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Herding towards carbon neutrality: The role of investor attention

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Herding towards Carbon Neutrality: The Role of Investor Attention

Abstract

This paper explores the herding towards carbon neutrality in the Chinese stock market. We find that herding towards carbon neutrality does dynamically exist in the Chinese stock market. Specifically, herding is pronounced during the bear markets and market stress periods such as the post-COVID-19 period. There is a size effect for the herding behavior. Investor attention could significantly decrease the magnitude of herding. Our results hold in various robustness tests. This paper provides some important implications on the style investing, fads, and carbon neutrality.

Keywords: Herding; Carbon neutrality; Investor attention; Cross-sectional volatility

1. Introduction

With the growing concern over climate issues, green investments have captured significant investor attention because green investments are viewed by many investors as investments in the future. Driven by such a fad, investors tend to trade a set of related or similar stocks (Dreman, 1979; Friedman, 1984). These fads can further give rise to herding (Andrikopoulos et al., 2021). Such a trading behavior is also well-known for the style investing. Assets within the same style tend to be closely related and usually move in tandem (Barberis and Shleifer, 2003; Barberis et al., 2005). The categorization into styles or industries is tailored to meet investors' preferences for specific sectors. This implies that investors within the same style or industry might exhibit more homogeneous behaviors (Barber et al., 2009; Kumar and Lee, 2006). Such investors are more inclined to emulate others when making trading decisions on specific stocks. Consequently, style-investing can promote herding and herding is strongly observed in sectors (Choi and Sias, 2009; Froot and Teo, 2008; Jame and Tong, 2014). In this paper, we explore the herding behavior for carbon neutrality in the Chinese stock market, since climate concepts are highly hot in China and both Chinese individual and institutional investors prefer to trade on hot concept-stocks.

Existing studies propose some measures of herding. Specifically, Christie and Huang (1995) use the cross-sectional standard deviation of stock returns (CSSD) to measure the potential influence of herding on stock prices. Under herding conditions, individual returns tend to align with market returns, leading to a reduced level of dispersion. Chang et al. (2000) introduced the cross-sectional absolute deviation (CSAD) to study herding in emerging markets. To further account for the influence of idiosyncratic components, Hwang and Salmon (2004) proposed a model focusing on the cross-sectional variability of factor sensitivities, as opposed to direct stock returns. In our study, after substituting the market index with the Wind Carbon Neutral Index, we employ the model suggested by Hwang and Salmon (2004) to detect herding behavior directed towards carbon neutrality.

Our results reveal pronounced and consistent herding in the Chinese market. These findings align with previous research in both emerging (Demirer et al., 2010; Kallinterakis, 2007; Lu et al., 2022; Ren and Lucey, 2023) and developed markets (Chen, 2013; Hwang and Salmon, 2004).

Then we further explore the potential factors that affect the degree of the herding towards carbon neutrality in the Chinese stock market. Because herding is a signal of market inefficiency (e.g., Bikhchandani and Sharma, 2001), some variables that have significant impact on market efficiency are

likely to affect the herding behavior. For example, the enhanced investor attention can foster efficient price discovery, thereby boosting market efficiency (Vozlyublennaia, 2014). A buoyant market sentiment might inspire investors to mimic leading ones to optimize returns (Blasco et al., 2012), magnify irrational noise trading (Xue et al., 2023), and trigger herding. Moreover, many studies show that US crude oil prices and financial market indices notably influence stock returns in emerging markets (Arouri and Rault, 2012; Basher and Sadorsky, 2006; Hammoudeh and Choi, 2006). While fluctuations in crude oil prices are often interpreted as positive signals for speculation, herding is inherently linked to speculative activities (Balclar et al., 2017; Froot et al., 1992). This suggests that uncertainty in oil prices might also influence herding behavior. Economic Policy Uncertainty index proposed by Baker et al. (2016) also has the potential to affect herding because risk-averse investors often replicate their peers' trades to mitigate the heightened economic policy uncertainty (Cui et al., 2019).

After incorporating these control variables (investor attention, investor sentiment, oil price uncertainty, and economic policy uncertainty) into our models, we discover that only heightened investor attention has a discernible negative impact on herding intensity, corroborating Vozlyublennaia's (2014) findings.

We further explore the dynamics of the herding towards carbon neutrality. Specifically, we categorize periods into pre-COVID-19 and post-COVID-19 to analyze the intensity of herding during these market stress periods. Additionally, we trace the evolution of herding to explore its asymmetry between bull and bear markets. Empirical findings suggest that herding is notably more evident in the post-COVID-19 phase than in the pre-COVID-19 era. While this aligns with earlier conclusions drawn by Christie and Huang (1995), Chang et al. (2000), Demirer et al. (2010), and Gleason et al. (2004), it contrasts with the findings of Hwang and Salmon (2004). One potential explanation is the distinctive character of the COVID-19 crisis. Unlike events such as the Dot Com crash or the global financial crisis, which were primarily rooted in financial vulnerabilities, the COVID-19 crisis has its unique origins (Didier et al., 2021). The COVID-19 situation represents an unanticipated jolt to the financial markets. Confronted with such unforeseen shocks, investors tend to exhibit more uniform trading behaviors, thus amplifying herding. Furthermore, our research indicates a greater prevalence of herding during market declines, a trend that resonates with Lao and Singh (2011) and Yao et al. (2014). This phenomenon is likely driven by declining investor confidence and an increased inclination toward risk aversion in bear markets.

In several robustness tests, we consistently find evidence of herding when recalculating the cross-sectional variability of factor sensitivities using both the FF3 and FF5 Models. We also assess the potential influence of a stock's market capitalization on herding. Herding is more pronounced but less sustained in large stocks, while it's less pronounced but more enduring in small stocks. Given the higher information asymmetry associated with small firms (Hasbrouck, 1991), and the elevated levels of uncertainty surrounding their values that often lead to attracting fewer analysts as pointed out by Wermers (1999), institutional investors tend to gravitate towards large stocks for herd trading (Dahlquist and Robertsson, 2001; Li and Wang, 2010). They also tend to concentrate trades on specific stocks, leading to increased herding (Campbell et al., 1993; Harris and Raviv, 1993; He and Wang, 1995; Li et al., 2017). Furthermore, institutional investors in large stocks typically have access to a richer set of private information, allowing for a more accurate evaluation of a firm's value. This means they are apt to discontinue herding faster than retail investors when herding significantly deviates from the intrinsic value of stocks, making herding in large stocks less persistent compared to their smaller counterparts.

This paper contributes to the literature on herding behavior in two main ways. First, most of prior studies emphasized herding across the entire stock market (e.g., Chang et al., 2000; Chiang and Zheng, 2010; Demirer and Kutan, 2006), our study focuses on herding at the industry level, specifically focusing on the carbon neutrality sector in the Chinese stock market, which is deemed as a new fad. While numerous studies have investigated industry-level herding (e.g., Litimi et al., 2016; Ukpong et al., 2021), our unique approach utilizes the Carbon Neutral Index to typify the carbon neutrality industry, aligning it with the methodology introduced by Hwang and Salmon (2004). Our findings indicate the presence of potential herding towards this sector, as deduced from the cross-sectional dispersion of factor sensitivity. Moreover, we observe the dynamics and asymmetric nature of herding towards carbon neutrality, consistent with studies like Chang et al. (2000) and Tan et al. (2008).

Second, while existing literature posits that investor attention can influence stock returns (Barber and Odean, 2008; Da et al., 2011; Xiong et al., 2018), market volatility (Andrei and Hasler, 2015), and market efficiency (Hou et al., 2009; Storms et al., 2015), there exists a research gap regarding its relationship with herding behavior within the carbon neutrality industry. Our study incorporates investor attention among other variables, revealing that heightened investor attention can potentially diminish the intensity of herding behavior. Consequently, this paper enriches the discourse on the pivotal role of investor attention in the financial markets.

The remainder of this paper is organized as follows: Section 2 illustrates the literature review and proposes our hypotheses. Section 3 explains measurements of herding. Section 4 describes the data that will be used in this study. Section 5 reports the empirical results. Section 6 concludes the paper.

2. Literature review

2.1 Herding in the new fads

Herding in finance is a phenomenon that has attracted significant attention, and several theories have been proposed to explain its occurrence. Among the prevailing theories are those surrounding informational cascades, reputation-based herding, and compensation-based herding. Informational cascades occur when investors observe the decisions of their predecessors and, deeming them informative, replicate those decisions in their own actions (Banerjee, 1992; Bikhchandani et al., 1992). However, this theory may not always be applicable to financial markets, where prices immediately reflect the decisions of previous investors. Reputation-based herding suggests that analysts, particularly when uncertain about their own abilities or when their private information conflicts with public data, might choose to follow the decisions of other analysts to safeguard their reputation (Scharfstein and Stein, 1990; Trueman, 1994). Drawing from agency theory, Roll (1992) introduced compensation-based herding, asserting that if a manager's remuneration is tied to their performance, it could skew their incentives, resulting in an inefficient portfolio and subsequent herding. Beyond these theories, herding has also been associated with factors like social identity (Devenow and Welch, 1996), influence from media coverage and social networks (Shiller, 1995), market uncertainty (Avery and Zemsky, 1998), and prevailing fads (Friedman, 1984).

Empirical evidence from prior literature has delved into herding behaviors associated with new investment fads. Notably, the craze for dot com stocks before the dot com bubble burst garnered significant academic interest. For instance, Ofek and Richardson (2003) proposed a model wherein agents with heterogeneous beliefs, facing short sale restrictions, explain the volatility of internet stock prices. Singh (2013) further explored the role of institutional investors during this period, noting intense herding by these investors toward internet stocks during the height of the bubble, which is consistent with previous findings of Brunnermeier and Nagel (2004) and Griffin et al. (2011). More recently, as cryptocurrencies emerged as a new investment trend, the examination of herding behaviors in this market gained prominence. Bouri et al. (2019) identified variability in herding over time, correlating intensified herding with heightened uncertainty. Kallinterakis and Wang (2019) noted pronounced herding during up-markets, specifically on low-volatility,

high-volume days, and more so in smaller cryptocurrencies. Ballis and Drakos (2020) highlighted the irrational tendencies of crypto investors, emphasizing their propensity to mimic others without personal belief assessment. Jia et al. (2022) linked herding behaviors to extreme market sentiments, finding them to be more dominant during periods of dysphoria than euphoria. In recent years, with growing concerns over climate risks, green investments have emerged as a new trend, often perceived as investments in the future. Consequently, research on herding in the energy sector has gained traction. Although several studies reported no significant evidence of herding in energy sectors across various nations (Chang et al., 2020; Shen, 2018; Trück and Yu, 2016), Ren and Lucey (2023) unearthed strong indications of time-varying herding behaviors within China's renewable energy industry. Based on these findings, we present our first hypothesis:

Hypothesis 1: Herding towards carbon neutrality is evident in the Chinese stock market.

