Informational Cascades, Financial Reporting, and Herding Intensity:

Evidence from the Chinese Stock Market

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Keywords: Financial reporting and disclosures; Herding intensity; Seasonality.

JEL classification: G10, G14, G40.

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1. Introduction

While herding among investors (i.e., investors tend to mimic each other and follow the group behavior instead of making independent investment decisions) has been extensively researched (see, among others, Chang et al., 2000; Chiang and Zheng, 2010; Galariotis et al., 2015), it is only until recently that the literature places emphasis on the time-varying feature of herding behavior (Klein, 2013; Babalos et al., 2015; Li et al., 2018; Fu and Wu, 2021). If herding is time-dependent rather than static, the empirical results testing the existence and intensity of herding could be sensitive to the sample period employed.[1] This recently documented time-varying feature of herding behavior hence offers a potential explanation for the incoherent empirical findings reported in previous literature. The studies of the possible mechanism under which this time-varying herding behavior is materialized nevertheless have been scarce, although they yield valuable insights into stock market dynamics. This study attempts to supplement the current literature by offering more empirical regularities regarding herding intensity, focusing on further exploring the role of informational cascades and event uncertainty in herding formation.[2]

As emphasized by the theoretical literature, a necessary condition for herding is there should be a certain level of event uncertainty, a scenario in which an event that can considerably influence assets price is known by informed traders in advance while not known by the market maker (Avery and Zemsky, 1998; Park and Sabourian, 2011; Cipriani and Guarino, 2014).[3] This information asymmetry triggers informed traders to herd when a large amount of buy or sell orders suddenly appear in a certain period.[4] According to this stream of literature, none of the traders herd on no-event days, while on event days, some informed traders herd, but noise traders do not. Therefore, if the model fits well with reality, we should observe an increase in herding intensity around the period when such informational events happen sweepingly. Consequently, one of the potential mechanisms through which time-

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[1] For instance, Tan et al. (2008) show that herding existed in the Chinese A-share market from 1996 to 2003, which contradicts the results documented in Demirer and Kutan (2006) when the sample period is slightly changed to the year 1999 to 2002.

[2] Theoretical wisdom on the cause of herding includes information-based herding and cascades (Banerjee, 1992; Bikhchandani et al., 1992; Avery and Zemsky, 1998), reputation-based herding (Scharfstein and Stein, 1990; Trueman, 1994; and Zweibel, 1995), and compensation-based herding (Brennan, 1993; Roll, 1992). However, in the case of China, where our data comes from, since individual investors hold the majority of the accounts while only around 0.3% of accounts are held by institutional investors (Fu and Wu, 2021), reputation-based herding and compensation-based herding, which focus on institutional investors' behavior, play a minor role in explaining the dynamics of herding in China while information-based herding and cascades is more proper than the former two to be the main reason.

[3] In these models, traders are classified as informed traders and noise traders according to their trading strategy and information accessibility. Informed traders know the happening of an informational event but do not know its exact effect on the underlying asset's valuation. Informed traders hence make trading decisions based on their information of the event and the price history, while noise traders trade randomly and thus supply liquidity.

[4] When such an informational event happens and an abrupt increase in the number of buying (selling) orders surfaces, due to information asymmetry, informed traders who are more experienced would interpret the trading history with the event that occurred while the market maker cannot. Consequently, informed traders attach a higher possibility that these orders come from some earlier traders with good (bad) signals than the market maker, as the market maker must consider the possibility that the coming orders may come from noise traders. Therefore, informed traders' valuation of the underlying asset would be higher (lower) than the market maker's, in which case informed traders would buy (sell) this asset and herd to the preceding traders (Bikhchandani et al., 1992; Avery and Zemsky, 1998; Cipriani and Guarino, 2014).

varying herding behavior materialized can be conjectured as investors with different levels of information accessibility react to informational events.

As the most regular informational events in the financial market, annual financial reporting and disclosures generally contain information related to the value of the firms to be disclosed to the public. Such information, nevertheless, might be divulged beforehand and known by a small group of market participants who will then become informed traders. For instance, some insiders can assess these reports before they are released to the public. When given an opportunity, insiders trade upon knowledge of specific and economically significant forthcoming financial disclosure reports (Lin and Howe, 1990; Lakonishok and Lee, 2001; Ke et al., 2003), especially when equities are undervalued (Veenman, 2013; Qiu et al., 2018). In this circumstance, it is likely that, based on the early trades conducted by insiders, sophisticated and informed investors in the market keep track of and learn from insiders' order flows and trade accordingly for profit (e.g., McNally et al., 2015; Chen et al., 2020). Once the fraction of the informed traders and sophisticated investors in the market accumulates to a certain level, such information cascades among sophisticated investors could easily trigger further market jitters and herd mentality around the period of annual financial report disclosures.[5]

We test the above conjectures using data from China.[6] While herding behavior in the Chinese stock markets has been widely studied (see, among others, Demirer and Kutan, 2006; Tan et al., 2008; Chong et al., 2020; Fu and Wu, 2021), research focusing on the association between herding intensity and informational events have been scarce. The empirical evidence documented in this paper thus unveils insights into the stock market in China and potentially contributes to our understanding of herding behavior in general, especially for young emerging markets.

