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WHAT DROVE THE MID-2000s' EXPLOSIVENESS IN ALTERNATIVE ENERGY STOCK PRICES?

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ABOUT THE PROJECT

This publication emerges from a project called Essays in Financial Governance: Promoting Cooperation in Financial Regulation and Policies. The project is supported by a 2011-2012 CIGI Collaborative Research Award held by Martin T. Bohl, Badye Essid, Arne Christian Klein, Pierre L. Siklos and Patrick Stephan. In this project, researchers investigate empirically policy makers' reactions to an unfolding financial crisis and the negative externalities that emerge in the form of poorly functioning financial markets. At the macro level, the project investigates whether the bond and equity markets in the throes of a financial crisis can be linked to overall economic performance. Ultimately, the aim is to propose policy responses leading to improved financial governance.

ACRONYMS

ADF	Augmented Dickey-Fuller
BSADF	backward supremum augmented Dickey-Fuller
CPI	consumer price indices
ERIX	European Renewable Energy Index
GSADF	generalized supremum Augmented Dickey-Fuller
GSCI	Goldman Sachs Commodity Index
IMI	Investable Market Indices
MSCI	Morgan Stanley Commodity Index
NYSE	New York Stock Exchange
REN21	Renewable Energy Policy Network for the 21st Century
SADF	supremum Augmented Dickey-Fuller
UNDP	United Nations Development Programme
WTI	West Texas Intermediate crude oil

EXECUTIVE SUMMARY

Soaring prices in European alternative energy stocks and their subsequent tumble have attracted attention from both investors and academics. This paper extends recent research to an international setting and analyzes whether the explosive price behaviour of the mid-2000s was driven by rising crude oil prices and an overall bullish market sentiment. Inflation-adjusted US alternative energy stock prices do not exhibit signs of explosiveness. By contrast, we find strong evidence of explosive price behaviour for European and global sector indices, even after controlling for a set of explanatory variables. Interestingly, while the sector indices plunged with the outbreak of the global financial crisis, idiosyncratic components continued to rise and did not start to decline until after world equity markets had already begun to recover in 2009. This finding suggests a substantial revaluation of alternative energy stock prices in light of intensifying sector competition and shrinking sales margins, and casts some doubts on the existence of a speculative bubble. Nevertheless, this paper observes temporary episodes of explosiveness between 2005 and 2007 followed by rapid collapses, indicating the presence of some irrational exuberance among investors.

INTRODUCTION

Optimistic investor sentiment is frequently viewed as having triggered the exceptional performance of renewable energy stocks in the mid-2000s. Promising

growth prospects and the anticipation of intensified government support even led to spikes in the stock price indices. The rapid growth and deployment of renewable energy sources has been promoted across the globe. According to Bloomberg New Energy Finance (2013), the global new investment volume in renewable energy rose from US$40 billion in 2004 to US$244 billion in 2012. Using a multi-country, fixed-effects panel approach, Eyraud, Clements and Wane (2013) find that green investment has been stimulated worldwide by economic growth, low long-term nominal interest rates, high fuel prices and the adoption of certain policy instruments, such as feed-in tariffs or carbon-pricing schemes. These types of support policies have been put into practice by 127 countries (see the Renewable Energy Policy Network for the 21st Century [REN21] 2013), whereas 138 countries have even set specific policy targets aimed at increasing the share of renewables in both electricity production and final energy consumption. Based on 2011 data assembled by REN21, the estimated renewable energy share of global energy consumption amounts to 9.7 percent, which is well short of most countries' long-term goals (ibid.). While new investment volumes are still higher in developed countries, emerging economies have experienced more stable growth paths and have been catching up recently (Bloomberg New Energy Finance 2013). In 2012, the three leading regions with respect to new investment activities were Europe, China and the United States.

Despite the promising future for renewable energy technologies, fierce competition and excess supply from Asian manufacturers have taken their toll on the sector's profit margins since the late 2000s. As a result, investor sentiment toward these fad stocks began to gradually deteriorate. Following the outbreak of the global financial and economic crisis, prices of alternative energy stocks plunged as quickly as they had risen, resulting in an almost hump-shaped performance pattern. Visual inspection of the price charts appears to suggest a speculative price bubble prior to 2008. However, previous research has not yet investigated whether there are exogenous risk factors that may have driven this apparent explosive behaviour. Intuitively, soaring crude oil prices could have promoted exuberance in renewable energy stocks. Furthermore, many have found price movements in technology stocks to be strongly correlated with those of alternative energy stocks (see Henriques and Sadorsky 2008; Kumar, Managi and Matsuda 2012; Sadorsky 2012a). Given the high market betas that renewable energy stocks usually possess, it also seems possible that the pronounced bull market between 2003 and 2007 partly encouraged the bubble-like behaviour. This paper aims to remove the systematic component of stock price movements and to focus the analysis on the idiosyncratic part of alternative energy stock prices.

For US alternative energy stocks, there is no evidence of an explosive root. By contrast, for European and global stock indices, even inflation-adjusted idiosyncratic price time series exhibit explosive behaviour. This paper concludes that the bubble-like pattern seen in the data was mostly sector-specific and cannot entirely be attributed to exogenous risk factors. Surprisingly, the idiosyncratic price components did not plummet simultaneously with the price indices during the global financial crisis, but instead continued to increase until May 2009. This finding suggests that the price crash in 2008 was not the burst of a bubble, but rather the result of the stocks' elevated sensitivity to market fluctuations. Nevertheless, this paper argues that corrections to price spikes observed between 2005 and 2007 indicate the presence of some sentiment-driven investor overreaction. Interestingly, the assumed positive correlation with crude oil prices only holds until the bursting of the oil price bubble in the second half of 2008. In the period that followed, the relationship breaks down and weakens considerably.

Furthermore, we find that our US, European and global sector indices are tilted toward the small-cap and growth stock segment. A subperiod analysis also reveals that alternative energy stocks belonged to the group of winner stocks between 2004 and 2007. Winner stocks are defined as those stocks in the cross-section of the market that performed relatively well over the previous year and tend to continue their outperformance in subsequent months — a phenomenon widely referred to as momentum. However, in the course of the global financial crisis, alternative energy stock indices have lost their positive momentum and have even produced significantly negative multifactor abnormal returns.

METHODOLOGY

PERFORMANCE MEASUREMENT MODELS

Previous research suggests that the performance patterns of alternative energy stocks differ substantially from those of conventional large-cap stocks. While the results in Henriques and Sadorsky (2008) as well as Sadorsky (2012b) indicate that US renewable energy stocks belong to the high-beta segment, Bohl, Kaufmann and Stephen (2013) report a pronounced small-cap tilt and time-varying momentum exposure for their German sample. To gain insight into how systematic factors contribute to the performance of our international sector indices, we employ the Carhart (1997) four-factor model:

$$R_t - r_{ft} = \alpha^{4F} + \beta_1 RMRF_t + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 WML_t + \varepsilon_t \quad (1)$$

$R_t - r_{ft}$ is the index excess return over the risk-free rate in month t. The unconditional Carhart (1997) four-factor alpha α^{4F} represents the abnormal return after adjusting for sensitivities to the four systematic risk factors. *RMRF*

denotes the value-weighted market portfolio return in excess of the risk-free rate. The return difference between small-cap and large-cap stocks is captured by *SMB*, while *HML* measures the return spread between high and low book-to-market equity stocks. *WML* stands for the price momentum factor defined as the difference between the returns of past winner and loser stocks. The error term is denoted by ε_t.

Henriques and Sadorsky (2008), Kumar, Managi and Matsuda (2012), as well as Broadstock, Cao and Zhang (2012) document a significant influence of crude oil prices on the prices of alternative energy stocks. Sadorsky (2012a) even suggests entering a short position in crude oil futures to hedge against falling clean energy stock prices. We therefore extend the four-factor model by additionally controlling for return variations in futures contracts of fossil fuels. This results in the following specification:

$$R_t - r_t = \alpha^{5F} + \beta_1 RMRF_t + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 WML_t + \beta_5 Energy_t + \varepsilon_t \,, \quad (2)$$

where a^{5F} denotes the monthly five-factor abnormal return and *Energy* is a proxy for the excess return on investments in the energy commodity market.

Bohl, Kaufmann and Stephan (2013) also uncover some considerable time variation in price momentum exposures and risk-adjusted returns, especially after the outbreak of the 2008-2009 global financial crisis. To allow for such a potential change in the parameters, we additionally run a dummy variable regression:

$$R_t - r_t = \alpha_1^{5F} + \alpha_2^{5F} D_t + \sum_{k=1}^{5} (\beta_{1k} + \beta_{2k} D_t) F_{kt} + \varepsilon_t \,, \quad (3)$$

where F_{kt} denotes one of the five factor portfolios of equation (2). The dummy variable D_t is equal to zero from January 2004 to December 2007 and equal to one from January 2008 to July 2013. This dummy coding enables us to examine the abnormal performance and factor exposures prior to and after the outbreak of the global financial crisis. It is also consistent with the fact that all of the renewable energy stock indices peaked at the end of 2007.[1]

BUBBLE DETECTION TESTS

To uncover potential explosiveness in the deflated price time series of renewable energy stock indices, we use recursive and rolling supremum Augmented Dickey-Fuller (SADF) tests (Phillips, Wu and Yu 2011) as well as the generalized SADF (GSADF) version introduced by Phillips, Shi and Yu (2013). These right-tailed unit root tests have proved useful in detecting exuberance or bubble-like behaviour in financial time series and are applied to daily real price data.[2] The SADF tests are based on the assumption that asset prices follow a random walk and thus contain a unit root. Exceptions to the rule are strong upward departures from fundamental values, which can lead to explosiveness in the underlying price time series. The recursive SADF test estimates the conventional Augmented Dickey-Fuller (ADF) regression repeatedly by using a forward expanding sample sequence:

$$\Delta y_t = \mu + \delta y_{t-1} + \sum_{p=1}^{P} \phi_p \Delta y_{t-p} + \varepsilon_t \,, \quad (4)$$

where y_t is the daily real alternative energy stock price index, Δ stands for the first difference operator, and μ, δ and ϕ_p are regression coefficients. The error term ε_t is independent and identically distributed with zero mean and constant variance. To determine the optimal lag length P in each subsample regression, we follow the procedure suggested by Campbell and Perron (1991). Starting with six lags, we reduce the lag order until the coefficient on the last included lag is significant at the five percent level (see also Phillips, Wu and Yu 2011).

