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Herding in the Chinese renewable energy market: Evidence from a bootstrapping time-varying coefficient autoregressive model

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ABSTRACT

In this paper, we examine the herd behaviour of the Chinese renewable energy sector using both static and time-varying coefficient models. Examining daily data from January 05, 2015 to April 29, 2022, we find strong evidence of herding behaviour changing over time in this market. We find that herding asymmetry is more pronounced during up markets and among smaller firms. When within-industry herding weakens, large price movements in the overall stock market provide additional trading signals for herding formation in this sector.

1. Introduction

Climate change is one of the greatest challenges in the 21st century, threatening and disrupting the lives of humans and other creatures. Easing carbon emissions by reducing the use of fossil based energy is an effective contributor to slowing the pace of global warming. Over the last twenty years, we have seen an exponential growth in renewable energy usage. Unlike crude oil, which was hit hard in price during the first wave of the COVID-19 outbreak, the global adoption and growth of renewable energy has been resilient and has continued to hit new records (Hannah Ritchie and Rosado, 2020). Energy price turbulence resulted by the energy shortage and insecurity can easily lift national and public concern and may cause higher inflation and greater economic recession (Kilian, 2008). Apart from bring substantial environmental benefits, investing in renewable energy technologies has many other advantages. For example, it reduces the reliance on foreign energy imports, which minimises the geopolitical risks and reduces the global shipping risks. It also reduces the unemployment rate by creating more jobs. Although these technologies require higher investments at the beginning, investing in them saves money by the long term adoption because of lower operational and maintenance costs and by improving the technology. Since early 2000s, renewable energy has become one of the most important emerging industries in the global economy. Alongside this we have seen a wide range of clean energy related equity indices has been created to capture the movements of publicly quoted clean energy related companies. Much research has emerged examining their usefulness in serving as portfolio components against conventional markets (examples include Shahbaz et al., 2021; Ahmad and Rais, 2018; Kuang, 2021; Ren and Lucey, 2022a, etc.).

In this paper, we examine investor behaviour in the Chinese renewable energy sector from a herding perspective. Herding in financial markets refers to the behaviour whereby investors mimic and follow others' trading actions without thinking rationally or using their own knowledge, which can easily push or drag price away from intrinsic values. There have been extensive studies of herding. See as examples in global equities (Christie and Huang, 1995; Chang et al., 2000; Chiang and Zheng, 2010; Zheng et al., 2015; Clements et al., 2017; Tan et al., 2008, etc.), options (Bernales et al., 2020), commodity (Demirer et al., 2015; Kumar et al., 2021; Youssef, 2022a; Aytaç et al., 2018; Adrangi and Chatrath, 2008, etc.), and cryptocurrency markets (Bouri et al.,

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2019; Kallinterakis and Wang, 2019; Vidal-Tomás et al., 2019; Ren and Lucey, 2022b, etc.).

Evidence from previous studies suggests that herding is subject to internal and external market conditions, and is thus intrinsically time-varying. Extant literature has shown that herding is asymmetric and the intensity varies between market states (Chang et al., 2000; Kizys et al., 2021, etc.). Some studies have suggested that herding may be more pronounced during periods of stress or heightened market uncertainty (for example, see Bikhchandani and Sharma, 2000; Aharon, 2021). Kizys et al. (2021) provided fresh evidence that investors tended to herd in stock markets during the first wave of Covid-19 as Covid-19 brought severe global economic uncertainty. Moreover, markets are interconnected (Chiou and Lee, 2009; Choi and Hammoudeh, 2010). Investors behaviour is likely to be affected by the performance of other associated markets (BenMabrouk and Litimi, 2018; Youssef, 2022b). For example, Balcilar et al. (2014) studied the impact of U.S. stock market and WTI oil volatilities on herd behaviour in Gulf Cooperation Council countries' stock markets. Economou et al. (2018), Youssef (2022b), and Youssef (2022a) analysed how external factors affect herd behaviour in stock, cryptocurrency, and commodity markets, respectively. Chiang and Zheng (2010) found that U.S market performance significantly influenced the behaviour in other global markets.

Despite this, there have been relatively few papers on herd effects at the sectoral level (BenMabrouk and Litimi, 2018), especially for renewable energy market. To the best of our knowledge, only three studies have paid attention to this emerging sectoral market, and only one has looked into the situation in China. This is remarkable when one considers that China has for years been the world leader in the renewable energy industry (Chiu, 2017; Pan, 2022) as policy makers in China have treated it as a priority for socioeconomic development. China has committed to hit peak emissions before 2030 and finally achieve carbon neutrality by 2060. According to data released by Organisation for Economic Co-operation and Development (OECD), China has been the largest producer of two primary renewable energy sources, wind and solar energy, and the largest investors in the renewable energy industry internationally.[1] China also remains the largest producer and exporter of electric vehicles, accounting for more than 50% shares of global production and sales of electric vehicles.[2] The support and promotion from the Chinese government greatly stimulated the growth of these renewable energy companies. Historically, the emerging Chinese equity market has been criticised for having high information asymmetry and market manipulation rates, low governance transparency, and low quantity and quality of information disclosed by the companies. Besides, Geretto and Pauluzzo (2012) added that the current regulation is considered excessive, making the market even less efficient and accessible than the other mature markets, such as the United States. These problems exacerbate market inefficiency, and may lead to herd trading.

Our study therefore contributes to the literature in several ways. First, we add to the scant literature on herding behaviour in the Chinese renewable energy industry. We find compelling evidence that Chinese investors significantly herd in these stocks, which contradicts the findings by Shen (2018). Second, we document significant general stock market effects on such behaviour among Chinese investors. Third, we use both static and time-varying coefficient models and consider a size effect in calculating and verifying the results. Finally, our study provides implications for the investors, analysts and regulators in the Chinese financial market. While China has ambitions to lead the global renewable energy production and investments, particular attention is required to stabilise the local financial market and improve the market efficiency.

The remainder of this paper is structured as follows. We review some past research in Section 2. We explain the methods in Section 3, followed by Section 4 where we describe the data. We discuss the results in Section 5 and present robustness checks in Section 6. Finally, we conclude and address implications of our study in Section 7.

2. Literature review

Academics have devoted considerable effort to studying the behaviour of market participants and its impact on asset prices. One strand of literature focuses on the herding phenomenon. Despite the fact that the efficient market hypothesis (Samuelson, 1965; Fama, 1965, 1970) is commonly applied as a heuristic in financial analysis, investors are observably likely to suppress their personal research base and simply copy the actions of others. Such behaviour, herd trading, can be either rational or completely irrational (Bikhchandani and Sharma, 2000).

There are different approaches to determining whether herd effects present. For example, Lakonishok et al. (1992) (LSV) defined a herding measure by testing the correlation of trade patterns that whether more than half of a particular group of participants (i.e., fund manager in their case) increase or decrease the holding of stocks at the same time (e.g., quarterly). Wermers (1999) improved the LSV approach by not just considering the change in numbers of participants, but the proportion of individual stocks in portfolios by different fund mangers. Hwang and Salmon (2004) proposed a state-space model which defines a latent herding parameter to capture whether individual stocks are moving towards wider market. Christie and Huang (1995) proposed that the dispersion level of asset returns in a market portfolio, measured by the cross-sectional standard deviation of returns (*CSSD*), can be used to detect the existence of herd effect in the market. They defined that if investors react individually based on their own views and do not herd around the market consensus, dispersion should be relatively high, according to the rational asset pricing models. However, since their model based on the *CSSD* measure is linear, it can be interpreted as showing *co-movements* of returns instead of herding. To counter this, Chang et al. (2000) suggested using the cross-sectional *absolute* deviation of returns (*CSAD*) to measure the dispersions and introduced a non-linear term to break rational asset pricing models and capture the presence of herding. Both models have been widely applied in research. Besides, we would also like to mention some studies which followed the initial idea of Christie and Huang (1995) and Chang et al. (2000), but used different proxies and approaches. For example, Li et al. (2017) used the standard deviation of the cross-sectional trading volume to investigate the differences between the herd behaviour of Chinese institutional and retail investors. Xie et al. (2015) proposed a model utilising the weighted cross-sectional variance to analyse the herding phenomenon in the Chinese stock market.

