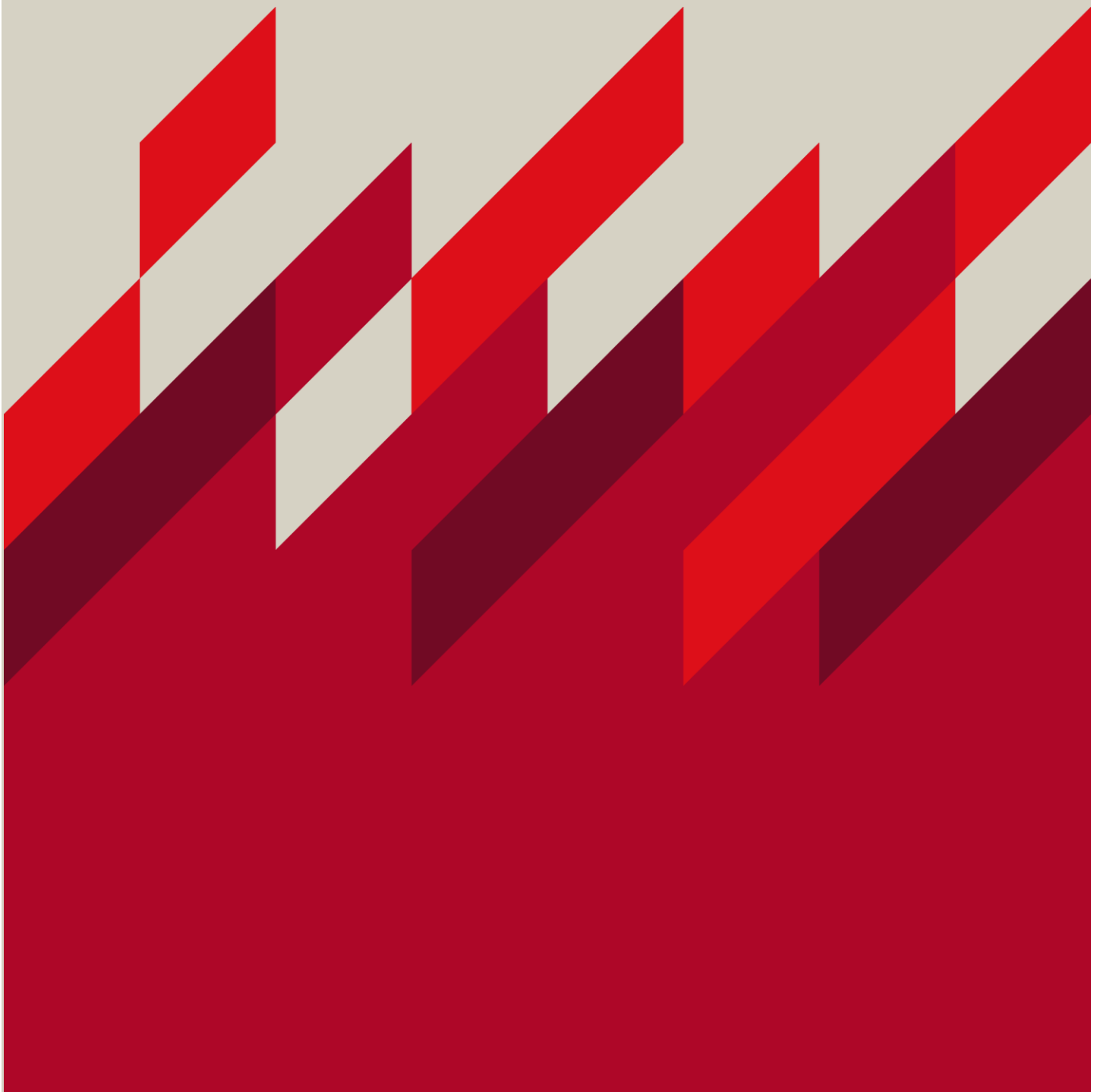




Investor Herding and Dispersing in the Renewable Energy Sector

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Abstract

We examine herding behaviour among investors in the renewable energy sector in the United States. Over the last decade, the renewable energy sector has demonstrated significant growth rates in the global economy. However, the sector has also shown variation in performance, with periods of relatively high active returns as well as substantial underperformance. In this study, we examine the relationship between the level of equity return dispersions - measured by the cross-sectional absolute deviation of returns - and the overall market return in the renewable sector. Using data from January 2000 to December 2015, we find significant evidence for excess return dispersion or so-called dispersing in the renewable energy sector. We also find evidence of asymmetric return dispersion, indicating a different impact of positive or negative market returns on return dispersion. These results also hold when considering risk-adjusted returns for the renewable sector based on a CAPM or multifactor model. Investigating different regimes of oil price behaviour, we find some evidence of investor herding during periods when the oil price dropped significantly. However, before and after this period, there is clear evidence of dispersing in renewable stocks. Our results indicate a quite unique behaviour of returns in the renewable energy sector in comparison to other equity markets. Overall, investors in renewable energy stocks seem to disagree on their interpretation of large market movements, leading to an even higher return dispersion than predicted by standard asset pricing models

Key Words: Renewable Energy, Investor Herding, Return Dispersion, Oil Price, Asset Pricing

JEL Classification: Q42, G12, Q43, G02

1. Introduction

There has been an increased interest in investor herding behaviour in financial markets over the past decade. Spyrou (2013) suggests herding as one of the major reasons for market instability and extreme market movements. Herding in financial economics refers to investors imitating the trading or investment behaviour of other investors. The consequence of herding is that investors are drawn to the consensus of the market, what may push stock prices further away from their economic fundamentals. Ionescu et al. (2012) note that herding behaviour of market participants can cause assets to be mispriced and might create additional risk in financial markets. Investor herding behaviour also occurs across different markets and countries. Marais and Bates (2006), Chiang and Zheng (2010) and Chiang et al. (2013) report co-movement and shift contagion among equity markets and suggest that, for example, the 1997 Asian financial crisis was dominated by cross-market herding. Interestingly, empirical results suggest that herding occurs mostly in emerging, but not so much in mature financial markets (Chang et al., 2000; Chiang and Zheng, 2010). Chang et al. (2000) suggest no obvious herding in advanced financial markets, while Christie and Huang (1995) scarcely find evidence of herding in the US equity market by examining periods of excessive market movements.

In this paper, we investigate investor herding and dispersing behaviour in the US renewable energy sector. Since the early 2000s, the renewable sector has grown substantially, drawing billions of USD in investments and making the sector one of the most important emerging industries in the global economy (REN21, 2010; UNEP, 2012). However, the sector is also characterised by a large number of firms going bankrupt or being restructured while only a small number of firms become ultimately established in the market. A key reason for this is the gap between innovation, adoption and diffusion of new energy technologies, the so-called ‘Valley of Death’ (Weyant, 2011). Stocks in the renewable sector are typically more volatile, and companies, therefore, often exhibit higher risks than traditional companies (Kumar et al., 2012; Sadorsky, 2015). Henriques and Sadorsky (2008) conclude that renewable energy stocks are similar to technology stocks or venture capital, often making them riskier than stocks in other sectors. Further, as pointed out by Bohl et al (2013, 2015) the sector has also shown significant variation in performance, with European renewable stocks earning considerable risk-adjusted returns between 2004 and 2007, and delivering negative returns between 2008-2011. Inchauspe et al (2015) also suggest time-varying active returns after adjusting for standard pricing factors for the WilderHill New Energy Global Innovation Index (NEX). The significant differences in risk-adjusted performance of the renewable sector may also be a result of mispricing of the stocks, possibly caused by herding.

Our study contributes to the literature in several dimensions. First, this is a pioneering analysis to focus in particular on investor herding in the renewable energy sector. The financial performance, investment behaviour as well as the dynamics of returns of renewable stocks have recently attracted a great interest in the literature (Henriques and Sadorsky, 2008; Kumar et al.,

2012; Sadorsky, 2012; Bohl et al, 2013; Managi and Okimoto, 2013; Ortas and Moneva, 2013; Inchauspe et al., 2015). However, none of these studies has examined the relationship between overall market behaviour in the renewable sector and return dispersion across individual stocks. We believe that such an analysis might also help to explain the substantial differences in risk-adjusted performance of the renewable sector, since it might reveal herding as a possible factor of mispricing. Second, by examining also asymmetric effects on return dispersion, we provide insights on how positive and negative market outcomes impact on investor beliefs about the performance of individual renewable stocks. Third, we provide additional insights on the relationship between oil price regimes and the dynamics of returns in the renewable sector. By examining herding behaviour during different phases of oil price behaviour, our results shed some light on co-movements of renewable stocks and investor behaviour under periods of rising or significantly falling oil prices. So far results on herding under crisis regimes are rather inconclusive, either suggesting that herding is weaker during periods of market stress (Hwang and Salmon, 2004) or becomes more intense (Economous et al., 2011). Finally, we propose an approach that allows us to examine herding behaviour also from a risk-adjusted perspective. By distinguishing between positive and negative active returns in the sector, we can examine under which performance regime in the renewable sector is more likely to occur.

Overall, we find strong evidence for a unique behaviour of the renewable energy sector with respect to return dispersion and herding. Comparing the cross-sectional absolute deviation for renewable energy stocks to results from earlier studies on other financial markets, we find typically higher levels of return dispersion in the renewable sector. We also find relatively strong and significant evidence for excess return dispersion – instead of herding - for renewable energy stocks. This is true in particular when daily and weekly returns are considered, but there is also some evidence for dispersing for monthly returns of renewables. These results are evidence for a rather specific behaviour of the renewable sector, since most prior studies on return dispersion in financial markets found either evidence of herding or a linear relationship between expected market returns and CSAD. We interpret these findings as investors in the renewable sector having a different interpretation of (large) market movements, leading to an even higher dispersion than predicted by standard asset pricing models. Our findings could also be interpreted as evidence for dispersion in investors' beliefs about future performance of the individual stocks.