2.2 Influential factors on herding

Recent research indicates a clear association between investor attention and herding behavior (Mavruk, 2022). The link between investor attention and herding is bifurcated into two predominant strands. The first suggests a positive correlation between investor attention and herding behavior, implying that heightened investor attention amplifies herding. Notably, Hsieh et al. (2020) utilized the Google Search Volume Index as a metric for investor attention, establishing that heightened attention to specific companies correlated with increased herding among retail investors. This view was echoed by Wanidwaranan et al. (2022), who found in 21 international equity markets that retail investor attention, gauged via the Google Search Volume Index, bolstered herding tendencies. Conversely, the second strand of studies believes that increased investor attention could inhibit herding. For example, when Peltomäki and Vähämaa (2015) measured investor attention concerning the European debt crisis using the Google Search Volume Index of "euro crisis", they discovered that heightened attention to the Eurozone crisis diminished herding. This is attributed to the fact that increased attention facilitates information processing, promoting efficient price discovery. This perspective is reinforced by Vozlyublenniaia (2014), who posits that heightened investor attention augments market efficiency. Given the dominance of retail investors in the Chinese market and the observation that increased retail investor attention mitigates stock price crash risk (Wen et al., 2019), the latter viewpoint is more apt for our study.

Additionally, the importance of investor sentiment in the stock market cannot be understated. Scholars have probed the connection between sentiment and herding. Bikhchandani and Sharma (2001) bifurcate herding into sentiment-driven herding and fundamentals-driven herding. Blasco et al. (2012) elaborated that market sentiment significantly influences investors to engage in herding, especially during volatile times. This is because optimistic market sentiment encourages investors to emulate leading investors to maximize returns. In the realm of mutual funds, DeVault et al. (2019) and Hudson et al. (2020) identified a substantial, positive correlation between investor sentiment and mutual fund herding. Xue et al. (2023) rationalized that heightened investor sentiment could amplify irrational noise trading, prompting mutual funds to display herding tendencies, especially when faced with high-risk, limited arbitrage scenarios.

Exploring the nexus between oil prices and herding, Balçılar et al. (2017) observed that traders in the Gulf Cooperation Council (GCC) countries perceive speculative cues from the oil market as bullish signals, often adopting contrarian positions in their domestic markets. In other words, there's a direct positive correlation between speculation levels and anti-herding in GCC countries. Delving into the impact of economic policy uncertainty on herding in the cryptocurrency market, Bouri et al. (2019) posited that such uncertainties could accentuate herding tendencies. Cui et al. (2019) made a similar observation for closed-end funds, documenting increased herding during times of elevated economic policy uncertainty. One plausible reason is that investors frequently mimic their peers' trades to alleviate heightened uncertainty, driven by risk aversion. This increased similarity in trading actions can lead to herding behavior. Therefore, in light of these findings, we propose the following hypotheses:

Hypothesis 2a. Higher investor attention could decrease the magnitude of herding.

Hypothesis 2b. Higher investor sentiment could increase the magnitude of herding.

Hypothesis 2c. Higher oil price uncertainty could increase the magnitude of herding.

Hypothesis 2d. Higher economic policy uncertainty could increase the magnitude of herding.

2.3 Herding under different market conditions

While probing the asymmetric effects of herding in the Chinese stock market, Chiang et al. (2010) observed herding during both upward and downward market trends, corroborating the findings of Tan et al. (2008). This simultaneous herding during both bull and bear markets can be ascribed to the over-enthusiastic or over-reactive behaviors of Chinese investors. Specifically, those investing in Chinese A-shares tend to actively buy when the market is bullish and sell during downturns. Concurrently, other

studies have underscored a more pronounced herding effect during market upswings (Chiang and Zheng, 2010; Lee et al., 2013). This could be because investors, during bull markets, are more readily swayed by collective optimism and hence more inclined to follow the majority. Bull markets also tend to lure a larger contingent of retail investors and market novices, who might be more prone to succumbing to prevailing market sentiments, leading them to join the buying frenzy. Nevertheless, herding is also anticipated to be more conspicuous during market downturns (Lao and Singh, 2011; Yao et al., 2014), likely spurred by dwindling investor confidence and a heightened proclivity for risk aversion. Additionally, herding tendencies often become more palpable during periods of market stress (Christie and Huang, 1995; Chang et al., 2000; Demirer et al., 2010; Gleason et al., 2004), as investors might suppress personal beliefs in favor of the prevailing market consensus, especially during significant price fluctuations.

In summation, findings pertaining to asymmetric effects in previous studies are somewhat inconclusive and seem to hinge heavily on specific time frames analyzed. However, given that bull markets are typically shorter-lived, while bear markets persist longer in China—distinct from most developed markets—it paves the way for our subsequent hypotheses:

Hypothesis 3a. Herding intensifies during periods of market stress.

Hypothesis 3b. Herding is more pronounced during bear markets.

3. Measurement of herding

Following Hwang and Salmon (2004), to evaluate how herding biases the equilibrium risk-return relationship, our study first considers what would happen to the conventional CAPM. The CAPM in equilibrium is described as follows.

$$E_t(r_{it}) = \beta_{imt}E_t(r_{mt}) \quad (1)$$

where r_{it} and r_{mt} are the excess returns on asset i and the market at time t , respectively, β_{imt} is the systematic risk measure, and $E_t(\cdot)$ is the conditional expectation at time t .

Since our goal is to investigate herding towards carbon neutrality, the market needs to be replaced by the Carbon Neutral Index. Thus, a new CAPM can be described as follows.

$$E_t(r_{it}) = \beta_{ict}E_t(r_{ct}) \quad (2)$$

where r_{ct} is the excess return of the carbon neutral index at time t , β_{ict} is the systematic risk measure of the carbon neutral index at time t , and $E_t(\cdot)$ is the conditional expectation at time t . In equilibrium, given the view of $E_t(r_{ct})$, we only need β_{ict} to price an asset i .

Empirical evidence shows that β_{ict} is not a constant, on the contrary, it would change over time (Harvey, 1989; Ferson and Harvey, 1991; Ferson and Harvey, 1993; Ferson and Korajczyk, 1995). Our study assumes that the time-variation of β_{ict} can reflect changes in investor sentiment and firm fundamentals. Given that the fundamentals of most companies change slowly, the significant variation of β_{ict} could be attributed to behavioral anomalies such as herding.

Herding leads to mispricing since particular assets are bought or sold at the same time. When there is herding towards the Carbon Neutral Index, the following relationship exists.

$$\frac{E_t^b(r_{it})}{E_t(r_{ct})} = \beta_{ict}^b = \beta_{ict} - h_{ct}(\beta_{ict} - 1) \quad (3)$$

where $E_t^b(r_{it})$ and β_{ict}^b are the Carbon Neutral Index's biased short-run conditional expectation on the excess returns of asset i and its beta at time t , and h_{ct} is a latent herding parameter that changes over time, $h_{ct} \leq 1$.

When $h_{ct}=0$, $\beta_{ict}^b = \beta_{ict}$ there is no herding. When $h_{ct}=1$, $\beta_{ict}^b = 1$ there is perfect herding towards the carbon neutral asset portfolio in the sense that all the individual assets move in the same direction with the carbon neutral asset portfolio. When $0 < h_{ct} < 1$ herding exists and is determined by the magnitude of h_{ct} .

To calculate the level of herding, we use the stocks that trade normally in the Chinese A-share market. Since the cross-sectional mean of β_{ict}^b (or β_{ict}) is always 1, the standard deviation of β_{ict}^b is calculated as follows.

$$\begin{aligned} Std_c(\beta_{ict}^b) &= \sqrt{E_c((\beta_{ict} - h_{ct}(\beta_{ict} - 1) - 1)^2)} \\ &= \sqrt{E_c((\beta_{ict} - 1)^2)(1 - h_{ct})} \\ &= Std_c(\beta_{ict})(1 - h_{ct}) \end{aligned} \quad (4)$$

where $E_c(\cdot)$ and $Std_c(\cdot)$ represent the cross-sectional expectation and standard deviation, respectively. The first component is the cross-sectional standard deviation of the equilibrium betas and the second is a direct function of the herding parameter.

To extract h_{ct} from $Std_c(\beta_{ict}^b)$, first take the logarithms of Equation (4).

$$\log [Std_c(\beta_{ict}^b)] = \log [Std_c(\beta_{ict})] + \log (1 - h_{ct}) \quad (5)$$

After allowing $Std_c(\beta_{ict})$ to be stochastic, Equation (6) can be written as follows.

$$\log [Std_c(\beta_{ict}^b)] = \mu_c + v_{ct} \quad (6)$$

where $\mu_c = E[\log [Std_c(\beta_{ict})]]$, and $v_{ct} \sim iid(0, \sigma_{cv}^2)$, then Equation (7) is described as follows.

$$\log [\text{Std}_c (\beta_{ict}^b)] = \mu_c + H_{ct} + v_{ct} \quad (7)$$

where $H_{ct} = \log(1-h_{ct})$.

If herding, H_{ct} , is allowed to evolve and follow a dynamic process; for instance, if H_{ct} follows a mean zero AR(1) process, this forms Model 1.

$$\log [\text{Std}_c (\beta_{ict}^b)] = \mu_c + H_{ct} + v_{ct} \quad (8)$$

$$H_{ct} = \phi_c H_{ct-1} + \eta_{ct}$$

where $\eta_{ct} \sim iid(0, \sigma_{c\eta}^2)$ and $|\phi_c| \leq 1$.

This is now a standard state-space model similar to those used in stochastic volatility modeling which can be estimated using the Kalman filter. It is worth noting that a significant value of $\sigma_{c\eta}^2$ can therefore be interpreted as the existence of herding and a significant ϕ_c supports this particular autoregressive structure.

We also include control variables related to herding and carbon neutrality.

$$\log [\text{Std}_c (\beta_{ict}^b)] = \mu_c + H_{ct} + c_i X_{it} + v_{ct} \quad (9)$$

$$H_{ct} = \phi_c H_{ct-1} + \eta_{ct}$$

where X_{it} is the control variable i at time t .

When investor attention (*Attention*), investor sentiment (*Sentiment*), oil price uncertainty (*OPU*), and economic policy uncertainty (*EPU*) are singly introduced as the control variable X_{it} , we obtain Models 2, 3, 4, and 5, respectively. To explore the comprehensive influence of these four control variables (*Attention*, *Sentiment*, *OPU*, *EPU*), our study incorporates all of them into Equation (9), resulting in Model 6.

