-Andrews unknown breakpoint tests, which measure the stability of the ADF coefficient in the conventional ADF equation, for daily and weekly real price indices of the ÖkoDAX and the DAXsubsector Renewable Energies, respectively. SupLR, ExpLR and AveLR are the values of the supremum, the exponential and the average likelihood ratio test statistic, respectively. The optimal lag length is determined by using the Schwarz information criterion. *, ** and *** denote statistical significance at the 10%, 5% and 1% level, respectively. The sample period contains 2043 daily and 417 weekly observations from January 2004 to December 2011.

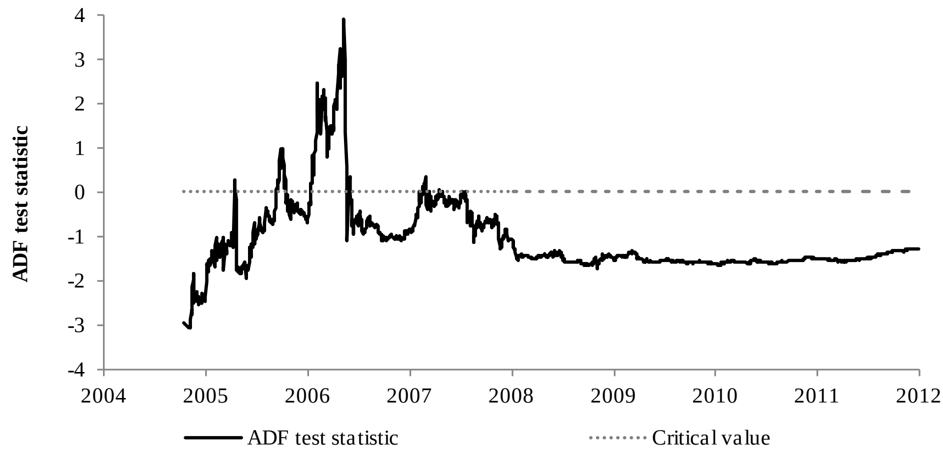
Table V. **Markov regime-switching ADF test**

	ÖkoDAX		Renewable Energies	
	$S_t = 0$	$S_t = 1$	$S_t = 0$	$S_t = 1$
	Panel A: Daily Data			
ω_{S_t}	0.0253 (1.245)	-0.0072** (-2.394)	0.0320 (1.381)	-0.0022 (-0.667)
δ_{S_t}	-0.0049 (-1.468)	0.0032*** (3.221)	-0.0041 (-1.500)	0.0010*** (0.950)
φ_{1,S_t}	0.0511 (1.422)	0.1154*** (4.448)	0.0652** (2.044)	0.1185*** (4.234)
φ_{2,S_t}	0.0515 (1.423)	-0.0586** (-2.377)	0.0384 (1.198)	-0.0463* (-1.802)
φ_{3,S_t}			-0.0030 (-0.092)	-0.0076 (-0.308)
φ_{4,S_t}			0.0316 (0.981)	-0.0068 (-0.285)
φ_{5,S_t}			-0.0774** (-2.402)	0.0097 (0.416)
σ_{S_t}	0.1826	0.0453	0.2624	0.0501
p_{S_t,S_t}	0.9660	0.9793	0.9755	0.9778
	Panel B: Weekly Data			
ω_{S_t}	0.1993 (1.548)	-0.0134 (-0.824)	0.3424 (1.526)	0.0090 (0.343)
δ_{S_t}	-0.0361 (-1.693)	0.0055*** (1.100)	-0.0387 (-1.618)	-0.0012* (-0.151)
φ_{1,S_t}	-0.0865 (-1.064)	0.0113 (0.196)	-0.0826 (-1.025)	0.0504 (0.858)
φ_{2,S_t}	-0.0594 (-0.726)	-0.0160 (-0.295)	-0.0260 (-0.322)	0.0192 (0.335)
φ_{3,S_t}	0.1704** (2.045)	-0.0814* (-1.681)	0.1310 (1.622)	0.0044 (0.078)
φ_{4,S_t}			0.0110 (0.135)	-0.1548*** (-2.841)
σ_{S_t}	0.4759	0.1241	0.7304	0.1693
p_{S_t,S_t}	0.9617	0.9803	0.9782	0.9891