We find that different periods of oil price behaviour have a clear impact on herding behaviour: we find evidence of excess return dispersion during the period of a steady oil price increase from 2000 to mid 2008 and for the post-oil price shock period from 2009 to mid 2014. On the other hand, our results suggest investor herding behaviour in the renewable sector during the period of a significant drop in the oil price for the second half of 2008. Finally, when examining herding behavior for different performance regimes of the renewable sector, we find that in particular during periods of positive active returns in the market, there is significant evidence for excess return dispersion.

Overall, our results point out the unique behavior of the renewable energy sector with respect to dispersion in investors' beliefs about future performance of the individual stocks. To the best of our knowledge, our study presents one of the first to actually document clear evidence for dispersing in a major US industry sector.

The remainder of this paper is organised as follows. Section 2 provides a brief review of related literature on herding as well as on studies measuring the performance of the renewable energy sector. Section 3 describes the data and applied models for examining herding behaviour. Section 4 provides the results of the conducted empirical analysis. Section 5 concludes and makes suggestions for future work.

2. Related Literature

2.1 Herding and Dispersing

Devenow and Welch (1996) distinguish theoretical motives for herding as being either irrational or rational. Irrational herding is based on investor psychology, where investors follow institutions and other investors blindly. Rational herding, on the other hand, suggests that investors herd as a result of either following advanced information or maintaining or compensating for the reputation of investors (Scharfstein and Stein, 1990; Banerjee, 1992; Bikhchandani et al., 1992; Admati and Pfleiderer, 1997).

Moving away from the theoretical literature and focusing on empirical measurement, the literature typically investigates using two different approaches. The first measure depends on investor portfolios and their buy or sell transaction flow, examining how institutional investors learn from others or herd in particular securities, through simultaneous buying or selling stocks (Lakonishok, 1992; Grinblatt et al., 1995; Wermer, 1999; Puckett and Yan, 2007; Frey et al., 2014). The second approach, which this paper focuses on, analyses investment herding behaviour considering the entire market and its relationship with return dispersion among individual stocks (Christie and Huang, 1995; Chang et al., 2000; Hwang and Salmon, 2004; Chiang and Zheng, 2010). Based on this approach, return dispersion below or in exceedance of a linear relationship with market returns is then characterized as herding or dispersing, respectively.

Christie and Huang (1995) propose the use of cross-sectional standard deviation of US equity market returns as an indicator of return dispersion, to examine the existence of herding behaviour during periods of extremely low or high market returns. Their results for both daily and monthly returns are inconsistent with the presence of herding during periods of large price movement. Instead, they find excess return dispersion, in particular during period of large market movements.

Chang et al. (2000) modify Christie and Huang (1995)'s model by using the cross-sectional absolute deviation to measure return dispersion and subsequently analyse investor herding

behaviour by examining the non-linear relationship between return dispersion and stock returns. In their study, the authors compare periods of up and down markets, using data from the US, Hong Kong, South Korea, Taiwan and Japan. Their findings suggest that herding occurs mostly in emerging, but not advanced financial markets: Herding behaviour in equity markets exists in South Korea and Taiwan, and is partially present in Japan, while the study detects no evidence of herding or dispersing for the US and Hong Kong.

As a measure of herding and dispersing, return dispersion is not only a result of equity market returns but also of the economic state beyond market level information (Stivers and Sun, 2010; Gomes et al., 2003). As a result beta-factors of shares typically vary with different market conditions and cannot be measured precisely. Therefore, it is likely that also a return dispersion measure such as the cross-sectional absolute deviation will contain incremental information about the aggregate economy or market volatility. Hwang and Salmon (2004) then examine herding by relating return dispersion to market volatility as well as additional macroeconomic variables. Examining data from US and South Korean equity markets, the authors conclude that herding has a significant impact on stock return movements but is independent of the considered macro factors. Interestingly, these findings are inconsistent with results reported by Stiver (2003) who suggests that return dispersion is positively dependent on macroeconomic news. Hwang and Salmon (2004) also argue that if the intensity of herding was severe before a crisis, then abnormally low return dispersion as a phenomenon of herding could possibly lead to major mispricing of shares. In such a scenario, financial market stress or a crisis would then help to push share prices back to their equilibrium levels. Interestingly, according to their findings, the intensity of herding is also weaker during periods of market stress, suggesting that the occurrence of a crisis may actually be a turning point for investor herding. On the other hand, results by Economou et al. (2011), based on European market data, suggest that herding is typically more intense during periods of a financial crisis.

An international herding study of 17 markets by Chiang and Zheng (2010) finds that herding exists in emerging as well as advanced markets, while the intensity of herding is more severe in emerging markets. The authors also find that herding not only occurs in local markets but also expands across countries. Their results suggest that a crisis triggers herding activity in the crisis country of origin and then produces a contagion effect, which possibly spreads the crisis to neighbouring countries. Chiang et al.'s (2013) follow-up study shows that herding behaviour is time-varying in Pacific-Basin financial markets. Further, herding is positively related to stock performance, and negatively related to market volatility. Distinct from Chiang et al. (2013), Ouarda et al. (2013) find that herding is positively related to equity volatility and transaction volume in European markets. Behaert and Harvey (1997) also suggest that the relationship between dispersion and market volatility varies in developed and emerging markets.

Moreover, studies of herding behaviour in the Chinese stock market (Demirer and Kutan, 2006; Tan et al., 2008) present conflicting evidence. Demirer and Kutan (2006) find evidence of

herding to be insignificant, whereas Tan et al. (2008), using data referring to shorter time horizons, suggest the presence of herding.

Overall, empirical findings of herding and dispersing behaviour in financial markets are inconsistent. The literature presents no definitive answer on the conditions under which investor herding is more likely to exist. While a number of studies suggest that for advanced financial markets there is rather no significant evidence of herding, none of these studies has particularly focused on the renewable energy sector. However, renewable markets are well known to exhibit a quite unique behaviour with regards to growth rates and performance. We therefore believe that our analysis will provide new and important insights for this emerging major industry sector.

2.2 Returns and Performance of the Renewable Energy Sector

While to the best of our knowledge, so far no study has investigated herding behaviour in the renewable energy sector, a number of authors have examined the performance of renewable stocks as well as the relationship between equity returns in the renewable sector and the oil price, technology stocks or other possible factors of influence on the sector.

Henriques and Sadorsky (2008) state that positive relationship between oil price and renewable energy stock price is widely accepted, despite there being little evidence of it. They examine the relationship between renewable energy stocks, technology stocks, crude oil price and interest rates in the US, using vector autoregression. Their results show that the oil price has only a small effect on renewable energy stocks returns. Sadorsky (2012a) examines volatility spillover effects between oil, technology stocks and renewable energy stocks and finds that dynamics of renewable energy stocks are more intensively correlated with technology stock prices than oil prices. One reason for this may be that the development of technology has direct impact on the renewable energy industry. However, the author suggests that the relatively lower correlation between oil prices and clean energy stock returns provides a more useful hedge between oil and renewable energy price movements.

Kumar et al. (2012) also apply a vector-autoregressive model to investigate the relationship between carbon, oil, interest rate, technology stocks, and renewable energy stock prices. They suggest that both oil price and technology stocks have a significant impact on renewable energy stock returns. In particular, rising oil prices are positively related to the returns of clean energy stocks. The authors also suggest that the effect of carbon allowance prices on renewable energy stocks is insignificant.

Managi and Okimoto (2013) highlight that there is a structural change in the relationship between oil prices, clean energy stocks and technology stock prices at the end of 2007. Consistent with Henriques and Sadorsky (2008), they find little evidence for a link between oil and renewable energy prices before 2007. After 2007, however, the oil price has a significant

positive impact on renewable energy stock return. Inchauspe et al. (2015) use a state-space multi-factor asset-pricing model to understand abnormal returns of renewable energy equities globally. Their results suggest that the influence of the oil price on the renewable energy index has gradually been increasing from 2005 onwards. They also find a strong influence of the MSCI World index and technology stocks throughout the considered sample period.¹

Next to studies examining the relationship between the renewable energy stocks, oil prices, technology stocks, interest rates and overall stock market returns, there is also a small number of papers focusing more on the risk-adjusted performance of the sector.

Bohl et al (2013) examine the risk-adjusted performance of the renewable sector. Focusing on the German market, their results indicate that the sector has shown significant variation in performance (*'from hero to zero'*), earning considerable risk-adjusted active returns between 2004 and 2007, while delivering negative returns between 2008-2011. Ortas and Moneva (2013) examine the time-varying beta coefficients of 21 clean-technology equity indices, suggesting that renewable indices yield higher returns and risk than conventional stock indices. Moreover, they also find a structural change in the dynamics of clean technology indices' return/risk performance that coincides with the beginning of the financial crisis. In a related study, Inchauspe et al. (2015) investigate the time-varying dynamics of risk-adjusted returns for the NEX renewable energy index. They find different regimes of active returns after adjusting for standard pricing factors such as equity returns and the oil price. In particular, they suggest that while the NEX initially provided returns in excess of its risk-adjusted premium during the period from 2003-2007, it yielded negative abnormal returns between 2009 and 2013. They propose that a major reason for this is that the renewable index did not recover from the losses experienced during the financial crisis by the same magnitude as the other considered pricing factors. Finally, Bohl et al. (2015) analyse whether the explosive price behavior of renewable energy stocks during the mid-2000s was driven by rising crude oil prices and overall bullish market sentiment. They suggest strong evidence of active returns and explosive price behaviour for European and global renewable sector indices, even after controlling for a set of explanatory variables.