4. Data

4.1 Carbon neutral index

The Carbon Neutral Index, sourced from Wind, establishes its base date on 12 March 2018, starting at 1000 points. It comprises example stocks from the entire A-share market, adhering to specific criteria for stock selection. Firstly, a stock must either have been listed for a minimum of three months or maintain an average daily market capitalization ranking in the top 30, applicable even if the listing time is under 10 days. Secondly, it includes stocks that rank in the top 80% of all stocks on the stock exchange based on the average daily transaction amount over the past year. Thirdly, the index excludes all stocks under Special Treatment (ST), at Delisting Risk (*ST), those that are delisted, and those under long-term

suspension. Fourthly, it omits stocks with non-standard audit opinions, any under regulatory punishment, or investigation by the China Securities Regulatory Commission in the previous year. Finally, the index selects the top 50 stocks in market capitalization from companies associated with new energy, energy conservation, environmental protection, ultra-high voltage, and other related fields. The example stocks in the Carbon Neutral Index are adjusted regularly, with changes occurring on the next trading day following the second Friday of March, June, September, and December. Chen et al. (2004) suggest that the inclusion and exclusion of firms from an index can have asymmetric price effects. However, we contend that these temporal changes in the index's composition do not directly influence our assessment of herding levels, as our primary focus is on the general market tendency towards carbon neutrality. Therefore, in subsequent sections, we will present our empirical results without accounting for these temporal changes, concentrating solely on the behavior of the Carbon Neutral Index itself.

The Carbon Neutral Index, weighted by free-float market capitalization, is depicted alongside the Shanghai Stock Exchange Index in Fig. 1, which serves to represent the broader Chinese stock market. It is evident from the illustration that the Carbon Neutral Index has significantly outperformed the Shanghai Stock Exchange Index, indicating a strong investor preference for the constituent stocks of the Carbon Neutral Index in recent years.

(Please insert Fig. 1 about here)

4.2 Variables summary

We collect daily return data for all firms listed on both the Shanghai Stock Exchange and the Shenzhen Stock Exchange, spanning from April 1, 2018, to October 31, 2022, using the CSMAR financial database. It is crucial to document the number of stocks involved in our study as we aim to analyze the collective response of all stocks to the Carbon Neutral Index in the context of herding behavior. After removing stocks with fewer than 15 trading days per month, our dataset includes 3276 stocks in 2018, 3478 in 2019, 3675 in 2020, 4123 in 2021, and 4512 in 2022 (see Bhattacharya et al., 2018; Liu et al., 2019).¹ We obtain data for the Carbon Neutral Index and the 3-Month Shibor interest rate, which serves as the risk-free interest rate, from Wind. For robustness testing, we source FF3 and FF5 model data from CSMAR. Utilizing those daily data, we first calculate each stock's monthly beta. From these beta values, we determine

¹ Actually, the number of stocks per year is averaged by month since the number of stocks per month is different from each other and we would use monthly data to conduct our empirical research.

the cross-sectional standard deviation of beta for each month, subsequently calculating the log-cross-sectional standard deviation of beta.

Table 1 reports the descriptive statistics of the log-cross-sectional standard deviation of beta calculated by the equal-weighting scheme (LOG_{EW}), the log-cross-sectional standard deviation of beta calculated by the value-weighting scheme (LOG_{VW}), and four control variables, i.e., *Attention*, *Sentiment*, *OPU*, *EPU*. All the information related to the variables is listed in Appendix A.

Attention is about investor attention on carbon neutrality which is reflected by Baidu Index (Zhang et al., 2013). *Sentiment* is from CSMAR to measure investor sentiment across the A-share market. *OPU* comes from Choice database in Eastmoney showing the fluctuation of crude oil prices. *EPU* can be downloaded from the policy uncertainty website: www.policyuncertainty.com. For *Attention*, *Sentiment* and *EPU*, we first add one to the monthly data and then take the logarithm of the resulting values. Following this, we calculate the log-returns to obtain the final form. For *OPU*, it is reflected by oil market volatility (BenMabrouk and Litimi, 2018), so the daily data per month is used to calculate the standard deviation. As Table 1 reports, the median log-cross-sectional standard deviation of beta calculated by the equal-weighting scheme is -0.817 and the median log-cross-sectional standard deviation of beta calculated by the value-weighting scheme is -0.757. *Attention* ranges from -0.057 to 0.160, *Sentiment* is between -0.077 and 0.090, *OPU* is from 0.010 to 0.054 and *EPU* is from -0.118 to 0.139.

(Please insert Table 1 about here)

Table 2 reports the correlation between variables, with the upper right matrix displaying the Spearman correlation and the bottom left showing the Pearson correlation. The control variables exhibit a positive Spearman correlation ranging from 0.005 to 0.240, whereas variables LOG_{EW} and LOG_{VW} demonstrate a negative correlation with the control variables. In terms of Pearson correlation, the positive correlation among control variables persists, ranging from 0.138 to 0.354, which is stronger than the Spearman correlation. Additionally, variable LOG_{EW} maintains a negative correlation with the control variables.

Fig. 2 illustrates the monthly data of log-cross-sectional standard deviation and control variables. Notable abnormal fluctuations in variables LOG_{EW} and LOG_{VW} suggest the potential presence of herding. Additionally, the time trends of control variables may influence the volatility of LOG_{EW} and LOG_{VW} , potentially impacting herding behavior.

(Please insert Table 2 about here)

(Please insert Fig. 2 about here)

5. Empirical results

5.1 Herding towards carbon neutrality

We first examine herding under CAPM without control variables. The result is estimated by Equation (8) and presented in Model 1 of Panel A in Table 3. The estimate of $\sigma_{c\eta}^2$ is 0.038 with a significant t -statistic of 5.44, denoting herding is present (thus leading us to accept hypothesis 1). Our finding is consistent with that of Demirer et al. (2010), who used the same model proposed by Hwang and Salmon (2004) and found strong evidence of herding in all sectors in the Taiwanese market. Additionally, herding in the Chinese energy funds and renewable energy sector also confirms our findings (Lu et al., 2022; Ren and Lucey, 2023).

The estimate of Φ_c is 0.313 and the t -statistic is 2.04 in Model 1 of Panel A in Table 3 which indicates that herding is significantly persistent over the whole sample period. The estimate of σ_{cv}^2 is rather low and this contributes to the high proportion of herding. The proportion of herding in Model 1 of Panel A in Table 3 is 0.941 which suggests that herding towards carbon neutrality takes up 94.1% of the volatility in the whole market. The proportion is higher than values documented by Hwang and Salmon (2004) since the proportion of herding is 0.437 in the US market and 0.436 in the South Korean market. However, this proportion is closer to the value estimated by Kallinterakis (2007) in the Vietnamese market, where the proportion in the original herding measure is 0.802. It is worth noting that the proportion of herding can vary across different countries. One plausible explanation for these variations is that emerging markets tend to exhibit higher levels of herding compared to their developed counterparts (Voronkova and Bohl, 2005; Wermers, 1999).

Although the proportion of herding in Model 1 of Panel A is very high, it reflects little information and we further pay more attention to the relative change after incorporating control variables into Model 1. The results in Models 2-6 in Panel A of Table 3 are estimated by Equation (9) where *Attention*, *Sentiment*, *OPU*, and *EPU* are treated as control variables. Herding are still present and persistent in Models 2-4 and Model 6 as the t -statistics of $\sigma_{c\eta}^2$ are all larger than 5 and the t -statistics of Φ_c are higher than 1.67. Furthermore, as seen in Model 2 of Panel A, the estimated coefficient of *Attention* is -1.761 with a significant t -statistic of -3.07. The proportion of herding in Model 2 of Panel A is 0.875 and decreases

by 6.6% compared with 0.941 in Model 1 of Panel A. This suggests that higher investor attention does significantly decrease the magnitude of herding. This finding is robust after adding all control variables into Equation (9) and estimating Model 6 in Panel A, thus supporting hypothesis 2a. However, after adding *Sentiment*, *OPU*, and *EPU* as the single control variable and estimating Models 3-5, the coefficients of those variables are statistically insignificant which mean that herding couldn't be enhanced or dampened by higher investor sentiment, oil price uncertainty and economic policy uncertainty in our models. Then, hypotheses 2b-2d are negated.

After we replicate the empirical results using the value-weighting scheme, Panel B of Table 3 is obtained. Compared with results in Panel A of Table 3, the significance levels of $\sigma_{c\eta}^2$ and control variables stay the same. However, the significance levels of Φ_c in Models 1-4 of Panel B decrease which denotes that the persistence of herding varies with weighted schemes. This observation is also consistent with the findings of Chen (2013), who employed a state space model to estimate herding across global markets. Chen (2013) reports that the estimate of herding persistence in China is 0.158, significant at the 10% level, and lower than that of most developed and emerging markets. We will provide a more in-depth analysis of the persistence of herding in Section 5.4.2.

(Please insert Table 3 about here)

5.2 Herding pre and post-COVID-19

As COVID-19 has affected almost all countries in the past few years, it can be identified as a crisis. Previous literature on crises, such as financial crises, illustrates that herding increases before the outbreak of a crisis and begins to decline once the crisis actually erupts (Hwang and Salmon, 2004). We then split the sample period into pre-COVID-19 and post-COVID-19 periods and estimate the empirical results to test hypothesis 3a. The pre-COVID-19 period spans from April 2018 to January 2020, while the post-COVID-19 period covers February 2020 to October 2022. The empirical results are reported in Table 4.

Table 4 presents the results for both the pre-COVID-19 and post-COVID-19 periods. Panels A and B detail the results for the pre-COVID-19 period, while Panels C and D focus on the post-COVID-19 period. From Panels A-D, it is evident that herding is present, as almost all estimates of $\sigma_{c\eta}^2$ are statistically significant. However, notable differences emerge. Specifically, herding appears to be more pronounced in the post-COVID-19 period compared to the pre-COVID-19 phase (thus leading us

to accept hypothesis 3a). For instance, the proportion of herding in Model 1 of Panel C stands at 0.977, which is an increase of 11.3% from the 0.864 value in Model 1 of Panel A. Other models exhibit a similar trend, which is at odds with findings from previous research. We argue that the nature of the COVID-19 crisis sets it apart from other crises, such as the Dot Com crash and the global financial crisis. The latter two were primarily driven by financial vulnerabilities (Didier et al., 2021). They were characterized by growing bubbles that inflated prior to their outbreaks, and herding behavior can be partly attributed to these bubbles. In contrast, the COVID-19 crisis was an unforeseen shock to the financial markets. When faced with an unexpected shock, investors tend to trade more uniformly, thereby intensifying herding.