This table shows the results of the Markov regime-switching ADF test for daily and weekly real price indices of the ÖkoDAX and the DAXsubsector Renewable Energies, respectively. S_t = (0, 1) is the stochastic regime variable that follows a first-order Markov process. ω_{S_t}, δ_{S_t} and φ_{p,S_t} with lag length p = 1, … , P are the regression coefficients. The optimal lag length is determined by starting with a maximum lag of $[T^{1/4}]$ and then reducing the model until the last lagged difference term has a statistically significant influence at the 5% level in at least one regime. All significance tests are two-sided except for δ_{S_t}, which is left-tailed (right-tailed) for the smaller (larger) coefficient. The *t*-statistics are reported in parentheses. *, ** and *** denote statistical significance at the 10%, 5% and 1% level, respectively. σ_{S_t} represents the standard error of the error term and p_{S_t,S_t} denotes the transition probability. The sample period contains 2043 daily and 417 weekly observations from January 2004 to December 2011.

Panel A: Real Price Index

Panel B: Recursive ADF Test Statistics



Panel C: Filter and Smoothed Probabilities

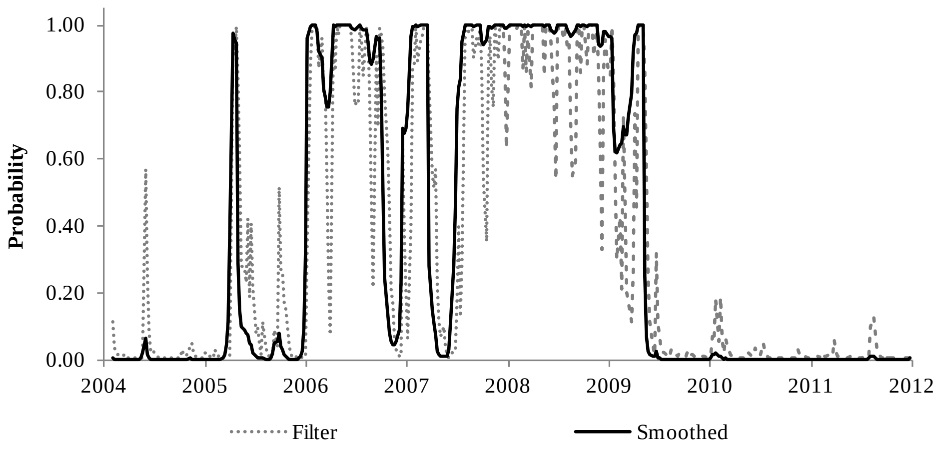
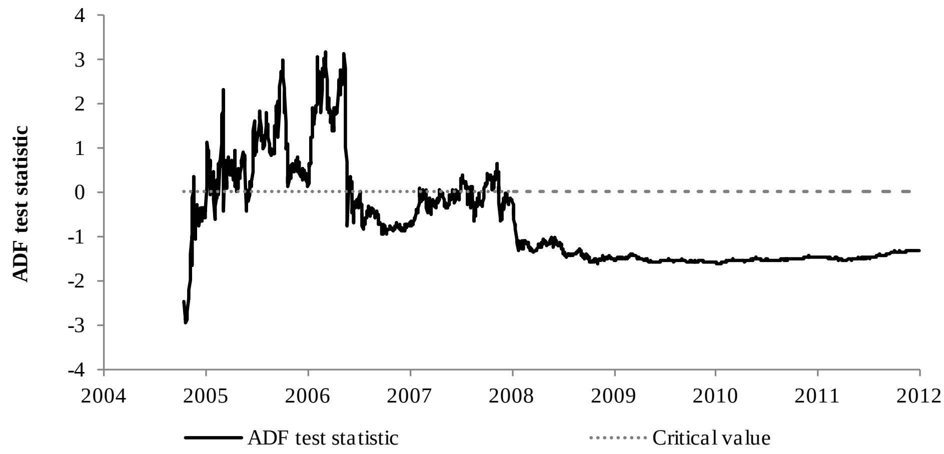