The literature offers a extensive list of studies on herding. For example, Chang et al. (2000) investigated asymmetric herd behaviour in international stock markets. Bernales et al. (2020) documented the presence of herding in the U.S. equity options market, and found that it was driven by increased volatility, position change, and information inflows. Bouri et al. (2019) studied the herd behaviour in the cryptocurrency market represented by 14 large coins and discovered that such behaviour is time-varying using a rolling window analysis. Demirer et al. (2015) analysed whether the volatility of the stock market has an impact on the herding phenomenon in the commodity market.

While most studies focus on the aggregated stock and commodity markets, some have examined equity sectors. For example, Litimi et al. (2016) examined the herding behaviour in U.S. listed companies across twelve NASDAQ sectors from 1985 to the end of 2013. The presence was only found in the public utilities and transportation sectors in general, albeit it might be induced in other sectors such as energy, health care, technology, etc by trading volume changes. Ukpong et al. (2021) paint a different picture by using ten Thompson Reuters Datastream

[1] More information can be retrieved from their website https://data.oecd.org/energy/renewable-energy.htm.

[2] https://thedriven.io/2022/02/08/china-regains-dominance-of-global-ev-market-with-53-of-global-sales-in-2021/.

sectors finding from 1990 to 2020 that herding was only found in financials, industrials and real estate. Similarly, Zheng et al. (2017) studied 10 sectors across 9 Asian markets and the US from 1993 to 2013. However, for the renewable energy market, specifically, the number of studies is still rare, and existing results are mixed. Shen (2018) applied tests on different energy sectors of the Chinese stock market. The author showed that herd behaviour presented in most sectors but *not* in the new energy and nuclear energy. Trück and Yu (2016) performed tests on 170 U.S. renewable energy companies that are included in indices. They showed that investors did not herd in most cases, except that the market was generally positive during a short period in 2008 when the oil market was experiencing sharp decreases. Chang et al. (2020), on the other hand, extended the works of Trück and Yu (2016) to the Europe and Asia markets and further analysed the dynamics in sub-periods of the 2008 global financial crisis, SARS, and COVID-19 by 2020 May end. Similarly, they confirmed the absence of herding in the local renewable energy sector in these markets, and highlighted the external pressure from the oil and the fossil energy markets to the behaviour in renewable energy markets. Overall therefore the results to date are mixed.

3. Methodology

3.1. Base econometric models

We tested whether the behaviour of herding exists in the Chinese renewable energy industry using the cross-sectional absolute deviation of returns (CSAD) approach proposed in Chang et al. (2000).

Chang et al. (2000) used the cross-sectional absolute deviation of returns in measuring the dispersions, expressed as:

$$CSAD_{m,t} = \frac{\sum_{i=1}^{N} \left| r_{i,t} - r_{m,t} \right|}{N}, \tag{1}$$

where N is the number of renewable energy stocks, $R_{i,t}$ is the logarithmic return of individual renewable energy stock i on day t, $R_{m,t}$ is the average market return on day t.

A general quadratic regression of $CSAD_{m,t}$ on variants of market returns was then built to discover the presence of herding behaviour during the sample period (Eq. (2)). Eq. (2) is a modification of Chang et al. (2000) approach by including a $R_{m,t}$ term on the right-hand side (Chiang and Zheng, 2010). The new form enables us to account for asymmetric investor behaviour in various market scenarios.[3] As suggested, herding phenomenon is detected when a non-linear instead of a linear relationship between $CSAD_{m,t}$ and the $R_{m,t}$ is found, inferred by a significantly negative coefficient γ_3, which breaks the rational pricing model which suggests that the dispersion of stock returns should linearly increase with the market-wide return. In the case of herd trading, stocks are clustering, so that the dispersion of individual returns decreases or increases at a nonproportional rate towards the market returns during periods of high volatility.

$$CSAD_{m,t} = \gamma_0 + \gamma_1 R_{m,t} + \gamma_2 \left| R_{m,t} \right| + \gamma_3 R_{m,t}^2 + \epsilon_t, \tag{2}$$

To avoid serial correlation, we introduce a one-day lagged dependent variable ($CSAD_{m,t-1}$) to improve the previous model as Eq. (3), following Yao et al. (2014) and Alhaj-Yaseen and Rao (2019). Additionally, the statistical inference is based on Newey and West (1994) standard errors to further account for heteroskedasticity and serial autocorrelation in the error terms.[4] We followed Chiang and Zheng (2010) to test the presence of herd behaviour twice to ensure robustness; we first tried using a constraint, $\gamma_1 = 0$, to make equations more consistent with that in Chang et al. (2000), followed by a second test of easing the restriction.

$$CSAD_{m,t} = \gamma_0 + \gamma_1 R_{m,t} + \gamma_2 \left| R_{m,t} \right| + \gamma_3 R_{m,t}^2 + \gamma_4 CSAD_{m,t-1} + \epsilon_t, \tag{3}$$

Moreover, we analysed whether such behaviour is asymmetric under different market status using a nested model (Eq. (4)), following Chang et al. (2000) and Chiang and Zheng (2010).[5] We classified the market returns into positive and negative returns using dummy variables and evaluated the intensity of herd or anti-herd effect under the two market conditions.

$$\begin{aligned} CSAD_{m,t} = {} & \gamma_0 + \gamma_1 D_{m,up} R_{m,t} + \gamma_2 D_{m,down} R_{m,t} + \gamma_3 D_{m,up} R_{m,t}^2 \\ & + \gamma_4 D_{m,down} R_{m,t}^2 + \gamma_5 CSAD_{m,t-1} + \epsilon_t \end{aligned} \tag{4}$$

where $D_{m,up}$ and $D_{m,down}$ are dummy variables with values of 1 if the return of the equally-weighted market portfolio at time t is positive and negative, respectively. A significantly negative coefficient γ_2 or γ_3 indicates that herding in renewable energy market exists in up or down market, respectively.

The above econometric models examine the presence of herd effects in general, which presumes the persistence of parameter in the whole sample period. However, this is usually not the case for time series data. Thus, following the approach in Bouri et al. (2019) and Evrim Mandaci and Cagli (2022), we applied the multiple breakpoint test proposed by Bai and Perron (2003) on Eq. (3) to detect structural breaks in the full period, which allows us to re-estimate the coefficients for different short time periods based on the dates detected.

3.2. Time-varying autoregressive model

The Bai and Perron (2003) multiple breakpoint test mentioned in the last section can estimate break points by minimising the global sum of squared residuals. However, this method does not allow us to track the time-varying transition from herd to anti-herd and vice versa. We therefore employed the Time-Varying Autoregressive ($TV-AR$) model to verify again the results obtained using previous models.

As a starting point, we first introduce the $AR(p)$ model which is written as, in general:

$$y_t = \gamma_0 + \gamma_1 y_{t-1} + \cdots + \gamma_p y_{t-p} + \epsilon_t, \tag{5}$$

where p is the lag order of the dependent variable.