Further, the estimates of Φ_c in both Panel C and Panel D of Table 4 are statistically insignificant. In contrast, nearly all estimates of Φ_c in Panel A and Panel B are statistically significant, either at the 1% or 5% level. This suggests a decrease in the persistence of herding during the COVID-19 crisis. We also observe differences in the coefficients of the control variables between the pre and post-COVID-19 periods. Specifically, the coefficients of *Attention* in Model 2 of both Panel C and Panel D become statistically significant, with t -statistics of -3.44 and -4.45, respectively. In Panel A, the proportion of herding in Model 2 is 1.5% lower than that in Model 1. Conversely, in Panel C, the proportion of herding in Model 2 is 10.3% lower than in Model 1. These findings suggest that investor attention began to mitigate herding during the post-COVID-19 period. Additionally, the coefficients of *Sentiment* in Model 3 of both Panel C and Panel D are also statistically significant, with t -statistics of -2.18 and -2.03, respectively. However, we contend that investor sentiment doesn't genuinely influence herding, as the effects of *Sentiment* disappear in Model 6 of both Panel C and Panel D.

(Please insert Table 4 about here)

5.3 The evolution of herding

To examine the trend of herding towards carbon neutrality in the Chinese stock market and to assess hypothesis 3b, we refer to Fig. 3, formulated using parameter h_{ct} ($h_{ct} = 1 - \exp(H_{ct})$). A value of $h_{ct} > 0$ indicates the occurrence of herding, while $h_{ct} < 0$ represents adverse herding. It's essential to understand that the manifestation of herding inevitably suggests the presence of adverse herding, given the inherent need for systematic adjustments towards the CAPM equilibrium to rectify any mispricings (Hwang and Salmon, 2004).

Fig. 3 distinctly illustrates that instances of adverse herding surpass those of positive herding, as evidenced by h_{ct} descending to -0.5 twice without ever reaching 0.5. We hypothesize this trend to be a reflection of the distinct dynamics of the Chinese stock market. As mentioned earlier, investors may resort to herding due to imitative behaviors. The Chinese market, however, is characterized by ephemeral bull phases and more prolonged bearish cycles, with retail investors being a significant presence. During extended bear markets, these investors, influenced by extraneous factors, might diverge from firm fundamentals, leading to a magnified pessimistic view of the market. Such circumstances could amplify the incidence of adverse herding.

In the absence of any herding behavior, h_{ct} would consistently hover around zero. Substantial deviations from this baseline suggest potential herding patterns. Utilizing the 95% confidence intervals, we identify periods where h_{ct} deviates significantly from zero, marking the herding episodes. Upon inspecting Panel A and Panel B of Fig. 3, we observe that while the upper 95% confidence limit touches 0.5 on four occasions, its lower counterpart reaches -1 just as many times. We demarcate herding phases based on these limits: the onset is marked by the lower limit reaching -1, and its cessation by the upper limit hitting 0.5. As an illustration, a noteworthy herding phase initiated in June 2018 when the lower 95% confidence limit first descended to -1. The trajectory of h_{ct} inclined in the subsequent months until the upper limit met 0.5 in October 2018, designating the end of this herding episode. Following this methodology, we delineate four significant herding periods within our study's timeframe: June 2018 to October 2018, October 2019 to March 2020, June 2020 to July 2020, and February 2022 to March 2022. These phases are intricately associated with the performance metrics of the Carbon Neutral Index and the overarching A-share market.

The first period spans from June 2018 to October 2018. During this time, the Chinese stock market saw a decline throughout the year, largely attributed to the trade war. As a result, the market in this period is characterized as bearish. Following this, the second period stretches from October 2019 to March 2020. This interval coincided with the outbreak of COVID-19, thus it is aptly termed as the market stress period. Subsequently, in response to the pandemic, various countries, including China, rolled out expansive fiscal and monetary policies to invigorate the economy. Consequently, the third period, ranging from June 2020 to July 2020, witnessed a bullish trend in the Chinese stock market as asset prices surged. However, by 2022, the global inflation rates became alarmingly high, prompting governments to adopt more stringent fiscal and monetary measures. This shift paved the way for a

bearish market, marking the fourth period. In a broader perspective, it is evident that herding is more prevalent during bear markets, which corroborates hypothesis 3b.

(Please insert Fig. 3 about here)

5.4 Robustness tests

5.4.1 Alternative measurement of beta

As mentioned above, we calculate β_{ict}^b using CAPM to obtain empirical results and identify the presence of herding. The FF3 Model and FF5 Model are also frequently used in conjunction with CAPM. Consequently, we calculate β_{ict}^b using both the FF3 and FF5 Models and replicate our tests using the state space model to verify the robustness of our findings.

Table 5 presents empirical results derived from the FF3 Model and FF5 Model. In Table 5, Panels A and B estimate β_{ict}^b using the FF3 Model with equal-weighting and value-weighting schemes, respectively. Similarly, Panels C and D estimate β_{ict}^b under the FF5 Model with the same respective weighting schemes. In comparison to Table 3, most estimates of $\sigma_{c\eta}^2$ in Table 5 are statistically significant, underscoring the consistent presence of herding. Notably, the proportion of herding in Model 1 of Panel A in Table 5 is 0.979, marking an increase of 3.8% when compared to Model 1 of Panel A in Table 3. Other models show a comparable trend, suggesting that herding is not only evident but also amplified under the FF3 and FF5 Models. Regarding control variables, the coefficients of *Attention* in Model 2 across Panels A-D in Table 5 are smaller than those in Table 3. For example, the coefficient of *Attention* in Model 2 of Panel B in Table 3 stands at -1.218 (with a t -statistic of -3.43), whereas in Table 5, the coefficients for the same model in Panels B and D are -1.987 and -1.959, with t -statistics of -4.17 and -3.16, respectively. In Table 3's Panel B, the proportion of herding in Model 2 is 3.8% less than in Model 1. This gap widens in Table 5's Panel B to 7.4% and in Panel D to 5.1%. These findings suggest that under the FF3 and FF5 Models, investor attention plays a more pronounced role in influencing herding. Additionally, the significance of *Sentiment* is heightened in Model 3 of Table 5 compared to its counterpart in Table 3. Moreover, evidence suggests a decrease in the persistence of herding as the estimates of Φ_c in Table 5, particularly in Panels A, B, and D, are statistically insignificant.

(Please insert Table 5 about here)

Given the significant presence of herding, our study endeavors to analyze the temporal evolution of herding within both the FF3 Model and the FF5 Model. Fig. 4 and Fig. 5 delineate herding patterns

within these models, respectively. In both figures, Panel A represents the log-cross-sectional standard deviation of beta as calculated by the equal-weighting scheme, while Panel B denotes the value-weighting scheme. A closer examination of Fig. 4 and Fig. 5 reveals that the trajectories of h_{ct} slightly deviate from what's depicted in Fig. 3. However, as previously mentioned, any deviation from zero indicates herding. This assertion further supports the patterns observed in the FF3 and FF5 models. The slight difference between Fig. 3 and Figs. 4-5 can be attributed to the reduced persistence of herding, as most of the estimates of Φ_c are statistically insignificant in Table 5. Notably, the fluctuations in h_{ct} remain consistent across the specified four periods: June 2018 to October 2018, October 2019 to March 2020, June 2020 to July 2020, and February 2022 to March 2022. Based on these observations, we contend that herding tendencies during these intervals are not merely robust but are especially evident during bear markets.

(Please insert Fig. 4 about here)

(Please insert Fig. 5 about here)

5.4.2 Size effect in herding

From the above, we can infer that results derived from an equal-weighting scheme differ slightly from those using a value-weighting scheme. Besides, since the Carbon Neutral Index is a blue-chip index of green-related stocks, it is essential to investigate whether stocks with different market capitalization herding towards carbon neutrality differ. To address this query, we equally categorize stocks into small, medium, and large groups on a monthly basis, replicate the state space model's estimates, and present the results in Table 6.

In contrast to Panels A-D in Table 6, the estimates of $\sigma_{c\eta}^2$ in Panels E and F are universally statistically significant. Moreover, the herding proportion in nearly all models from Panels E and F is greater than their counterparts in Panels A-D. For example, the herding proportion in Model 2 of Panel E stands at 0.890, surpassing the 0.844 in Model 2 of Panel C and 0.847 in Model 2 of Panel A.

The results in Table 6 suggest that large-cap stocks exhibit stronger herding tendencies. This contradicts previous findings that posited herding to be more pronounced in smaller stocks than in larger ones (Lakonishok et al., 1992; Sias, 2004). One possible explanation is that large-cap stocks primarily consist of blue-chip stocks, which aligns with the composition of the Carbon Neutral Index. Given that assets with similar characteristics tend to move in unison, it's not surprising to observe a more pronounced herding

effect in large-cap stocks. However, since herding behavior is also evident in medium and small-cap stocks, an alternative explanation could be the distinct distribution of investors between small-cap and large-cap stocks. Given that smaller firms are characterized by greater information asymmetry (Hasbrouck, 1991) and face higher uncertainty, they tend to attract fewer analysts (Wermers, 1999). As a result, institutional investors are more prone to engage in herd-trading with large stocks, regardless of the market's maturity level, be it developed or emerging (Dahlquist and Robertsson, 2001; Li and Wang, 2010). The heightened presence of institutional investors in larger stocks leads to more pronounced herding. This is because institutional investors, being more homogeneous, often concentrate their trades on specific stocks (Campbell et al., 1993; Harris and Raviv, 1993; He and Wang, 1995; Li et al., 2017).

We also observe that the persistence of herding is stronger in small and medium stocks compared to large stocks. The overall significance level of Φ_c in Panels A-D is higher than that in Panels E-F. For instance, the estimate of Φ_c for Model 2 in Panel E of Table 6 stands at 0.289, with a t -statistic of 1.69. In contrast, the estimates of Φ_c for Model 2 in Panels A and C are 0.417 and 0.411, with t -statistics of 3.73 and 2.81, respectively. This finding suggests that while institutional investors exhibit stronger herding in large-cap stocks, they possess more private information to evaluate firms' values. When herding deviates significantly from the intrinsic value of stocks, institutional investors are likely to halt such behavior swiftly. Thus, while herding might be more pronounced in large-cap stocks, its persistence is shorter. Conversely, herding is less intense in small-cap and medium-cap stocks but tends to last longer.