A right-tailed hypothesis test is conducted on the supremum test statistic, which is determined by the maximum value of the corresponding sequence of ADF statistics δ. Following Phillips, Wu and Yu (2011), we determine the initial window length by the integer part of Tr_0, where T denotes the total sample size and the fraction r_0 is equal to 0.10. Given our sample size of 2,406 trading days, the initial window roughly covers the first sample year and therefore yields a sufficient number of observations to ensure estimation efficiency. The window size expands by one observation after each pass. Hence, the recursive SADF statistic is defined as:

$$SADF(r_0) = \sup_{s \in [r_0, 1]} ADF_s \,. \quad (5)$$

Note that for the rolling SADF test the window length is not forward expanding but held constant with r equal to 0.20.

In the presence of multiple bubbles, the GSADF test proposed by Phillips, Shi and Yu (2013) is assumed to be a more powerful method. The test procedure is designed to consistently detect the existence of periodically collapsing

1 We also use the Quandt-Andrews unknown breakpoint test (Andrews 1993; Andrews and Ploberger 1994) to formally check whether there is a structural change in all of the five-factor model's parameters. The tests reveal that a breakpoint occurs in February 2008 for the US stock index, in January 2008 for the European stock index and in July 2008 for the global stock indices. For ease of comparability, we date only one common breakpoint in January 2008 in the regression specifications.

2 SADF-type tests have been employed to test for speculative bubbles in equity (Phillips, Wu and Yu 2011; Homm and Breitung 2012; Bohl, Kaufmann and Stephan 2013), currency (Bettendorf and Chen 2013), commodity (Gutierrez 2013) and housing markets (Phillips and Yu 2011; Yiu, Yu and Jin 2013).

bubbles. Given the findings in Bohl, Kaufmann and Stephan (2013) for a comparable sample period, we conjecture that there is mainly one single extended phase of price run-ups. However, there could also be several temporary episodes of explosiveness in the price indices. Recall that the recursive SADF test fixes the start points of the subsamples on the first observation of the total sample, while the rolling approach keeps the window length constant. By contrast, the GSADF procedure extends the subsample sequence by changing both the start points and the end points of the subsamples over a feasible range of flexible windows. The GSADF test implements the backward expanding SADF test repeatedly for varying end points Tr_2 with $r_2 \epsilon [r_0,1]$ and makes inferences based on the supremum value of the backward SADF statistic sequence denoted by $BSADF_{r_2 \in [r_0,1]}(r_0)$. The GSADF test statistic is thus given by

(6)

$$BSADF_{r_2}(r_0) = \sup_{r_1 \in [0, r_2 - r_0]} ADF_{r_1}^{r_2},$$

$$GSADF(r_0) = \sup_{r_2 \in [r_0, 1]} BSADF_{r_2}(r_0)$$

Note that the recursive and rolling SADF tests are nested in the GSADF procedure. The fraction r_0, which determines the minimum window length, is again equal to 0.10. For the GSADF test, we set the lag order P to zero because Phillips, Shi and Yu (2013) show that size distortion is smallest when a fixed lag length is used.

A primary advantage of the SADF tests is that they allow for date-stamping the origination and termination of explosive price behaviour. Provided that the full sample supremum test statistic exceeds the right-sided critical value, it is possible to locate episodes of exuberance. For instance, using the recursive SADF test we can compare the sequence of subsample ADF coefficients ADF_s with the corresponding right-tailed critical value sequence $cv(s)$:

(7)

$$\hat{\tau}_e = \inf_{s \in [r_0, 1]} \{ s : ADF_s > cv(s) \}, \quad \hat{\tau}_f = [T\hat{r}_f], \quad \{ s : ADF_s < cv(s) \}$$

The origination date of explosive price behaviour is eventually derived from $\hat{\tau}_e = [T\hat{r}_e]$ and the expression $\hat{\tau}_f = [T\hat{r}_f]$ yields the subsequent collapse date.

Finite sample critical values for the SADF and GSADF tests are obtained from Monte Carlo simulations with 5,000 replications. The sample size T is chosen to correspond to the 2,406 trading days in our period of investigation. The fraction r_0, which determines the initial window length, is set to 0.10 for the recursive and generalized procedures, whereas for the rolling regressions r is fixed at 0.20. As suggested by Phillips, Shi and Yu (2013), the data generating process is specified as a random walk with drift component T^1 and the ADF regressions' lag order P is set to zero. While the empirical supremum test statistics have to be compared with the right-tailed quantiles of the distribution of simulated test statistics, the date-stamping procedure is based on expanding sequences of ADF test statistics. The corresponding critical value sequences $cv(s)$ are obtained by first running 5,000 Monte Carlo simulations for the varying subsample windows and then concatenating the right-tailed quantiles of the resulting simulated distributions.

CONSTRUCTION OF IDIOSYNCRATIC PRICE TIME SERIES

Bohl, Kaufmann and Stephan (2013) report substantial evidence of explosiveness in the real prices of German alternative energy stocks. The goal of the present study is to examine the extent to which the explosive price behaviour can be explained by rising crude oil prices and the prevailing bull market between 2003 and 2007. Such an analysis enables us to determine whether the explosiveness was sector-specific and can thus be regarded as a genuine speculative bubble. Besides the strong sensitivity to stock market fluctuations and the positive correlation with oil prices, previous studies identify the prices of technology stocks as a third influential variable of clean energy stock prices (Henriques and Sadorsky 2008; Kumar, Managi and Matsuda 2012; Sadorsky 2012a). There are also signs of a short-lived crude oil bubble, which collapsed rapidly following the price surge in 2008 (see, for example, Tokic 2010; 2012; Kesicki 2010). Since renewable energies are perceived as a long-term substitute for conventional energy sources, it is likely that prices of alternative energy stocks have been initially driven by soaring oil prices. However, after the oil bubble burst in July 2008, the positive correlation may have broken down. In order to capture such dynamic sensitivity patterns, we allow for time variation in our linear multifactor model. Whether the explosive price behaviour was sector-specific can be investigated by orthogonalizing the price time series with respect to the aforementioned systematic risk factors and then analyzing the remaining idiosyncratic component. To construct a daily sector-specific price time series, we first estimate the raw index returns' time-varying exposures to a set of systematic factors:

(8)

(9)

$$R_t = \alpha_t + \beta_{1t} Market_t + \beta_{2t} Market_{t-1} + \beta_{3t} Tech_t + \beta_{4t} Tech_{t-1} + \beta_{5t} Oil_t + \beta_{6t} Oil_{t-1} + \varepsilon_t, \quad (10)$$

$\alpha_t = \alpha_{t-1} + \gamma_t, \gamma_t \sim N(0, \sigma_\gamma^2)$

$\beta_{it} = \beta_{it-1} + \eta_t, \eta_t \sim N(0, \sigma_\eta^2)$

Market and *Tech* represent the returns of a broad stock market index and a technology stock index, respectively, while *Oil* reflects the spot price variations of crude oil. Although the alternative energy stock indices comprise mostly liquid and frequently traded stocks that quickly

assimilate market-wide news, delayed information processing or non-synchronicity in the trading of stocks and explanatory factors could arise due to time zone differences. We therefore apply Dimson's (1979) correction and additionally include lagged values of the right-hand side exogenous variables.

The time-varying coefficients of the state-space model are assumed to follow a pure random walk and are denoted by a_t and β_{kt} with $k = 1, \ldots, 6$. The normally distributed error terms ε_t, v_t and η_{kt} are independent of each other with zero mean and variances denoted by σ_ε^2, σ_v^2 and $\sigma_{\eta_k}^2$. Equation (8) represents the measurement equation, whereas the transition equations (9) and (10) describe the evolution of the unobserved state variables. We use the Kalman filter technique to estimate the time-varying coefficients. The Kalman filter is a recursive procedure for computing the optimal estimates of the state variables for each period t, conditional on the information set available up to time t (Kim and Nelson 1999; Durbin and Koopman 2001). We first estimate the parameters of the model σ_ε^2, σ_v^2 and $\sigma_{\eta_k}^2$ via maximum likelihood and then derive the filtered values of the state variables α_t and β_{kt}. We specify the initial one-step-ahead predicted values of the state variables by taking the ordinary least squares estimates from a static regression over the first 252 trading days.

