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Intraday herding drivers in China's A-share market: evidence from the China Securities Smallcap 500 Index

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ABSTRACT

Using tick-by-tick data from China Securities Smallcap 500 Index (CSI 500) constituent stocks, we document stock-specific herding at a 5-min frequency across three trading directions: buyer-initiated, seller-initiated, and neutral. Investor sentiment and attention factors jointly provide strong explanatory power for herding. Our newly introduced sentiment proxies reveal asymmetric effects, where relative margin-trading interest driven by retail participation amplifies herding, whereas relative short-selling interest dominated by institutions dampens it, highlighting divergent retail and institutional impacts. Furthermore, stocks with strong performance in the previous five minutes encourage buy-side herding but suppress sell-side herding, consistent with the tendency to chase rising prices and sell during declines.

1. Introduction

Herding behavior, in which investors converge on the same trading direction within short intervals, is a persistent feature of modern financial markets. Prior studies have documented its effects on asset pricing efficiency, volatility, and stability (Hirshleifer et al., 1994; Devenow and Welch, 1996; Baker and Wurgler, 2006; Wang et al., 2022; Sun and Fu, 2025), yet few have examined the behavioral drivers of herding at minute-level frequencies.

Most research has focused on low-frequency determinants using daily or monthly data. These studies often attribute herding to informational cascades (Banerjee, 1992; Bikhchandani et al., 1992), reputation costs (Scharfstein and Stein, 1990), cultural constraints (El Hajjar et al., 2024; Xing et al., 2025), and behavioral biases (Shleifer and Summers, 1990; Daniel et al., 1998; Li et al., 2023; Nguyen et al., 2023). However, this framework overlooks the real-time dynamics that emerge at hourly and minute intervals. To address this gap, we investigate the microstructural mechanisms behind herding in China's A-share market.

In China, herding is more pronounced during rising markets and among small-cap or illiquid stocks, and is closely tied to speculative sentiment and information asymmetry (Tan et al., 2008; Li et al., 2017; Wang et al., 2022; Liu et al., 2023). Contributing factors include the dominance of retail investors, weak short-selling mechanisms, and the heavy use of margin leverage (Chang et al., 2014; Gao et al., 2021; Eaton et al., 2022; Xing et al., 2024). The market also exhibits distinctive intraday momenta and asymmetric overnight returns, shaped by behavioral reactions to information shocks (Chong et al., 2017; Gao et al., 2019a; Jin et al., 2020; An et al., 2022; Guo et al., 2025; Gao et al., 2025).

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We construct a 5-min herding intensity measure for constituents of the capitalization-weighted China Securities Smallcap 500 Index (CSI 500), containing small- and mid-cap companies widely used by domestic investors (Li and Selvam, 2021). A key advance of this approach is the use of the herding intensity statistic (Blasco et al., 2012; Wu et al., 2023), which more effectively captures ultra-short-term order flow clustering than traditional dispersion or cross-sectional correlation metrics (Chang et al., 2000; Fei and Liu, 2021).

This study contributes to the literature by examining investor sentiment and attention, the former referring to systematic pricing biases driven by psychological factors (Daniel et al., 1998; Barberis and Thaler, 2003; Sun et al., 2016; Filip and Pochea, 2023; Chen and Nguyen, 2024). Limited attention arises from cognitive constraints that lead investors to process only part of the available information (Odean, 1999; Peng and Xiong, 2006; Barber and Odean, 2008; Da et al., 2011). Although sentiment distorts decisions through emotional bias, limited attention constrains information processing capacity. To empirically capture these dynamics, we construct behavioral drivers of herding at both 5-min and daily frequencies. At high frequency, we use order imbalances, short-term extreme returns, and trading in high-attention stocks[1]; at daily frequency, we add overnight returns. We also propose new competing sentiment proxies—relative margin-trading interest (*RMI*) and relative short-selling interest (*RSI*)—representing two leveraged mechanisms with divergent impacts on herding (Chang et al., 2014; Wu and Zhang, 2019; Lin et al., 2025).

Our empirical results show that persistent intraday herding in China's small- and mid-cap stocks is significantly shaped by investor sentiment and attention, often in irrational directions. Applying the herding intensity measure at the intraday level with high- and daily-frequency factors allows for a more precise capture of stock-specific microstructure dynamics.

The remainder of the paper is organized as follows. Section 2 introduces the data, herding measure, and methodology. Section 3 presents descriptive statistics and empirical results. Section 4 reports robustness tests. Section 5 concludes the study.

2. Methods and materials

2.1. Data

We examine CSI 500 constituents in China's A-share market from January 4, 2020, to December 30, 2024, covering regular trading hours (9:30–15:00[2]). Tick-by-tick records include transaction prices, trade indices, and timestamps. We also employ daily data on overnight stock returns, free-float market capitalization, margin lending balances, and securities borrowing balances to construct behavioral factors. The dataset was sourced exclusively from Zheshang Securities Co., Ltd., a leading brokerage headquartered in Hangzhou, China.

2.2. Herding proxy

To capture intraday herding patterns, a trade is classified as an *uptick* if its price exceeds the previous transaction price, a *downtick* if lower, and otherwise as a $zero-tick$ (Blasco et al., 2012). We then calculate trade direction reversals, defined as transitions between modes:

- R_{buy}: Buyer-initiated reversal, when a transaction shifts from a $downtick/zero-tick$ to an *uptick*.
- R_{sell}: Seller-initiated reversal, when a transaction shifts from an $uptick/zero-tick$ to a *downtick*.
- R_{zero}: Neutral reversal, when a transaction shifts from an *uptick/downtick* to a $zero-tick$.