(Please insert Table 6 about here)

6. Conclusions

Using stock and Carbon Neutral Index data from the Chinese stock market, our study employs the method proposed by Hwang and Salmon (2004) to detect herding towards carbon neutrality. We find evidence of such herding in the Chinese stock market, particularly during bear markets, indicating asymmetry consistent with previous research (Chang et al., 2000; Tan et al., 2008). Interestingly, we also observe herding during market stress periods, such as the COVID-19 pandemic, a finding that diverges from Hwang and Salmon (2004). Moreover, our results suggest that increased investor attention, as proxied by the Baidu Index, can mitigate herding. Our findings are robust to alternative measurement of market

beta and various subsamples (e.g., small/medium/large firms). Results provide implications for herding in the new fads such as carbon neutrality.

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Table 1. Summary statistics

This table reports the median, 25% quartile, 75% quartile, minimums (Min), maximums (Max), standard deviation (Std), skewness (Skew), kurtosis (Kurt.), of the two dependent variables and the four control variables. The dependent variables include the following: the log-cross-sectional standard deviation of beta calculated by the equal-weighting scheme (LOG_{EW}) and the log-cross-sectional standard deviation of beta calculated by the value-weighting scheme (LOG_{VW}). The control variables include the following: *Attention*, *Sentiment*, *OPU*, and *EPU*. The sample period is from April 2018 to October 2022.

	Median	25% Quartile	75% Quartile	Min	Max	Std	Skew	Kurt	Period
<i>LOG_{EW}</i>	-0.817	-0.994	-0.673	-1.239	-0.383	0.207	-0.058	2.398	2018/04/01-2022/10/31
<i>LOG_{VW}</i>	-0.757	-0.911	-0.674	-1.224	-0.393	0.178	0.044	2.985	2018/04/01-2022/10/31
<i>Attention</i>	-0.002	-0.011	0.013	-0.057	0.160	0.038	1.984	8.371	2018/04/01-2022/10/31
<i>Sentiment</i>	-0.007	-0.029	0.019	-0.077	0.090	0.037	0.459	3.084	2018/04/01-2022/10/31
<i>OPU</i>	0.022	0.016	0.030	0.010	0.054	0.010	1.198	4.790	2018/04/01-2022/10/31
<i>EPU</i>	-0.008	-0.036	0.027	-0.118	0.139	0.055	0.324	2.860	2018/04/01-2022/10/31

Table 2. Correlation matrix

This table reports the correlations among the variables measured by the monthly frequency and those variables are the log-cross-sectional standard deviation of beta calculated by the equal-weighting scheme (LOG_{EW}), the log-cross-sectional standard deviation of beta calculated by the value-weighting scheme (LOG_{VW}), *Attention*, *Sentiment*, *OPU* and *EPU*. The upper right of the matrix represents the Spearman correlation and the bottom left of the matrix represents the Pearson correlation. The sample period is from April 2018 to October 2022.

	LOG_{EW}	LOG_{VW}	<i>Attention</i>	<i>Sentiment</i>	<i>OPU</i>	<i>EPU</i>
LOG_{EW}	1	0.825	-0.308	-0.166	-0.202	-0.095
LOG_{VW}	0.847	1	-0.291	-0.181	-0.027	-0.175
<i>Attention</i>	-0.351	-0.260	1	0.240	0.154	0.187
<i>Sentiment</i>	-0.214	-0.202	0.354	1	0.005	0.114
<i>OPU</i>	-0.228	-0.108	0.217	0.138	1	0.032
<i>EPU</i>	-0.125	-0.194	0.174	0.206	0.165	1

Table 3. Estimates of herding in the A-share market

This table reports empirical results from Model 1 to Model 6 where the beta is calculated in the CAPM. In Panel A, the log-cross-sectional standard deviation of beta is calculated using the equal-weighting scheme, while in Panel B, it is calculated using the value-weighting scheme. Model 1 is a standard state space model and is described as follows:

$$\log [\text{Std}_c (\beta_{ict}^b)] = \mu_c + H_{ct} + v_{ct}, \quad H_{ct} = \phi_c H_{ct-1} + \eta_{ct}$$

Where the first equation is an observation equation and the second is a state equation, $\log [\text{Std}_c (\beta_{ict}^b)]$ is the observation data and need to be calculated by stock data and the Carbon Neutral Index data, $\mu_c = E[\log[\text{Std}_c(\beta_{ict})]]$, $H_{ct} = \log(1-h_{ct})$ and h_{ct} is the herding parameter whose results are unobserved and can only be predicted in the state space model, $v_{ct} \sim iid(0, \sigma_{cv}^2)$, $\eta_{ct} \sim iid(0, \sigma_{c\eta}^2)$ and $|\phi_c| \leq 1$. A significant $\sigma_{c\eta}^2$ means the herding behavior exists. Model 2 to Model 5 add *Attention*, *Sentiment*, *OPU*, and *EPU* in the base of Model 1, respectively. Model 6 takes all of the control variables into consideration. $\sigma_{c\eta}$ is the measure of herding and the standard deviation of $\log [\text{Std}_c (\beta_{ict}^b)]$ (we use σ_c to represent it) is the volatility of the whole market. The proportion of herding is $\sigma_{c\eta}/\sigma_c$ which means that herding can explain how much of the total variability in $\log [\text{Std}_c (\beta_{ict}^b)]$. *t* statistics are in parentheses. The standard errors are robust. *, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively. The sample period is from April 2018 to October 2022.

	Panel A: CAPM Equal-Weighted						Panel B: CAPM Value-Weighted					
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
μ	-0.839*** (-21.93)	-0.831** (-23.31)	-0.842*** (-21.81)	-0.742*** (-9.01)	-0.839*** (-21.88)	-0.788*** (-9.49)	-0.777*** (-26.58)	-0.771*** (-26.59)	-0.779*** (-26.16)	-0.731*** (-9.90)	-0.777*** (-27.07)	-0.770*** (-11.00)
Φ_c	0.313** (2.04)	0.332** (2.15)	0.339** (2.29)	0.281* (1.67)	0.331 (0.66)	0.313* (1.86)	0.215 (1.52)	0.240* (1.76)	0.249* (1.96)	0.210 (1.44)	0.213 (1.54)	0.241* (1.84)
σ_{cv}^2	0.000 (.)	0.000 (.)	0.000 (.)	0.000 (.)	0.002 (0.05)	0.000 (.)	0.000 (.)	0.000 (.)	0.000 (.)	0.000 (.)	0.000 (.)	0.000 (.)
$\sigma_{c\eta}^2$	0.038*** (5.44)	0.033*** (5.69)	0.035*** (6.05)	0.037*** (5.23)	0.035 (0.57)	0.032*** (5.76)	0.029*** (5.38)	0.027*** (5.01)	0.028*** (5.36)	0.029*** (5.35)	0.028*** (5.35)	0.026*** (5.06)
<i>Attention</i>		-1.761*** (-3.07)				-1.452** (-2.41)		-1.218*** (-3.43)				-0.910** (-2.02)
<i>Sentiment</i>			-1.221 (-1.59)			-0.449 (-0.56)			-1.046* (-1.73)			-0.492 (-0.73)
<i>OPU</i>				-4.177 (-1.20)		-1.924 (-0.57)				-1.949 (-0.63)		-0.173 (-0.06)
<i>EPU</i>					-0.371 (-0.72)	-0.088 (-0.22)					-0.549 (-1.62)	-0.355 (-1.07)
Proportion of herding	0.941	0.875	0.910	0.926	0.900	0.866	0.967	0.929	0.941	0.962	0.949	0.913
Log likelihood	11.907	15.907	13.719	12.793	12.291	16.439	18.833	21.066	20.398	19.098	19.855	22.012
Observations	55	55	55	55	55	55	55	55	55	55	55	55

Table 4. Estimates of herding pre and post-COVID-19

This table reports empirical results from Model 1 to Model 6 where the beta is calculated in the CAPM. The sample period is split into pre-COVID-19 and post-COVID-19 periods. The pre-COVID-19 period spans from April 2018 to January 2020, while the post-COVID-19 period covers February 2020 to October 2022. In Panel A and Panel C, the log-cross-sectional standard deviation of beta is calculated using the equal-weighting scheme, while in Panel B and Panel D, it is calculated using the value-weighting scheme. Model 1 is a standard state space model and is described as follows:

$$\log [\text{Std}_c (\beta_{ict}^b)] = \mu_c + H_{ct} + v_{ct}, \quad H_{ct} = \phi_c H_{ct-1} + \eta_{ct}$$

Where the first equation is an observation equation and the second is a state equation, $\log [\text{Std}_c (\beta_{ict}^b)]$ is the observation data and need to be calculated by stock data and the Carbon Neutral Index data, $\mu_c = E[\log[\text{Std}_c(\beta_{ict})]]$, $H_{ct} = \log(1-h_{ct})$ and h_{ct} is the herding parameter whose results are unobserved and can only be predicted in the state space model, $v_{ct} \sim iid(0, \sigma_{cv}^2)$, $\eta_{ct} \sim iid(0, \sigma_{c\eta}^2)$ and $|\phi_c| \leq 1$. A significant $\sigma_{c\eta}^2$ means the herding behavior exists. Model 2 to Model 5 add *Attention*, *Sentiment*, *OPU*, and *EPU* in the base of Model 1, respectively. Model 6 takes all of the control variables into consideration. $\sigma_{c\eta}$ is the measure of herding and the standard deviation of $\log [\text{Std}_c (\beta_{ict}^b)]$ (we use σ_c to represent it) is the volatility of the whole market. The proportion of herding is $\sigma_{c\eta}/\sigma_c$ which means that herding can explain how much of the total variability in $\log [\text{Std}_c (\beta_{ict}^b)]$. *t* statistics are in parentheses. The standard errors are robust. *, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively. The sample period is from April 2018 to October 2022.