As the first step of our empirical analysis, Newey–West regressions are employed to test the possibly statistical significance of the amplifying in herding intensity during the period around which annual financial reports are released.[7] We then adopt semiparametric analysis to illustrate the dynamics of herding intensity over time and against the daily frequency of annual financial report disclosures.

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[5] See Bikhchandani and Sharma (2001) for a theoretical illustration of the relationship between herding formation and the fraction of informed traders in the market. Boortz et al. (2013) present simulation results to show that both buy and sell herding intensity would increase as the fraction of informed traders increases.

[6] We believe that the Chinese setting is suitable for our study for the following reason: China has unique institutional frameworks and corporate governance arrangements, which feature concentrated ownership, government ownership, weak legal enforcement, and weak investor protection (Chen et al., 2019). Consequently, insiders' information advantages are more evident in Chinese stock markets. Moreover, this unique setting provides insiders opportunity, motivation, and the ability to derive private interests through a wide range of transactions at the expense of minority stockholders (La Porta et al., 1998; Djankov et al., 2008). Non-tradable share reform in 2007 and the 2015 China Securities Regulatory Commission (CSRC) regulation on forbidding insiders from selling their stocks in secondary markets have changed insider trading patterns but have been ineffective in preventing insider trading due to rigid administrative supervision and a lack of civil litigation and flexible market monitoring (Zhao et al., 2020).

[7] Choosing financial reporting and disclosures as information events also accords with the relationship between information and stock market dynamics documented in the literature. Glosten and Milgrom (1985) illustrate that enlarged information asymmetry between the market maker and traders can be used to explain the small firm effect (Banz et al., 1981) and the neglected firm effect (Arbel and Strebel, 1983), in which much of the excess returns occur in January when annual financial reports are released. Recent literature also highlights the associations between financial report disclosures, stock price volatility, and herd behavior (see, among others, Tse and Tucker, 2010; Heinle and Verrecchia, 2015; and Cao and Wang, 2021).

Finally, a simulation-oriented Bayesian approach is used to tabulate the probability of increased herding intensity under different market conditions. Our empirical results document compelling evidence of the seasonality of herding intensity among investors in China's financial market, with herding behavior significantly amplified during massive annual financial report disclosures.

2. Data and empirical strategy

Data employed in this paper consists of 1) daily returns of China's A-share stocks from 1st January 2000 to 14th August 2020, obtained from the Wind database (www.wind.com.cn); and 2) daily frequency of annual financial report disclosures, obtained from the CSMAR database (https://cn.gtadata.com/). Listed firms in China are required to release their annual financial reports between January to April each year, during which informational events would be more intensively and asymmetrically prevailing in the market than usual.[8] Table 1 presents the total number of annual financial reports released by year during the sample period. Due to various reasons, some firms released their annual financial reports after April; nevertheless, such cases are rare.[9]

Table 1

Total number of annual financial reports released in China (2000 – 2020)

Year	Total number of annual financial reports released	Financial reports released between Jan. and Apr.	Financial reports released after Apr.
2000	739	734	5
2001	889	888	1
2002	1027	1025	2
2003	949	942	7
2004	989	986	3
2005	1060	1056	4
2006	999	990	9
2007	1123	1123	0
2008	1249	1247	2
2009	1278	1278	0
2010	1449	1449	0
2011	1719	1719	0
2012	1982	1981	1
2013	2004	2004	0
2014	2012	2011	1
2015	2115	2114	1
2016	2333	2333	0
2017	2538	2538	0
2018	2786	2778	8
2019	2821	2818	3
2020	3203	3108	95

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[8] According to the Securities Law of the People's Republic of China, listed firms are required to release annual reports within four months from the end of an accounting year, which is the period from Jan. to Apr. (sources: www.sse.com.cn and www.szse.cn).

[9] In 2020, the year with the most temporized cases in the sample, 95 companies released their annual report after April, accounting for less than 3% of the total number of annual financial reports released in the same year.