Herding effects for each trade type are measured as

$$x(i,t) = \frac{\left(R_{i,t} + \frac{1}{2}\right) - np_s(1-p_s)}{\sqrt{n}}, \quad i = buy, sell, zero \tag{1}$$

Here, $x(i, t)$ is the herding effect of transaction type i for a stock in interval t. $R_{i,t}$ is the number of trades of type i in t, $\frac{1}{2}$ is a discontinuity adjustment, n is the total trades in t, and p_s is the prior probability of each trading direction, set to $\frac{1}{3}$. We assume $x(i, t)$ follows a normal distribution with mean zero. The standardized herding measure is

$$H(i,t) = \frac{x(i,t)}{\sqrt{\sigma^2(i,t)}} \xrightarrow{a.d.} N(0,\ 1), \tag{2}$$

[1] A variety of proxies have been used in the literature to capture investor attention, including abnormal trading volume (Barber and Odean, 2008; Da et al., 2011), news coverage and advertising (Loh, 2010; Lou, 2014; Yuan, 2015), search engine activity (Da et al., 2011; Ben-Rephael et al., 2017), and social media engagement (Gao et al., 2019b; Meng et al., 2020). Due to the limited availability of high-frequency versions of most attention proxies, our study adopts return sorts (i.e., identifying 5-min returns in the top or bottom 5%) as an attention proxy.

[2] Notably, the Chinese stock market operates with a scheduled midday trading suspension (11:30 to 13:00 local time), premarket call auctions (09:15-09:25) and closing call auctions (14:57-15:00) where orders are matched to determine opening/closing prices. Consequently, the 5-min herding intensity is only calculated in continuous trading sessions (09:30-11:30 and 13:00-14:55) where time-stamped bid and ask prices are available.

where $\sigma^2(i,t) = p_s(1-p_s) - 3p_s^2(1-p_s)^2$.

2.3. Driving factors of high-frequency herding

We identify two behavioral sources: investor sentiment and market attention.

2.3.1. Investor sentiment

We first use 5-min order imbalance $OIB^d_{j,t}$ as a proxy for sentiment in high-frequency settings (Chordia et al., 2002; Kaniel et al., 2008):

$$OIB^d_{j,t} = \frac{Buy\ volume^d_{j,t} - Sell\ volume^d_{j,t}}{Buy\ volume^d_{j,t} + Sell\ volume^d_{j,t}}. \tag{3}$$

Order imbalances reflect net buying or selling pressure, often interpreted as bullish versus bearish sentiment. We also include overnight returns as a proxy for aggregated sentiment. These provide a forward-looking signal of investor mood (Aboody et al., 2018; Guo et al., 2019). Because Chinese investors cannot trade overnight, they react the following morning, leading to price adjustments at the open (Gao et al., 2019b, 2021). Positive overnight returns imply optimism, while negative returns suggest pessimism or anxiety.

$$OvntRet^d_j = \frac{Open^d_j}{Close^{d-1}_j} - 1 \tag{4}$$

To capture heterogeneity in investor sentiment, we introduce daily RMI (RMI^d_j) and RSI (RSI^d_j; Chang et al., 2014; Wu and Zhang, 2019; Lin et al., 2025):

$$RMI^d_j = \frac{MarginTradingBalance^d_j}{FreeFloatMktCap^d_j}, \tag{5}$$

$$RSI^d_j = \frac{ShortSellingBalance^d_j}{FreeFloatMktCap^d_j}. \tag{6}$$

Because of added costs and limited access, short-selling is largely institutional; between 2020 and 2024, about 60 % of CSI 500 lending balances were held by institutions.[3] By contrast, margin trading involves more retail participation and substantially greater volume.

2.3.2. Limited attention

We also include a 5-min extreme return dummy to capture limited investor attention and potential overreaction (Barber and Odean, 2008):

$$5min\_ret^d_{j,t} = log\left(\frac{Close^d_{j,t}}{Close^d_{j,t-1}}\right), \tag{7}$$

where $Close^d_{j,t}$ and $Close^d_{j,t-1}$ are the closing prices of stock j at times t and $t-1$. For each interval, t, stocks in the top 5% by return are assigned $RetHigh^d_{j,t} = 1$, those in the bottom 5% $RetLow^d_{j,t} = 1$, and all others $= 0$. $RetHigh^d_{j,t}$ indicates concentrated buying attention, and $RetLow^d_{j,t}$ reflects panic selling.

3. Empirical results

3.1. Summary statistics

Table 1 reports the annual averages of H_{buy}, H_{sell}, and H_{zero} from 2020–2024. In all five years, the herding intensity indicators remain negative, confirming persistent intraday herding in CSI 500 constituent trading.

Table 2 summarizes the statistical characteristics of the main variables.

3.2. Herding behavior drivers

Table 3 presents the impact of sentiment factors on herding. Panel A shows that order imbalance coefficients are negative and highly significant for buy-initiated and zero-tick groups (−0.1917 for buyers, $t = -104.897$; −0.0105 for $zero - tick$, $t = -5.909$), but

[3] The investor participation ratios in margin trading and short-selling provided by CSI 500-relevant institutions have been coarsened in compliance with privacy policies and source confidentiality requirements.

Table 1
Annual mean herding indicator values.