In above model (Eq. (5)), y_t only depends on its own lags. However, there are other exogenous variables in our case, such as the $R_{m,t}$, $\left|R_{m,t}\right|$, $R_{m,t}^2$. Hence, we rewrite the equation as:

$$y_t = \beta_0 + \beta_1 y_{t-1} + \cdots + \beta_p y_{t-p} + \gamma_1 x_{1t} + \cdots + \gamma_d x_{dt} + \epsilon_t, \tag{6}$$

The $TV-AR(p)$ model fits the $AR(p)$ model with time-varying coefficients. To calculate the coefficients, we view the $TV-AR(p)$ model as a special case of TV linear regression model which has a general form of:

$$y_t = \beta\left(z_t\right) X_t' + \epsilon_t, \quad t = 1, \ldots, T, \tag{7}$$

where y_t is the dependent variable, ϵ_t is the error term, X_t' is a vector of independent variables, and $\beta\left(z_t\right)$ is the vector of time-varying coefficients which is a function of z_t, a rescaled changing time period (t/T) or a random variable at time t. We combined both ordinary least squares estimator and the local polynomial kernel estimator (in our case, we used the Nadaraya–Watson estimator) to minimise the following[6]:

$$\left(\hat\beta\left(z_t\right), \hat\beta^{(1)}\left(z_t\right)\right) = \arg\min_{\theta_0,\theta_1} \sum_{t=1}^{T} \left[y_t - x_t^\top \theta_0 - \left(z_t - z\right) x_t^\top \theta_1 \right]^2 K_b\left(z_t - z\right) \tag{8}$$

[3] Please refer to Chiang and Zheng (2010) and Duffee (2001) for more details.

[4] Specifically, we used a Bartlett kernel based HAC covariance estimation using AR(1) prewhitened residuals and automatically selected bandwidth by Newey and West (1994).

[5] Check Alhaj-Yaseen and Rao (2019) and Kumar (2020) for more examples.

[6] See Casas and Fernandez-Casal (2019) for more clarifications.

where b is the bandwidth, $K(\cdot)$ is the kernel function which in our case is the Triweight kernel for weights calculation.

Note that, for $TV-AR(p)$, the regressors in Eq. (7) also contain p lagged value of the response variable. We re-write the equation in a more intuitive way as:

$$y_t = \beta_0(z_t) + \beta_1(z_t) y_{t-1} + \cdots + \beta_p(z_t) y_{t-p} + \gamma_1(z_t) x_{1t} + \cdots + \gamma_d(z_t) x_{dt} + \epsilon_t, \quad \text{for } t = 1, \ldots, T. \tag{9}$$

For consistency, we used $p = 1$ so that our independent variables include a one-day lagged dependent variable ($CSAD_{m,t-1}$) and exogenous variables $R_{m,t}$, $|R_{m,t}|$, $R^2_{m,t}$. Ultimately, our model is specified below (Eq. (10)).

$$CSAD_{m,t} = \gamma_0(z_t) + \gamma_1(z_t) R_{m,t} + \gamma_2(z_t)|R_{m,t}| + \gamma_3(z_t) R^2_{m,t} + \gamma_4(z_t) CSAD_{m,t-1} + \epsilon_t, \quad \text{for } t = 1, \ldots, T. \tag{10}$$

where all γ coefficients are time-varying.

4. Data

We collected daily price data and the year-end market capitalisation data for the constituents of the China Securities Index Co., Ltd. (CSI) New Energy Index. CSI company is a leading Chinese financial market index provider that is jointly funded and supported by the Shanghai Stock Exchange and the Shenzhen Stock Exchange. The CSI has managed more than 5000 indices, providing benchmarks for domestic and international markets, with focus on China Mainland and Hong Kong markets. The CSI New Energy Index includes 80 major companies involved in renewable energy production, applications, storage and interaction devices, or other new energy service, which represents the overall performance of the Chinese renewable or new energy industry. We also collected the CSI 300 Index price data, a benchmark for the overall performance of the China A-share market, which tracks the top 300 Chinese companies in terms of market capitalisation and liquidity listed on either the Shanghai Stock Exchange or the Shenzhen Stock Exchange.

All data were sourced from Bloomberg Database, spanning from January 5, 2015 to April 29, 2022. Note that prices are denominated in the Chinese Yuan and were transformed to their first-differenced natural logarithms as log-returns before use.

5. Empirical results

5.1. Full and sub- samples analysis

The coefficient estimates of general herd effects in the Chinese renewable energy market are reported in Table 1. As we mentioned earlier, we tested the presence of herd effect twice for robustness; we first imposed a constraint, $\gamma_1 = 0$, to make Eq. (3) more consistent with that in Chang et al. (2000) and then we eased the constraint for the second time. We found that the dispersion of individual returns, the $CSAD_{m,t}$, is not linearly increasing with $|R_{m,t}|$ as all γ_3 for $R^2_{m,t}$ are significantly negative (−3.2483*** when $\gamma_1 = 0$ and −3.7699*** when $\gamma_1 \neq 0$) in the full sample analysis. In other words, the company returns tend to cluster around the market and this indicates that herding exists, which contradicts the results reported by Shen (2018) who concluded that Chinese investors do not herd in the new energy industry, which is reasonable as they only analysed the market in 2015.

We continued to test the herding intensity in asymmetric market states. The coefficient estimates of asymmetric herd behaviour in the up and down Chinese renewable energy market are reported in Table 2. Consistent with previous results, the values of both herding coefficients γ_3 and γ_4 are negative and statistically significant, which implies the herding in Chinese renewable energy market has existed in the study period regardless of the market conditions. In addition, evidence show that the herd effects are generally more profound in the up (−4.1552***) than in the down (−3.6424***) conditions, which is consistent with the general findings of Chinese equity market by Chiang and Zheng (2010).

Given behaviour can be changing over time, we tested Eq. (3) for candidate breakdates using (Bai and Perron, 2003) approach. Five structural breaks were selected by most metrics, which are 2016/3/07 2017/4/10, 2018/6/26, 2019/11/22, and 2021/1/05 (Table A.1).[7] We then re-tested the presence of herding in different timeframe based on these breakpoints using the Eq. (3). Results are reported in Table 3. We found interesting evidence that significant herding only existed in the period from 2015/1/05 to 2016/3/07 (sub-sample 1) and 2021/1/05 to 2022/4/29 (sub-sample 6), where the intensity was stronger in the former than the latter period. These, again, contradict the results reported by Shen (2018) who concluded that Chinese new energy investors did not herd in 2015. There is a common characteristic in these two that in both periods, the index price increased and decreased to greater extent compared to other periods, and both were initiated with a sharp and rapid increase. However, the reason why the magnitude of the herd effect in the first period is greater than the last period was possibly due to the recognition of this emerging industry by stock funds and exchanges as well as the Paris agreement was proposed.[8] Investors had strong belief that the market was going to boost and would like to invest in as early as possible. In recent years, especially during the last period, while most of the industries were suffered from the restriction imposed for the COVID-19 and global energy shortage, local new energy (electric) car industry being one of the markets that have great potential to grow received much policy support from government and expectation from investors, which helped the other streams within this sector grow. There was no significant herding in the rest of periods. However, one might argue that in these period weak herding might exist as although (Chang et al., 2000) did not propose the definition of weak herd behaviour, Zheng et al. (2017) and Bouri et al. (2019), among others, suggested, qualitatively, so-called weak herding is because it is less significant and/or having a lower negative herding coefficient.

Moreover, it is also essential to know that the tests following the Chang et al. (2000) framework only test for herding within the specific asset, or in our case, the industry, which is a particular type and strong form of herding (Richards, 1999). In other words, while the investors do not herding within the industry, we should allow the possibility of herd trading according to other markets' performance. In light of this, we focused on the period from 2016/3/07–1/05/2021 when no significant local herding was found, and we followed a common approach in literature such as Demirer et al. (2015), among others, to augment a term of squared returns of a particular market that we want to explore the impact of. Because we were curious about how investors were reacting to large price movements in the overall financial market, we used the squared returns of CSI 300 Index as a proxy for the Chinese equity market uncertainty to study the stock market effect in the herding context. The equation is written as follows:

$$CSAD_{m,t} = \gamma_0 + \gamma_1 R_{m,t} + \gamma_2 |R_{m,t}| + \gamma_3 R^2_{m,t} + \gamma_4 R^2_{C300,t}$$

[7] We note that the Chinese new energy industry had experienced sharp rises and falls in 2015 and early 2016 till the first breakdate. The market was bearish for a long time and kept trending lower from 2018 till early 2019, and started recovering in late 2019, which is close to our penultimate breakdate. After around our last breakdate which is the first day after the public holiday of the New Year's Day, the market has frequently spiked to new records, although fell sharply in the following month, recovered quickly and peaked in the fourth quarter of 2021 and started to fall.