We first test the possible existence of herding in China's stock market and then investigate the time-varying feature of the herding intensity with a focus on the period with massive annual financial report disclosures. Following the literature on testing herding towards market consensus, this study employs the empirical approach proposed by Christie and Huang (1995), Chang et al. (2000), and Chiang and Zheng (2010). We use the measure proposed by Chang et al. (2000) to calculate the cross-sectional absolute deviation ($CSAD$) at time t as:

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

where $R_{i,t}$ is the actual stock return of firm i at time t, and $R_{m,t}$ is the cross-sectional average of all N stock returns in the returns on an (equally weighted) market portfolio at time t. Chang et al. (2000) illustrate that, in the presence of herding, there exists a non-linear relationship between $CSAD_t$ and $R_{m,t}$, leading to disproportional changes in the $CSAD_t$ when investors follow aggregate market behavior during periods of large average price movements. To detect the potential asymmetry of the relationship between market return and return dispersion in different market directions, Chiang and Zheng (2010) incorporate a dummy variable that differentiates up- and down-market days. Following this strand of literature, a benchmark regression model employed in this study is:

$$CSAD_t = \zeta_0 + \zeta_1 D_u R_{m,t} + \zeta_2(1 - D_u)R_{m,t} + \zeta_3 D_u R_{m,t}^2 + \zeta_4(1 - D_u)R_{m,t}^2 + \varepsilon_t \tag{2}$$

where the dummy variable D_u equals 1 when $R_{m,t}$ is larger than or equal to 0, and 0 otherwise. Under this specification, the existence of herding would be indicated by significant and negative estimates of ζ_3 (up-market days) and/or ζ_4 (down-market days).

Following Galariotis et al. (2015), before running the benchmark model, we decompose $CSAD_t$ into two components, aiming to purge out the impact of spurious (fundamental) herding so as to isolate and identify true (non-fundamental) herding.[10] This is achieved by, under the CAMP framework, regressing $CSAD_t$ on high minus low return factor (HML), the small minus big return factor (SMB), and the momentum return factor (MOM):

$$CSAD_t = \delta_0 + \delta_1(R_{m,t} - R_f) + \delta_2 HML_t + \delta_3 SMB_t + \delta_4 MOM_t + \varepsilon_t \tag{3}$$

The fitted values of $CSAD_t$ from equation (3) are defined as deviations due to fundamentals $(CSAD_{FUND,t})$ and the residuals are defined as deviations due to non-fundamentals ($CSAD_{NONFUND,t}$).

To test our conjecture that herding intensity increases during the period of financial report disclosures in China's stock market, we extend Eq.(2) to:

$$CSAD_{NONFUND,t} = \beta_0 + \beta_1 D_u R_{m,t} + \beta_2(1 - D_u)R_{m,t} + \beta_3 D_u R_{m,t}^2$$
$$+ \beta_4(1 - D_u)R_{m,t}^2 + \beta_5 D_u D_r R_{m,t} + \beta_6(1 - D_u)D_r R_{m,t}$$
$$+ \beta_7 D_u D_r R_{m,t}^2 + \beta_8(1 - D_u)D_r R_{m,t}^2 + \varepsilon_t \tag{4}$$

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[10] As the information on the macro aggregate market is commonly known to the public, convergence in investors' behavior based on such information most likely does not necessarily involve investors reversing their decisions; thus, strictly speaking, it is not herding (Bikhchandani and Sharma, 2001). Therefore, it is important to factor out such fundamental-driven (spurious) herding before further exploring the possibility of intentional herding.

where $D_r = 1$ if day t falls within the period from January to April, and $D_r = 0$ otherwise.[11] Under this specification, the existence of an increase in the herding intensity during the period of financial report disclosures would be indicated by significant and negative estimates of β_7 (up-market days) and/or β_8 (down-market days).