The alternative energy stock index return can be decomposed into a factor-related return contribution and a sector-specific component. For each trading day, the idiosyncratic part is computed as the sum of the estimated alpha coefficient $\hat{\alpha}_t$ and the residual $\hat{\varepsilon}_t$ (see Elton et al. 1993) and then compounded over time such that:

$$P_t^* = \prod_{\tau=1}^{t} (\hat{\alpha}_\tau + \hat{\varepsilon}_\tau + 1) \times P_0^* \qquad (11)$$

The base value P_0^* is set to 100. The orthogonalized price time series can be interpreted as the accumulated value of an investment in renewable energy stocks that is fully hedged against price variations in the risk factors. The sector-specific time series P_t^* will be deflated before being tested for an explosive root. Note that we do not interpret the linear combination of the exogenous variables as the true fundamental value, but as a set of explanatory factors that the aforementioned literature identified as key determinants of renewable energy stocks' return behaviour.[3]

DATA

We examine five widely followed alternative energy stock indices for the sample period from January 2004 to July 2013. For ease of comparability, the sample begins when data for all indices become available. The time series are denominated in US dollars. Unless otherwise stated, we collect data from Thomson Reuters Datastream.

For the US market, we focus on the WilderHill Clean Energy Index, which tracks the performance of clean energy companies listed on major US stock exchanges. In July 2013, the index consisted of 51 stocks. We obtain monthly total return data directly from the New York Stock Exchange (NYSE) Euronext. The European Renewable Energy Index (ERIX), which incorporates the 10 largest and most liquid companies from the wind, solar, biomass and water energy sector, is employed to cover the European market. Both price and total return data are provided by the index proprietor Société Générale. Our international stock indices comprise the S&P Global Clean Energy Index, the WilderHill New Energy Global Innovation Index and the Ardour Global Alternative Energy Index Composite. The S&P Global Clean Energy Index contains 30 of the largest publicly traded clean energy companies, whereas the WilderHill New Energy Global Innovation Index is much broader with 96 constituents from 25 countries. The latter index has a more comprehensive stock universe, as it not only includes pure plays but also considers companies with a focus on energy efficiency or on the reduction of carbon dioxide emissions. Our third international index, the Ardour Global Alternative Energy Index Composite, consists of 115 clean energy stocks as of July 2013. Performance data for this index are retrieved from the online database of Ardour Global Indexes.

For the multifactor performance evaluation, we follow the literature and use monthly total returns including dividends. Performance measurement is usually based on monthly data to obtain more robust regression estimates. As our benchmarks, we employ the US, European and global factor-mimicking portfolios from Kenneth French's data library.[4] The traditional US factors are described in Fama and French (1993) and comprise the market excess return, the size portfolio *SMB*, the value portfolio *HML* and the momentum portfolio *WML*. The construction of the European and global factors is based on 16 and 23 developed countries, respectively, and their total returns are measured in US dollars (see Fama and French 2012 for a more detailed description). To calculate excess returns, we use the one-month US Treasury bill rate. As a proxy for the excess return on investments in fossil fuels, we employ the S&P Goldman Sachs Commodity Index (GSCI) Energy Total Return Index. This benchmark index provides

3 As a robustness check, we also run rolling regressions with a fixed window length of 252 trading days. Results are very similar compared to the Kalman filter approach.

4 French makes the data available at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

Table 1: Summary Statistics

Index	Mean Return (in %)	Minimum (in %)	Maximum (in %)	Standard Deviation (in %)	Skewness	Kurtosis
WilderHill Clean Energy Index	–0.26 (–0.25)	–32.06	26.72	9.42	–0.42	3.87
ERIX	0.79 (0.65)	–40.82	33.45	11.03	–0.51	4.70
S&P Global Clean Energy Index	0.09 (0.08)	–39.94	22.56	9.57	–1.15	5.81
WilderHill New Energy Global Innovation Index	0.50 (0.53)	–35.00	21.63	8.29	–0.96	5.74
Ardour Global Alternative Energy Index Composite	0.32 (0.32)	–38.72	23.92	8.96	–1.06	6.13

Note: This table reports summary statistics for monthly total return alternative energy stock indices. The sample period runs from January 2004 to July 2013. Heteroskedasticity and autocorrelation consistent standard errors (Newey and West 1987) are used to compute the *t*-statistics reported in parentheses.

exposure to six energy commodities including crude oil, Brent crude oil, unleaded gasoline, heating oil, gas oil and natural gas. The index tracks not only the prices of the underlying first nearby futures contracts (spot yield), but also factors in the discount or premium obtained by rolling forward hypothetical positions in such contracts as they approach delivery (roll yield) as well as the interest earned on hypothetical fully collateralized contract positions (collateral yield).

For the bubble detection tests, we use daily price data as this frequency enables more powerful tests. We deflate the daily price time series in order to obtain real index prices. To this end, we use the following consumer price indices (CPI): CPI All Urban Consumers from the US Bureau of Labor Statistics, the Euro Area HICP All Items from Eurostat and the OECD-Total CPI All Items. As the CPIs are only available at monthly frequency, they are linearly interpolated to obtain daily time series (see, for example, Homm and Breitung 2012).

To construct sector-specific indices, the stock price indices are orthogonalized with respect to the return variations of a leading stock market index, a technology stock index and the WTI crude oil spot price.[5] For the broad stock market portfolios, we use the US price index S&P 500, the Morgan Stanley Commodity Index (MSCI) Europe Investable Market Indices (IMI) and the MSCI World IMI, respectively. Note that the MSCI World IMI also contain small-cap stocks and thus have broader market coverage than the standard index versions. To control for the exposure to technology stocks, we employ the NYSE Arca Tech 100 for the United States, the STOXX Europe TMI Technology and the MSCI World IMI Information Technology, respectively.

5 Our results are robust to the use of the S&P GSCI Energy Spot Index that tracks the prices of the futures contracts of six different fossil fuels. The index is highly correlated with WTI (West Texas Intermediate, or Texas light sweet) crude oil (Pearson's $r = 0.89$).

EMPIRICAL RESULTS

PERFORMANCE ANALYSIS

To obtain a first impression of the return behaviour of our alternative energy stock indices, we report descriptive statistics in Table 1. Note that none of the indices is able to produce a significantly positive total return over the sample period between January 2004 and July 2013. The monthly mean raw return of the US WilderHill Clean Energy Index is even slightly negative. The minimum and maximum return statistics are quite extreme and a result of the relatively high monthly volatility. Moreover, the return distributions exhibit negative skewness and elevated kurtosis.

Table 2 reports that US, European and global renewable energy stock indices deliver negative monthly risk-adjusted returns over the entire sample period. For the WilderHill Clean Energy Index and the S&P Global Clean Energy Index, the negative abnormal returns are quite substantial and even statistically significant. Given their high market betas and the mostly significant loadings on the size factor, the indices not only turn out to be low-return, but also rather risky investments. Except for the ERIX, the indices are somewhat tilted toward the growth segment. Moreover, the loadings on price momentum are insignificant over the entire sample period.

Controlling for exposure to fossil fuels yields an interesting picture. First, the five-factor model alphas and the factor loadings in Panel B of Table 2 do not change much compared to their four-factor counterparts in Panel A. Second, only the US index has a significantly positive sensitivity to price variations in the oil futures market. For the international index S&P Global Clean Energy Index, the coefficient is significant at the 10 percent level, but quite low in economic terms. This finding suggests some subtle differences in the perception of renewable energies

Table 2: Multifactor Model Performance

Index	Alpha (in %)	RMRF	SMB	HML	WML	Energy	Adj. R2
Panel A: Four-Factor Model							
WilderHill Clean Energy Index	–1.38** (-2.36)	1.60*** (12.66)	0.85*** (3.09)	–0.43* (–1.92)	0.03 (0.25)		0.67
ERIX	–0.62 (–0.83)	1.40*** (9.99)	1.16*** (3.64)	0.52 (1.20)	0.27 (1.51)		0.63
S&P Global Clean Energy Index	–1.08* (–1.76)	1.68*** (14.47)	0.44 (1.19)	–0.08 (–0.19)	0.13 (0.83)		0.68
WilderHill New Energy Global Innovation Index	–0.49 (–1.13)	1.51*** (17.80)	0.67** (2.54)	–0.23 (–0.84)	–0.04 (–0.42)		0.78
Ardour Global Alternative Energy Index Composite	–0.80 (–1.48)	1.60*** (14.10)	0.66** (2.05)	–0.12 (–0.34)	0.10 (0.65)		0.73
Panel B: Five-Factor Model							
WilderHill Clean Energy Index	–1.31** (–2.37)	1.34*** (10.03)	1.00*** (3.87)	–0.52** (–2.50)	–0.08 (–0.80)	0.23*** (3.72)	0.71
ERIX	–0.57 (–0.82)	1.31*** (7.31)	1.12*** (3.31)	0.60 (1.41)	0.24 (1.40)	0.08 (1.05)	0.63
S&P Global Clean Energy Index	–1.04* (–1.72)	1.59*** (13.74)	0.40 (1.10)	–0.03 (–0.09)	0.09 (0.61)	0.08* (1.87)	0.68
WilderHill New Energy Global Innovation Index	–0.46 (–1.06)	1.45*** (15.92)	0.65** (2.30)	–0.20 (–0.73)	–0.07 (–0.66)	0.06 (1.58)	0.79
Ardour Global Alternative Energy Index Composite	–0.78 (–1.43)	1.54*** (12.12)	0.64* (1.94)	–0.09 (–0.25)	0.08 (0.52)	0.05 (1.07)	0.73

Note: This table reports results for the Carhart (1997) four-factor model and the five-factor model of equations (1) and (2), respectively. The regressions are performed using monthly total return data. The sample period runs from January 2004 to July 2013. 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, five and one percent levels, respectively.

across continents. In the United States, investors appear to view alternative energy stocks as a hedge against rising crude oil prices (Sadorsky 2012a) and could thus be more likely to adopt a cost-benefit attitude toward the further deployment of renewable energy technologies. In Europe, however, the promotion of renewable energies is mostly independent of the price developments in oil markets. Instead, it is viewed not only as a means of achieving climate targets or replacing nuclear power in the long run, but also as a device to increase public awareness of a sustainable energy supply.