[8] The CSI New Energy Index was launched on 10 February 2015, and in our study, we traced it back to the first trading day of the year, that is, 5 January 2015, by obtaining the stock prices of each constituent including previous and current ones.

Table 1
Regression results of $CSAD_{m,t}$ on unconditional renewable energy market returns.

$CSAD_{m,t}$	Cons.	$R_{m,t}$	$\|R_{m,t}\|$	$R^2_{m,t}$	$CSAD_{m,t-1}$	Adj. R^2
Full sample	0.0059***		0.3073***	**−3.2483*****	0.5161***	0.4365
	(0.0000)		(0.0000)	(0.0000)	(0.0000)	
	0.0056***	−0.0365***	0.3332***	**−3.7699*****	0.5256***	0.4493
	(0.0000)	(0.0004)	(0.0000)	(0.0000)	(0.0000)	

Notes:
1. Eq. (3): $CSAD_{m,t} = \gamma_0 + \gamma_1 R_{m,t} + \gamma_2 \left|R_{m,t}\right| + \gamma_3 R^2_{m,t} + \gamma_4 CSAD_{m,t-1} + \epsilon_t$ was used;
2. The data range is from 2015/1/05 to 2022/4/29;
3. ***, ** and * denote the rejections of the null hypothesis at the 1%, 5%, and 10% significance levels, respectively.

Table 2
Regression results of $CSAD_{m,t}$ on asymmetric renewable energy market returns.

$CSAD_{m,t}$	Cons.	$D_{up}R_{m,t}$	$D_{down}R_{m,t}$	$D_{up}R^2_{m,t}$	$D_{down}R^2_{m,t}$	$CSAD_{m,t-1}$	Adj. R^2
Full sample	0.0056***	0.3136***	−0.3634***	**−4.1552*****	**−3.6424*****	0.5253***	0.4494
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	

Notes:
1. Eq. (4): $CSAD_{m,t} = \gamma_0 + \gamma_1 D_{m,up} R_{m,t} + \gamma_2 D_{m,down} R_{m,t} + \gamma_3 D_{m,up} R^2_{m,t} + \gamma_4 D_{m,down} R^2_{m,t} + \gamma_5 CSAD_{m,t-1} + \epsilon_t$ was used;
2. The data range is from 2015/1/05 to 2022/4/29;
3. ***, ** and * denote the rejections of the null hypothesis at the 1%, 5%, and 10% significance levels, respectively.

Table 3
Regression results of $CSAD_{m,t}$ on unconditional renewable energy market returns in sub-samples.

$CSAD_{m,t}$	Cons.	$R_{m,t}$	$\|R_{m,t}\|$	$R^2_{m,t}$	$CSAD_{m,t-1}$	Adj. R^2
Sub-sample 1	0.0144***		0.2297***	**−2.8764*****	0.2714***	0.1450
	(0.0000)		(0.0145)	(0.0019)	(0.0022)	
	0.0132***	−0.0919***	0.3511***	**−4.8017*****	0.2976***	0.2910
	(0.0000)	(0.0000)	(0.0001)	(0.0000)	(0.0003)	
Sub-sample 2	0.0075***		0.2103**	−0.1899	0.3251***	0.3160
	(0.0000)		(0.0106)	(0.9075)	(0.0000)	
	0.0074***	−0.0292*	0.2233***	−0.4367	0.3294***	0.3208
	(0.0000)	(0.0586)	(0.0074)	(0.8013)	(0.0000)	
Sub-sample 3	0.0098***		0.3076***	−0.1264	0.1647***	0.4849
	(0.0000)		(0.0000)	(0.8895)	0.0062	
	0.0098***	0.0003	0.3074***	−0.1185	0.1645***	0.4831
	(0.0000)	(0.9793)	(0.0000)	(0.8966)	0.0065	
Sub-sample 4	0.0077***		0.0810**	−0.1744	0.4452***	0.2598
	(0.0000)		(0.0276)	(0.7438)	(0.0000)	
	0.0076***	−0.0286**	0.0954***	−0.5350	0.4453***	0.2708
	(0.0000)	(0.0487)	(0.0087)	(0.3333)	(0.0000)	
Sub-sample 5	0.0095***		0.2160***	−1.6491	0.4142***	0.3269
	(0.0000)		(0.0013)	(0.1032)	(0.0000)	
	0.0097***	0.0237	0.1868***	−1.1564	0.4124***	0.3312
	(0.0000)	(0.1140)	(0.0014)	(0.1878)	(0.0000)	
Sub-sample 6	0.0054***		0.2494***	**−2.7000*****	0.6414***	0.4912
	(0.0000)		(0.0000)	(0.0001)	(0.0000)	
	0.0054***	0.0097	0.2487***	**−2.6832*****	0.6394***	0.4908
	(0.0000)	(0.4360)	(0.0000)	(0.0001)	(0.0000)	

Notes:
1. Eq. (3): $CSAD_{m,t} = \gamma_0 + \gamma_1 R_{m,t} + \gamma_2 \left|R_{m,t}\right| + \gamma_3 R^2_{m,t} + \gamma_4 CSAD_{m,t-1} + \epsilon_t$ was used;
2. The range of sub-sample 1 is from 2015/1/05 to 2016/3/07; The range of sub-sample 2 is from 2016/3/07 to 2017/4/10; The range of sub-sample 3 is from 2017/4/10 to 2018/6/26; The range of sub-sample 4 is from 2018/6/26 to 2019/11/22; The range of sub-sample 5 is from 2019/11/22 to 2021/1/05; The range of sub-sample 6 is from 2021/1/05 to 2022/4/29.
3. ***, ** and * denote the rejections of the null hypothesis at the 1%, 5%, and 10% significance levels, respectively.

$$+ \gamma_5 CSAD_{m,t-1} + \epsilon_t, \tag{11}$$

where $R_{C300,t}$ is the logarithmic return of CSI 300 Index on day t.

The results using the Eq. (11) are presented in Table 4. Consistent with previous results, there was no within-industry herding from 2016/3/07–1/05/2021 as γ_3s are not significantly negative. Instead, the dispersion was found significantly negatively correlated to the squared returns of the general stock market (e.g., −2.3913***). In other words, the dispersions of individual renewable energy companies linearly increase with the industry-wide return, but not with the overall stock market (the overall expectation to fundamentals), which reveals that renewable energy investors still herd around the equity market in the absence of local herding. The large price movements in the overall stock market, either in up or down direction, may have impact on the industry. In this case, we could say investors from the renewable energy industry take trading signals from the overall stock market performance as a sign of potential positive or negative movement in the industry and use these signals to buy or sell rather than using their own analysis.

We further investigate the asymmetric impact of the overall stock market on the investor behaviour of renewable energy stocks by using dummy variables to capture the upturns and downturns of the general Chinese stock market (Eq. (12)).

$$CSAD_{m,t} = \gamma_0 + \gamma_1 R_{m,t} + \gamma_2 \left|R_{m,t}\right| + \gamma_3 R^2_{m,t} + \gamma_4 D_{C300,up} R^2_{C300,t}$$

Table 4
Regression results of $CSAD_{m,t}$ on unconditional renewable energy market returns incorporating the stock market effect.