While the above parametric regressions based on the conventional literature help identify the possible existence of herding, we conduct further investigations to offer additional empirical regularities in the response of herding intensity to annual financial report disclosures. To illustrate the time-varying feature of the herding intensity, we conduct a rolling window estimation using Eq. (2) and plot to demonstrate the dynamics of estimated ζ_3 and ζ_4 over the sample period. This allows us to observe the possible changes in herding intensity over time. Assuming that ζ_3 and ζ_4 are smooth functions of daily frequency of annual financial disclosure, following Hastie and Tibshirani (1993) and Rios-Avila (2020), we also estimate a smooth varying-coefficient model and plot the estimated ζ_3 and ζ_4 to visualize their changes against the daily frequency of annual financial disclosure. This helps to cross-validate the association between herding intensity and annual financial report disclosures in China's stock market with a semiparametric approach combining the flexibility of non-parametric with the structure of standard linear models. Finally, given the complexity of the stock market dynamics and investors' behavior involved, herding intensity could be a non-smooth function of model parameters, as stated in Eq. (4). To draw reliable statistical inference from the sampling theory perspective, we apply the asymptotic theory in Kwan (1999) to interpret the asymptotic normal distribution of the OLS estimator as an approximate posterior distribution. This allows us to use a simulation-oriented Bayesian approach to compute the posterior distribution of herding intensity measures (i.e., β_3 and β_7 for the up-market days, and β_4 and β_8 for the down-market days). More specifically, a random draw from the approximate posterior distribution of the parameter vector $\theta = (\beta_0, \beta_1, \beta_2, \beta_3, \beta_4, \beta_5, \beta_6, \beta_7, \beta_8)$ is $\theta_d = P\delta + \hat{\theta}$, where $\hat{\theta}$ is the value of the OLS estimate, P is the lower-triangular Cholesky decomposition of the asymptotic covariance matrix of the OLS estimator, and δ is a vector containing random draws from a standard normal distribution. Each draw will result in one parameter combination. Based on 5,000 random draws, we can compute a very accurate estimate of the moments and percentiles of the posterior distribution of herding intensity measures for inference.

3. Empirical results

Table 2 reports Newey–West regression results based on Eq. (2) and Eq. (4). Results based on Eq. (2) are shown in columns (a) and (b), with the dependent variables are $CSAD_t$ and $CSAD_{NONFUND,t}$, respectively. In both cases, the estimated coefficients on $D_u R_{m,t}^2$ (i.e., ζ_3) and $(1 - D_u)R_{m,t}^2$ (i.e., ζ_4) are significant and negative, indicating the existence of herding behavior in both up and down markets in China's stock market, with herding being stronger on up-market days than on down-market days.[12] Since $CSAD_{NONFUND,t}$ does not contain changes in cross-sectional absolute deviation associated with the information on the macro aggregate market, significant and negative estimates of ζ_3 and ζ_4

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[11] Appendix A reports the results of unit-root test of all key variables. All variables, including $CSAD_{NONFUND,t}$ and $R_{m,t}$, are stationary.

[12] These results are consistent with previous studies on herds in Asian financial markets (see, among others, Chang et al., 2000; Chiang and Zheng, 2010; Dang and Lin, 2016).

documented in column (b) indicate the existence of non-fundamental herding during the sample period. Regression results based on Eq. (4) are reported in column (c) of Table 2. Consistent with our conjecture, the estimated coefficients on $D_u D_r R_{m,t}^2$ (i.e., β_7) and $(1 - D_u) D_r R_{m,t}^2$ (i.e., β_8) are both negative and significant, indicating a prevailing pattern of herding intensity enhancement during the period of annual financial report disclosures. As indicated by the estimated coefficients, such amplification in herding intensity is stronger on the down-market days ($\hat{\beta}_8 = -0.027$) than on the up-market days ($\hat{\beta}_7 = -0.016$).

Table 2

Newey–West regression based on Eq. (2) and Eq. (4).

Explanatory variables	(a)	(b)	(c)
	Eq. (2): $CSAD_t$	Eq. (2): $CSAD_{NONFUND,t}$	Eq. (4): $CSAD_{NONFUND,t}$
$D_u R_{m,t}$	0.215***	0.277***	0.258***
	(0.022)	(0.021)	(0.029)
$(1 - D_u) R_{m,t}$	−0.319***	−0.235***	−0.194***
	(0.020)	(0.020)	(0.025)
$D_u R_{m,t}^2$	−0.016***	−0.013***	−0.007
	(0.005)	(0.005)	(0.007)
$(1 - D_u) R_{m,t}^2$	−0.010***	−0.011***	−0.001
	(0.003)	(0.003)	(0.004)
$D_u D_r R_{m,t}$			0.049
			(0.036)
$(1 - D_u) D_r R_{m,t}$			−0.113***
			(0.035)
$D_u D_r R_{m,t}^2$			−0.016*
			(0.009)
$(1 - D_u) D_r R_{m,t}^2$			−0.027***
			(0.006)
Constant	1.302***	−0.292***	−0.289***
	(0.018)	(0.018)	(0.018)
F-statistic			5.554***
$\overline{R^2}$	0.274	0.213	0.219
N	4996	4996	4996

Notes:

a) *, **, and *** indicate statistical significance at 10%, 5%, and 1%, respectively.