The subperiod regressions in Table 3 split the sample into two periods from January 2004 to December 2007 and from January 2008 to July 2013, respectively. Some insightful patterns emerge in comparison to the full sample results. All sector indices exhibit a severe deterioration in abnormal performance from the first to the second subperiod. Since 2008, the S&P Global Clean Energy Index, for instance, loses 2.58 percent per month on average after adjusting for factor risks. From 2004 to 2007, however, the index earns a positive though insignificant five-factor abnormal return. This pronounced reversal from slightly positive to significantly negative alphas is also mirrored in the coefficients on price momentum. A large portion of the strikingly positive performance until December 2007 can be explained by momentum. With the exception of the US index, all indices load significantly on the *WML* factor during the first subperiod, indicating that renewable energy stocks belonged to the group of winner stocks in the cross-section of the market. However, the momentum exposure completely disappears in the second subperiod and becomes even significantly negative for the US index. As discussed previously, positive payoffs from an investment in fossil fuels only have a positive impact on US alternative energy stocks. The sensitivity becomes insignificant after 2007, suggesting a structural break in the relationship.

With regard to the other benchmarks, the indices are somewhat more sensitive to market fluctuations and mostly have a stronger small-cap tilt in the second subperiod. Note that the systematic factors explain the return variations of our indices fairly well. For the subperiod regressions, the adjusted R^2 attains values of up to 0.81. By contrast, Bohl, Kaufmann and Stephan (2013) show that the explanatory power for their German sample stocks often does not exceed the value of 0.5, which indicates a larger idiosyncratic component.

IDIOSYNCRATIC PRICE TIME SERIES AND FACTOR EXPOSURES

Having analyzed the performance drivers of our international renewable energy stock sample, we now consider whether the indices contained a speculative

Table 3: Subperiod Performance Analysis

Index	Alpha1	Alpha2	RMRF1	RMRF2	SMB1	SMB2	HML1	HML2	WML1	WML2	Energy1	Energy2	Adj. R2
WilderHill Clean Energy Index	0.79% (1.54)	–2.89%*** (–4.45)	0.75*** (2.62)	1.54*** (11.11)	1.52*** (3.67)	0.77** (2.61)	–0.69** (–2.05)	–0.69*** (–3.52)	0.55 (1.48)	–0.18** (–2.59)	0.21** (2.27)	0.10 (1.39)	0.76
Difference	–3.67%*** (–4.19)		+0.79** (2.15)		–0.75 (–1.41)		0.00 (0.00)		–0.73** (-2.15)		–0.11 (–1.03)		
European Renewable Energy Index	0.19% (0.23)	–1.92%* (–1.70)	1.13*** (3.40)	1.29*** (4.73)	0.73* (1.74)	1.18*** (3.78)	–0.73 (–0.82)	0.39 (0.69)	2.14*** (3.26)	0.01 (0.06)	0.09 (1.18)	–0.01 (–0.06)	0.68
Difference	–2.11% (–1.51)		+0.17 (0.38)		+0.45 (0.87)		+1.13 (1.04)		–2.13*** (–3.16)		–0.10 (–0.51)		
S&P Global Clean Energy Index	0.58% (1.06)	–2.58%*** (–3.13)	1.23*** (5.39)	1.65*** (9.67)	–0.12 (–0.35)	0.61 (1.20)	–0.27 (–0.41)	–0.27 (–0.64)	1.15*** (3.21)	–0.03 (–0.22)	0.06 (0.96)	–0.02 (–0.15)	0.72
Difference	–3.16%*** (–3.13)		+0.43 (1.35)		+0.73 (1.19)		0.00 (0.00)		–1.18*** (–3.28)		–0.07 (–0.70)		
WilderHill New Energy Global Innovation Index	0.61% (1.20)	–1.48%** (–2.59)	1.02*** (5.52)	1.49*** (10.22)	0.42 (1.56)	0.69* (1.93)	–0.38 (–0.97)	–0.38 (–1.17)	0.90*** (3.41)	–0.17 (–1.64)	0.00 (0.04)	0.00 (–0.02)	0.81
Difference	–2.09%*** (–2.65)		+0.47* (1.85)		+0.27 (0.57)		0.00 (0.00)		–1.08*** (–3.84)		0.00 (–0.04)		
Ardour Global Alternative Energy Index Composite	–0.20% (–0.24)	–1.72%** (–2.44)	1.43*** (3.89)	1.54*** (8.06)	–0.16 (–0.37)	0.93** (2.54)	–0.61 (–0.91)	–0.11 (–0.27)	1.28** (2.35)	–0.05 (–0.34)	0.05 (0.62)	–0.02 (–0.22)	0.76
Difference	–1.52% (–1.33)		+0.11 (0.24)		+1.10* (1.95)		+0.50 (0.62)		–1.32*** (–2.77)		–0.07 (–0.67)		

Note: This table reports results for the dummy variable five-factor model regression of equation (3). The binary dummy is equal to zero from January 2004 to December 2007 and equal to one from January 2008 to July 2013. This approach yields monthly estimates for two subperiods indicated by a subscript. The corresponding differences between subperiods are presented below. 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, five and one percent levels, respectively.

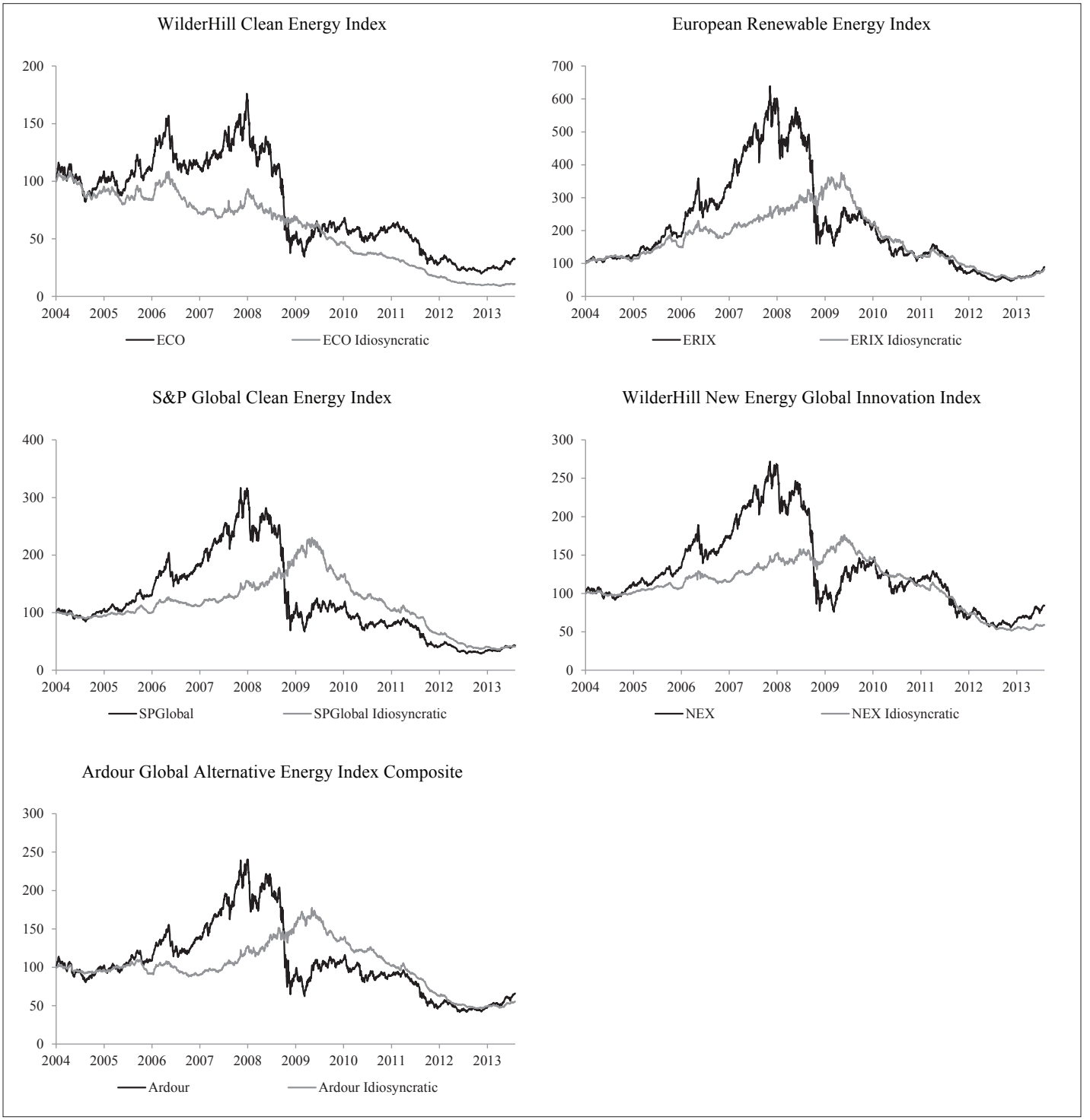
bubble in the mid-2000s. Bohl, Kaufmann and Stephan (2013) are the first to tackle this issue and conclude that German alternative energy stocks exhibited explosive price behaviour. However, they remain silent on potential explanations for the explosiveness and merely associate the price surge between 2005 and 2007 with exuberant investor sentiment toward the promising energy sector. We extend this line of research by examining factors that may explain the bubble-like phenomenon.