Year	H_{buy}	H_{sell}	H_{zero}
2020	−2.5226	−2.5648	−2.1467
2021	−3.8235	−3.8732	−3.3440
2022	−5.5348	−5.5883	−4.9175
2023	−4.5180	−4.5700	−3.9456
2024	−5.3812	−5.4366	−4.6973

Notes: This table reports annual mean values of herding indicators from 2020 to 2024. H_{buy}, H_{sell}, and H_{zero} are herding indicators across three trading directions: buyer-initiated, seller-initiated, and neutral-trend, respectively, at a 5-min frequency.

Table 2
Descriptive statistics of main variables.

	Mean	Std. Dev.	Min.	25%	Median	75%	Max.	Obs.
H_{buy}	−4.3766	3.9702	180.2595	−6.4363	−3.6321	−1.5411	15.0629	26,393,384
H_{sell}	−4.3262	3.9961	180.1142	−6.4066	−3.5762	−1.4659	14.7967	26,393,384
H_{zero}	−3.7906	3.7763	178.3229	−5.6528	−2.9527	−1.0933	21.2350	26,393,384
OIB	−0.0695	0.3927	−1.0000	−0.3519	−0.0740	0.2076	1.0000	26,393,384
RetHigh	0.0507	0.2194	0.0000	0.0000	0.0000	0.0000	1.0000	26,393,384
RetLow	0.0506	0.2191	0.0000	0.0000	0.0000	0.0000	1.0000	26,393,384
OvntRet	−0.0003	0.0118	−0.2008	−0.0004	0.0000	0.0029	0.2002	1,232,167
RMI	304.7934	258.9845	0.0000	83.5120	263.8924	468.7172	1973.2378	1,232,167
RSI	15.1121	31.3059	0.0000	3.3075	8.8785	15.9512	980.9202	1,232,167

Notes: This table reports annual mean values of herding indicators from 2020 to 2024. H_{buy}, H_{sell}, and H_{zero} are herding indicators across three trading directions: buyer-initiated, seller-initiated, and neutral-trend, respectively, at a 5-min frequency, t.
$OIB^d_{j,t}$ is the 5-min order imbalance for stock j on day d during time interval t. $OvntRet^d_j$ is the overnight return, RMI^d_j is the RMI, and RSI^d_j is the RSI.

positive for sellers (0.1399, $t = 75.631$). Thus, stronger buying pressure reinforces buy-side and neutral-trend herding. Panel B indicates that overnight returns carry negative, highly significant coefficients (e.g., −1.8351 for the buy group, $t = -29.635$). Across specifications, R^2 values cluster around 33%–35%, implying the model captures a meaningful share of the variation in herding intensity.\

$$H^d_{i,j,t} = \alpha + \beta_1 H^d_{i,j,t-1} + \beta_2 OIB^d_{j,\ t-1} + \varepsilon^d_{i,j,t}, \tag{8}$$

$$H^d_{i,j,t} = \alpha + \beta_1 H^d_{i,j,t-1} + \beta_2 OvntRet^{d-1}_j + \varepsilon^d_{i,j,t}, \tag{9}$$

Table 4 lists relative margin trading and short-selling interests, *RMI* and *RSI*, into the herding regressions (Eqs. (10)–(12)):

$$H^d_{i,j,t} = \alpha + \beta_1 H^d_{i,j,t-1} + \beta_2 RMI^{d-1}_j + \varepsilon^d_{i,j,t}, \tag{10}$$

$$H^d_{i,j,t} = \alpha + \beta_1 H^d_{i,j,t-1} + \beta_2 RSI^{d-1}_j + \varepsilon^d_{i,j,t}, \tag{11}$$

$$H^d_{i,j,t} = \alpha + \beta_1 H^d_{i,j,t-1} + \beta_2 RMI^{d-1}_j + \beta_3 RSI^{d-1}_j + \varepsilon^d_{i,j,t}. \tag{12}$$

Both margin-trading and short-selling intensity show a consistent, significant relationship with herding. A negative *RMI* coefficient (Panel A) indicates that higher RMI values strengthen herding, whereas a positive *RSI* coefficient (Panel B) suggests that greater RSI mitigates it. Panel C, which combines both measures, confirms the joint significance of relative margin-trading and short-selling interests.

Table 5 examines the effect of investor attention on intraday herding using extreme past returns:

$$H^d_{i,j,t} = \alpha + \beta_1 H^d_{i,j,t-1} + \beta_2 RetHigh^d_{j,t-1} + \beta_3 RetLow^d_{j,t-1} + \varepsilon^d_{i,j,t}. \tag{13}$$

Results show that greater attention, proxied by lagged top- and bottom-5 % returns, can either amplify or dampen herding, depending on trading direction. Attention to high-yield stocks increases buy-side herding but may reduce sell-side herding, while attention to low-yield stocks has the opposite effect. These findings support the view that attention interacts with behavioral biases in driving herding.

We next run regressions including all sentiment and attention variables simultaneously (Table 6):

$$H^d_{i,j,t} = \alpha + \beta_1 H^d_{i,j,t-1} + \beta_2 OIB^{\mathrm{d}}_{\mathrm{j,t-1}} + \beta_3 RMI^{d-1}_j + \beta_4 RSI^{d-1}_j + \beta_5 OvntRet^{\mathrm{d}}_{\mathrm{j}} + \beta_6 RetHigh^d_{j,t-1} + \beta_7 RetLow^d_{j,t-1} + \varepsilon^d_{i,j,t} \tag{14}$$

The results largely align with earlier regressions: order imbalances, overnight returns, RMI, and RSI all significantly explain

Table 3
Regression results of order imbalances and overnight returns on herding intensity.