b) Newey-West HAC standard errors are reported in parentheses. Following the conventional truncation parameter guideline suggested in Stock and Watson (2011), the reported standard errors in this paper were estimated using a lag length of 6 for HAC standard errors, as $CSAD_t$ and $CSAD_{NONFUND,t}$ do not exhibit statistically significant autocorrelation of order 7 or above. The significance of the coefficients and conclusions would remain unchanged if we increased the lag length to 12.

c) F-statistic reported is for testing the joint significance of the coefficients on $D_u D_r R_{m,t}$, $(1 - D_u) D_r R_{m,t}$, $D_u D_r R_{m,t}^2$, and $(1 - D_u) D_r R_{m,t}^2$.

Fig. 1 plots 90-day rolling window estimates of ζ_3 and ζ_4 (grey long-dash lines) based on Eq. (2) and with $CSAD_{NONFUND,t}$ as the dependent variable. Estimated ζ_3 and ζ_4 within the annual financial reporting periods (shaded areas in grey) are highlighted in blue, and further highlighted in red if they are negative and statistically significant at the 5% level. It is evident that, compared to other periods, herding intensity often tends to amplify (i.e., estimated ζ_3 or ζ_4 become more negative) around the annual financial reporting periods, regardless of up or down markets. Statistically significant estimates are more likely to appear on down-market days than up-market days.[13]
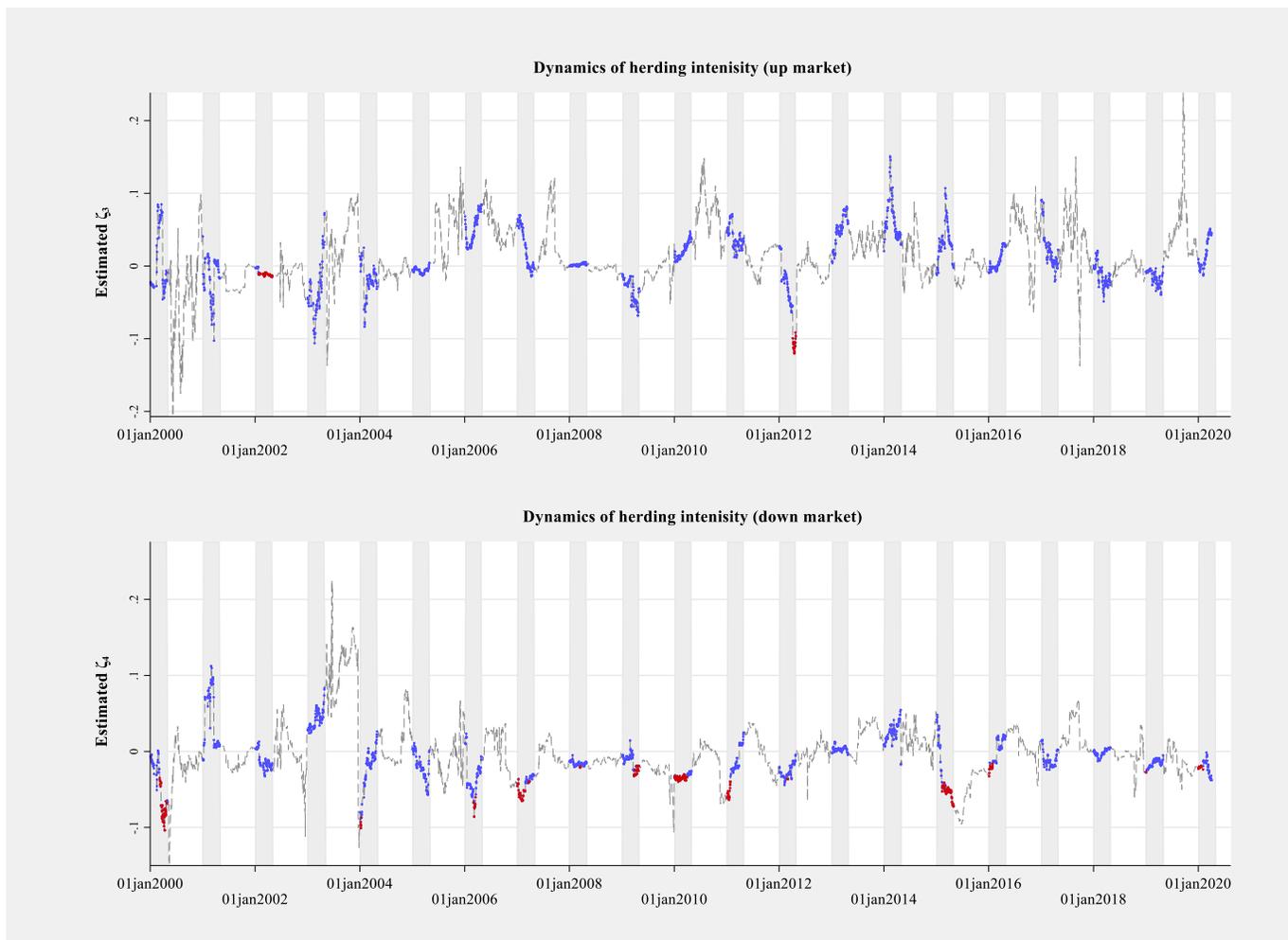