Overall, there seems to be quite some evidence for the systematic influence of other factors such as the oil price or returns from technology stocks on renewable stocks. Further, the sector has exhibited periods of explosive returns, high active returns, followed by a regime of rather poor performance also relative to other equity markets. This suggests that at least for some

¹ A number of other studies also suggest that the oil price has a significant impact on energy stocks without focusing on the renewable sector (Sadorsky, 2001; Broadstock et al., 2012; Wen et al., 2014). Sadorsky (2001) finds significant positive effects of oil prices on returns from oil and gas companies in the Canadian market. Broadstock et al. (2012) and Wen et al. (2014) show that oil price dynamics have an obvious impact on energy stock prices in Chinese markets. Moreover, the correlation between oil and energy stock price increases significantly after the 2007-2009 global financial crisis.

periods prices in the renewable sector have most likely deviated significantly from their fundamentals. This motivates us to investigate whether this behaviour has also been related to investor herding or dispersing in the renewable sector. We are also interested in examining whether for different regimes of oil price behaviour as well as for the period of the global financial crisis, we can detect differences in investor behaviour with regards to return dispersion.

3. Applied Models and Data

3.1 Methodology

In our analysis, we build on the approach originally established by Christie and Huang (1995) and Chang et al. (2000). We use the cross-sectional absolute deviation ($CSAD_t$) as a measure of return dispersion in order to detect herding behaviour in the renewable sector.

The CSAD can be defined as

$$CSAD_t = \frac{\sum_{i=1}^N |R_{i,t} - R_{m,t}|}{N}, \quad (1)$$

where $R_{i,t}$ denotes the individual return of stock i at time t , $R_{m,t}$ is the market (or sector) return, and N is the number of observed stocks in the market (sector) at time t . Chang et al. (2000) propose to investigate the relationship between return dispersion - measured by CSAD - and the overall sector or market return, using the following equation:

$$CSAD_t = \alpha + \gamma_1 |R_{m,t}| + \gamma_2 R_{m,t}^2 + \varepsilon. \quad (2)$$

Hereby, the coefficients γ_1 and γ_2 represent the linear and non-linear relationships between $CSAD_t$ and $|R_{m,t}|$.

To understand why equation (2) provides an appropriate approach for examining herding in financial markets, let us first illustrate the expected linear relationship between CSAD and market returns.² Based on the conditional version of the Black (1972) CAPM model, the expected return of stock i at time t , $E_t[R_i]$, can be expressed as:

$$E_t[R_i] = \alpha + \beta_i E_t[R_m - \alpha]. \quad (3)$$

² For more details on the derivation of the relationship, see, e.g. Chang et al. (2000).

Hereby, α is the return on the zero-beta portfolio, while β_i is the systematic risk measure of stock i . Let further β_m denote the systematic risk of the equally-weighted market portfolio for all stocks $i=1, \dots, N$. Then the absolute value of the deviation (AD) between expected return of stock i and the market portfolio is $AD_{i,t} = |\beta_i - \beta_m| E_t[R_m - \alpha]$ such that the expected cross-sectional absolute deviation of the returns for all N stocks at time t can be expressed as:

$$E[CSAD_t] = \frac{1}{N} \sum_{i=1}^N |\beta_i - \beta_m| E_t[R_m - \alpha] \quad (4)$$

Based on equation (4), it is easy to show that under the assumption of the CAPM, the relationship between cross-sectional absolute deviation and the market returns is expected to be linear and increasing.³

Herding behavior can then be tested based on deviations from the linear relationship between market returns and the CSAD. If herding occurs in a market, investors will trade toward one direction and the corresponding CSAD will be below what is suggested by this linear relationship, i.e. the estimate for γ_2 will be significantly negative. On the other hand, in the presence of dispersing, we would expect γ_2 to be positive and significant, suggesting an increase in return dispersion with expected market returns beyond the linear relationship. Therefore, equation (2), including a coefficient for the quadratic relationship between market returns and return dispersion measured by CSAD is appropriate to examine herding (or dispersing) in a financial market.

In order to analyse asymmetric herding behaviour in both up and down markets, following Chang et al. (2000), we examine the relationship between market returns in the renewable energy sector and the $CSAD_t$ of individual stocks also separately for positive and negative market outcomes. The corresponding model equation are then given by:

$$CSAD_t = \alpha + \gamma_1 |R_{m,t}^+| + \gamma_2 R_{m,t}^{+2} + \varepsilon \quad (5)$$

and

$$CSAD_t = \alpha + \gamma_1 |R_{m,t}^-| + \gamma_2 R_{m,t}^{-2} + \varepsilon \quad (6)$$

where $R_{m,t}^+$ denote positive and $R_{m,t}^-$ negative returns if the market index. It is important to note that in order to allow for a comparison of the coefficients of the linear term for up- and down-markets, absolute values of market returns are used in equation (5) and (6).

The literature also proposes a significant relationship between returns of renewable energy companies, the oil price, technology stocks and overall equity markets, see e.g. Henriques and

³It is straightforward to show that $\frac{\partial E[CSAD_t]}{\partial E_t[R_m]} = \frac{1}{N} \sum_{i=1}^N |\beta_i - \beta_m| > 0$ holds, while for the second derivative one obtains $\frac{\partial^2 E[CSAD_t]}{\partial E_t[R_m]^2} = 0$.

Sadorsky (2008), Kumar et al. (2012), Bohl et al (2013), Ortas and Moneva (2013), Inchauspe et al. (2015). Therefore, we are also interested in the degree of investor herding behaviour conditional on other factors such as the behaviour of oil prices, the global financial crisis or the risk-adjusted performance of the renewable sector. The latter will then allow us to draw some conclusions on whether investors in renewable stocks behave differently during periods of good or bad performance of the sector with regards to its pricing factors. It might well be the case, that herding behaviour is more prevalent during periods of relatively high or low active returns for renewable stocks.

To examine the risk-adjusted performance of the sector, in a first step we apply two simple asset pricing models to returns in the renewable sector. The first model we apply is the Capital Asset Pricing Model (CAPM), where observed excess returns of a stock or portfolio are simply related to the excess return of the overall market portfolio as a pricing factor:

$$(R_{P,t} - R_{F,t}) = \alpha^{CAPM} + \beta (R_{M,t} - R_{F,t}) + \varepsilon_t . \quad (7)$$

Hereby, $R_{P,t}$ denotes the return of a portfolio p at time t , $R_{F,t}$ is the risk-free rate and $R_{M,t}$ denotes the return of the market portfolio. Note that in this approach, we will then examine the relationship between returns of the equally weighted portfolio of renewable energy stocks and the return of the market portfolio. Note that given our focus on US renewable stocks we decided to choose the S&P 500 as a proxy for the market portfolio

The second model we apply is based on Inchauspe et al. (2015). The authors suggest that excess returns of the renewable sector can be modelled as a function of the following pricing factors: excess market returns (again measured by the S&P 500 as a proxy for the market portfolio), excess returns of a technology stock index (we use the ARCA Tech 100 Index (PSE) as a benchmark), and excess returns for the WTI oil price:

$$(R_{P,t} - R_{F,t}) = \alpha^{MF} + \beta_{SP}(R_{SP,t} - R_{F,t}) + \beta_{PSE}(R_{PSE,t} - R_{F,t}) + \beta_{OIL}(R_{OIL,t} - R_{F,t}) + \varepsilon_t \quad (8)$$

Based on these estimated models, one can then calculate time series of active returns α^{CAPM} and α^{MF} . The calculated active returns will allow us to classify different periods of risk-adjusted performance for the renewable market according to the suggested pricing factors. Based on this classification, we can then also examine the relationship between investor herding behavior and the risk-adjusted performance of the sector.

3.2 Data

Our sample of renewable energy companies contains US stocks listed on the NYSE, AMEX, or NASDAQ stock exchanges. Our sample period covers the time period from January 2000 to December 2015. The considered companies were components of the following renewable,

clean or alternative energy indices for at least some time interval throughout the sample period: the WilderHill Clean Energy Index (ECO), the WilderHill New Energy Global Innovation Index (NEX), the Ardour Global Alternative Energy Index North America (AGINA), the Renewable Energy Industrial Index (RENIXX World), the ALTEXGlobal Index (ALTEXGlobal), the NASDAQ Clean Edge Green Energy Index (CELS), and the ISE Global Wind Energy Index (GWE). Naturally, many of the companies in our sample are, or were, components of two or more of these indices.

The WilderHill Clean Energy Index (ECO) tracks approximately 50 Clean Energy companies as of December 2015, focussing on businesses that stand to benefit substantially from a societal transition towards the use of cleaner energy and conservation. Inclusion of a stock into the index is based on its significance for clean energy, technological influence and relevance to preventing pollution in the first place.⁴ The index has six sub-sectors: renewable energy harvesting (approximately 25% sector weight), power delivery and conservation (approximately 20%), energy conversion (approximately 20%), greener utilities (approximately 15%), energy storage (approximately 10%), and cleaner fuels (approximately 10%). There is a strong focus in favour of pure-play companies in wind power, solar power, hydrogen and fuel cells, biofuels, and related fields. Market capitalisation for a majority of Clean Energy Index stocks is typically \$US200 million and above. The index focuses on North American companies only. The WilderHill New Energy Global Innovation Index (NEX) focuses on the generation and use of renewable energy, and the efficiency, conservation and advancement in renewable energy in general.⁵ The index was composed of more than 100 companies in 27 countries as of December 2015. Investments are distributed by regions with weights of 41.2% for the Americas, 29.6% for Asia and Oceania, and 29.2% for Europe, the Middle East and Africa. For a stock to be included in this index, the company must be identified as one that has a meaningful exposure to clean energy, either as a technology, equipment, service or finance provider, such that profitable growth of the industry can be expected to have a positive impact on that company's performance. Market capitalisation for a majority of NEX index stocks is typically \$US250 million and above. For our herding analysis, we only consider US companies from the NEX universe of stocks.

The AGINA index, as a part of the Ardour Global Alternative Energy Indices, merely focuses on North American renewable companies and tracks over 50 companies as of January 2016. Companies included in this index are involved in alternative energy resources (solar, wind, hydro, tidal, wave, geothermal and bio-energy), energy efficiency, and others. The RENIXX World Index is administrated by the International Economic Platform for Renewable Energies and was established in May 2006. It is the first global stock index that tracks the performance of the world's 30 largest companies in the renewable energy sector. Companies must achieve

⁴ Source: <http://www.wildershires.com/>. Accessed: January 2016.