Panel A	$H^d_{i,j,t}$		
	$i = buy$	$i = sell$	$i = zero$
$H^d_{i,j,t-1}$	0.5859***	0.5884***	0.5722***
	(2433.158)	(2448.118)	(2252.790)
$OIB^d_{j,t-1}$	−0.1917***	0.1399***	−0.0105***
	(−104.897)	(75.631)	(−5.909)
Constant	−1.7733***	−1.7199***	−1.5807***
	(−1553.438)	(−1499.086)	(−1516.051)
R^2	0.3489	0.3508	0.3317
Panel B	$H^d_{i,j,t}$		
	$i = buy$	$i = sell$	$i = zero$
$H^d_{i,j,t-1}$	0.5856***	0.5870***	0.5718***
	(2430.731)	(2450.399)	(2251.060)
$OvntRet^d_j$	−1.8351***	−1.9247***	−1.8511***
	(−29.635)	(−30.273)	(−31.905)
Constant	−1.7637***	−1.7382***	−1.5838***
	(−1547.250)	(−1546.961)	(−1532.407)
R^2	0.3483	0.3503	0.3313

Notes: This table reports results for the following equations:
Panel A: $H^d_{i,j,t} = \alpha + \beta_1 H^d_{i,j,t-1} + \beta_2 OIB^d_{j,\,t-1} + \varepsilon^d_{i,j,t}$, $i = buy, sell, zero$(8)
Panel B: $H^d_{i,j,t} = \alpha + \beta_1 H^d_{i,j,t-1} + \beta_2 OvntRet^{d-1}_j + \varepsilon^d_{i,j,t}$, $i = buy, sell, zero$ (9)
$H^d_{i,j,t}$, $i = buy, sell, zero$ reflect the herding indicators for stock *j* on day *d* across three trading directions: buyer-initiated, seller-initiated, and neutral-trend during 5-min intervals, *t*. $OIB^d_{j,t} = \frac{Buy\ volume^d_{j,t} - Sell\ volume^d_{j,t}}{Buy\ volume^d_{j,t} + Sell\ volume^d_{j,t}}$ is the 5-min order imbalance for stock *j* on day *d* during time interval *t*. $Buy\ volume^d_{j,t}$ is the buy trading volume, $Sell\ volume^d_{j,t}$ is the sell trading volume, $OvntRet^d_j = \frac{Open^d_j}{Close^{d-1}_j} - 1$ is the overnight return, $Open^d_j$ is the opening price, and $Close^{d-1}_j$ is the closing price of stock j on day d-1. Newey–West adjusted *t*-values are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

intraday herding. Most coefficients retain expected signs, and the model's R^2 improves slightly, confirming the explanatory power of the combined specification. High-yield stocks show a sign reversal in their effect on seller herding, though the coefficients are weak, suggesting limited significance. Table 7 presents the variance inflation factors for Eq. (14); all values hover near 1, indicating no multicollinearity concerns.

4. Robustness test

This study accounts for the compound impact of multiple crises within the sample period, including COVID-19, covering January 3–May 14, 2020 (Alexakis et al., 2023; Xing et al., 2024) and the property sector crisis (September 24, 2020–December 17, 2021). Table 8 examines how herding responds to these market stress events.

Panel A shows that during the pandemic, systemic breakdown is evident: the effect of order imbalances in promoting buyer herding weakens sharply, and overnight returns lose sensitivity in driving herding. This fragility is confirmed by a marked drop in (34 % to 18 %). By contrast, Panel B indicates that during the property crisis, overnight returns strengthened their influence on herding, with only a marginal decline in R^2, suggesting the shock did not fundamentally disrupt market stability.

Across both crises, investor sentiment and attention factors remain significant. However, RMI's herding-promoting effect intensifies, while RSI reverses from suppressing herding to actively promoting it, particularly during the pandemic. Low-yield stocks also switch from dampening to encouraging buyer herding, a shift especially pronounced during the property crisis.

5. Conclusion

Using high-frequency data from CSI 500 constituent stocks in China's A-share market, this study uncovers distinctive micro dynamics of stock-level herding. Unlike prior research that emphasizes market-wide herding (e.g., Wang et al., 2022; Liu et al., 2023; Chen and Nguyen, 2024), our analysis highlights stock-specific drivers. Empirically, investor sentiment, captured by order imbalances and overnight returns, exerts significant and asymmetric effects. Margin-trading interest, introduced here as a novel proxy, shows a strong positive link to herding, whereas institution-driven short-selling interest suppresses it. Attention to high-return stocks heightens buy-side herding, while attention to low-return stocks fuels selling, consistent with the tendency to chase rising prices and sell during declines.

Event studies further reveal that crises distort these dynamics, amplifying irrational behavior (e.g., inducing herding among buyers

Table 4
Regression results of relative margin-trading/short-selling interests on herding.