Fig. 1. Dynamics of herding intensity in up and down markets. Note: The grey lines plot the estimated ζ_3 and ζ_4 obtained from a 90-day rolling window process conducted based on Eq. (2). Estimated ζ_3 and ζ_4 within the annual financial reporting periods (shaded areas in grey) are highlighted in blue, with red segments highlighting the negative and significant (at 5% level) portions.

Fig. 2 illustrates the association between the daily frequency of annual financial report disclosures and the estimates of ζ_3 and ζ_4. Estimates of ζ_3 and ζ_4 are obtained from a varying coefficient model based on Eq. (2), assuming that all coefficients in Eq. (2) are smooth functions of the daily frequency of annual financial report disclosures. The results reported in Fig. 2 suggest that the level of herding

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[13] Similar pattern are observed when the widow is changed to 40, 50, or 60 days. These results are available upon request.

intensity is conditional on the frequency of annual financial report disclosures. In both up and down markets, the herding intensity increases (i.e., estimated ζ_3 or ζ_4 become more negative) with the daily frequency of annual financial report disclosures. When the daily frequency of annual financial report disclosures exceeds 200, the magnification in herding intensity is more profound and statistically significant. In the down market, herding intensity also increases and is statistically different from zero when the frequency of annual financial report disclosures is around 10 to 40.
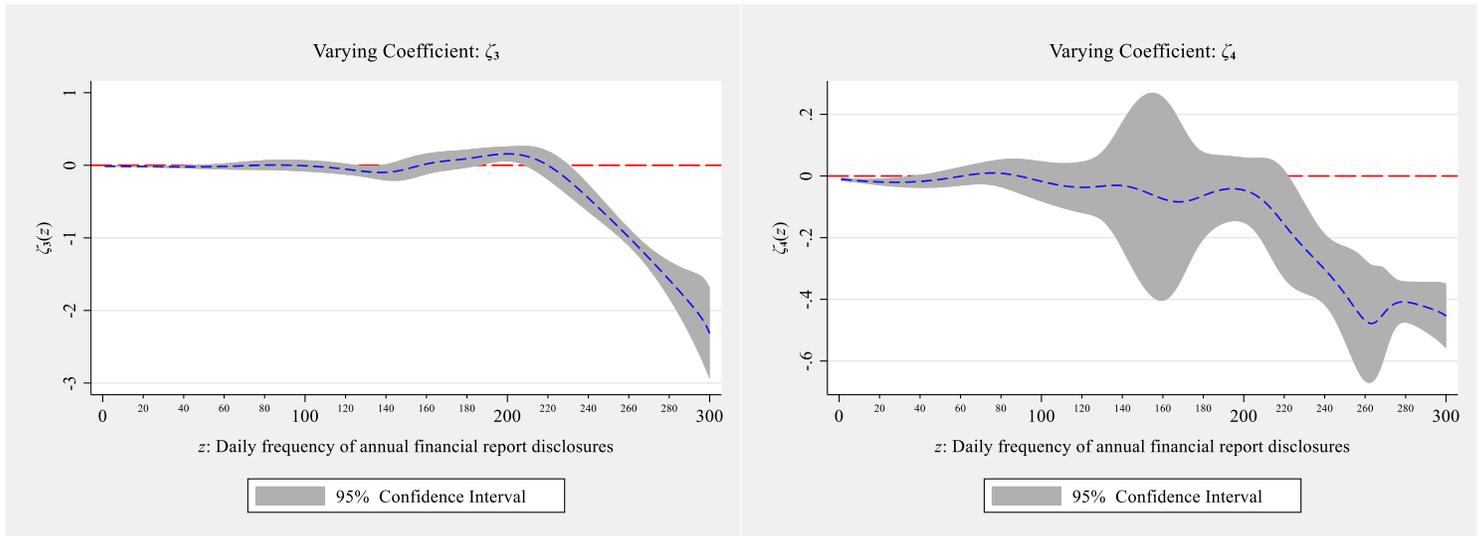