2018.04-2020.01	Panel A: CAPM Equal-Weighted						Panel B: CAPM Value-Weighted					
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
μ	-0.743*** (-11.50)	-0.740** (-11.68)	-0.759*** (-7.32)	-0.733*** (-6.56)	-0.743*** (-11.39)	-0.771*** (-5.04)	-0.760*** (-13.46)	-0.753*** (-12.07)	-0.759*** (-13.60)	-0.803*** (-6.04)	-0.761*** (-13.73)	-0.786*** (-6.17)
ϕ_c	0.461*** (2.62)	0.482** (2.32)	0.622*** (2.92)	0.571*** (2.87)	0.470*** (2.75)	0.515 (1.31)	0.363** (2.38)	0.435** (2.26)	0.368** (2.33)	0.363** (2.54)	0.352** (2.51)	0.459** (2.51)
σ_{cv}^2	0.000 (.)	0.000 (.)	0.000 (.)	0.000 (.)	0.000 (.)	0.002 (0.07)	0.000 (.)	0.000 (.)	0.000 (.)	0.000 (.)	0.000 (.)	0.000 (.)
$\sigma_{c\eta}^2$	0.030*** (3.21)	0.029*** (3.25)	0.042 (1.59)	0.045 (1.37)	0.030*** (3.22)	0.026 (0.70)	0.030*** (3.09)	0.028*** (3.33)	0.030*** (3.07)	0.030*** (2.94)	0.030*** (3.05)	0.027*** (3.24)
<i>Attention</i>		0.408 (0.41)				-0.521 (-0.39)		1.444 (1.32)				2.324 (1.40)
<i>Sentiment</i>			0.431 (0.56)			1.281 (1.05)			0.290 (0.46)			-0.620 (-0.53)
<i>OPU</i>				-1.366 (-0.18)		1.886 (0.18)				2.459 (0.35)		2.038 (0.30)
<i>EPU</i>					0.103 (0.30)	-0.007 (-0.01)					-0.231 (-0.64)	-0.368 (-0.85)
Proportion of herding	0.864	0.849	1.022	1.058	0.864	0.804	0.907	0.876	0.907	0.907	0.907	0.861

Log likelihood	7.372	7.420	6.730	6.309	7.394	7.864	7.338	7.953	7.372	7.393	7.438	8.497
Observations	22	22	22	22	22	22	22	22	22	22	22	22
2020.02-2022.10	Panel C: CAPM Equal-Weighted						Panel D: CAPM Value-Weighted					
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
μ	-0.900*** (-25.63)	-0.882*** (-24.50)	-0.903*** (-24.58)	-0.858*** (-7.67)	-0.900*** (-24.89)	-0.981*** (-9.33)	-0.788*** (-24.65)	-0.773*** (-23.20)	-0.792*** (-22.94)	-0.720*** (-8.28)	-0.788*** (-24.40)	-0.830*** (-6.21)
Φ_c	0.088 (0.36)	0.221 (0.86)	0.206 (1.02)	0.093 (0.37)	0.128 (0.46)	0.306 (1.13)	0.103 (0.45)	0.229 (0.94)	0.217 (1.18)	0.093 (0.40)	0.132 (0.52)	0.665** (2.15)
σ_{cv}^2	0.000 (.)	0.000 (.)	0.000 (.)	0.000 (.)	0.000 (.)	0.000 (.)	0.000 (.)	0.000 (.)	0.000 (.)	0.000 (.)	0.000 (.)	0.000 (.)
σ_{cn}^2	0.035*** (4.15)	0.028*** (4.06)	0.030*** (3.47)	0.035*** (4.05)	0.034*** (4.20)	0.025*** (4.03)	0.028*** (4.82)	0.022*** (4.55)	0.024*** (4.15)	0.027*** (4.55)	0.026*** (4.70)	0.031** (2.04)
<i>Attention</i>		-1.939*** (-3.44)				-1.644*** (-2.61)		-1.737*** (-4.45)				-1.363** (-2.52)
<i>Sentiment</i>			-1.813** (-2.18)			-1.215 (-1.26)			-1.461** (-2.03)			-0.884 (-1.25)
<i>OPU</i>				-1.528 (-0.37)		3.405 (0.88)				-2.476 (-0.74)		0.985 (0.25)
<i>EPU</i>					-0.595 (-0.79)	-0.538 (-0.82)					-0.746 (-1.32)	-0.567 (-1.21)
Proportion of herding	0.977	0.874	0.905	0.977	0.963	0.826	0.983	0.872	0.910	0.966	0.947	1.035
Log likelihood	8.369	11.995	11.141	8.463	8.821	14.168	12.285	16.064	14.534	12.601	13.242	14.972
Observations	33	33	33	33	33	33	33	33	33	33	33	33

Table 5. Estimates of herding under FF3 and FF5 Models

This table reports empirical results from Model 1 to Model 6 where the beta is calculated in the Fama-French Three Factor Model and Fama-French Five Factor Model. In Panel A and Panel C, the log-cross-sectional standard deviation of beta is calculated using the equal-weighting scheme, while in Panel B and Panel D, it is calculated using the value-weighting scheme. Model 1 is a standard state space model and is described as follows:

$$\log [\text{Std}_c (\beta_{ict}^b)] = \mu_c + H_{ct} + v_{ct}, \quad H_{ct} = \phi_c H_{ct-1} + \eta_{ct}$$

Where the first equation is an observation equation and the second is a state equation, $\log [\text{Std}_c (\beta_{ict}^b)]$ is the observation data and need to be calculated by stock data and the Carbon Neutral Index data, $\mu_c = E[\log[\text{Std}_c(\beta_{ict})]]$, $H_{ct} = \log(1-h_{ct})$ and h_{ct} is the herding parameter whose results are unobserved and can only be predicted in the state space model, $v_{ct} \sim iid(0, \sigma_{cv}^2)$, $\eta_{ct} \sim iid(0, \sigma_{c\eta}^2)$ and $|\phi_c| \leq 1$. A significant $\sigma_{c\eta}^2$ means the herding behavior exists. Model 2 to Model 5 add *Attention*, *Sentiment*, *OPU*, and *EPU* in the base of Model 1, respectively. Model 6 takes all of the control variables into consideration. $\sigma_{c\eta}$ is the measure of herding and the standard deviation of $\log [\text{Std}_c (\beta_{ict}^b)]$ (we use σ_c to represent it) is the volatility of the whole market. The proportion of herding is $\sigma_{c\eta}/\sigma_c$ which means that herding can explain how much of the total variability in $\log [\text{Std}_c (\beta_{ict}^b)]$. *t* statistics are in parentheses. The standard errors are robust. *, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively. The sample period is from April 2018 to October 2022.

	Panel A: FF3 Equal-Weighted						Panel B: FF3 Value-Weighted					
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
μ	-0.664*** (-20.16)	-0.655*** (-20.15)	-0.667*** (-20.09)	-0.616*** (-8.37)	-0.664*** (-20.20)	-0.674*** (-8.52)	-0.688*** (-23.53)	-0.679*** (-21.44)	-0.691*** (-22.66)	-0.666*** (-9.59)	-0.688*** (-23.91)	-0.729*** (-10.41)
ϕ_c	0.153 (0.99)	0.213 (1.42)	0.192 (1.34)	0.137 (0.88)	0.159 (1.03)	0.219 (1.41)	0.100 (0.68)	0.232* (1.67)	0.166 (1.34)	0.096 (0.65)	0.098 (0.24)	0.248* (1.85)
σ_{cv}^2	0.000 (.)	0.000 (.)	0.000 (.)	0.000 (.)	0.000 (.)	0.000 (.)	0.000 (.)	0.000 (.)	0.000 (.)	0.000 (.)	0.000 (0.00)	0.000 (.)
$\sigma_{c\eta}^2$	0.042*** (5.12)	0.037*** (5.24)	0.039*** (5.48)	0.042*** (4.98)	0.042*** (5.02)	0.036*** (5.50)	0.038*** (5.44)	0.032*** (4.98)	0.035*** (5.12)	0.038*** (5.42)	0.037 (0.26)	0.031*** (5.04)
<i>Attention</i>		-1.840*** (-3.64)				-1.445** (-2.40)		-1.987*** (-4.17)				-1.707*** (-2.67)
<i>Sentiment</i>			-1.591* (-1.88)			-0.925 (-0.96)			-1.502** (-2.05)			-0.762 (-0.92)
<i>OPU</i>				-2.031 (-0.66)		0.667 (0.21)				-0.950 (-0.31)		2.020 (0.72)
<i>EPU</i>					-0.472 (-1.00)	-0.172 (-0.37)					-0.585 (-1.38)	-0.282 (-0.74)
Proportion of herding	0.979	0.919	0.936	0.976	0.970	0.902	0.986	0.912	0.945	0.985	0.971	0.892
Log likelihood	8.822	12.305	11.281	9.026	9.316	13.256	12.056	16.362	14.386	12.109	12.870	17.513
Observations	55	55	55	55	55	55	55	55	55	55	55	55

	Panel C: FF5 Equal-Weighted						Panel D: FF5 Value-Weighted					
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
μ	-0.567*** (-10.72)	-0.557*** (-13.75)	-0.572*** (-14.45)	-0.479*** (-6.66)	-0.568*** (-10.65)	-0.561*** (-6.59)	-0.613*** (-22.11)	-0.604*** (-20.22)	-0.617*** (-21.17)	-0.574*** (-10.32)	-0.587*** (-16.52)	-0.631*** (-10.67)
Φ_c	0.884*** (6.67)	0.242** (1.97)	0.234** (2.34)	0.117 (0.93)	0.876*** (5.76)	0.262** (2.15)	-0.071 (-0.52)	0.047 (0.33)	0.029 (0.27)	-0.076 (-0.56)	0.056 (0.37)	0.079 (0.69)
σ_{cv}^2	0.052*** (4.63)	0.000 (.)	0.000 (.)	0.000 (.)	0.050*** (4.29)	0.000 (.)	0.000 (.)	0.000 (.)	0.000 (0.00)	0.000 (.)	0.000 (.)	0.000 (.)
σ_{cn}^2	0.002 (0.71)	0.051*** (4.83)	0.051*** (4.60)	0.057*** (4.71)	0.002 (0.65)	0.048*** (4.55)	0.048*** (5.07)	0.043*** (4.50)	0.043*** (12.25)	0.047*** (4.93)	0.053*** (3.90)	0.040*** (4.22)
<i>Attention</i>		-2.212*** (-4.41)				-1.536** (-2.42)		-1.959*** (-3.16)				-1.503** (-2.18)
<i>Sentiment</i>			-2.236*** (-2.70)			-1.491 (-1.60)			-1.878** (-2.40)			-1.262 (-1.41)
<i>OPU</i>				-3.790 (-1.28)		-0.118 (-0.03)				-1.666 (-0.68)		0.979 (0.39)
<i>EPU</i>					-0.634 (-0.98)	-0.191 (-0.32)					-0.750 (-1.31)	-0.378 (-0.66)
Proportion of herding	0.167	0.919	0.919	0.971	0.183	0.890	0.988	0.937	0.944	0.985	1.045	0.908
Log likelihood	0.407	3.560	3.541	0.543	1.030	5.306	5.748	8.702	8.288	5.903	5.688	10.393
Observations	55	55	55	55	55	55	55	55	55	55	55	55