Figure 1 shows the performance of both the real price indices and the real idiosyncratic price indices. The latter reflect the sector-specific performance after removing the effects of general market fluctuations, technology stocks and oil prices. The graphs also reveal the weaker performance of US alternative energy stocks compared to their European and international counterparts — a result that we have already encountered in the previous section. Overall, investor sentiment toward the clean energy sector seems to have been far less exuberant in the United States than in Europe. Consistent with the mean raw return reported in Table 1, the ERIX exhibits the sharpest rise in prices prior to 2008.

The sector-specific components of our European and global indices gradually increase and do not start to decline until after the world stock markets have begun their recovery in early 2009. Except for the US sample, the peaks in the idiosyncratic price indices are all located in May 2009. This suggests that the severe crashes following the outbreak of the global financial crisis in 2008 were mainly driven by systematic risk factors, such as the relatively high market betas. By contrast, the US idiosyncratic price index steadily declines throughout the sample period. This is an indication that the positive performance until the end of 2007 can largely be attributed to our set of exogenous factors, whereas the sector-specific component was mostly negative.

Figures 2–6 display the alpha coefficients as well as the time-varying exposures of the multifactor model in equation (8). The factor loadings are computed as the sum of the contemporaneous and lagged coefficients (see Dimson 1979). The daily alphas somewhat reflect the aforementioned reversal in abnormal returns after 2008. However, they should not be directly compared with the estimates in Tables 2 and 3, as the latter are based on

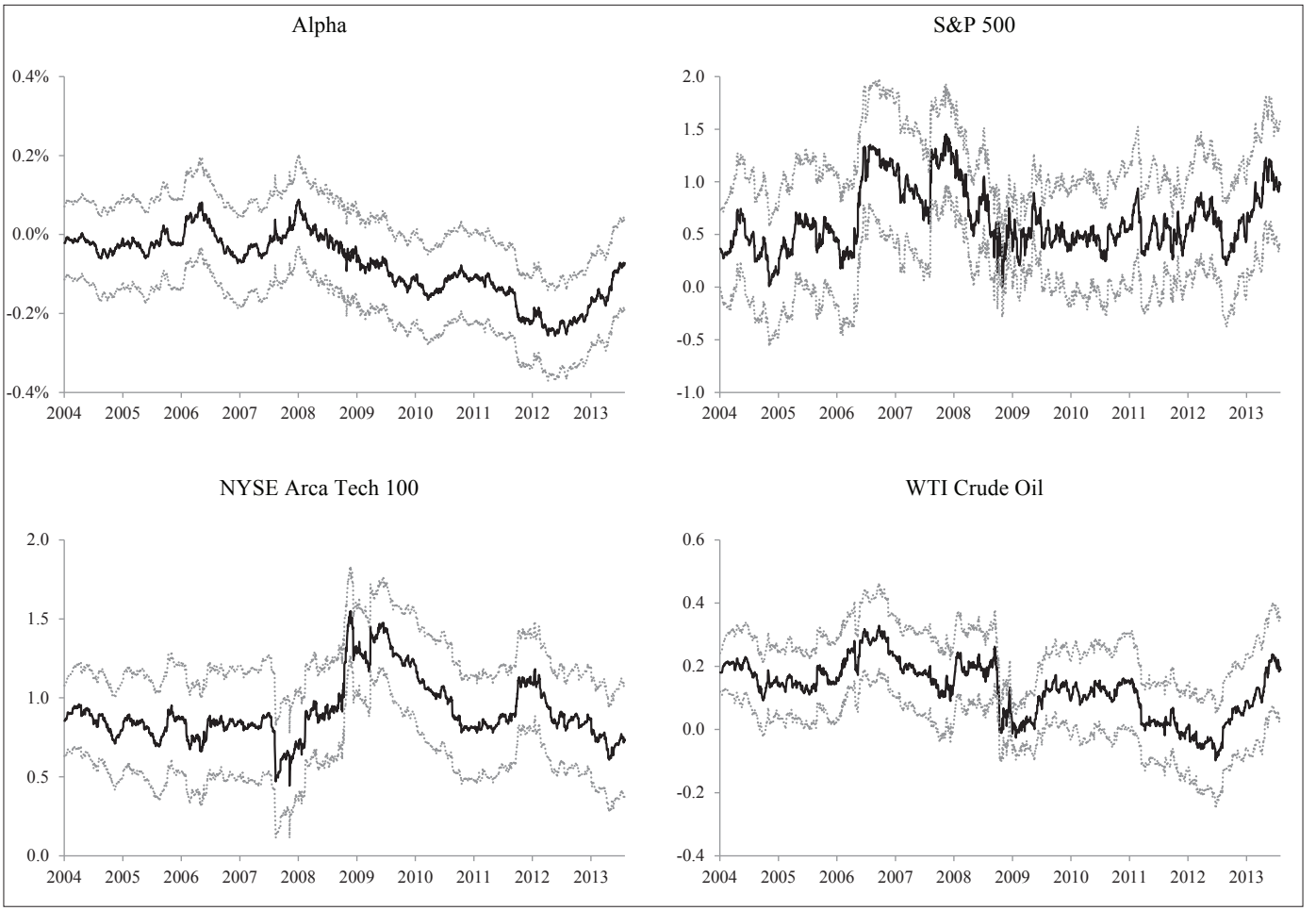
Figure 1: Real Price Indices and Real Idiosyncratic Price Indices



This figure shows the inflation-adjusted stock price indices and the inflation-adjusted, sector-specific price indices. The latter represent the idiosyncratic portion after controlling for time-varying exposures to a set of explanatory variables. Both indices are based on daily data for the sample period from January 2004 to July 2013.

monthly excess returns and on a different set of benchmark factors. For all indices, the sensitivity to the broad market index is relatively strong, corroborating our earlier findings for the monthly performance evaluation. For example, the daily market beta of the S&P Global Clean Energy Index fluctuates quite heavily between 0.59 and 2.71, averaging 1.49. Interestingly, the correlation with technology stocks is strongest for the US index, while the European and global indices are less exposed to return variations in the tech sector. The loading of the WilderHill Clean Energy Index on the NYSE Arca Tech 100 ranges between 0.44 and 1.55, whereas the exposure of the European Renewable Energy

Figure 2: Time-varying Factor Exposures of the WilderHill Clean Energy Index



This figure shows daily time-varying factor exposures for the WilderHill Clean Energy Index. The Kalman filter is used to estimate the time-varying factor loadings of equations (8) to (10) for the period from January 2004 to July 2013. Except for the alpha, the solid lines represent the sum of the contemporaneous and lagged coefficients, whereas the dotted lines represent confidence bands for the 10 percent level of statistical significance.

Index to the STOXX Europe TMI Technology lies only in a narrow and mostly insignificant range between –0.04 and 0.18. For the global indices, the sensitivity to technology stocks sometimes falls into deeper negative territory.

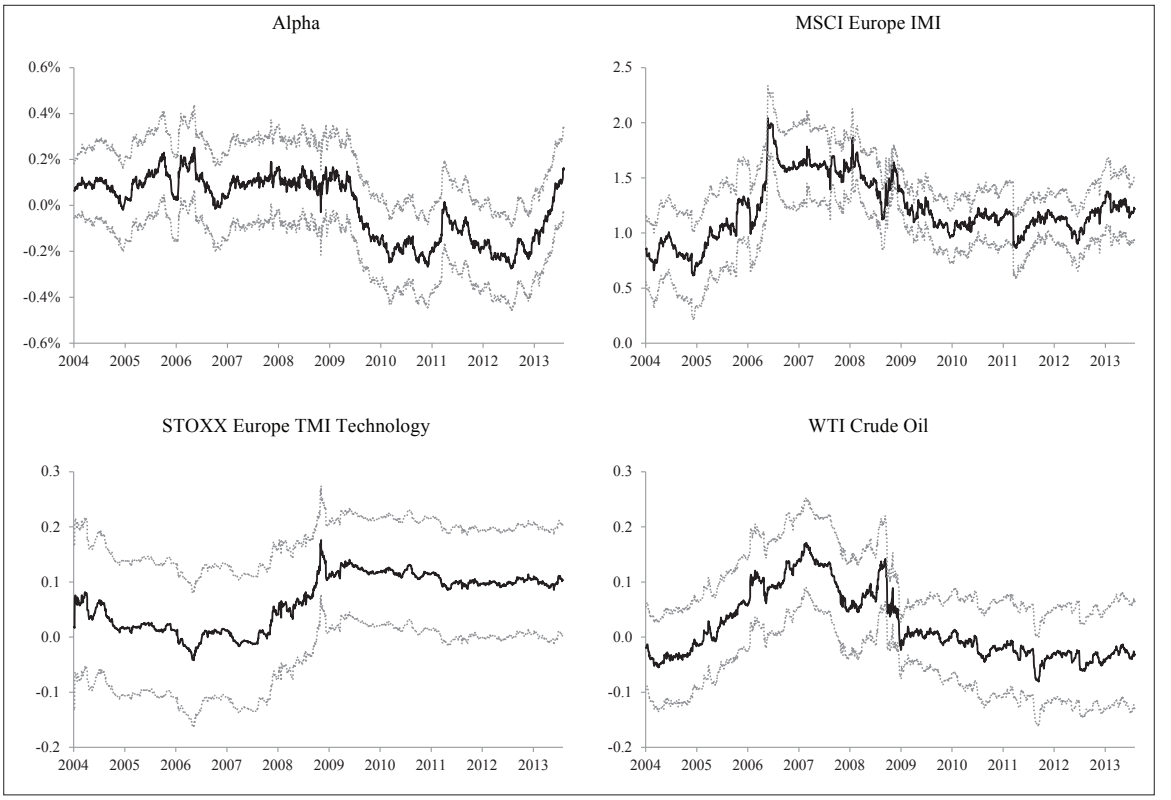
As far as the sensitivity to oil price fluctuations is concerned, we find an interesting pattern. Prior to the burst of the oil price bubble in mid-2008, all indices show a positive and mostly significant reaction to an increase in crude oil prices. For the WilderHill Clean Energy Index, the exposure to oil price changes ranges between 0.09 and 0.33 during that period of time. However, the positive relationship breaks down over the course of the bubble crash in October 2008. For the European and global indices, the oil sensitivity is lower prior to 2008, but still of some economic relevance. In summary, we can conclude that rising oil prices partly drove the performance of alternative energy stocks across the globe, with the effect being most pronounced for the US sector. However, in the aftermath of the global economic crisis and the bursting of the 2008 oil bubble, the positive relationship diminishes or even disappears entirely.