Fig. 2. Conditional herding intensity across the daily frequency of annual financial report disclosures. Notes: These two graphs plot estimated ζ_3 and ζ_4 obtained from $CSAD_{NONFUND,t} = \zeta_0(z) + \zeta_1(z)D_uR_{m,t} + \zeta_2(z)(1 - D_u)R_{m,t} + \zeta_3(z)D_uR_{m,t}^2 + \zeta_4(z)(1 - D_u)R_{m,t}^2 + \varepsilon_t$, where all coefficients (ζs) are assumed to be smooth functions of the daily frequency of annual financial report disclosures (z). This setup essentially results in a varying-coefficient model proposed by Hastie and Tabshiran (1993). The coefficients are estimated using local linear kernel-weighted regression following Li and Racine (2007).

Results obtained based on semi-parametric Bayesian analyses resonate with the results reported above. Table 3 presents the marginal posterior distributions of herding intensity measures (specifically, β_3 and β_7 for the up-market days and β_4 and β_8 for the down-market days). Following Kwan (1999), we first apply OLS on Eq. (4) to obtain consistent parameter estimates as an initial step. We then apply a simulation-oriented Bayesian approach to generate a posterior distribution of the herding intensity measures. Results reported in Table 3 indicate that, with the existence of herding (the posterior means of β_3 and β_4 are negative), the herding intensity tends to increase on reporting days (the posterior means of β_7 and β_8 are negative). Furthermore, the marginal posterior distributions of β_7 and β_8 are negative at all percentiles. Table 4 illustrates the posterior probabilities of herding intensity measures. In each 2×2 panel, we calculate the probabilities of positive or negative estimates for both up and down markets based on simulated data. Regardless of the market situation, conditional on the existence of herding, the probability for a further enhanced herd mentality in the period of annual financial report disclosures is the highest in all four scenarios (0.817 in the up market and 0.621 in the down market, respectively). In a down market, as the probability of β_8 being negative is almost 1 (0.621 + 0.379), the increase in herding intensity during the reporting period is nearly certain. All these results suggest

compelling evidence of herding amplification during the annual financial reporting period, with a more substantial likelihood of an increase in herding intensity in a down market.

Table 3

Marginal posterior distributions of herding intensity

		Mean	Std Dev	Percentile 5%	25%	50%	75%	95%
Up-market days								
	β_3	−0.007	0.007	−0.019	−0.012	−0.007	−0.003	0.005
	β_7	−0.016	0.009	−0.031	−0.022	−0.016	−0.010	−0.002
Down-market days								
	β_4	−0.001	0.005	−0.009	−0.004	−0.001	0.002	0.006
	β_8	−0.027	0.006	−0.037	−0.031	−0.027	−0.023	−0.017

Note: All statistics reported are results from 5,000 simulations.

Table 4

Posterior probabilities

Panel A: Up-market days

		β_3	
		Negative	Positive
β_7	Negative	**0.817**	0.154
	Positive	0.028	< 0.001

Panel B: Down-market days

		β_4	
		Negative	Positive
β_8	Negative	**0.621**	0.379
	Positive	< 0.001	< 0.001

Note: All statistics reported are results from 5,000 simulations.

Fig. 3 depicts density-distribution sunflower plots, which visualize in a two-dimensional graph the density of bivariate data, e.g., herding intensity in the non-reporting period (measured by β_3 in the up market and β_4 in the down market) versus herding intensity in the reporting period (measured by β_7 in the up market and β_8 in the down market). As presented in the figures, regardless of the market condition, high- and medium-density regions are mainly located in the quadrant where both herding intensity measures of reporting and non-reporting periods are negative. These results are consistent