$CSAD_{m,t}$	Cons.	$R_{m,t}$	$\lvert R_{m,t}\rvert$	$R^2_{m,t}$	$R^2_{C300,t}$	$CSAD_{m,t-1}$	Adj. R^2
	0.0073***		0.2075***	0.0999	**−2.3913*****	0.4222***	0.4017
	(0.0000)		(0.0000)	(0.8330)	(0.0000)	(0.0000)	
	0.0072***	−0.0115	0.2144***	−0.0449	**−2.4313*****	0.4255***	0.4024
	(0.0000)	(0.1786)	(0.0000)	(0.9301)	(0.0000)	(0.0000)	

Notes:
1. Eq. (11): $CSAD_{m,t} = \gamma_0 + \gamma_1 R_{m,t} + \gamma_2 \left|R_{m,t}\right| + \gamma_3 R^2_{m,t} + \gamma_4 R^2_{C300,t} + \gamma_5 CSAD_{m,t-1} + \epsilon_t$ was used;
2. The data range is from 2016/3/07 to 1/05/2021 when the local herding was absent;
3. ***, ** and * denote the rejections of the null hypothesis at the 1%, 5%, and 10% significance levels, respectively.

Table 5
Regression results of $CSAD_{m,t}$ on unconditional renewable energy market returns incorporating the asymmetric stock market effect.

$CSAD_{m,t}$	Cons.	$R_{m,t}$	$\lvert R_{m,t}\rvert$	$R^2_{m,t}$	$D_{C300,up}R^2_{C300,t}$	$D_{C300,down}R^2_{C300,t}$	$CSAD_{m,t-1}$	Adj. R^2
	0.0071***		0.2384***	−0.5421	**−4.1258*****	**−1.5658*****	0.4227***	0.4085
	0.0000		0.0000	0.3293	0.0000	0.0017	0.0000	
	0.0072***	0.0049	0.2385***	−0.5435	**−4.2776*****	**−1.4687*****	0.4214***	0.4081
	0.0000	0.5876	0.0000	0.3209	0.0000	0.0023	0.0000	

Notes:
1. Eq. (12): $CSAD_{m,t} = \gamma_0 + \gamma_1 R_{m,t} + \gamma_2 \left|R_{m,t}\right| + \gamma_3 R^2_{m,t} + \gamma_4 D_{C300,up} R^2_{C300,t} + \gamma_5 D_{C300,down} R^2_{C300,t} + \gamma_6 CSAD_{m,t-1} + \epsilon_t$ was used;
2. The data range is from 2016/3/07 to 1/05/2021 when the local herding was absent;
3. ***, ** and * denote the rejections of the null hypothesis at the 1%, 5%, and 10% significance levels, respectively.

$$+ \gamma_5 D_{C300,down} R^2_{C300,t} + \gamma_6 CSAD_{m,t-1} + \epsilon_t, \tag{12}$$

where $D_{C300,up}$ and $D_{C300,down}$ are dummy variables with values of 1 if the return of the CSI 300 Index on day t is positive and negative, respectively.

Results of asymmetric stock market impact are presented in Table 5. We confirmed that the overall equity market performance had influenced the investors' self-confidence in renewable energy stocks. This phenomenon is more common during stock market ups than downs. This adds to previous finding that investors in renewable energy stocks follow more the large positive trend in general market and use these signals to trade in the these stocks.

5.2. Time-varying analysis

In this section, we present the results of time-varying herding coefficient. We first employed the Eq. (12), where the bandwidth was automatically selected by cross validation and the wild bootstrap 95% confidence levels were estimated after 30,000 runs based on Chen et al. (2018). Fig. 1 plots the mean of the herding coefficient estimates over time ($\gamma_3\left(z_t\right)$) and their mean confidence intervals. The vertical dash lines are the breakdates detected as in Table A.1. The result is qualitatively similar to our previous results in Table 3, which confirms that herding in the Chinese renewable energy industry is indeed time-varying. From the plot, we can see that most of the herding coefficients in the sub-sample 1 and 6 are significantly negative, which confirms that strong form of herding within the industry happened during these periods, and was more intense in the former. Industry herding was also evidenced during other periods in a much weaker form, which is also consistent with our previous findings. Overall, we found that the herd effect is time-varying and is likely to persist.

Furthermore, based on previous results of the potential impact of stock market performance on the herding behaviour (Table 4). We employed the Eq. (11) again, but this time we estimated it using the time-varying coefficients as follows (Eq. (13)).

$$\begin{aligned} CSAD_{m,t} = {} & \gamma_0\left(z_t\right) + \gamma_1\left(z_t\right) R_{m,t} + \gamma_2\left(z_t\right) \left|R_{m,t}\right| + \gamma_3\left(z_t\right) R^2_{m,t} \\ & + \gamma_4\left(z_t\right) R^2_{C300,t} + \\ & \gamma_5\left(z_t\right) CSAD_{m,t-1} + \epsilon_t, \quad \text{for } t = 1, \ldots, T. \end{aligned} \tag{13}$$

We plot the mean of the coefficient estimates of stock market effect over time ($\gamma_4\left(z_t\right)$) and their mean confidence intervals. Evidence confirms that the volatility of the stock market influences the behaviour in the renewable energy market, especially during the period from 2016/3/07–1/05/2021 (sub-sample 2–5). Combining with results from last section, we finally argue that renewable energy stock investors react to the overall performance of the stock market, either being very confident when the large movements are positive, which is more likely as evidenced in Table 5, or feeling panic during periods of extreme price drops. Hence, they simply follow the market dynamics hoping to obtain better profits (see Fig. 2).

6. Robustness check

6.1. Sized-based portfolios

In previous sections, we have presented the evidence of using equally-weighted market portfolio. However, one might suggest that small stocks may react differently to large stock portfolios in some cases (McQueen et al., 1996). Therefore, we applied similar approach by Chang et al. (2000) that we discretised the stocks into quantiles based on the market capitalisation of each stock at the end of the year. Given our sample size,[9] we specified the top 25% as the largest, 25%–75% as the medium, the last 25% as the smallest firms, and we reconstructed these portfolios each year. We then re-estimated the Eqs. (3) and (4) for the industry herding using the new size-based portfolios, and empirical results are shown in Tables 6 and 7, respectively. The new evidence still fully supports our previous results that Chinese investors do herd in the renewable energy market and such behaviour is generally more prevalent during upturns. We also found that the herd effect is more significant among smaller than larger stocks. This can be reasonably related to the circumstance that larger firms usually have more public information and is harder for them to hide information. At the same time, larger firms are usually the investment bellwether. A strong or weak performance among the leading firms may induce the same for small firms and investors seeing this will very likely to quickly turn heads to the latter to capture more potential profits. Overall, our results remain robust taking into account the size effect.

6.2. CSSD as the measure of dispersion

Gleason et al. (2004) proposed that the *CSAD* and the *CSSD* as measures of the return dispersion can be swapped. Therefore, we replaced the dependent variable ($CSAD_{m,t}$) in Eqs. (3), (4), (10), and

[9] We have 80 firms at most.