Note that prior to mid-2008, the daily exposures to WTI crude oil are somewhat higher than the average monthly loadings on the S&P GSCI Energy Total Return Index reported in Tables 2 and 3. These two assets do not necessarily move in tandem, as the latter total return index also captures gains or losses associated with rolling forward futures contracts once they reach their expiry dates. This so-called roll yield is positive if the futures market is in backwardation, meaning that the expected spot price exceeds the futures prices. The roll yield is negative if the futures market is in contango, a situation where the futures curve is upward sloping. For instance, after the oil bubble burst in July 2008, the oil futures market was quickly entering a sustained period of contango (see, for example, Kesicki 2010). As a result, the payoff from the S&P GSCI Energy Total Return Index was rather moderate, although spot prices of fossil fuels began to rise again.

SADF TESTS

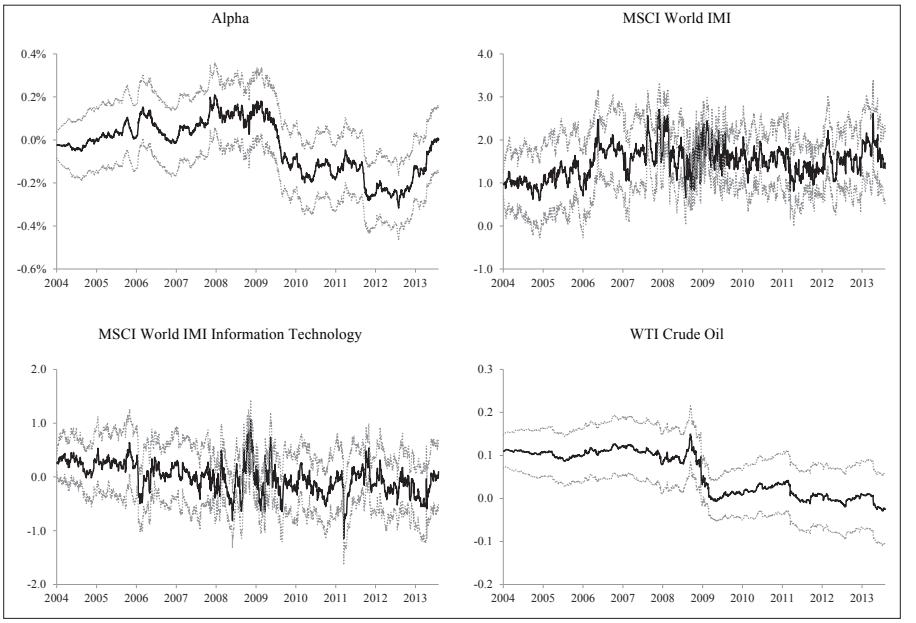
Visual inspection of the charts in Figure 1 indicates some explosive price behaviour, at least for the European and

Figure 3: Time-varying Factor Exposures of the European Renewable Energy Index



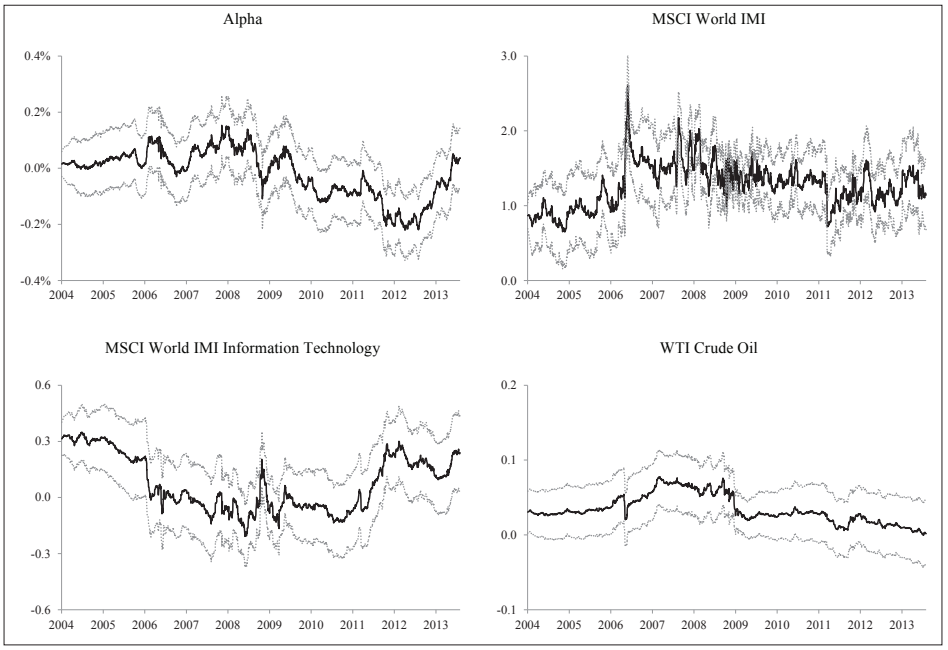
This figure shows daily time-varying factor exposures for the European Renewable Energy Index. The Kalman filter is used to estimate the time-varying factor loadings of equations (8) to (10) for the period from January 2004 to July 2013. Except for the alpha, the solid lines represent the sum of the contemporaneous and lagged coefficients, whereas the dotted lines represent confidence bands for the 10 percent level of statistical significance.

Figure 4: Time-varying Factor Exposures of the S&P Global Clean Energy Index



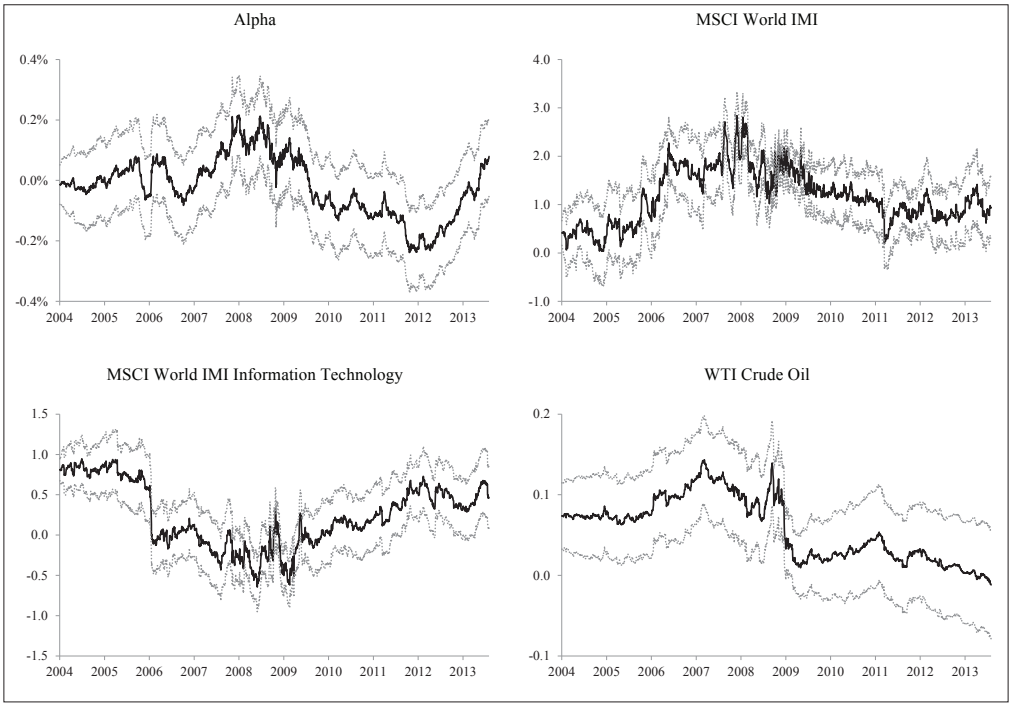
This figure shows daily time-varying factor exposures for the S&P Global Clean Energy Index. The Kalman filter is used to estimate the time-varying factor loadings of equations (8) to (10) for the period from January 2004 to July 2013. Except for the alpha, the solid lines represent the sum of the contemporaneous and lagged coefficients, whereas the dotted lines represent confidence bands for the 10 percent level of statistical significance.