Table 6. Estimates of herding in different size groups

This table reports empirical results from Model 1 to Model 6 where the beta is calculated in the CAPM. The stocks are categorized based on their size into small, medium, and large groups. In Panels A, C, and E, the log-cross-sectional standard deviation of beta is calculated using the equal-weighting scheme. In Panels B, D, and F, it is calculated using the value-weighting scheme. Model 1 is a standard state space model and is described as follows:

$$\log [\text{Std}_c (\beta_{ict}^b)] = \mu_c + H_{ct} + v_{ct}, \quad H_{ct} = \phi_c H_{ct-1} + \eta_{ct}$$

Where the first equation is an observation equation and the second is a state equation, $\log [\text{Std}_c (\beta_{ict}^b)]$ is the observation data and need to be calculated by stock data and the Carbon Neutral Index data, $\mu_c = E[\log[\text{Std}_c(\beta_{ict})]]$, $H_{ct} = \log(1-h_{ct})$ and h_{ct} is the herding parameter whose results are unobserved and can only be predicted in the state space model, $v_{ct} \sim iid(0, \sigma_{cv}^2)$, $\eta_{ct} \sim iid(0, \sigma_{c\eta}^2)$ and $|\phi_c| \leq 1$. A significant $\sigma_{c\eta}^2$ means the herding behavior exists. Model 2 to Model 5 add *Attention*, *Sentiment*, *OPU*, and *EPU* in the base of Model 1, respectively. Model 6 takes all of the control variables into consideration. $\sigma_{c\eta}$ is the measure of herding and the standard deviation of $\log [\text{Std}_c (\beta_{ict}^b)]$ (we use σ_c to represent it) is the volatility of the whole market. The proportion of herding is $\sigma_{c\eta}/\sigma_c$ which means that herding can explain how much of the total variability in $\log [\text{Std}_c (\beta_{ict}^b)]$. t statistics are in parentheses. The standard errors are robust. *, **, and *** represent significance at the 10%, 5%, and 1% levels, respectively. The sample period is from April 2018 to October 2022.

Small-cap	Panel A: CAPM Equal-Weighted						Panel B: CAPM Value-Weighted					
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
μ	-0.966*** (-14.53)	-0.961*** (-18.87)	-0.969*** (-13.89)	-0.837*** (-8.85)	-0.966*** (-14.40)	-0.882*** (-8.42)	-0.949*** (-14.60)	-0.943*** (-18.76)	-0.953*** (-14.26)	-0.826*** (-8.57)	-0.949*** (-14.36)	-0.875*** (-8.26)
Φ_c	0.636 (1.17)	0.417*** (3.73)	0.706* (1.68)	0.492 (0.59)	0.643 (1.16)	0.376*** (2.70)	0.631 (1.23)	0.424*** (3.73)	0.686* (1.85)	0.512 (0.69)	0.643 (1.24)	0.388*** (2.79)
σ_{cv}^2	0.027 (0.64)	0.000 (.)	0.029 (1.00)	0.019 (0.26)	0.027 (0.66)	0.000 (.)	0.025 (0.64)	0.000 (.)	0.026 (1.00)	0.020 (0.31)	0.026 (0.68)	0.000 (.)
$\sigma_{c\eta}^2$	0.025 (0.49)	0.050*** (5.79)	0.018 (0.52)	0.033 (0.36)	0.024 (0.47)	0.049*** (6.18)	0.025 (0.53)	0.048*** (5.87)	0.020 (0.63)	0.031 (0.41)	0.024 (0.51)	0.047*** (6.26)
<i>Attention</i>		-2.073** (-2.28)				-1.709* (-1.75)		-2.121** (-2.40)				-1.759* (-1.88)
<i>Sentiment</i>			-1.527* (-1.65)			-0.660 (-0.77)			-1.541* (-1.71)			-0.661 (-0.79)
<i>OPU</i>				-5.649 (-1.55)		-3.545 (-0.86)				-5.390 (-1.46)		-3.094 (-0.75)
<i>EPU</i>					-0.071 (-0.12)	0.358 (0.73)					-0.127 (-0.23)	0.298 (0.63)
Proportion of herding	0.599	0.847	0.508	0.688	0.587	0.839	0.608	0.843	0.544	0.677	0.596	0.834
Log likelihood	0.350	4.015	2.277	1.320	0.360	4.845	1.266	5.298	3.325	2.193	1.297	6.024
Observations	55	55	55	55	55	55	55	55	55	55	55	55
Medium-cap	Panel C: CAPM Equal-Weighted						Panel D: CAPM Value-Weighted					
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
μ	-0.844***	-0.837***	-0.848***	-0.735***	-0.843***	-0.786***	-0.839***	-0.829***	-0.843***	-0.732***	-0.838***	-0.836***

	(-16.57)	(-19.77)	(-16.54)	(-7.56)	(-15.85)	(-8.69)	(-16.80)	(-22.96)	(-16.78)	(-7.46)	(-16.06)	(-5.91)
Φ_c	0.573*	0.411***	0.572**	0.563	0.634**	0.424	0.566*	0.301*	0.558**	0.551	0.631**	0.661***
	(1.79)	(2.81)	(2.28)	(1.56)	(2.54)	(0.19)	(1.75)	(1.88)	(2.20)	(1.49)	(2.51)	(3.99)
σ_{cv}^2	0.016	0.000	0.013	0.016	0.019	0.002	0.016	0.000	0.012	0.015	0.019	0.000
	(0.70)	(.)	(0.70)	(0.74)	(1.19)	(0.01)	(0.70)	(.)	(0.65)	(0.69)	(1.22)	(.)
σ_{cn}^2	0.024	0.037***	0.024	0.022	0.019	0.033	0.024	0.045***	0.025	0.023	0.019	0.050***
	(0.92)	(5.49)	(1.11)	(0.85)	(1.14)	(0.13)	(0.93)	(4.05)	(1.13)	(0.86)	(1.15)	(3.14)
<i>Attention</i>		-1.876**						-1.980**				-1.745**
		(-2.69)						(-2.74)				(-2.72)
<i>Sentiment</i>			-1.203			-0.305			-1.245			-0.518
			(-1.47)			(-0.23)			(-1.53)			(-0.73)
<i>OPU</i>				-4.714		-2.308				-4.586		-0.832
				(-1.22)		(-0.65)				(-1.17)		(-0.19)
<i>EPU</i>					-0.507	-0.158					-0.527	-0.232
					(-1.02)	(-0.16)					(-1.06)	(-0.64)
Proportion of herding	0.680	0.844	0.680	0.651	0.605	0.797	0.684	0.936	0.698	0.669	0.608	0.987
Log likelihood	8.646	12.809	10.307	9.652	9.311	13.332	8.816	12.229	10.602	9.777	9.534	10.454
Observations	55	55	55	55	55	55	55	55	55	55	55	55

Large-cap	Panel E: CAPM Equal-Weighted						Panel F: CAPM Value-Weighted					
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
μ	-0.773***	-0.766**	-0.776**	-0.713***	-0.773***	-0.761***	-0.778**	-0.773***	-0.781***	-0.751***	-0.778***	-0.788**
	(-22.99)	(-23.85)	(-22.45)	(-8.63)	(-23.43)	(-9.92)	(-26.94)	(-26.52)	(-26.36)	(-10.04)	(-27.36)	(-11.33)
Φ_c	0.264	0.289*	0.310**	0.255	0.258	0.293*	0.210	0.238*	0.247**	0.210	0.208	0.242*
	(1.54)	(1.69)	(1.97)	(1.41)	(1.50)	(1.76)	(1.51)	(1.75)	(2.02)	(1.48)	(1.53)	(1.93)
σ_{cv}^2	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)	(.)
σ_{cn}^2	0.035***	0.030***	0.032***	0.034***	0.034***	0.030***	0.029***	0.027***	0.027***	0.029***	0.028***	0.026***
	(5.33)	(5.14)	(5.35)	(5.14)	(5.43)	(5.22)	(5.49)	(5.13)	(5.33)	(5.49)	(5.48)	(5.15)
<i>Attention</i>		-1.642**				-1.330**		-1.136**				-0.853*
		(-4.11)				(-2.75)		(-3.16)				(-1.81)
<i>Sentiment</i>			-1.256*			-0.544			-1.020*			-0.521
			(-1.80)			(-0.71)			(-1.74)			(-0.79)
<i>OPU</i>				-2.577		-0.330				-1.190		0.512
				(-0.71)		(-0.10)				(-0.38)		(0.18)
<i>EPU</i>					-0.476	-0.219					-0.523	-0.345
					(-1.23)	(-0.61)					(-1.57)	(-1.05)
Proportion of herding	0.961	0.890	0.919	0.947	0.947	0.890	0.968	0.934	0.934	0.968	0.951	0.917

Log likelihood	14.463	18.137	16.481	14.846	15.142	18.782	19.276	21.231	20.778	19.376	20.215	22.169
Observations	55	55	55	55	55	55	55	55	55	55	55	55



Fig. 1. Index tendency

This figure shows the tendency of Carbon Neutral Index and Shanghai Stock Exchange Index. Shanghai Stock Exchange Index could reflect the situation of the Chinese stock market. The sample period is from March 12, 2018, to October 31, 2022.

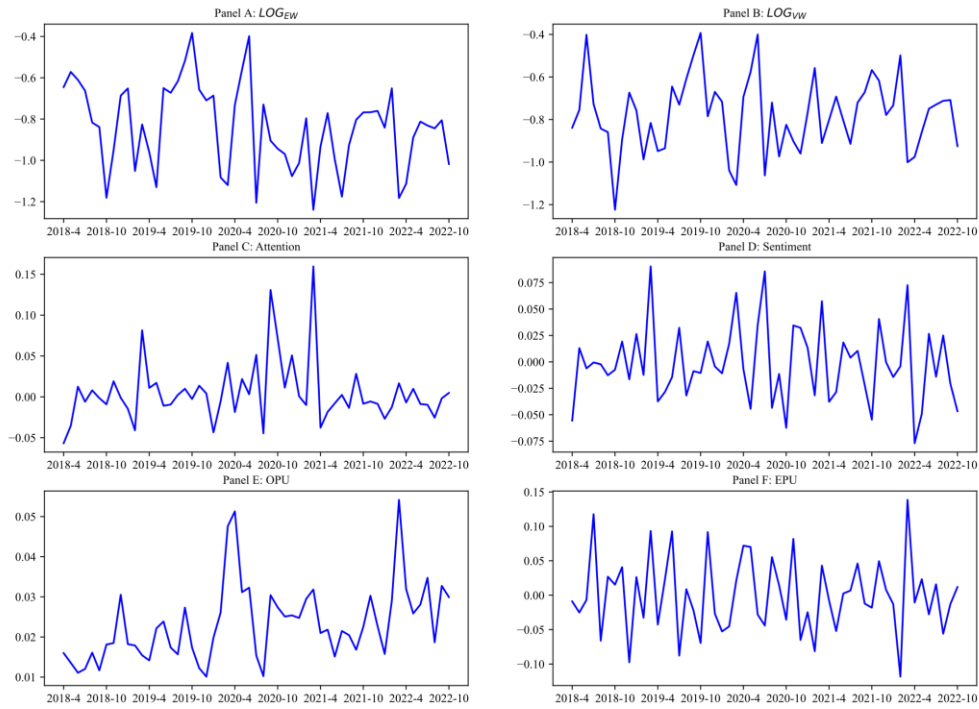


Fig. 2. Log-cross-sectional standard deviation and control variables

This figure shows the variable data measured by the monthly frequency and those variables are the log-cross-sectional standard deviation calculated by the equal-weighting scheme (LOG_{EW}), the log-cross-sectional standard deviation calculated by the value-weighting scheme (LOG_{VW}), *Attention*, *Sentiment*, *OPU*, and *EPU*. The sample period is from April 2018 to October 2022.