Panel A	$H^d_{i,j,t}$		
	i = buy	i = sell	i = zero
$H^d_{i,j,t-1}$	0.5852*** (2427.250)	0.5865*** (2446.548)	0.5711*** (2245.111)
RMI_j^{d-1}	−0.0002*** (−80.673)	−0.0002*** (−84.600)	−0.0003*** (−101.886)
Constant	−1.6994*** (−1233.076)	−1.6706*** (−1222.513)	−1.5065*** (−1194.584)
R^2	0.3485	0.3505	0.3316
Panel B	$H^d_{i,j,t}$		
	i = buy	i = sell	i = zero
$H^d_{i,j,t-1}$	0.5850*** (2426.702)	0.5863*** (2446.084)	0.5711*** (2247.192)
RSI_j^{d-1}	0.0022*** (105.212)	0.0023*** (109.496)	0.0021*** (110.040)
Constant	−1.7987*** (−1499.805)	−1.7753*** (−1498.843)	−1.6182*** (−1480.484)
R^2	0.3485	0.3506	0.3316
Panel C	$H^d_{i,j,t}$		
	i = buy	i = sell	i = zero
$H^d_{i,j,t-1}$	0.5841*** (2420.707)	0.5853*** (2439.434)	0.5699*** (2238.247)
RMI_j^{d-1}	−0.0003*** (−105.348)	−0.0003*** (−110.542)	−0.0003*** (−128.206)
RSI_j^{d-1}	0.0027*** (127.090)	0.0028*** (132.040)	0.0027*** (137.077)
Constant	−1.7232*** (−1233.694)	−1.6958*** (−1224.174)	−1.5305*** (−1194.959)
R^2	0.3489	0.3509	0.3321

Notes: This table reports results for the following equations:

Panel A: $H^d_{i,j,t} = \alpha + \beta_1 H^d_{i,j,t-1} + \beta_2 RMI_j^{d-1} + \varepsilon^d_{i,j,t}$, $i = buy, sell, zero$(10)

Panel B: $H^d_{i,j,t} = \alpha + \beta_1 H^d_{i,j,t-1} + \beta_2 RSI_j^{d-1} + \varepsilon^d_{i,j,t}$, $i = buy, sell, zero$ (11)

Panel C: $H^d_{i,j,t} = \alpha + \beta_1 H^d_{i,j,t-1} + \beta_2 RMI_j^{d-1} + \beta_3 RSI_j^{d-1} + \varepsilon^d_{i,j,t}$, $i = buy, sell, zero$ (12)

$H^d_{i,j,t}$, $i = buy, sell, zero$ are the herding indicators for stock *j* on day *d* across three trading directions: buyer-initiated, seller-initiated, and neutral-trend during 5-min intervals, *t*. $RMI_j^d = \frac{MarginTradingBalance_j^d}{FreeFloatMktCap_j^d}$ is the RMI for stock *j* on day *d*, $MarginTradingBalance_j^d$ is the margin trading balance, $FreeFloatMktCap_j^d$ is the free-float market capitalization, $RSI_j^d = \frac{ShortSellingBalance_j^d}{FreeFloatMktCap_j^d}$ is the RSI, $ShortSellingBalance_j^d$ is the short selling balance, and $FreeFloatMktCap_j^d$ is the free-float market capitalization. Newey–West adjusted *t*-values are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 5
Regression results of attention factors on herding intensity.

	$H^d_{i,j,t}$		
	i = buy	*i = sell*	*i = zero*
$H^d_{i,j,t-1}$	0.5857***	0.5873***	0.5717***
	(2432.758)	(2449.717)	(2252.533)
$RetHigh^d_{j,t-1}$	−0.3248***	0.0160***	−0.1698***
	(−98.779)	(4.733)	(−53.673)
$RetLow^d_{j,t-1}$	0.1015***	−0.1717***	−0.0387***
	(32.180)	(−54.818)	(−12.949)
Constant	−1.7498***	−1.7265***	−1.5713***
	(−1513.981)	(−1514.691)	(−1495.468)
R^2	0.3489	0.3507	0.3318

Notes: This table reports results for the following equation:

$H^d_{i,j,t} = \alpha + \beta_1 H^d_{i,j,t-1} + \beta_2 RetHigh^d_{j,t-1} + \beta_3 RetLow^d_{j,t-1} + \varepsilon^d_{i,j,t}$, $i = buy, sell, zero$ (13)

$H^d_{i,j,t}$, $i = buy, sell, zero$ are the herding indicators for stock *j* on day *d* across three trading directions: buyer-initiated, seller-initiated, and neutral-trend during 5-min time intervals, *t*. $RetHigh^d_{j,t}$ and $RetLow^d_{j,t}$ are investor attention factors. At every *t*, stocks ranking in top 5% by 5-min returns are assigned a dummy variable, $RetHigh^d_{j,t} = 1$, while those in the bottom 5% receive $RetLow^d_{j,t} = 1$, with all other stocks coded as zero. Newey–West adjusted *t*-values are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 6
Regression of combined sentiment and attention factors on herding intensity.

	$H^d_{i,j,t}$		
	$i = buy$	$i = sell$	$i = zero$
$H^d_{i,j,t-1}$	0.5836***	0.5859***	0.5691***
	(2419.238)	(2430.840)	(2235.008)
$OIB^d_{j,t-1}$	−0.1669***	0.1242***	−0.0047**
	(−89.481)	(65.894)	(−2.565)
$OvntRet^d_j$	−1.9035***	−1.9507***	−1.9241***
	(−30.675)	(−30.652)	(−33.075)
RMI^{d-1}_j	−0.0003***	−0.0003***	−0.0003***
	(−111.234)	(−110.605)	(−131.389)
RSI^{d-1}_j	0.0027***	0.0029***	0.0028***
	(129.550)	(132.869)	(138.979)
$RetHigh^d_{j,t-1}$	−0.2930***	−0.0423***	−0.1900***
	(−87.880)	(−12.357)	(−59.172)
$RetLow^d_{j,t-1}$	0.0493***	−0.1691***	−0.0620***
	(15.527)	(−53.631)	(−20.581)
Constant	−1.7212***	−1.6744***	−1.5196***
	(−1213.822)	(−1178.265)	(−1161.873)
R^2	0.3495	0.3512	0.3322