Figure 5: Time-varying Factor Exposures of the WilderHill New Energy Global Innovation Index



This figure shows daily time-varying factor exposures for the WilderHill New Energy Global Innovation Index. The Kalman filter is used to estimate the time-varying factor loadings of equations (8) to (10) for the period from January 2004 to July 2013. Except for the alpha, the solid lines represent the sum of the contemporaneous and lagged coefficients, whereas the dotted lines represent confidence bands for the 10 percent level of statistical significance.

Figure 6: Time-varying Factor Exposures of the Ardour Global Alternative Energy Index Composite



This figure shows daily time-varying factor exposures for the Ardour Global Alternative Energy Index Composite. The Kalman filter is used to estimate the time-varying factor loadings of equations (8) to (10) for the period from January 2004 to July 2013. Except for the alpha, the solid lines represent the sum of the contemporaneous and lagged coefficients, whereas the dotted lines represent confidence bands for the 10 percent level of statistical significance.

Table 4: Bubble Detection Tests

Index	Recursive SADF	Rolling SADF	GSADF
Panel A: Test Statistics			
WilderHill Clean Energy Index			
Price index	0.742	1.136	1.757
Idiosyncratic price index	–0.026	1.352	2.382**
European Renewable Energy Index			
Price index	3.880***	3.519***	4.647***
Idiosyncratic price index	2.212***	1.368	2.660**
S&P Global Clean Energy Index			
Price index	3.309***	3.094***	4.417***
Idiosyncratic price index	2.329***	1.490*	3.234***
WilderHill New Energy Global Innovation Index			
Price index	3.074***	2.925***	3.749***
Idiosyncratic price index	2.202***	1.680*	2.334**
Ardour Global Alternative Energy Index Composite			
Price index	2.437***	1.450	2.910***
Idiosyncratic price index	1.665**	1.588*	2.733***
Panel B: Finite Sample Critical Values			
CV 90%	1.253	1.465	1.958
CV 95%	1.526	1.694	2.195
CV 99%	2.023	2.145	2.722

This table reports the test statistics of the three SADF procedures. Results are shown for both inflation-adjusted stock price indices and the deflated idiosyncratic portion of the stock price indices. For the recursive SADF and GSADF tests, the sample fraction *r0*, which determines the initial window length, is set to 0.1, while for the rolling SADF test the constant fraction *r* equals 0.2. Right-tailed critical values are obtained from Monte Carlo simulations with 5,000 replications. The sample period runs from January 2004 to July 2013. *, ** and *** denote statistical significance at the 10, five and one percent levels, respectively.

global indices. To formally test this supposition, we perform the recursive, rolling and generalized versions of the SADF test outlined in the section on "Bubble Detection Tests." Table 4 presents the supremum test statistics as well as the associated finite sample critical values. Based on these results, we do not find any signs of explosiveness for US alternative energy stocks, which leads us to reject the possibility of a bubble. By contrast, for European and international stocks we can reject — in most cases even at the one percent level — the unit root null hypothesis in favour of the explosive alternative. The test statistics for the idiosyncratic price indices shed light on the degree to which the explosive price behaviour was driven by exogenous factors. Even after controlling for return variations in the aggregate equity market, technology stocks and crude oil, we overwhelmingly reject the null hypothesis of a unit root. This finding suggests that the explosiveness in the mid-2000s was sector-specific and not merely a result of rising oil prices or the bullish market trend in general.

However, inferences cannot be solely drawn on the basis of the supremum test statistics. The date-stamping procedure has to be taken into account as well. As an example of this, Figures 7 and 8 show the sequences of backward supremum augmented Dickey-Fuller (BSADF) test statistics and their simulated right-tailed critical values at the 95 percent significance level. Both series pertain to the GSADF test. Table 5 provides similar information and specifies the months where episodes of explosiveness occurred. These are the months when the sequences of test statistics exceeded and subsequently fell below again the critical value at the 95 percent level. Note that the date-stamping procedure is only applicable if the corresponding supremum test statistic in Table 4 is statistically significant. We only report those months that exhibit genuine explosive behaviour due to sharp rises in the real price indices and disregard explosiveness that stems from falling stock prices. Yiu, Yu and Jin (2013) refer to the latter episodes as negative bubbles. However, from a rational standpoint it remains questionable whether such a phenomenon even exists. Besides, we do not consider explosiveness in the real idiosyncratic price time series in the midst of the 2008-2009 global financial crisis, since the underlying real price indices had already begun to drop substantially in value at that time. The significant GSADF test statistic for the

Table 5: Date-stamping Periods of Explosiveness

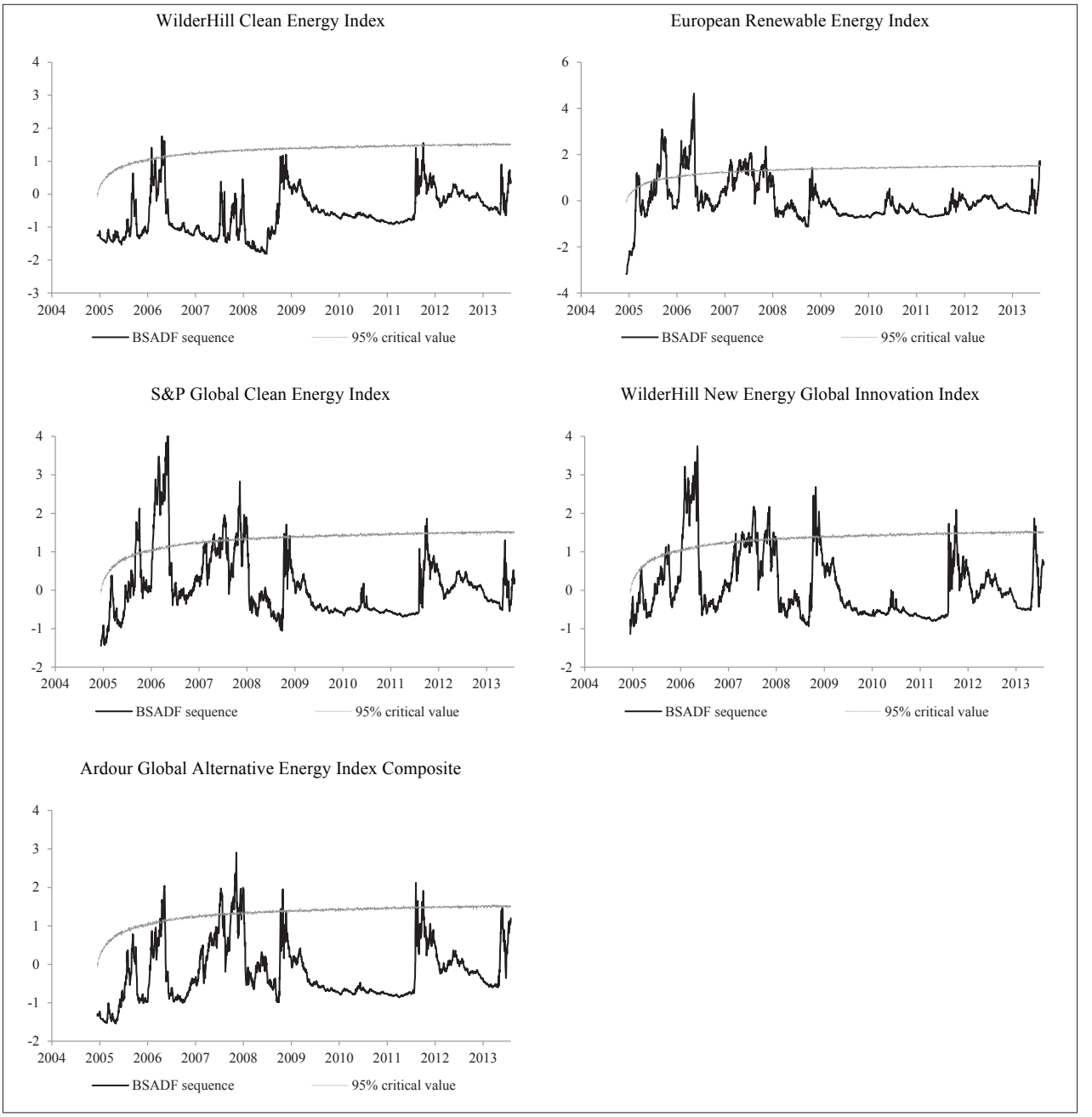
Index	Recursive SADF	Rolling SADF	GSADF
WilderHill Clean Energy Index			
Price index	n/a	n/a	n/a
Idiosyncratic price index	n/a	n/a	n/a
European Renewable Energy Index			
Price index	06/2005–05/2006 12/2006–01/2008	01/2006–05/2006 04/2007–07/2007	08/2005–10/2005 01/2006–05/2006 02/2007–11/2007
Idiosyncratic price index	06/2005–11/2005 01/2006–05/2006	n/a	08/2005–10/2005 04/2006–05/2006
S&P Global Clean Energy Index			
Price index	09/2005–10/2005 01/2006–05/2006 12/2006–01/2008	01/2006–05/2006 10/2007–12/2007	09/2005–10/2005 01/2006–05/2006 04/2007–12/2007
Idiosyncratic price index	09/2005–10/2005 02/2006–06/2006 10/2007–02/2008	02/2006–05/2006 12/2007–02/2008	09/2005–10/2005 02/2006–05/2006 11/2007–01/2008
WilderHill New Energy Global Innovation Index			
Price index	08/2005–10/2005 01/2006–06/2006 12/2006–01/2008	01/2006–05/2006 04/2007–08/2007	01/2006–05/2006 04/2007–11/2007
Idiosyncratic price index	06/2005–10/2005 01/2006–07/2006 07/2007–02/2008	01/2006–06/2006 12/2007–01/2008	02/2006–05/2006 11/2007–12/2007
Ardour Global Alternative Energy Index Composite			
Price index	04/2006–05/2006 04/2007–01/2008	n/a	04/2006–05/2006 07/2007–12/2007
Idiosyncratic price index	12/2007–01/2008	12/2007–02/2008	11/2007–01/2008

This table reports the months in which episodes of explosiveness originated and subsequently terminated again. The sample period runs from January 2004 to July 2013.

idiosyncratic WilderHill Clean Energy Index is therefore also misleading because Figure 8 shows that it stems from late 2011, a time where the real price index was tumbling and thus caused negative explosiveness. The bottom line is that one has to be cautious when it comes to interpreting the results of sequential ADF-type bubble tests.