Figure 1. **ÖkoDAX**

Panel A of this figure displays the daily real price index of the ÖkoDAX, which is deflated by the German CPI, for the time period from January 2004 to December 2011. Panel B shows the sequence of the recursive ADF test statistics and the corresponding right-tailed critical values at the 5% significance level. The recursive sup ADF test is performed for the daily real price index of the ÖkoDAX. Panel C presents the filter and smoothed probabilities of being in the possible bubble regime. These probabilities are derived from the Markov regime-switching ADF test based on the weekly real price index of the ÖkoDAX.

Panel A: Real Price Index

Panel B: Recursive ADF Test Statistics



Panel C: Filter and Smoothed Probabilities

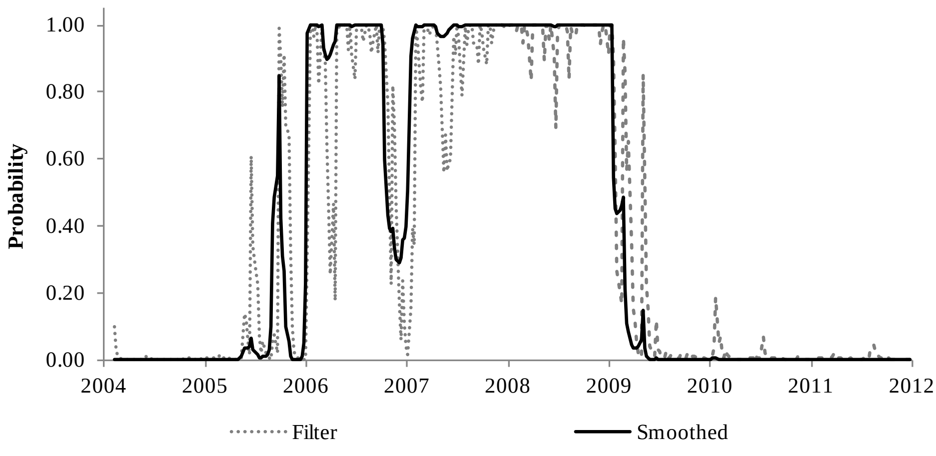


Figure 2. **DAXsubsector Renewable Energies**

Panel A of this figure displays the daily real price index of the DAXsubsector Renewable Energies, which is deflated by the German CPI, for the time period from January 2004 to December 2011. Panel B shows the sequence of the recursive ADF test statistics and the corresponding right-tailed critical values at the 5% significance level. The recursive sup ADF test is performed for the daily real price index of the DAXsubsector Renewable Energies. Panel C presents the filter and smoothed probabilities of being in the possible bubble regime. These probabilities are derived from the Markov regime-switching ADF test based on the weekly real price index of the DAXsubsector Renewable Energies.

Figure 3. **Time-varying four-factor model coefficients of the ÖkoDAX**

The solid lines of this figure display monthly time-varying coefficients of the Carhart (1997) four-factor model for the period from January 2004 to December 2011. The coefficients are estimated for the ÖkoDAX using the Kalman filter. The dotted lines represent confidence bands for the 10% level of statistical significance.