⁵ Source: <http://www.nexindex.com/>. Accessed: January 2016.

at least 50% of their revenue in the renewable energy industry coming from wind energy, solar power, biomass, geothermal energy, hydropower or fuel cells to be included in the index. The ALTEX Global index is managed by Bakers Investment Group and serves as a benchmark index for Alternate Energy internationally. Tracking 138 companies it is the world's largest Alternative Energy Index with an aggregated market capitalisation of \$US1.16 trillion. The CELS index is a modified market capitalisation-weighted index designed to track the performance of US-traded clean energy companies. As of January 2016, the index was composed of almost 50 companies. Finally, the GWE index provides a benchmark for investors interested in tracking public companies identified as providing goods and services exclusively to the wind energy industry. Note that for the international indices, we only include US companies in our sample of renewable / clean energy stocks.

For the considered companies, we source daily, weekly, and monthly stock prices and returns from the Centre for Research in Security Prices (CRSP) database. Altogether, our sample includes 170 renewable energy companies and data from January 2000 to December 2015. Given the prominent role that has been suggested for the impact of the oil price and technology stocks on the renewable sector (Henriques and Sadorsky, 2008; Kumar et al., 2012; Inchauspe et al., 2015; Sadorsky, 2015) we also include these factors in our analysis. For oil, we use the WTI crude oil price to define different oil price regimes in order to analyse herding behaviour in the renewable energy sector under different regimes. For technology stocks, we use the Arca Technology 100 Index (formerly known as the Pacific Stock Exchange Technology Index and, therefore, denoted by PSE) as a benchmark. The index is designed '*to provide a benchmark for measuring the performance of technology related companies across a broad spectrum of industries.*'⁶ Also, unlike the Nasdaq, the PSE includes over-the-counter transactions, which may cover a broader coverage of returns of emerging technology companies. Note that despite its broad focus, the PSE does not have a huge overlap with the identified renewable energy stocks in our sample.

Figure 1 shows a time series plot for two of the major renewable indices, namely the Wilderhill ECO and NEX, as well as for the constructed equally-weighted renewable market index and the WTI crude oil price for the sample period January 2000 to December 2015. To make it easier to compare the performance of the indices, each series is set equal to a base value of 100 at the start of the sample period in January 2001. The graph illustrates that the renewable energy indices indicate a trend similar to the price behaviour of the WTI crude oil price. The constructed renewable market index, ECO, and NEX reach their highest price level at the end of the year 2007 and drop significantly during the period of falling oil prices during July 2008 – December 2008, when the oil price dropped from \$130 to \$30. Overall, the plot also gives an indication of the initial strong growth of renewable energy stocks before 2008 and the rather

⁶ Source: http://www.nyse.com/pdfs/NYSEuronext_ArcaTech100.pdf

poor performance of the sector after the global financial crisis as it has been suggested, e.g. by Bohl et al (2013) and Inchauspe et al. (2015).

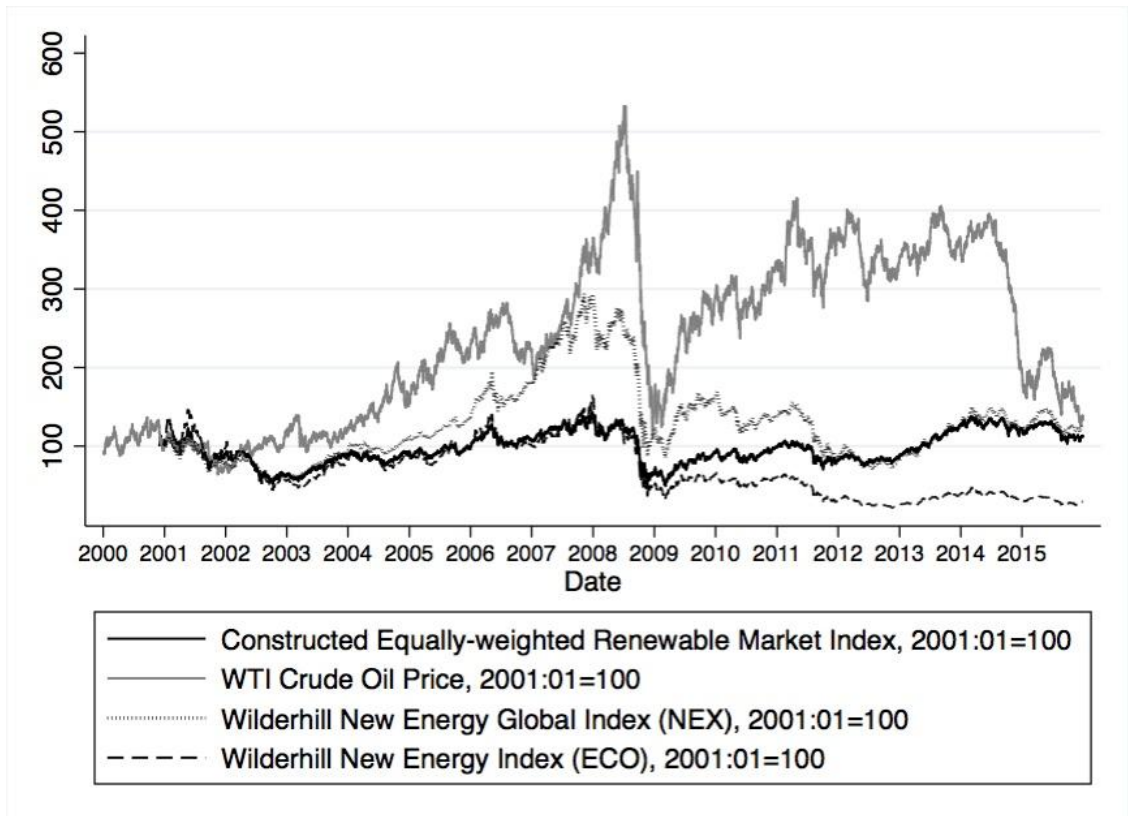


Figure 1: Index values for the constructed equally-weighted renewable market index, WTI Crude Oil Price, ECO, and NEX for the considered time period January 2000 – December 2015. Note that for easier comparison of the performance, each index is set to a base value of 100 at the start of the sample period.

4. Empirical Results

4.1 Preliminary Analysis

In a first step, using daily, weekly and monthly returns for the identified renewable energy stocks, we calculate sector-specific returns at each of these frequencies that will be denoted by $R_{m,t}$ in the following. Since available renewable energy indices either do not explicitly focus on the US market or only contain a sub-sample of the identified US renewable energy stocks, we decided to use the entire universe of identified renewable energy stocks to calculate a

‘renewable sector return’ $R_{m,t}$.⁷ Then in a next step, based on equation (1), we calculate the time series of CSADs at the daily, monthly and weekly frequency.

Table 1 provides summary statistics for daily, weekly, and monthly returns $R_{m,t}$ for the constructed portfolio as well as the calculated cross-sectional absolute deviation based on daily (CSADD), weekly (CSADW), and monthly (CSADM) return observations for the renewable stocks. As expected, daily index returns exhibit the lowest mean returns and standard deviation, while monthly index returns are more volatile but also yield a higher average return. We also find that cross-sectional absolute deviation is the lowest at the daily frequency with a mean of 0.0242, while it is significantly larger (0.1146) when renewable returns are considered at the monthly frequency. Table 1b displays a correlation matrix between daily returns of the constructed equally-weighted renewable market index (R_m), and returns from other major traded renewable energy indices, namely the Wilderhill ECO and NEX index as well as for the WTI crude oil price. The correlation between R_m and R_{ECO} is equal to $\rho=0.9453$ over the sample period from January 2000 to December 2015, indicating a very similar return behavior. This does not come as a huge surprise, since both indices focus on US renewable energy stocks. The correlation between returns from the constructed market index and R_{NEX} are a bit lower ($\rho=0.8122$) due to the focus of the index also on international renewable companies.

Table 1. Descriptive statistics for daily, weekly, and monthly sector market returns $R_{m,t}$ and daily, weekly, and monthly cross-sectional absolute deviation CSADD, CSADW and CSADM.

Variable	Obs.	Mean	Std. Dev.	Min	Max
R_{m,t_daily}	4025	0.0007	0.0176	-0.1154	0.1476
R_{m,t_weekly}	805	0.0029	0.0420	-0.2036	0.1632
$R_{m,t_monthly}$	192	0.0117	0.0842	-0.2690	0.2292
CSADD	4025	0.0242	0.0086	0.0104	0.1055
CSADW	805	0.0542	0.0185	0.0263	0.1673
CSADM	192	0.1146	0.0363	0.0690	0.3143