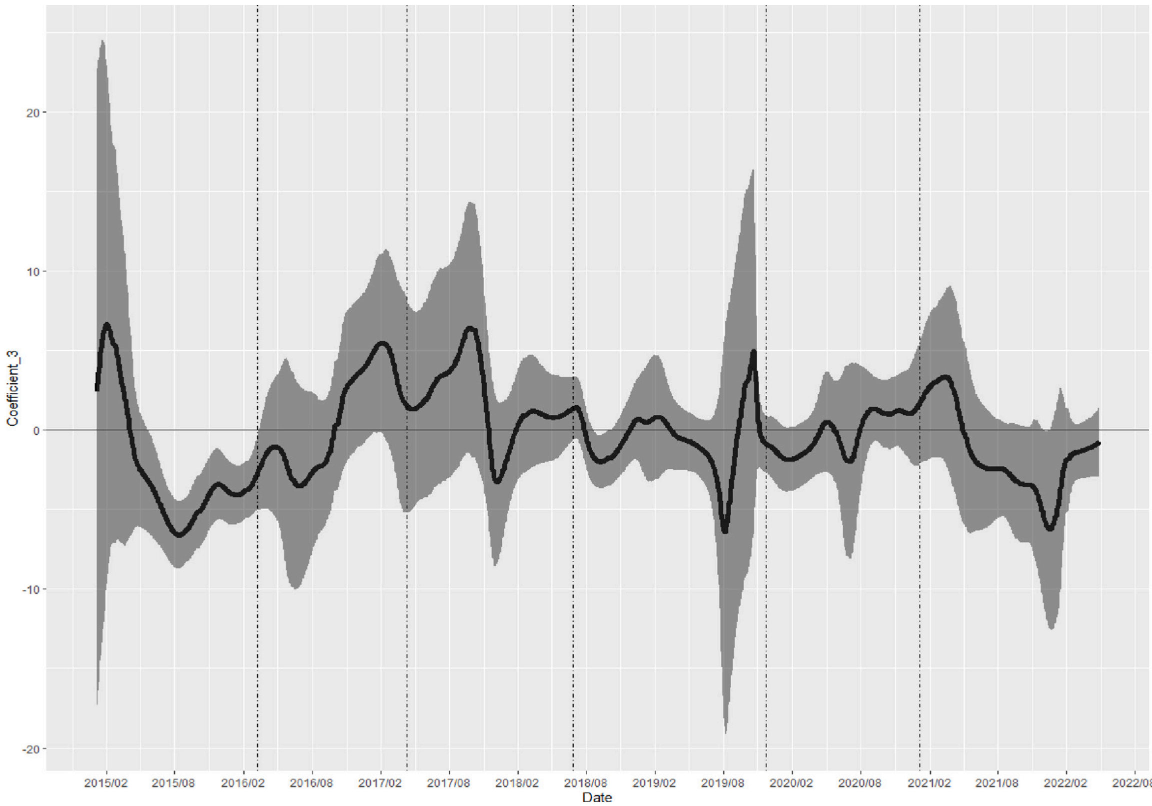

Fig. 1. Time-varying herding coefficient using Eq. (10).

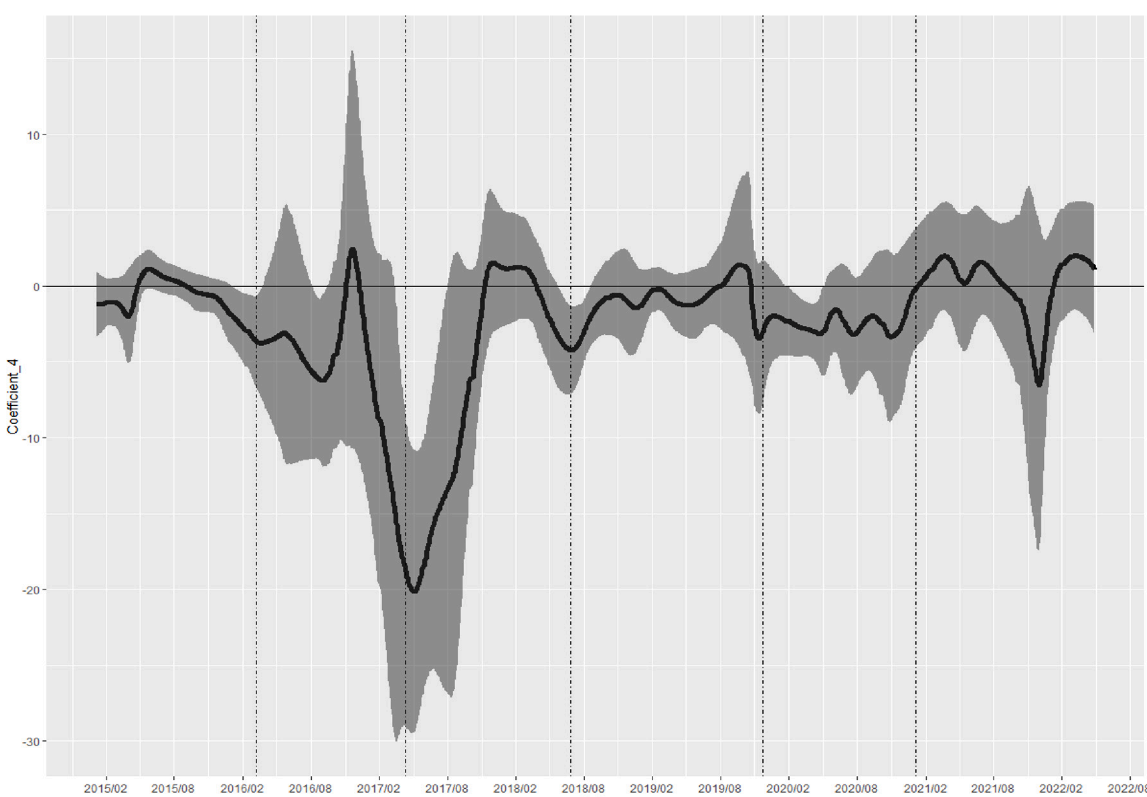

Fig. 2. Time-varying herding coefficient using Eq. (13).

Table 6
Regression results of $CSAD_{m,t}$ on sized-based unconditional renewable energy market returns.

$CSAD_{m,t}$	Constant	$R_{m,t}$	$\lvert R_{m,t}\rvert$	$R^2_{m,t}$	$CSAD_{m,t-1}$	Adjusted R^2
Panel A: Largest	0.0079***		0.2725***	**−2.4216*****	0.4080***	0.2815
	(0.0000)		(0.0000)	(0.0000)	(0.0000)	
	0.0078***	−0.0172*	0.2857***	**−2.7097*****	0.4109***	0.2832
	(0.0000)	(0.0668)	(0.0000)	(0.0000)	(0.0000)	
Panel B: Medium	0.0064***		0.3534***	**−4.0480*****	0.4584***	0.3708
	(0.0000)		(0.0000)	(0.0000)	(0.0000)	
	0.0062***	−0.0272*	0.3719***	**−4.3963*****	0.4649***	0.3770
	(0.0000)	(0.0530)	(0.0000)	(0.0000)	(0.0000)	
Panel C: Smallest	0.0069***		0.4299***	**−4.4046*****	0.3542***	0.3233
	(0.0000)		(0.0000)	(0.0000)	(0.0000)	
	0.0068***	−0.0140	0.4402***	**−4.5820*****	0.3553***	0.3246
	(0.0000)	(0.2510)	(0.0000)	(0.0000)	(0.0000)	

Notes:
1. Eq. (3): $CSAD_{m,t} = \gamma_0 + \gamma_1 R_{m,t} + \gamma_2 \lvert R_{m,t}\rvert + \gamma_3 R^2_{m,t} + \gamma_4 CSAD_{m,t-1} + \epsilon_t$ was used;
2. The data range is from 2015/1/05 to 2022/4/29;
3. ***, ** and * denote the rejections of the null hypothesis at the 1%, 5%, and 10% significance levels, respectively.

Table 7
Regression results of $CSAD_{m,t}$ on sized-based asymmetric renewable energy market returns.

$CSAD_{m,t}$	Constant	$D_{up}R_{m,t}$	$D_{down}R_{m,t}$	$D_{up}R^2_{m,t}$	$D_{down}R^2_{m,t}$	$CSAD_{m,t-1}$	Adjusted R^2
Panel A: Largest	0.0078***	0.2859***	−2.3000***	**−3.1269*****	**−2.6324*****	0.4105***	0.2830
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	
Panel B: Medium	0.0061***	0.3716***	−0.3866***	**−4.9820*****	**−4.1675*****	0.4647***	0.3778
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	
Panel C: Smallest	0.0068***	0.4555***	−0.4403***	**−5.2152*****	**−4.3073*****	0.3529***	0.3253
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	

Notes:
1. Eq. (4): $CSAD_{m,t} = \gamma_0 + \gamma_1 D_{m,up} R_{m,t} + \gamma_2 D_{m,down} R_{m,t} + \gamma_3 D_{m,up} R^2_{m,t} + \gamma_4 D_{m,down} R^2_{m,t} + \gamma_5 CSAD_{m,t-1} + \epsilon_t$ was used;
2. The data range is from 2015/1/05 to 2022/4/29;
3. ***, ** and * denote the rejections of the null hypothesis at the 1%, 5%, and 10% significance levels, respectively.