with the posterior probabilities presented in Table 4. An additional and interesting finding is that, as shown by the fitted line, for both up and down markets, herding intensity measures of reporting and non-reporting periods are significantly (at 5% level) and negatively correlated, with slope coefficients are −0.817 and −0.745 respectively. These negative correlations, together with the posterior probabilities reported above, seem to suggest the existence of reversion in herding momentum between the non-reporting period and reporting period. This empirical observation warrants further investigation in future research.
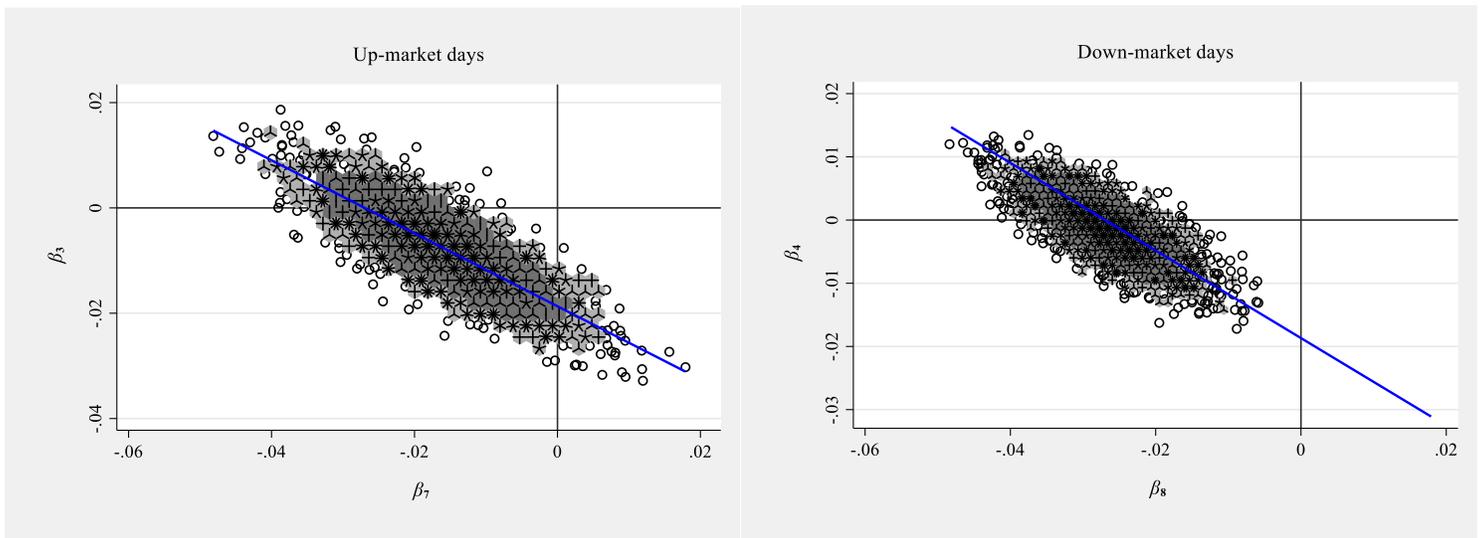

Fig. 3. Joint posterior distribution of herding intensity measures. Notes: Light and dark sunflowers in these plots represent observations' density. A petal in a sunflower plot is several line segments of equal length that radiate from a central point. Each petal of a light sunflower represents 1 observation. Each petal of a dark sunflower represents several observations. Dark and light sunflowers represent the data's high- and medium-density regions, and circles represent individual observations in low-density regions.

4. Conclusion

By further exploring the relationship between return dispersion and return on the market during the annual financial reporting period, this paper documents some new empirical regularities regarding the dynamics of herding intensity in the stock market. The results presented confirm the presence of herding amplification around the period of annual financial reporting and disclosures, with a more substantial likelihood of an increase in herding intensity in a down market. There is also evidence that herding intensity in the non-reporting period is negatively correlated with the herding intensity in the reporting period; an observation remains puzzling and warrants further investigation in future research.

Herding generally increases the correlation among individual returns. The empirical findings documented in this paper suggest that, compared to other periods, investors would need an even larger number of securities with a low correlation to achieve the same desired level of diversification during the annual financial reporting period. The results also signify inadequate information for decision-making for investors in the Chinese stock market, which calls for appropriate regulations and policies that could facilitate better information, in terms of quality and quantity.

Appendix.

A. Unit-root test for key variables

Variable	Mean (%)	Std Dev (%)	Minimum (%)	Maximum (%)	ADF Statistic
$R_{m,t}$	0.078	1.876	−8.832	9.327	−50.650***
$CSAD_t$	1.667	0.522	0.894	5.567	−5.966***
$CSAD_{FUND,t}$	1.605	0.174	0.752	2.380	−3.711***
$CSAD_{NONFUND,t}$	0.062	0.485	−0.713	3.839	−17.398***

Notes:
a) Augmented Dickey-Fuller (ADF) test statistics are listed in the rightmost column.
b) $CSAD_{FUND,t}$ and $CSAD_{NONFUND,t}$ are constructed based on Eq. (3) and respectively measure the cross-sectional absolute deviations of stock returns that are due to fundamentals and non-fundamentals.
c) *, **, and *** indicate statistical significance at the 10%, 5%, and 1%, respectively.

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