Table 1b. Correlation matrix

	R_{NEX}	R_{ECO}	R_{WTI}	R_m
R_{NEX}	1			
R_{ECO}	0.8155	1		
R_{WTI}	0.2864	0.2574	1	
R_m	0.8122	0.9453	0.2985	1

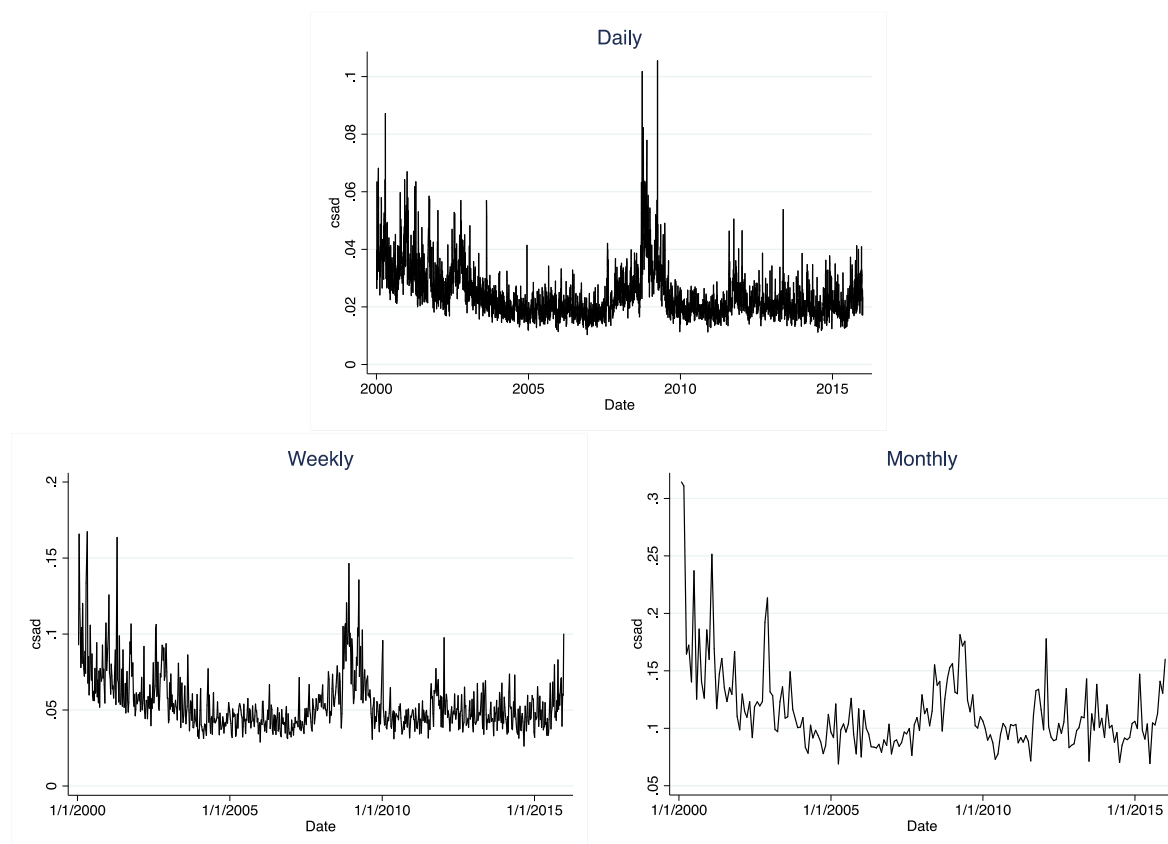
We notice that the correlation between R_m and oil price returns R_{WTI} is significantly lower ($\rho=0.2985$), however, the oil price is still likely to have a significant impact on the renewable

⁷ Note that in the following we report the results for index returns based on an equally-weighted portfolio of all US renewable stocks. Results for using the US-focused ECO or a constructed value-weighted index based on all renewable energy companies in our sample were qualitatively the same. They are not reported in the following, but are available upon request to the authors.

sector throughout the considered sample period. Recall that Bohl et al. (2015) suggest that the ECO index was positively correlated with the oil price prior to the oil price shock in 2008, and that this positive relationship diminishes afterwards. Our results also indicate that when considering daily returns, over the entire sample from 2000 -2015 there is a significant positive correlation between returns from renewable energy stocks and oil.

Figure 2 shows the daily, weekly, and monthly cross-sectional absolute deviation (CSAD) for the sample period. As indicated in Table 1a, the cross-sectional absolute deviation based on monthly returns (CSSADM) is typically the largest, while the cross-sectional absolute deviation based on daily returns (CSADD) is the lowest. We also find that independent of the frequency of measuring returns, the CSAD shows a tendency of gradually decrease from 2000 to 2007, before exhibiting a significant increase during the GFC and the subsequent oil price shock period. After the GFC period, return dispersion initially returned to its pre-crisis levels, while since 2012 the market seems to exhibit higher levels of return dispersion at the daily, weekly and monthly frequency. These results also motivate us to examine investor herding during various sub-periods based on different regimes of the oil price, market behaviour as well as during the GFC period.

Figure 2. Daily, Weekly, and Monthly cross-sectional absolute deviation (CSAD) over the sample period January 2000 – December 2015.



In comparison to previous studies on herding behaviour, we also find that the calculated cross-sectional absolute deviation is significantly higher for the US renewable sector in comparison to other sectors. Chang et al. (2000), using daily returns, suggest that the CSAD in various

countries (US, Hongkong, Japan, South Korea, Taiwan) are all lower (between 0.012 to 0.018) in comparison to the CSAD we observe for the renewable sector (CSADD=0.0242) when considering daily returns. Similar conclusions can be drawn, when comparing our results to those of Chiang and Zhang (2010) who examine CSAD for Asian markets. Ouarda et al (2013), using monthly return data across different industries in Europe, also typically find lower values of CSAD than we do for the renewable energy sector. This provides some indication of the unique behaviour of the renewable sector, where return dispersion seems to be at higher levels in comparison to other financial markets.

4.2 Herding Behaviour

In this section, we investigate investor herding and dispersing behaviour in the US renewable energy sector. Table 2 presents results for the estimated relationship between market returns and return dispersion, using daily (CSADD), weekly (CSADW), and monthly (CSADM) data. Note that next to the generally suggested model for the relationship between expected market returns and return dispersion in (2) we also examine asymmetric effects using equations (5) and (6), i.e. separately examining the relationship between CSAD for positive ($R_{m,t}^+$) and negative ($R_{m,t}^-$) market returns.

Recall that since we expect an overall positive impact of market returns on return dispersion, we are particularly interested in the estimated coefficient γ_2 for the squared market returns $R_{m,t}^2$. The sign of the coefficient will allow us to draw conclusions on the existence of herding or dispersing in the renewable energy market. As indicated by the results in Table 2, for daily and weekly returns, the linear coefficient is significant and positive, indicating that with increasing volatility in the renewable energy sector, also the return dispersion increases. Surprisingly, for all estimated equations at the daily and weekly frequency also the coefficient γ_2 for the quadratic effect of market return on return dispersion is significantly positive. These results provide clear evidence of dispersing, i.e. return dispersion increasing with daily market returns beyond what is suggested by a linear relationship. Note that this indicates a rather unique behaviour of the renewable energy sector, since typically empirical studies either find evidence of herding (i.e. a significantly negative coefficient for the quadratic term) or an insignificant coefficient. Results are not that clear cut at the monthly frequency: while the quadratic coefficient is also positive for all three equations, it is only significant for model (2) and (6), suggesting that in particular positive market returns initiate dispersing. Figure 3 also provides plots of the estimated relationship based on equation (2), (5) and (6), using daily, weekly and monthly returns. The plots clearly confirm the typically positive quadratic relationship between market returns in the renewable sector and return dispersion measured by CSAD.

Overall, our findings provide strong evidence of excess dispersion, in particular at the daily and weekly frequency.

Table 2. Coefficients for estimated relationship between market returns and cross-sectional absolute deviation at daily (CSSAD), weekly (CSADW) and monthly (CSADM) frequency for the sample period January 2000 – December 2015.

VARIABLES	(1) CSADD	(2) CSADD	(3) CSADD	(4) CSADW	(5) CSADW	(6) CSADW	(7) CSADM	(8) CSADM	(9) CSADM
$ R_{m,t} $	0.353*** (19.68)			0.212*** (5.21)			-0.077 (-0.66)		
$ R^+_{m,t} $		0.456*** (18.44)			0.280*** (5.08)			-0.334** (-2.25)	
$ R^-_{m,t} $			0.249*** (9.98)			0.147*** (2.73)			0.012 (0.08)
$R^2_{m,t}$	0.800*** (2.94)	0.686* (1.85)	0.984** (2.56)	1.480*** (4.98)	1.848*** (4.61)	1.059*** (2.67)	2.519*** (4.50)	4.759*** (6.57)	0.834 (1.31)
Constant	0.019*** (99.62)	0.019*** (69.51)	0.020*** (73.86)	0.045*** (45.99)	0.045*** (33.28)	0.045*** (35.12)	0.102*** (21.26)	0.108*** (18.08)	0.101*** (17.77)
Observations	4,025	2,180	1,845	805	451	354	192	109	83
Adjusted R-squared	0.322	0.394	0.258	0.379	0.469	0.306	0.414	0.649	0.144

At each frequency (daily, weekly and monthly), the following equations are estimated:

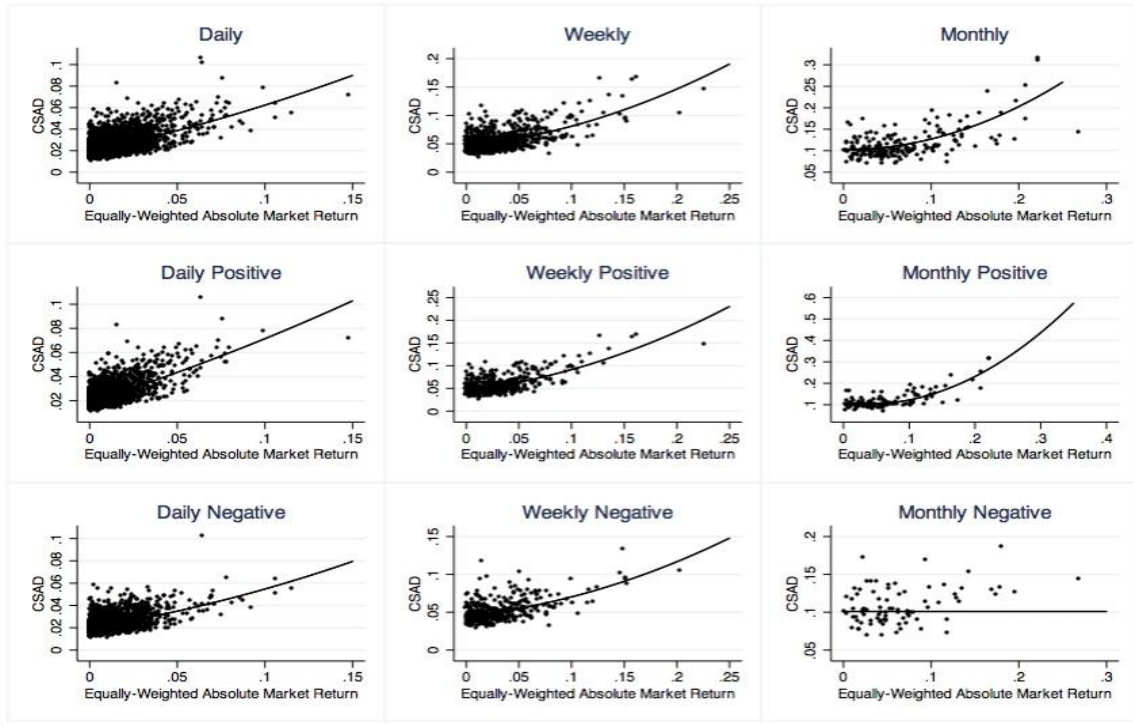
$$CSAD_t = \alpha + \gamma_1 |R_{m,t}| + \gamma_2 R^2_{m,t} + \varepsilon \quad (2)$$

$$CSAD_t = \alpha + \gamma_1 |R^+_{m,t}| + \gamma_2 R^{+2}_{m,t} + \varepsilon \quad (5)$$

$$CSAD_t = \alpha + \gamma_1 |R^-_{m,t}| + \gamma_2 R^{-2}_{m,t} + \varepsilon \quad (6)$$