(13) by the $CSSD_{m,t}$ and re-checked the herding results for robustness. The new equations are written as:

$$CSSD_{m,t} = \gamma_0 + \gamma_1 R_{m,t} + \gamma_2 \lvert R_{m,t}\rvert + \gamma_3 R^2_{m,t} + \gamma_4 CSSD_{m,t-1} + \epsilon_t, \tag{14}$$

$$\begin{aligned} CSSD_{m,t} = {} & \gamma_0 + \gamma_1 D_{m,up} R_{m,t} + \gamma_2 D_{m,down} R_{m,t} + \gamma_3 D_{m,up} R^2_{m,t} \\ & + \gamma_4 D_{m,down} R^2_{m,t} + \gamma_5 CSSD_{m,t-1} + \epsilon_t \end{aligned} \tag{15}$$

$$\begin{aligned} CSSD_{m,t} = {} & \gamma_0\left(z_t\right) + \gamma_1\left(z_t\right) R_{m,t} + \gamma_2\left(z_t\right) \lvert R_{m,t}\rvert + \gamma_3\left(z_t\right) R^2_{m,t} \\ & + \gamma_4\left(z_t\right) CSSD_{m,t-1} + \epsilon_t, \quad \text{for } t = 1, \dots, T. \end{aligned} \tag{16}$$

$$\begin{aligned} CSSD_{m,t} = {} & \gamma_0\left(z_t\right) + \gamma_1\left(z_t\right) R_{m,t} + \gamma_2\left(z_t\right) \lvert R_{m,t}\rvert + \gamma_3\left(z_t\right) R^2_{m,t} \\ & + \gamma_4\left(z_t\right) R^2_{C300,t} + \\ & \gamma_5\left(z_t\right) CSSD_{m,t-1} + \epsilon_t, \quad \text{for } t = 1, \dots, T. \end{aligned} \tag{17}$$

Results in Tables 8 and 9 provide exactly same information as before that herding significantly exists in the Chinese renewable energy market and is more pronounced during up than down markets even when we used *CSSD* as an alternative measure. Figs. 3 and 4 plot the time-varying coefficient $\gamma_3\left(z_t\right)$ and $\gamma_4\left(z_t\right)$ in Eqs. (16) and (17), respectively. Similar conclusion can be drawn that the within-industry herding has been time-varying and was more pronounced in the first and the last period. Weak herd or anti-herd behaviour appeared more frequently in other periods, where the stock market has taken part as a trading signals transmitter. Overall, our results remain robust when using the *CSSD* as a measure of the market return dispersion.

7. Conclusions

This paper contributes to the literature exploring the formation of herding in Chinese renewable energy market. The growth of renewable energy generation capacity and adoption has been tremendous over the years, while China certainly is taking the lead. The support from the Chinese government significantly triggered the rapid growth and development of Chinese renewable energy companies. However, there has been a paucity of research on the financial market dynamics of this hype market from a behavioural aspect, especially with a focus on China. Our paper attempts to fill this gap.

We used modifications of the original static models proposed by Chang et al. (2000) and Chiang and Zheng (2010), which account for multicollinearity and autocorrelation problems, as well as a time-varying coefficient autoregressive model, for robustness, to detect the potential herding behaviour among renewable energy investors. By employing daily data from January 05, 2015, through April 29, 2022, covering both major peaks and troughs and bullish and bearish times, we documented significant time-varying herding pattern by sub-sample analysis and time-varying modelling, which stands on the contrary to earlier literature that pointed no local herding (herding within industry) in the U.S. (Trück and Yu, 2016) or North America, Europe, and Asia markets (Chang et al., 2020) or in the Chinese market (Shen, 2018). The behaviour is more profound during up than down markets and among smaller firms. When there was an absence of local herding, we showed that large price volatility in the general equity market affects the trading behaviour.

The findings support the idea that the Chinese stock market is immature due to the inefficiency (Geretto and Pauluzzo, 2012). Herd trading has serious consequences and implications for investors and market regulators. Herding exacerbate the market inefficiency, such that the stock price is significantly pushed or dragged away from the true fundamentals of companies, which could result in price bubbles, induce high volatility in the market and finally lead to investors fears and overreactions. We have seen a clear pattern that after each "carnival", the stock price always experienced sort of crashes, which may destroy

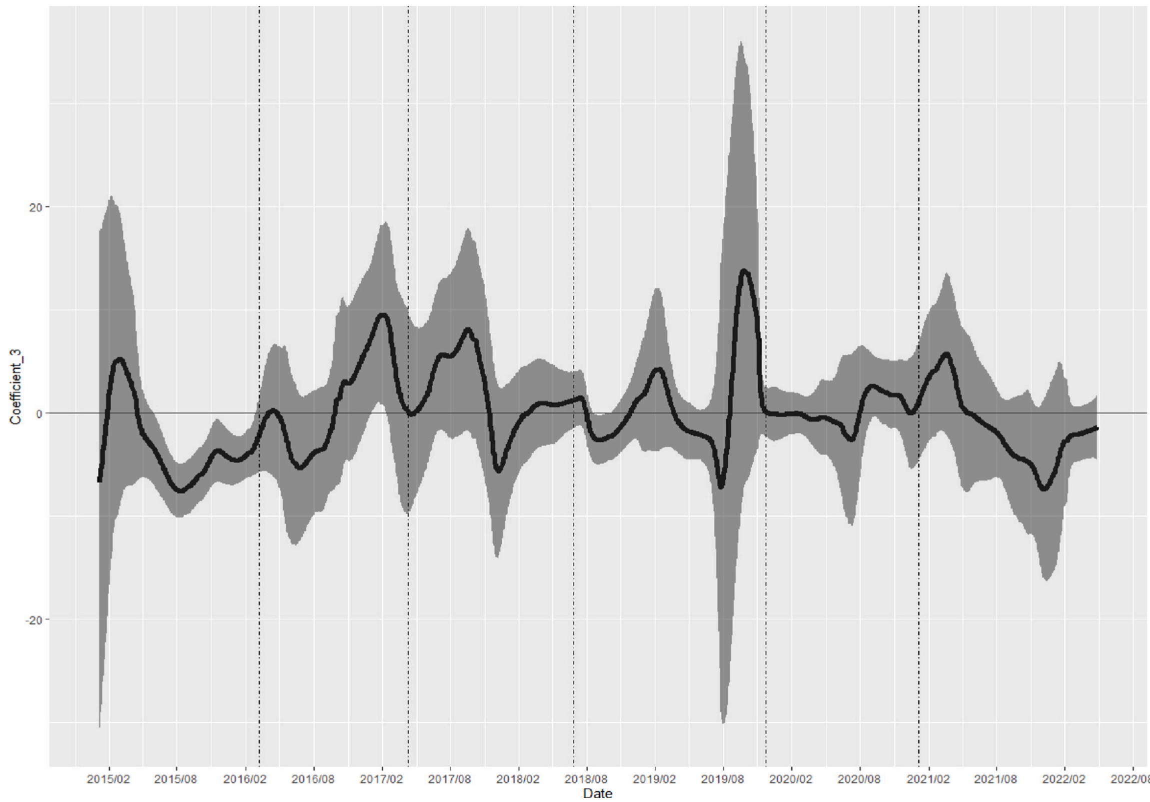

Fig. 3. Time-varying herding coefficient using Eq. (16).