Notes: This table reports results for the following equation:
$H^d_{i,j,t} = \alpha + \beta_1 H^d_{i,j,t-1} + \beta_2 OIB^d_{j,t-1} + \beta_3 RMI^{d-1}_j + \beta_4 RSI^{d-1}_j + \beta_5 OvntRet^d_j + \beta_6 RetHigh^d_{j,t-1} + \beta_7 RetLow^d_{j,t-1} + \varepsilon^d_{i,j,t}$, $i = buy$, $sell$, $zero$ (14)
$H^d_{i,j,t}$, $i = buy, sell, zero$ are the herding indicators for stock *j* on day *d* across three trading directions: buyer-initiated, seller-initiated, and neutral-trend during 5-min time intervals, *t*. $OIB^d_{j,t}$ is the 5-min order imbalance for stock *j* on day *d* during time interval *t*, RMI^d_j *and* RSI^d_j are the relative margin-trading and short-selling interests, $OvntRet^d_j$ is the overnight return, and $RetHigh^d_{j,t}$ and $RetLow^d_{j,t}$ are 5-min investor attention factors. The sample period spans from January 4 2020 to December 30, 2024. Newey–West adjusted *t*-values are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 7
Multicollinearity Assessment: VIF Statistics.

	$H^d_{i,j,t}$		
	$i = buy$	$i = sell$	$i = zero$
$H^d_{i,j,t-1}$	1.0079	1.0161	1.0095
$OIB^d_{j,t-1}$	1.0442	1.0494	1.0451
$OvntRet^d_j$	1.0009	1.0010	1.0010
RMI^{d-1}_j	1.0548	1.0553	1.0557
RSI^{d-1}_j	1.0528	1.0531	1.0529
$RetHigh^d_{j,t-1}$	1.0354	1.0387	1.0365
$RetLow^d_{j,t-1}$	1.0183	1.0162	1.0169

Notes: This table reports variance inflation factor (VIF) values for independent variables in the regression model for the following equation:
$H^d_{i,j,t} = \alpha + \beta_1 H^d_{i,j,t-1} + \beta_2 OIB^d_{j,t-1} + \beta_3 RMI^{d-1}_j + \beta_4 RSI^{d-1}_j + \beta_5 OvntRet^d_j + \beta_6 RetHigh^d_{j,t-1} + \beta_7 RetLow^d_{j,t-1} + \varepsilon^d_{i,j,t}$, $i = buy$, $sell$, $zero$ (14)
$H^d_{i,j,t}$, $i = buy, sell, zero$ are the herding indicators for stock *j* on day *d* across three trading directions: buyer-initiated, seller-initiated, and neutral-trend during 5-min time intervals, *t*. $OIB^d_{j,t}$ is the 5-min order imbalance for stock *j* on day *d* during time interval *t*. RMI^d_j *and* RSI^d_j are the relative margin-trading and short-selling interests, $OvntRet^d_j$ is the overnight return, and $RetHigh^d_{j,t}$ and $RetLow^d_{j,t}$ are 5-min investor attention factors. VIF values around one indicate no concerning multicollinearity among factors.

Table 8
Event study on herding during the COVID-19 pandemic and property crisis periods.

Panel A COVID-19	$H^d_{i,j,t}$		
	i = buy	i = sell	i = zero
$H^d_{i,j,t-1}$	0.4126***	0.4094***	0.3910***
	(356.451)	(352.734)	(301.464)
$OIB^d_{j,t-1}$	−0.0504***	0.1327***	0.0570***
	(−10.048)	(25.965)	(11.943)
$OvntRet^d_j$	−0.7385***	−0.7909***	−0.6012***
	(−6.799)	(−7.073)	(−5.964)
RMI^{d-1}_j	−0.0005***	−0.0005***	−0.0006***
	(−60.951)	(−62.490)	(−74.569)
RSI^{d-1}_j	−0.0222***	−0.0212***	−0.0190***
	(−47.700)	(−45.161)	(−44.725)
$RetHigh^d_{j,t-1}$	−0.3657***	−0.1955***	−0.3257***
	(−36.028)	(−18.834)	(−34.525)
$RetLow^d_{j,t-1}$	−0.0542***	−0.2076***	−0.1543***
	(−5.937)	(−22.623)	(−18.580)
Constant	−1.1454***	−1.1134***	−0.9492***
	(−279.197)	(−269.026)	(−255.021)
R^2	0.1896	0.1862	0.1754
Panel B Property Sector Crisis	$H^d_{i,j,t}$		
	i = buy	i = sell	i = zero
$H^d_{i,j,t-1}$	0.5728***	0.5722***	0.5503***
	(1158.018)	(1154.570)	(1038.957)
$OIB^d_{j,t-1}$	−0.1484***	0.1168***	−0.0012
	(−49.401)	(38.318)	(−0.428)
$OvntRet^d_j$	−3.8083***	−3.8106***	−3.3272***
	(−32.030)	(−31.726)	(−29.709)
RMI^{d-1}_j	−0.0006***	−0.0006***	−0.0006***
	(−133.757)	(−135.814)	(−143.292)
RSI^{d-1}_j	−0.0010***	−0.0010***	−0.0009***
	(−27.137)	(−25.651)	(−25.660)
$RetHigh^d_{j,t-1}$	−0.4774***	−0.1935***	−0.3581***
	(−79.055)	(−30.994)	(−62.646)
$RetLow^d_{j,t-1}$	−0.1883***	−0.4448***	−0.2987***
	(−33.413)	(−79.295)	(−57.416)
Constant	−1.2316***	−1.1902***	−1.0784***
	(−540.504)	(−519.241)	(−518.463)
R^2	0.3471	0.3450	0.3215