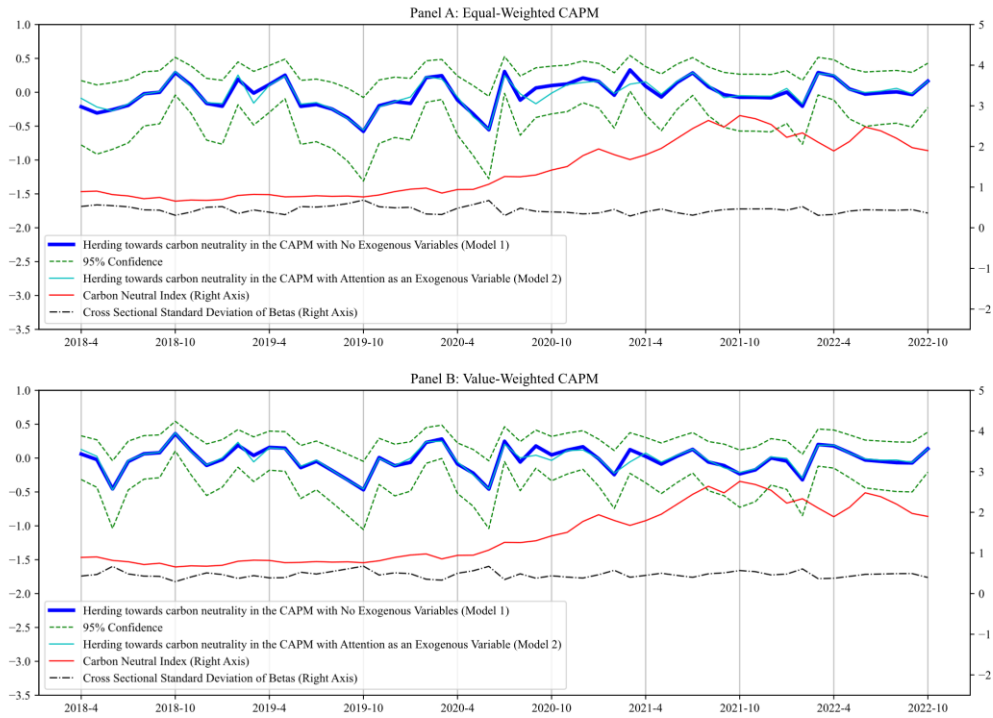


Fig. 3. The evolution of herding towards carbon neutrality

This figure shows the evolution of herding towards carbon neutrality in the CAPM and the log-cross-sectional standard deviation of beta is calculated by the equal-weighting scheme and value-weighting scheme. Model 1 is the initial standard state space model and Model 2 adds *Attention* as the control variable. The sample period is from April 2018 to October 2022.

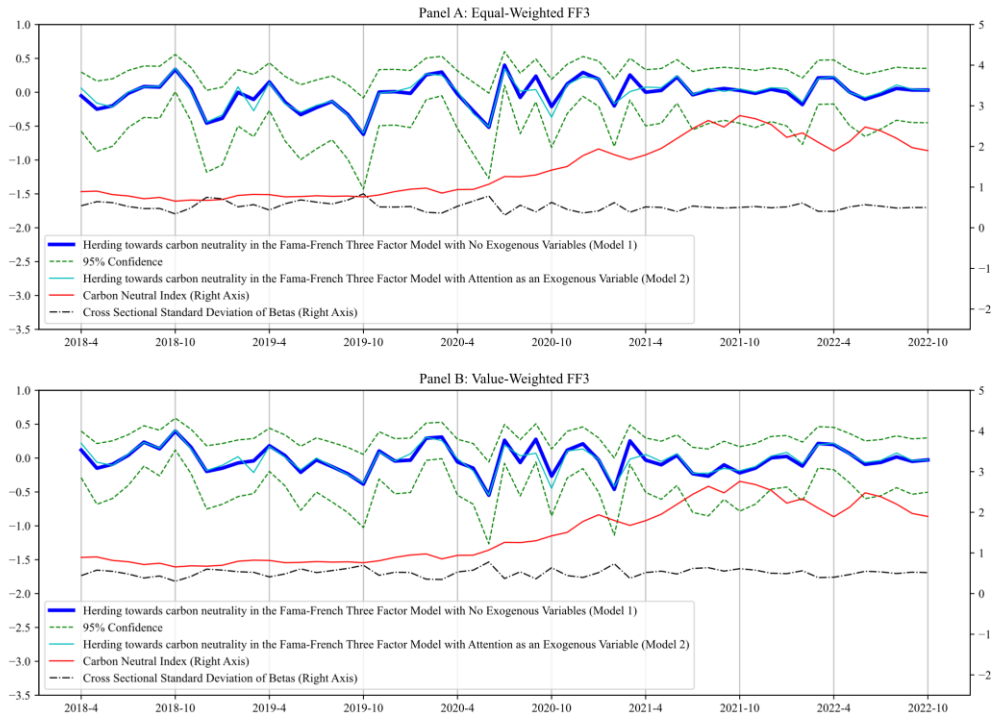


Fig. 4. The evolution of herding towards carbon neutrality in the FF3 Model

This figure shows the evolution of herding towards carbon neutrality in the Fama-French Three Factor Model and the log-cross-sectional standard deviation of beta is calculated by the equal-weighting scheme and value-weighting scheme. Model 1 is the initial standard state space model and Model 2 adds *Attention* as the control variable. The sample period is from April 2018 to October 2022.

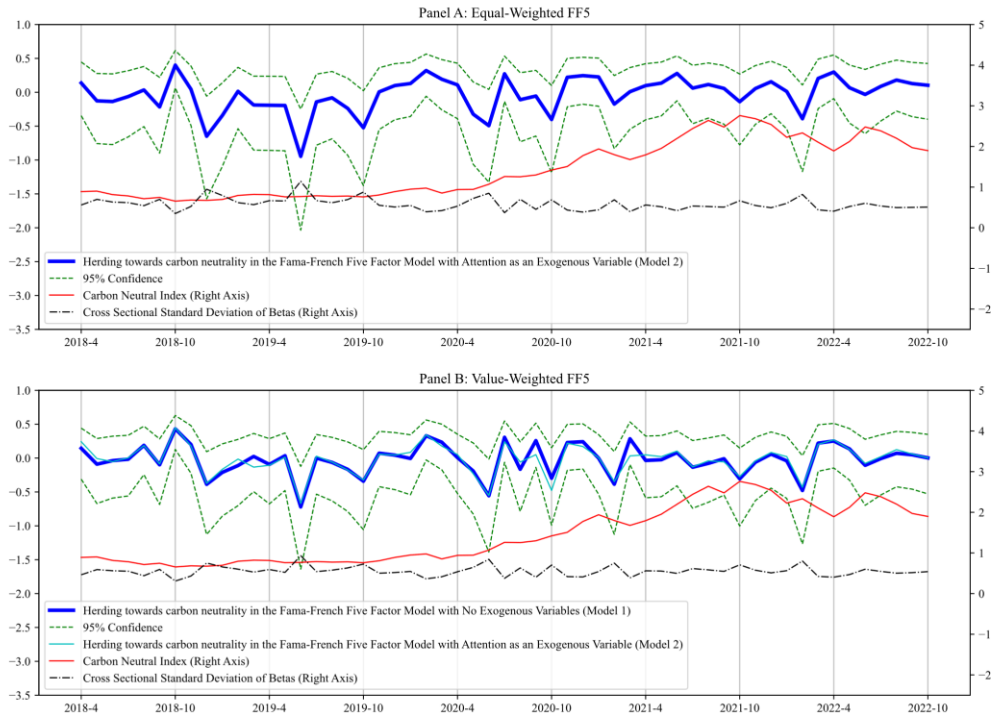


Fig. 5. The evolution of herding towards carbon neutrality in the FF5 Model

This figure shows the evolution of herding towards carbon neutrality in the Fama-French Five Factor Model and the log-cross-sectional standard deviation of beta is calculated by the equal-weighting scheme and value-weighting scheme. Model 1 is the initial standard state space model and Model 2 adds *Attention* as the control variable. The sample period is from April 2018 to October 2022.

Appendix A Variable definitions

This table reports the definition of variables. We use the log-cross-sectional standard deviation of beta calculated by the equal-weighting scheme and by the value-weighting scheme as dependent variables and they would be input into the state space model as observation data, respectively. By applying the Kalman filter, the results of herding are obtained. To explore whether different factors could influence the significance of herding, we add four control variables to the state space model which are *Attention*, *Sentiment*, *OPU*, and *EPU*.

Variables	Definitions
Dependent variable	
<i>LOG_{EW}</i>	The log-cross-sectional standard deviation of beta calculated by the equal-weighting scheme
<i>LOG_{VW}</i>	The log-cross-sectional standard deviation of beta calculated by the value-weighting scheme
Control variables	
<i>Attention</i>	The investor attention is reflected by the keywords “carbon neutrality” in Baidu Index and the calculation method is by first adding 1 to its monthly data, then taking logarithms, and taking log-return to get the final form.
<i>Sentiment</i>	The investor sentiment across the A-share market and the calculation method is by first adding 1 to its monthly data, then taking logarithms, and taking log-return to get the final form.
<i>OPU</i>	The oil price uncertainty of China is reflected by oil market volatility which uses the daily data per month to calculate the standard deviation and attain 55 calculation results in 55 months.
<i>EPU</i>	The economic price uncertainty of China and the calculation method is by first adding 1 to its monthly data, then taking logarithms, and taking log-return to get the final form.