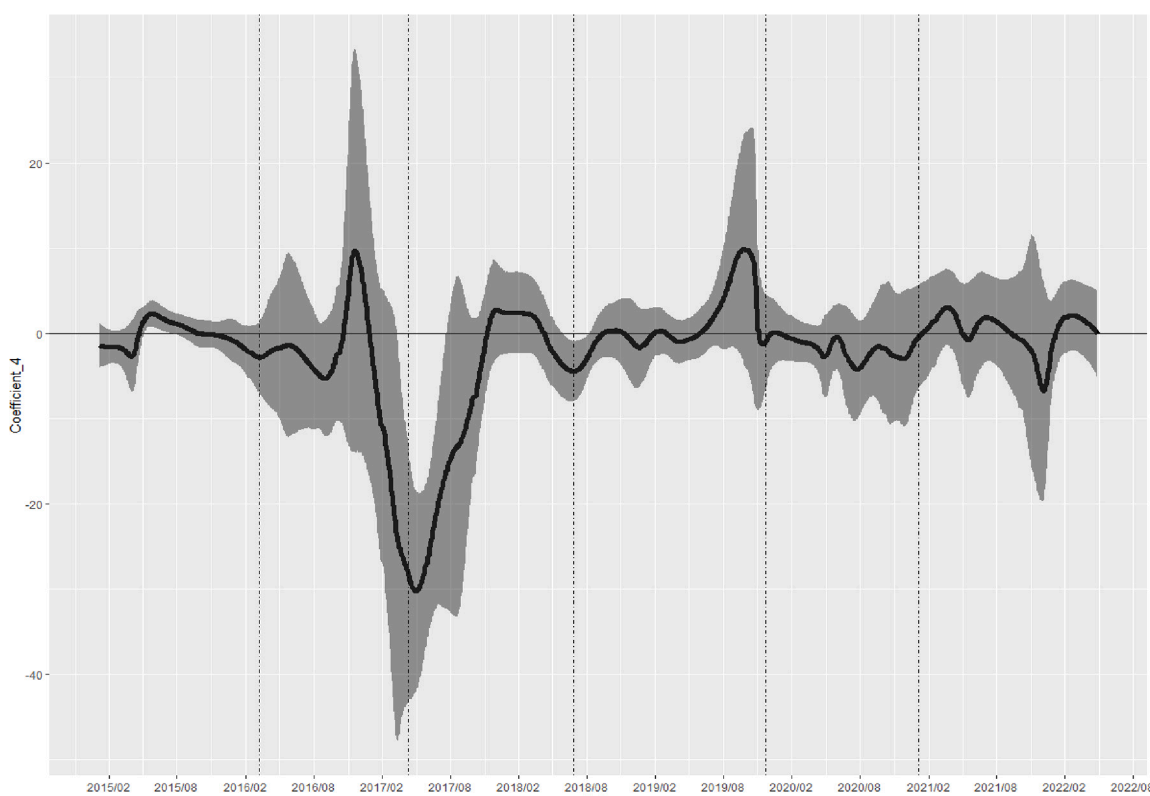

Fig. 4. Time-varying herding coefficient using Eq. (17).

Table 8
Regression results of $CSSD_{m,t}$ on unconditional renewable energy market returns.

$CSSD_{m,t}$	Constant	$R_{m,t}$	$\|R_{m,t}\|$	$R^2_{m,t}$	$CSSD_{m,t-1}$	Adjusted R^2
Full sample	0.0090***		0.2990***	**−3.1393***	0.5289***	0.4007
	(0.0000)		(0.0000)	(0.0000)	(0.0000)	
	0.0085***	−0.0522***	0.3360***	**−3.8858***	0.5402***	0.4182
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	

Notes:
1. Eq. (14): $CSSD_{m,t} = \gamma_0 + \gamma_1 R_{m,t} + \gamma_2 \left|R_{m,t}\right| + \gamma_3 R^2_{m,t} + \gamma_4 CSSD_{m,t-1} + \epsilon_t$ was used;
2. The data range is from 2015/1/05 to 2022/4/29;
3. ***, ** and * denote the rejections of the null hypothesis at the 1%, 5%, and 10% significance levels, respectively.

Table 9
Regression results of $CSSD_{m,t}$ on asymmetric renewable energy market returns.

$CSSD_{m,t}$	Constant	$D_{up}R_{m,t}$	$D_{down}R_{m,t}$	$D_{up}R^2_{m,t}$	$D_{down}R^2_{m,t}$	$CSSD_{m,t-1}$	Adjusted R^2
Full sample	0.0085***	0.3023***	−0.3813***	**−4.3102***	**−3.7453***	0.5400***	0.4182
	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	

Notes:
1. Eq. (15): $CSSD_{m,t} = \gamma_0 + \gamma_1 D_{m,up} R_{m,t} + \gamma_2 D_{m,down} R_{m,t} + \gamma_3 D_{m,up} R^2_{m,t} + \gamma_4 D_{m,down} R^2_{m,t} + \gamma_5 CSSD_{m,t-1} + \epsilon_t$ was used;
2. The data range is from 2015/1/05 to 2022/4/29;
3. ***, ** and * denote the rejections of the null hypothesis at the 1%, 5%, and 10% significance levels, respectively.

investors' confidence and cause market pessimism. This is unhealthy for the development of stock exchanges and companies themselves. While the number and size of renewable energy companies in China are growing, policy-makers should pay particular attention to preventing the vicious growth of stock prices, mitigating the risk of financial bubbles, and increasing market transparency. Investors should also be aware of that, when the renewable energy industry is susceptible to herd trading, a greater number of equities are required to achieve a satisfying level of diversification than an otherwise no-herd market. This is important for both domestic and foreign fund managers wishing to trade in the Chinese renewable energy market

CRediT authorship contribution statement

Boru Ren: Data collection, Preliminary estimation, Initial draft. **Brian Lucey:** Conceptualisation, Final editing.

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Appendix A. Structural breaks

See Table A.1.

Table A.1
Bai and Perron (2003) test of multiple structural breaks in Eq. (3) for full sample.

Sample: (2015/01/01 – 2022/04/29)				
Breaks	F-statistic	Scaled F-statistic	Weighted F-statistic	Critical value
1*	21.7665	108.8325	108.8325	22.40
2*	23.6232	118.1162	144.0285	18.37
3*	21.1570	105.7849	146.6325	16.16
4*	18.2022	91.0109	143.0628	14.25
5*	16.4864	82.4319	152.0984	12.14
UDMax statistic*: 118.1162, UDMax critical value**: 22.49				
WDMax statistic*: 152.0984, WDMax critical value**: 24.50				
Sequential F-statistic determined breaks:				5
Significant F-statistic largest breaks:				5
UDmax determined breaks:				2
WDmax determined breaks:				5
Estimated break dates:				
1: 3/09/2016				
2: 2016/3/07, 12/23/2019				
3: 2016/3/07, 8/15/2018, 12/23/2019				
4: 2016/3/07, 9/26/2018, 11/22/2019, 1/05/2021				
5: 2016/3/07, 4/10/2017, 6/26/2018, 11/22/2019, 01/05/2021				
Break test options:				
Bartlett kernel				
Prewhitening with AR(1)				
Newey–West automatic bandwidth and Lag lengths				
Different error distributions across breaks are allowed.				
Trimming = 0.15, Max. breaks = 5,				
*: Sig. level 0.01, **: Bai-Perron (2003) critical values				

Appendix B. Data and program

Daily price data and the year-end market capitalisation data for the constituents of the CSI New Energy Index were exported from Bloomberg. Due to the copyright, we should not provide the raw data. We provide the tickers of the constituents and the input data (e.g., CSAD, CSSD, etc.) for calculation as online supplementary materials. Equations and inputs are described in the Methodology section.

The program used for detection of static herding is EViews. Equations and input variables are described in Section 3.1. We provide the sample EViews implementations in online supplementary materials. We estimate OLS equations with HAC. The HAC settings are:

- Bartlett kernel,
- Prewhitening with AR(1),
- Newey–West automatic bandwidth and Lag lengths.

The program used for examining the time-varying herding is RStudio and *tvReg* (R-package). The manual and instruction are available at https://cran.r-project.org/web/packages/tvReg/tvReg.pdf. Input variables and specifications are described in details in Section 3.2. We provide the code in online supplementary materials.

Appendix C. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.eneco.2023.106526.

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