The independent variables $R_{m,t}$, $R^+_{m,t}$ and $R^-_{m,t}$ denote the equally-weighted return of all available securities at time t , respectively, the positive and negative equally-weighted return of all available securities at time t . Figures in parentheses are t -statistics. *** (**, *) indicates significance at the 1% (5%, 10%) level for a two-tailed test.

Figure 3. Estimated relationship between market returns and cross-sectional absolute deviation at daily (CSSAD), weekly (CSADW) and monthly (CSADM) frequency for the sample period January 2000 – December 2015. The upper panel presents the estimated relationship for equation (2) $CSAD_t = \alpha + \gamma_1 |R_{m,t}| + \gamma_2 R_{m,t}^2 + \varepsilon$ for daily, weekly and monthly returns.. The middle panel presents the estimated relationship for equation (5) $CSAD_t = \alpha + \gamma_1 |R_{m,t}^+| + \gamma_2 R_{m,t}^{+2} + \varepsilon$ examining only positive market returns, while the lower panel examines the relationship based on equation (6) $CSAD_t = \alpha + \gamma_1 |R_{m,t}^-| + \gamma_2 R_{m,t}^{-2} + \varepsilon$, using only negative observations for the market return.



4.3 Impact of different Oil Price Regimes

Given the strong relationship between oil prices and returns of renewable energy companies proposed in the literature, in the following we examine the relationship between market returns and return dispersion for different oil price regimes. We distinguish between the initial period of continuously increasing oil prices from January 1, 2000 – June 30, 2008; the period from of July 1, 2008 to December 31, 2008, when the oil price dropped sharply from over \$140 to \$45 within six month; and the period from January 1, 2009 to June 30, 2014, when oil prices recovered from \$45 to over \$100. Results for these different sub-periods are reported in Tables 3a, 3b and 3c. Let us first consider our findings for the sub-period January 1, 2000 – June 30, 2008 in Table 3a. We find results consistent with those reported for the entire sample period. We find a significant positive quadratic relationship between market returns and return dispersion, i.e. evidence for dispersing. For daily returns - columns (1)-(3) – both linear and quadratic coefficients are all positive and significant. Considering weekly data in columns (4) – (6), the coefficients γ_1 for the absolute portfolio return $|R_{m,t}|$, $|R_{m,t}^+|$, and $|R_{m,t}^-|$ are all insignificant, however the significantly positive coefficient for γ_2 indicates excess return dispersion beyond the linear relationship suggested by asset pricing theory. For monthly data

results are reported in columns (7) – (9). We find some evidence for an asymmetric relationship between market returns and return dispersion in up and down markets. The significantly positive coefficient for γ_2 ($\gamma_2 = 5.229, t = 5.66$) in column (8) indicates that dispersing is more severe in up markets. The positive but insignificant γ_2 ($\gamma_2 = 1.590, t = 0.97$) in column (9) suggests that dispersing is not significant in down markets.

Table 3b contains results for our analysis based on daily and weekly returns for the period July 1, 2008 to December 31, 2008, when oil prices dropped sharply from over \$140 to \$45. Note that given the short time period of six months only, we decided to estimate the model only for daily and weekly observations, due to an insufficient number of observations at the monthly frequency. Interestingly, we find that the coefficient γ_2 is significant and negative in column (2) ($\gamma_2 = -1.841, t = -1.70$) and column (5) ($\gamma_2 = -1.978, t = -2.66$), providing some evidence for herding behaviour for positive market outcomes in the renewable sector. Along with significant positive γ_1 in columns (2) ($\gamma_1 = 0.580, t = 4.62$) and (5) ($\gamma_1 = 0.831, t = 4.86$), the values in column (2) and (5) indicate an increase in CSAD at a decreasing rate, i.e. herding behaviour in the renewable energy sector existed for positive market outcomes during the extreme oil price shock period.

Finally, Table 3c reports results for the sub-period January 1, 2009 to June 30, 2014, when the oil price recovered from \$45 to over \$100. We find that the estimated coefficients for γ_2 in columns (1) – (9) are either significantly positive or insignificant. These findings suggest that during the period of recovery of the oil price after the GFC, the market behaved similar to the pre-crisis period with regards to return dispersion. Again, instead of herding we find significant evidence for excess return dispersion beyond the suggested linear relationship between market returns and cross-sectional absolute deviation. Looking at the estimated coefficients, dispersing seems to be most pronounced for days and weeks with positive market returns. For daily and weekly returns, estimated coefficients for γ_2 are of higher magnitude and significant for positive returns, while they are typically insignificant for negative market outcomes. Note that the opposite is the case, when looking at the monthly frequency, where dispersing is more pronounced for negative market outcomes.

Overall, our sub-period analysis reveals clear evidence of dispersing during regimes of increasing oil prices in the renewable sector. These results confirm our findings for the entire sample period. At the same time, we also find that during the period where oil prices dropped dramatically, there is some evidence of investor herding in the renewable sector. Overall, our results suggest that during the long periods of increasing oil prices, individual stocks in the renewable sector tend to react quite differently to overall market movements. Return dispersion is even higher than predicted by standard asset pricing models, suggesting evidence for dispersion in investors' beliefs about future performance of the individual stocks. However, during the period of a dramatic drop in the oil price, individual stock returns indicate a tendency among investors to be drawn to the consensus of the market what results in herding.

Table 3a. Coefficients for estimated relationship between market returns and cross-sectional absolute deviation at daily (CSAD), weekly (CSADW) and monthly (CSADM) frequency for the sample period January 1, 2000 – June 30, 2008. The period is characterised by a continuous increase in the oil price.

VARIABLES	(1) CSADD	(2) CSADD	(3) CSADD	(4) CSADW	(5) CSADW	(6) CSADW	(7) CSADM	(8) CSADM	(9) CSADM
$ R_{m,t} $	0.155*** (4.14)			0.040 (0.63)			-0.429** (-2.59)		
$ R^+_{m,t} $		0.215*** (4.22)			0.066 (0.77)			-0.375* (-1.88)	
$ R^-_{m,t} $			0.127** (2.37)			0.060 (0.65)			-0.052 (-0.18)
$R^2_{m,t}$	8.535*** (9.64)	9.480*** (8.09)	6.150*** (4.65)	3.999*** (7.31)	4.574*** (6.51)	2.502*** (3.05)	5.044*** (6.22)	5.229*** (5.66)	1.590 (0.97)
Constant	0.021*** (69.79)	0.021*** (49.44)	0.022*** (50.23)	0.048*** (34.20)	0.048*** (25.81)	0.048*** (23.80)	0.111*** (17.34)	0.107*** (13.02)	0.106*** (11.12)
Observations	2,135	1,169	966	429	250	179	102	61	41
Adjusted R-squared	0.322	0.411	0.213	0.432	0.526	0.276	0.609	0.741	0.125

At each frequency (daily, weekly and monthly), for the sub-period January 1, 2000 – June 30, 2008, the following equations are estimated:

$$CSAD_t = \alpha + \gamma_1 |R_{m,t}| + \gamma_2 R^2_{m,t} + \varepsilon \quad (2)$$

$$CSAD_t = \alpha + \gamma_1 |R^+_{m,t}| + \gamma_2 R^{+2}_{m,t} + \varepsilon \quad (5)$$

$$CSAD_t = \alpha + \gamma_1 |R^-_{m,t}| + \gamma_2 R^{-2}_{m,t} + \varepsilon \quad (6)$$

The independent variables $R_{m,t}$, $R^+_{m,t}$ and $R^-_{m,t}$ denote the equally-weighted return of all available securities at time t , respectively, the positive and negative equally-weighted return of all available securities at time t . Figures in parentheses are t -statistics. *** (**, *) indicates significance at the 1% (5%, 10%) level for a two-tailed test.

Table 3b. Coefficients for estimated relationship between market returns and cross-sectional absolute deviation at daily (CSAD), weekly (CSADW) and monthly (CSADM) frequency for the sample period July 1, 2008 – December 31, 2008. The period is characterised by a significant drop in the oil price.