Notes: This table reports results for the following equation during two subsamples based on Eq. (14):

$$H^d_{i,j,t} = \alpha + \beta_1 H^d_{i,j,t-1} + \beta_2 OIB^d_{j,t-1} + \beta_3 RMI^{d-1}_j + \beta_4 RSI^{d-1}_j + \beta_5 OvntRet^d_j + \beta_6 RetHigh^d_{j,t-1} + \beta_7 RetLow^d_{j,t-1} + \varepsilon^d_{i,j,t}, i = buy, sell, zero \quad (14)$$

Panel A examines the COVID-19 sample (January 3 2020-May 14 2020), while Panel B analyzes the Evergrande crisis sample (September 24, 2020–December 17, 2021). $H^d_{i,j,t}$, $i = buy, sell, zero$ are the herding indicators for stock *j* on day *d* across three trading directions: buyer-initiated, seller-initiated, and neutral-trend during 5-min time intervals, *t*. $OIB^d_{j,t}$ is the 5-min order imbalance for stock *j* on day *d*, RMI^d_j *and* RSI^d_j are the relative margin-trading and short-selling interests, and $OvntRet^d_j$ is the overnight return, $RetHigh^d_{j,t}$ and $RetLow^d_{j,t}$ are 5-min investor attention factors. Newey–West adjusted *t*-values are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

even in extremely low-return stocks).

Ethics approval

Not applicable.

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CRediT authorship contribution statement

Jingxing Guo: Writing – review & editing, Writing – original draft, Software, Methodology, Formal analysis, Data curation. **Xingguo Luo:** Supervision, Resources, Project administration, Methodology, Funding acquisition, Conceptualization. **Liu Yang:** Writing – review & editing, Writing – original draft, Methodology.

Declaration of competing interest

The authors declare no conflicts of interest.

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Data availability

The authors do not have permission to share data.

References

Aboody, D., Even-Tov, O., Lehavy, R., Trueman, B., 2018. Overnight returns and firm-specific investor sentiment. J. Financ. Quant. Anal. 53, 485–505. https://doi.org/10.1017/S0022109017000989.

Alexakis, C., Chantziaras, A., Economou, F., Eleftheriou, K., Grose, C., 2023. Animal behavior in capital markets: the role of COVID-19. N. Am. J. Econ. Finance 67, 101946. https://doi.org/10.1016/j.najef.2023.101946.

An, Y., Huang, L., Li, Y., 2022. The asymmetric overnight return anomaly in the Chinese stock market. J. Risk Financ. Manag. 15, 534. https://doi.org/10.3390/jrfm15110534.

Baker, M., Wurgler, J., 2006. Investor sentiment and the cross-section of stock returns. J. Finance 61, 1645–1680. https://doi.org/10.1111/j.1540-6261.2006.00885.x.

Banerjee, A.V., 1992. A simple model of herd behavior. Q. J. Econ. 107, 797–817. https://doi.org/10.2307/2118364.

Barber, B.M., Odean, T., 2008. All that glitters: the effect of attention and news on buying behavior. Rev. Financ. Stud. 21, 785–818. https://doi.org/10.1093/rfs/hhm079.

Barberis, N., Thaler, R.H., 2003. A survey of behavioral finance. In: Constantinides, G.M., Harris, M., Stulz, R.M. (Eds.), Handbook of the Economics of Finance, Handbook of the Economics of Finance, 1. Elsevier, pp. 1053–1128. https://doi.org/10.1016/S1574-0102(03)01027-6.

Ben-Rephael, A., Da, Z., Israelsen, R.D., 2017. It depends on where you search: institutional investor attention and underreaction to news. Rev. Financ. Stud. 30, 3009–3047. https://doi.org/10.1093/rfs/hhx031.

Bikhchandani, S., Hirshleifer, D., Welch, I., 1992. A theory of fads, fashion, custom, and cultural change. J. Polit. Econ. 100, 992–1026. https://doi.org/10.1086/261849.

Blasco, N., Corredor, P., Ferreruela, S., 2012. Does herding affect volatility? Implications for Spain. Quant. Finance 12, 311–327. https://doi.org/10.1080/14697688.2010.516766.

Chang, E.C., Cheng, J.W., Khorana, A., 2000. An examination of herd behavior in equity markets: an international perspective. J. Bank. Financ. 24, 1651–1679. https://doi.org/10.1016/S0378-4266(99)00096-5.

Chang, E.C., Luo, Y., Ren, J., 2014. Short-selling, margin-trading, and price efficiency: evidence from the Chinese market. J. Bank. Financ. 48, 411–424. https://doi.org/10.1016/j.jbankfin.2013.10.002.

Chen, A.S., Nguyen, H.T., 2024. A new perspective on how investor sentiment affects herding behavior in the cryptocurrency market. Finance Res. Lett. 67, 105737. https://doi.org/10.1016/j.frl.2024.105737.

Chong, T.T.L., Liu, X., Zhu, C., 2017. What explains herd behavior in the Chinese stock market? J. Behav. Finance 18, 448–456. https://doi.org/10.1080/15427560.2017.1365365.

Chordia, T., Roll, R., Subrahmanyam, A., 2002. Order imbalance, liquidity, and market returns. J. Financ. Econ. 65, 111–130. https://doi.org/10.1016/S0304-405X(02)00136-8.

Da, Z., Engelberg, J., Gao, P., 2011. In search of attention. J. Finance 66, 1461–1499. https://doi.org/10.1111/j.1540-6261.2011.01679.x.