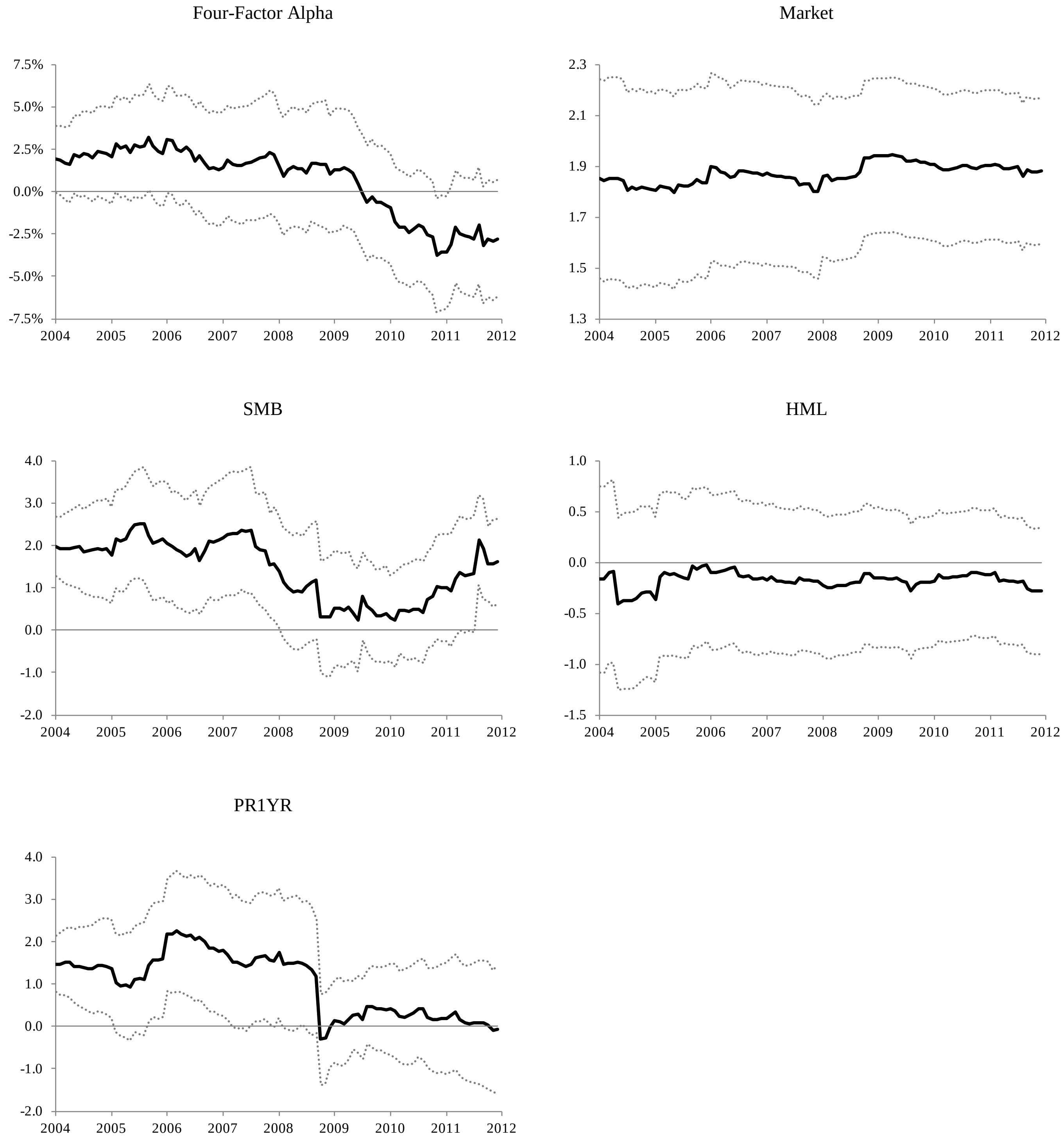


Figure 4. **Time-varying four-factor model coefficients of the DAXsubsector Renewable Energies**

The solid lines of this figure display monthly time-varying coefficients of the Carhart (1997) four-factor model for the period from January 2004 to December 2011. The coefficients are estimated for the DAXsubsector Renewable Energies using the Kalman filter. The dotted lines represent confidence bands for the 10% level of statistical significance.