VARIABLES	(1) CSADD	(2) CSADD	(3) CSADD	(4) CSADW	(5) CSADW	(6) CSADW
$ R_{m,t} $	0.454*** (4.80)			0.278 (1.39)		
$ R^+_{m,t} $		0.580*** (4.62)			0.831*** (4.86)	
$ R^-_{m,t} $			0.421*** (3.01)			0.187 (0.69)
$R^2_{m,t}$	-1.289 (-1.48)	-1.841* (-1.70)	-1.386 (-1.01)	-0.094 (-0.10)	-1.978** (-2.66)	0.079 (0.06)
Constant	0.027*** (14.34)	0.028*** (10.87)	0.025*** (9.60)	0.065*** (8.73)	0.058*** (10.22)	0.062*** (6.09)
Observations	128	62	66	25	11	14
Adjusted R-squared	0.415	0.501	0.400	0.414	0.868	0.308

Using daily and weekly observations, for the sub-period July 1, 2008 – December 31, 2008, the following equations are estimated:

$$CSAD_t = \alpha + \gamma_1 |R_{m,t}| + \gamma_2 R^2_{m,t} + \varepsilon \quad (2)$$

$$CSAD_t = \alpha + \gamma_1 |R^+_{m,t}| + \gamma_2 R^{+2}_{m,t} + \varepsilon \quad (5)$$

$$CSAD_t = \alpha + \gamma_1 |R^-_{m,t}| + \gamma_2 R^{-2}_{m,t} + \varepsilon \quad (6)$$

The independent variables $R_{m,t}$, $R^+_{m,t}$ and $R^-_{m,t}$ denote the equally-weighted return of all available securities at time t , respectively, the positive and negative equally-weighted return of all available securities at time t . Figures in parentheses are t -statistics. *** (**, *) indicates significance at the 1% (5%, 10%) level for a two-tailed test.

Table 3c. Coefficients for estimated relationship between market returns and cross-sectional absolute deviation at daily (CSAD), weekly (CSADW) and monthly (CSADM) frequency for the sample period January 1, 2009 – June 30, 2014. The period is characterised by a recovery of oil price up to a level of above \$100.

VARIABLES	(1) CSADD	(2) CSADD	(3) CSADD	(4) CSADW	(5) CSADW	(6) CSADW	(7) CSADM	(8) CSADM	(9) CSADM
$ R_{m,t} $	0.184*** (6.62)			0.106 (1.36)			-0.123 (-0.66)		
$ R^+_{m,t} $		0.169*** (4.04)			0.027 (0.26)			0.065 (0.29)	
$ R^-_{m,t} $			0.165*** (4.94)			0.152 (1.64)			-0.596** (-2.35)
$R^2_{m,t}$	2.190*** (4.39)	4.370*** (5.63)	0.853 (1.47)	1.984*** (2.70)	3.843*** (3.80)	0.360 (0.42)	2.410** (2.36)	1.801 (1.47)	4.107*** (2.91)
Constant	0.019*** (70.12)	0.019*** (49.39)	0.019*** (55.11)	0.044*** (28.17)	0.046*** (21.24)	0.042*** (23.26)	0.100*** (14.79)	0.096*** (11.53)	0.112*** (12.68)
Observations	1,382	774	608	277	157	120	66	41	25
Adjusted R-squared	0.321	0.409	0.259	0.333	0.459	0.238	0.307	0.390	0.276

At each frequency (daily, weekly and monthly), for the sub-period January 1, 2009 – June 30, 2014, the following equations are estimated:

$$CSAD_t = \alpha + \gamma_1 |R_{m,t}| + \gamma_2 R^2_{m,t} + \varepsilon \quad (2)$$

$$CSAD_t = \alpha + \gamma_1 |R^+_{m,t}| + \gamma_2 R^{+2}_{m,t} + \varepsilon \quad (5)$$

$$CSAD_t = \alpha + \gamma_1 |R^-_{m,t}| + \gamma_2 R^{-2}_{m,t} + \varepsilon \quad (6)$$

The independent variables $R_{m,t}$, $R^+_{m,t}$ and $R^-_{m,t}$ denote the equally-weighted return of all available securities at time t , respectively, the positive and negative equally-weighted return of all available securities at time t . Figures in parentheses are t -statistics. *** (**, *) indicates significance at the 1% (5%, 10%) level for a two-tailed test.

4.4 Herding and Performance of the Renewable Sector

In a last step, we examine herding behaviour with respect to the risk-adjusted performance of the renewable sector. Ionescu et al. (2012) suggest that herding behaviour can cause assets to be mispriced and might create additional risk in financial markets. Christie and Huang (1994) report dispersion to be significantly higher during extreme markets (i.e. recession periods) than for normal market behaviour. Connolly and Stivers (2010) suggest higher dispersion as an indicator of greater market uncertainty. Stivers (2003) finds that the positive relationship between return dispersion and absolute market returns is typically much larger than estimated by rational asset pricing models. In addition, both Christie and Huang (1994) and Stivers (2003) suggest that abnormal high dispersion might be observed with changing investment opportunities and investors' reallocation of funds.

These results motivate us to examine more thoroughly the relationship between return dispersion and risk-adjusted returns in the renewable energy sector. To conduct such an analysis, in a first step we apply a Capital Asset Pricing Model (CAPM) and a multifactor asset pricing model for the renewable sector as proposed, e.g., by Inchauspe et al. (2015). Thus, we examine active returns of the renewable sector with respect to suggested pricing factors for the sector. For the simple CAPM, active returns for the sector are calculated with respect to the market portfolio as a pricing factor, using the S&P 500 as a proxy, see model (7). For the multifactor model (8), excess returns of the renewable sector are examined in relation to excess returns of the market portfolio (the S&P 500), excess returns of a technology stock index (the PSE index) and excess returns of the WTI oil price. Note that for our risk-adjusted analysis, we use monthly returns of the renewable equally-weighted index and the pricing factors only, since this is typically the chosen frequency for the application of asset pricing models.

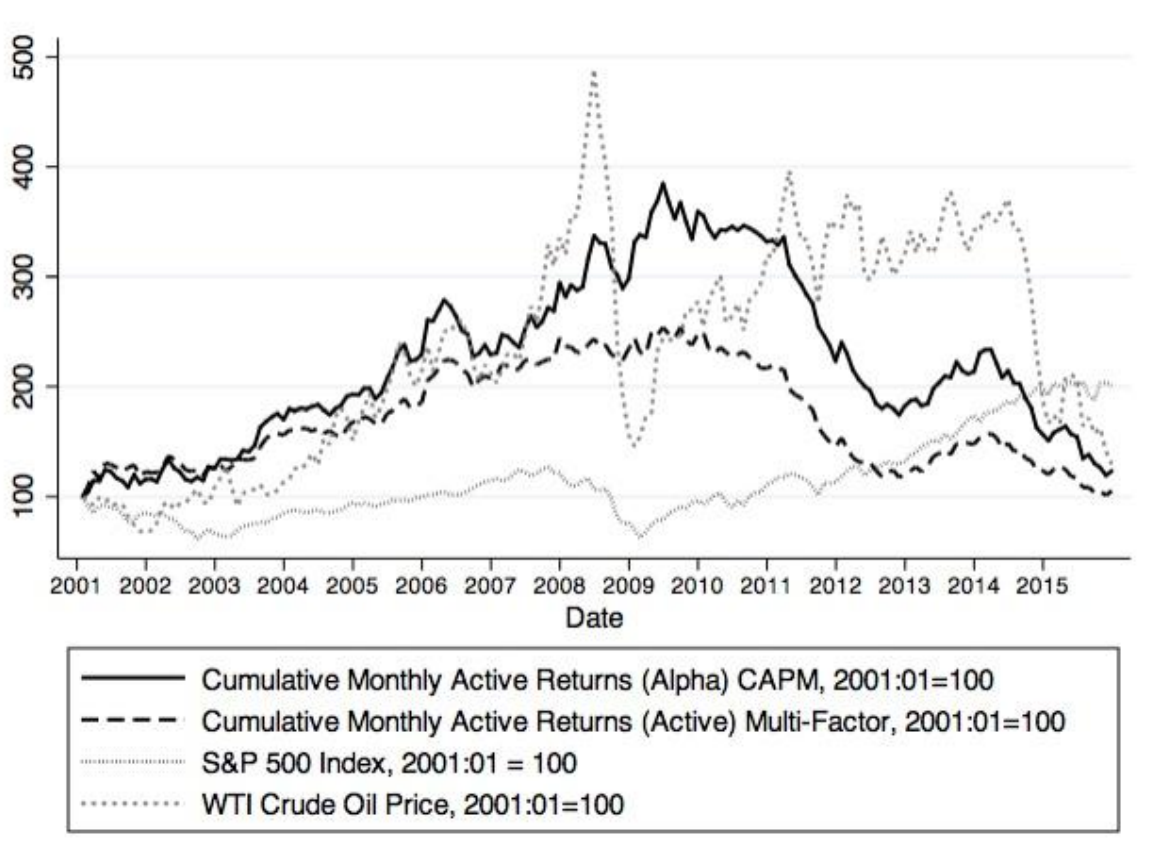
Table 4. Coefficients for estimated relationship between excess returns of the equally-weighted renewable energy portfolio and excess returns of the market portfolio (S&P 500), the ARCA Tech 100 Index, and WTI oil price for the sample period January 2000 – December 2015.

VARIABLES	Model (7)	Model (8)
$\alpha^{CAPM} / \alpha^{MF}$	0.005 (1.19)	0.003 (1.06)
β / β_{SP}	1.467*** (16.83)	0.379*** (3.08)
β_{PSE}		0.787*** (9.62)
β_{OIL}		0.180*** (5.54)
# Obs.	191	191
Adjusted R-squared	0.598	0.762

*Figures in parentheses are t – statistics. *** (**, *) indicates significance of the coefficients at the 1% (5%, 10%) level for a two-tailed test.*

Figure 4 provides a plot of the risk-adjusted performance of the renewable sector, measured by the cumulative active returns, α_t^{CAPM} and α_t^{MF} , based on the estimated CAPM and multi-factor model for the considered sample period January 2000 – December 2015. The figure also illustrates the risk-adjusted performance in comparison to the S&P 500 Index and the WTI Crude Oil price. The plot confirms the relatively strong performance of the sector up to the year 2009, as well as the diminishing performance of the sector afterwards. From the year 2009 onwards, the S&P 500 performs better than the risk-adjusted active returns (Alpha). Similar results on the risk-adjusted performance of the renewable sector have also been reported by earlier studies, see, e.g., Bohl et al. (2013, 2015), Inchauspe et al (2015).