The explosive episodes reported in Table 5 mainly cover months in the second half of 2005, the first half of 2006 as well as throughout 2007 and early 2008. These periods refer to both the real price and real sector-specific price time series, and thus suggest temporary episodes of bubble-like behaviour in European and global renewable energy stock indices. However, these periods are rather short-lived because the price overreactions were relatively quickly corrected. Recall that the sector-specific indices continued to rise until May 2009, a time when global equity markets had already begun their strong recovery from the preceding bear market (see Figure 1). As a result, the crash of the alternative energy stock indices that coincided with the outbreak of the 2008-2009 global financial crisis was not the burst of a bubble but rather attributable to the relatively high sensitivity to market fluctuations. We therefore have reason to doubt the existence of an inflated speculative bubble similar to the one occurring during the dotcom era in the late 1990s. The delayed decline of idiosyncratic price time series suggests a substantial revaluation of alternative energy stock prices in light of intensifying competition and shrinking sales margins. This reassessment in early 2009 is consistent with substantial changes in the underlying fundamentals. First, soaring fossil fuel prices were not an issue any more as they fell back to sustainable levels after the global economic crisis. This probably dampened investors' anticipation of further immediate government support for the promotion of renewable energies as a long-term substitute. Second, growing excess supply and overcapacity in the solar and wind turbine sector have left their mark on the industry's profitability. Average factory-gate prices for crystalline silicon solar modules began to drop in the third quarter of 2008 after having reached their peak at US$4.13 per watt of generating capacity. Since

Figure 7: Sequences of BSADF Test Statistics for Real Price Indices



This figure shows the sequences of BSADF test statistics and their simulated right-tailed critical values at the 95 percent level. Both series are part of the GSADF test, which is performed for daily inflation-adjusted price index data in the sample period from January 2004 to July 2013.

then, the decline has continued to levels well below US$1 per watt. Similarly, the Bloomberg New Energy Finance Wind Turbine Price Index started to decline from €1.21 million per megawatt for delivery in the first half of 2009 to around €0.90 million for delivery in 2013.[6]

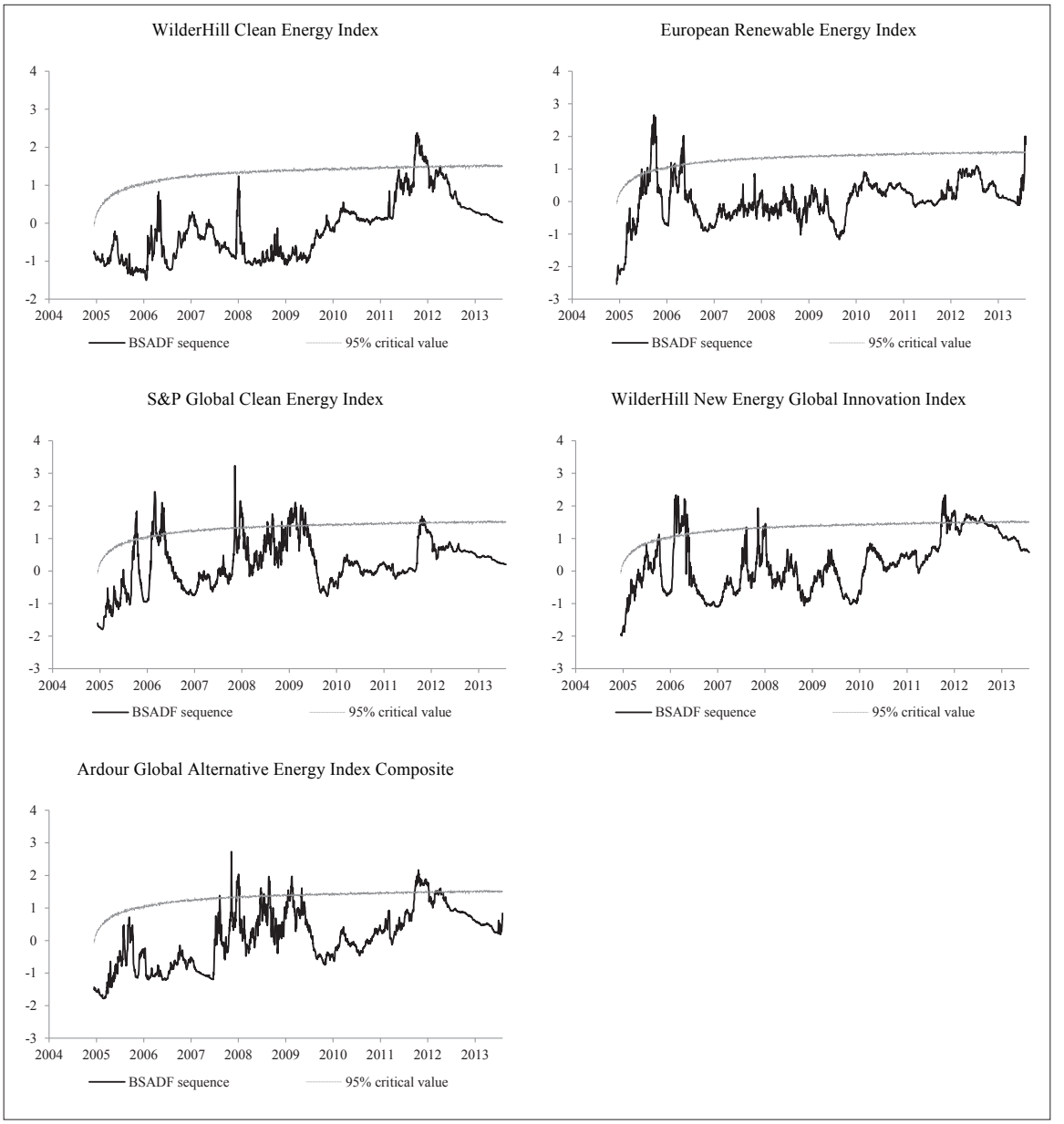
CONCLUDING REMARKS

Recent evidence suggests that a wave of exuberant investor sentiment pushed up prices of alternative energy stocks in the mid-2000s. We investigate whether the sector rally could have been driven by a speculative price bubble or whether it was merely a manifestation of rising crude oil prices and the prevailing bullish market conditions.

We show that US, European and international renewable energy stocks are highly sensitive to market fluctuations and are tilted toward the small-cap and growth stock segment. Based on a five-factor regression model,

6 We are grateful to Bloomberg New Energy Finance for making available their proprietary index data.

Figure 8: Sequences of BSADF Test Statistics for Real Idiosyncratic Price Indices



This figure shows the sequences of BSADF test statistics and their simulated right-tailed critical values at the 95 percent level. Both series are part of the GSADF test, which is performed for daily inflation-adjusted idiosyncratic price index data in the sample period from January 2004 to July 2013.

we uncover a substantial deterioration in abnormal performance after the outbreak of the 2008-2009 global financial crisis. Monthly alphas turned from positive to significantly negative in the period between 2008 and 2013. Interestingly, most of the positive raw performance of European and international indices during the mid-2000s can be explained by price momentum. Loadings on this factor are significantly positive until the end of 2007, but become negligibly small afterwards. By contrast, US alternative energy stocks display a rather moderate return pattern and are positively correlated with fossil fuel prices, indicating a possible hedging relationship. European and global total return indices are, however, mainly unexposed to investment payoffs from the energy futures market.

While US alternative energy stock prices do not exhibit any signs of explosiveness in the mid-2000s, we find strong evidence of such behaviour for European and international indices. We extend previous research by accounting for factors that may be able to explain the explosive price behaviour. After controlling for market beta and exposures to technology stocks and crude oil, we still detect significant explosive deviations from the random walk path for European and international stocks. However, the idiosyncratic components did not collapse simultaneously

with their underlying price indices during the 2008 stock market crash. Instead, they continued to increase until May 2009, when the global stock markets had already begun their recovery from the preceding bear market. This finding is suggestive of a substantial reassessment of alternative energy stock prices against the background of intensified sector competition and shrinking profit margins and does not provide conclusive evidence of a speculative bubble. The severe crash of alternative energy stock prices in 2008 is thus unlikely to result from the bursting of a bubble, but can primarily be explained by the high market betas the stocks possess. Nevertheless, some quickly collapsing price spikes between 2005 and 2007 indicate the presence of at least some irrational exuberance among investors.

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