Figure 4. Risk-adjusted performance measured by cumulative active returns (α^{CAPM} and α^{MF}) for the applied CAPM (7) and multi-factor model (8). The figure also illustrates the risk-adjusted performance in comparison to S&P 500 index, and WTI Crude Oil price for the considered sample period January 2001 – December 2015. Each series is set to a base value of 100 at the beginning of the sample period for comparison of the performance.



Based on the calculated time series for α_t^{CAPM} and α_t^{MF} , we now distinguish between periods of positive and negative active returns for the renewable sector. Then we apply model (2) separately for each of these series. Results for the estimated coefficients are reported in Table 5. We find that for negative active returns the relationship between the CSAD and overall renewable market returns is rather inconclusive: both the estimated coefficients for the linear and quadratic relationship are insignificant and the explanatory power of the model is relatively

low. On the other hand, the model yields a significantly higher explanatory power for observations that are conditioned on positive active returns in the renewable sector. For this group of observations we find evidence for a quadratic relationship between returns of the constructed equally-weighted renewable energy portfolio and the CSAD. Interestingly, the coefficient for the linear relationship is negative, while the coefficient for the quadratic relationship is positive and significant. This is true for both the CAPM as well as for the applied multi-factor asset pricing model.

Table 5. Coefficients for estimated relationship between equally-weighted market returns and cross-sectional absolute deviation $CSADM_t = \alpha + \gamma_1 |R_{m,t}| + \gamma_2 R_{m,t}^2 + \varepsilon$ for the sample period January 2000 – December 2015. Note that the observations are divided based on positive and negative active returns α_t^{CAPM} and α_t^{MF} based on the estimated CAPM and multi-factor asset pricing models.

VARIABLES	Negative α_t^{CAPM}	Positive α_t^{CAPM}	Negative α_t^{MF}	Positive α_t^{MF}
	CSADM	CSADM	CSADM	CSADM
$ R_{m,t} $	0.148 (1.23)	-0.390*** (-2.20)	0.205 (1.51)	-0.353** (-2.12)
$R_{m,t}^2$	0.422 (0.74)	4.610*** (5.26)	0.329 (0.51)	4.321*** (5.24)
Constant	0.094*** (19.49)	0.114*** (15.89)	0.092*** (16.64)	0.112*** (16.95)
Observations	100	91	96	95
Adjusted R-squared	0.212	0.548	0.239	0.531

*Figures in parentheses are t – statistics. *** (**, *) indicates significance at the 1% (5%, 10%) level for a two-tailed test.*

Figure 5 provides a plot of the estimated models and clearly illustrates the quadratic relationship between renewable market returns and CSAD for time periods with positive active returns in the renewable sector. The figure also shows that for time periods with negative active returns, there seems to be no clear relationship between market returns and CSAD.

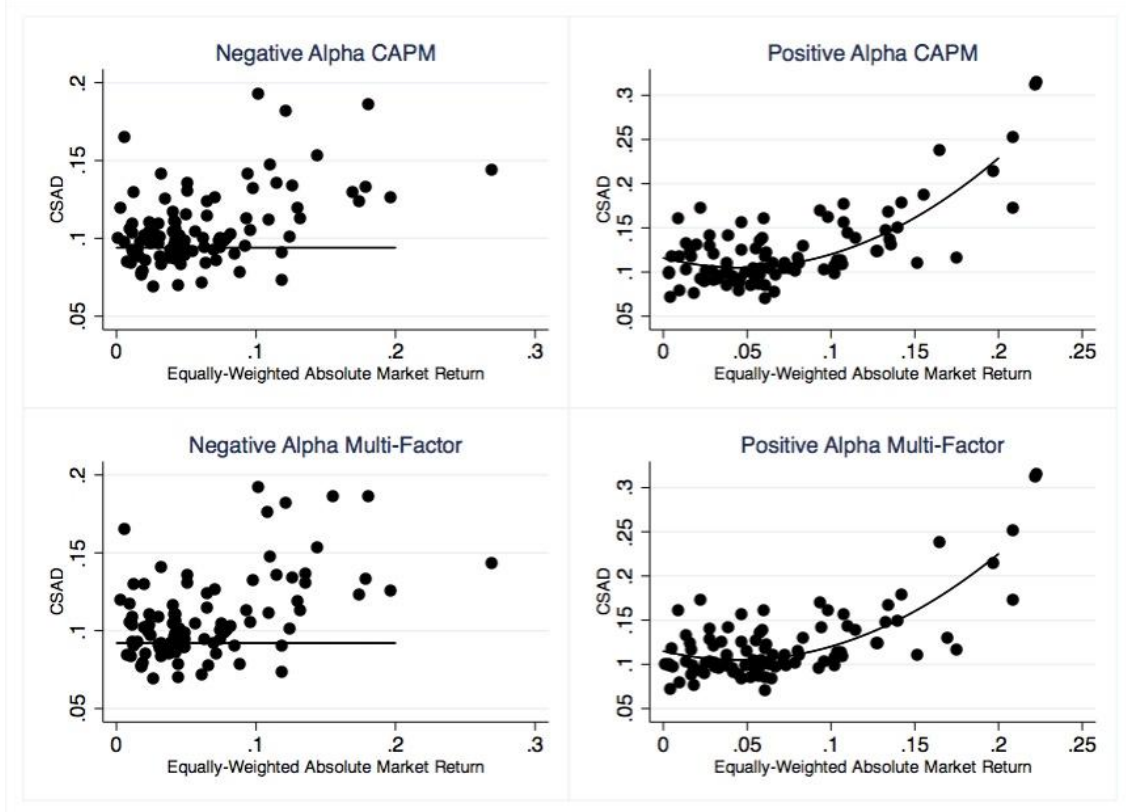
Overall, our findings suggest that in particular during periods of outperformance of the renewable sector (positive active returns), there is significant evidence for dispersing. We consider this as evidence for investors' disagreement on their interpretation of large market movements during periods where the sector performs well. Thus, during these intervals, larger market movements lead to dispersing, i.e. a return dispersion that is higher than predicted by standard asset pricing models.

5. Conclusion

We provide a pioneer study to examine investor herding behaviour in the US renewable energy sector. Using 170 US listed firms, we consider a sample period of 16 years from January 2000 to December 2015. Over this period, the renewable energy sector has demonstrated substantial

growth rates and huge investments, making it one of the most important emerging industries in the global economy. However, the sector has also shown significant variation in performance, with periods of relatively high active returns before 2008 as well as substantial underperformance afterwards (Bohl et al, 2013; Inchauspe et al., 2015).

Figure 5: Estimated relationship between equally-weighted absolute market returns and cross-sectional absolute deviation: $CSAD_t = \alpha + \gamma_1|R_{m,t}| + \gamma_2R_{m,t}^2 + \varepsilon$ for the sample period January 2000 – December 2015. The figure illustrates the estimated relationship for observations classified by negative (upper left panel) and positive (upper right panel) active returns based on a CAPM mode, as well as for observations classified by negative (lower left panel) and positive (lower right panel) active returns based on the applied multi-factor model.



Following Chang et al. (2000), we use cross-sectional absolute deviation as a measure of dispersion across individual stocks and find significant and consistent evidence for excess return dispersion (or so-called dispersing) in the renewable sector. This is true in particular when considering daily and weekly returns, but there is also some evidence for dispersing when examining monthly returns of renewable energy stocks. These results are evidence for a rather unique behaviour of the renewable sector, since most prior studies on return dispersion in financial markets either found evidence of herding or, alternatively, suggested a linear relationship between expected market returns and CSAD as it can be established based on the CAPM. In contrast to these studies, our results clearly suggest a non-linear positive quadratic relationship, indicating dispersing instead of herding behaviour in the US market for renewable stocks.

We interpret these results the following way: investors in the renewable sector seem to deviate in their interpretation of news and overall market movements in the sector, leading to an even higher return dispersion than predicted by standard asset pricing models such as the CAPM. Our findings can also be interpreted as evidence for dispersion in investors' beliefs about the future performance of different individual renewable stocks.

Further investigating the issue, we also find evidence of asymmetric return dispersion, i.e. a different impact of positive or negative market returns on return dispersion. Overall, positive market returns lead to a higher dispersing effect across individual stocks in comparison to negative market returns. This suggests that 'good news' for the entire sector is typically interpreted very differently for individual renewable stocks, while negative market returns seem to have a less pronounced effect on dispersion among investor beliefs.

We also find that different periods of oil price behaviour have a clear impact on herding behaviour: our results suggest excess return dispersion during the period of a steady oil price increase from 2000 to mid 2008 and for the post-oil price shock period from 2009 to mid 2014. On the other hand, we find some evidence for investor herding behaviour in the renewable sector during the period of a significant drop in the oil price for the second half of 2008.

Finally, we conduct a risk-adjusted analysis of the performance of the renewable energy market to examine herding behaviour during different regimes of sector performance. We find that in particular during periods of positive active returns in the sector, there is significant evidence for dispersing. At the same time, during intervals of negative active returns there seems to be no clear relationship between market returns for the sector and return dispersion.

Overall, in contrast to previous studies on herding behaviour in financial markets, our results for the renewable market are quite unique. Investors in renewable energy stocks seem to have a strong tendency to disagree on their interpretation of market movements in the renewable sector. This dispersion in investor beliefs leads then to excess return dispersion across individual stocks, i.e. the dispersion is higher than predicted by standard asset pricing models. One could also argue that the highly volatile behaviour of renewable stocks as well as its variation in performance, also leads to dispersion in performance expectation for individual stocks. Interestingly, as our findings for the conducted risk-adjusted analysis indicate, dispersion in investors' beliefs about the performance of individual renewable stocks seems to be even more pronounced during periods when the sector performs quite well. Therefore, our results do not provide any evidence for investor herding having contributed to a common mispricing of the entire renewable sector. They rather suggest that in particular during times of outperformance of the sector, individual renewable energy stocks exhibit a very different return behaviour. Maybe an additional analysis that examines the performance of different sub-sectors in the renewable market could shed more light into this important issue. We leave this question to future research.

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