Daniel, K., Hirshleifer, D., Subrahmanyam, A., 1998. Investor psychology and security market under-and overreactions. J. Finance 53, 1839–1885. https://doi.org/10.1111/0022-1082.00077.

Devenow, A., Welch, I., 1996. Rational herding in financial economics. Eur. Econ. Rev. 40, 603–615. https://doi.org/10.1016/0014-2921(95)00073-9.

Eaton, G.W., Green, T.C., Roseman, B.S., Wu, Y., Zhang, Y., 2022. Retail trader sophistication and stock market quality: evidence from brokerage outages. J. Financ. Econ. 146, 502–528. https://doi.org/10.1016/j.jfineco.2022.08.002.

El Hajjar, S., Gebka, B., Duxbury, D., Su, C., 2024. Does religiosity affect stock investors' herding behaviour? Global evidence. Finance Res. Lett. 62, 105165. https://doi.org/10.1016/j.frl.2024.105165.

Fei, T., Liu, X., 2021. Herding and market volatility. Int. Rev. Financ. Anal. 78, 101880. https://doi.org/10.1016/j.irfa.2021.101880.

Filip, A.M., Pochea, M.M., 2023. Intentional and spurious herding behavior: a sentiment driven analysis. J. Behav. Exp. Finance 38, 100810. https://doi.org/10.1016/j.jbef.2023.100810.

Gao, Y., Han, X., Li, Y., Vigne, S.A., Xiong, X., 2025. Attention allocation: an empirical analysis of the asymmetric market responses to information shocks in China. Financ. Rev. 60, 623–652. https://doi.org/10.1111/fire.12425.

Gao, Y., Han, X., Li, Y., Xiong, X., 2019a. Overnight momentum, informational shocks, and late informed trading in China. Int. Rev. Financ. Anal. 66, 101394. https://doi.org/10.1016/j.irfa.2019.101394.

Gao, Y., Han, X., Li, Y., Xiong, X., 2021. Investor heterogeneity and momentum-based trading strategies in China. Int. Rev. Financ. Anal. 74, 101654. https://doi.org/10.1016/j.irfa.2020.101654.

Gao, Y., Xiong, X., Feng, X., Li, Y., Vigne, S.A., 2019b. A new attention proxy and order imbalance: evidence from China. Finance Res. Lett. 29, 411–417. https://doi.org/10.1016/j.frl.2018.11.009.

Guo, J., Han, X., Li, K., Li, Y., 2025. The nexus of overnight trend and asset prices in China. J. Econ. Dyn. Control 170, 104997. https://doi.org/10.1016/j.jedc.2024.104997.

Guo, J., Li, Y., Zheng, M., 2019. Bottom–up sentiment and return predictability of the market portfolio. Finance Res. Lett. 29, 57–60. https://doi.org/10.1016/j.frl.2019.03.008.

Hirshleifer, D., Subrahmanyam, A., Titman, S., 1994. Security analysis and trading patterns when some investors receive information before others. J. Finance 49, 1665–1698. https://doi.org/10.1111/j.1540-6261.1994.tb04777.x.

Jin, M., Kearney, F., Li, Y., Yang, Y.C., 2020. Intraday time-series momentum: evidence from China. J. Futures Mark. 40, 632–650. https://doi.org/10.1002/fut.22084.

Kaniel, R., Saar, G., Titman, S., 2008. Individual investor trading and stock returns. J. Finance 63, 273–310. https://doi.org/10.1111/j.1540-6261.2008.01316.x.

Li, T., Chen, H., Liu, W., Yu, G., Yu, Y., 2023. Understanding the role of social media sentiment in identifying irrational herding behavior in the stock market. Int. Rev. Econ. Finance 87, 163–179. https://doi.org/10.1016/j.iref.2023.04.016.

Li, W., Rhee, G., Wang, S.S., 2017. Differences in herding: individual vs. institutional investors. Pac.-Basin Finance J. 45, 174–185. https://doi.org/10.1016/j.pacfin.2016.11.005.

Li, H., Selvam, S., 2021. CSI index reconstitutions: a quasi-natural experiment in China. Asia Pac. J. Financ. Stud. 50, 119–146. https://doi.org/10.1111/ajfs.12332.

Lin, H., Liu, P., Zhang, C., 2025. Information, sentiment, and margin trading of Chinese stock market. Account. Finance 65, 81–108. https://doi.org/10.1111/acfi.13319.

Liu, T., Zheng, D., Zheng, S., Lu, Y., 2023. Herding in Chinese stock markets: evidence from the dual-investor-group. Pac.-Basin Finance J. 79, 101992. https://doi.org/10.1016/j.pacfin.2023.101992.

Loh, R.K., 2010. Investor inattention and the underreaction to stock recommendations. Financ. Manage 39, 1223–1252. https://doi.org/10.1111/j.1755-053X.2010.01110.x.

Lou, D., 2014. Attracting investor attention through advertising. Rev. Financ. Stud. 27, 1797–1829. https://doi.org/10.1093/rfs/hhu019.

Meng, X., Zhang, W., Li, Y., Cao, X., Feng, X., 2020. Social media effect, investor recognition and the cross-section of stock returns. Int. Rev. Financ. Anal. 67, 101432. https://doi.org/10.1016/j.irfa.2019.101432.

Nguyen, H.M., Bakry, W., Vuong, T.H.G., 2023. COVID-19 pandemic and herd behavior: evidence from a frontier market. J. Behav. Exp. Finance 38, 100807. https://doi.org/10.1016/j.jbef.2023.100807.

Odean, T., 1999. Do investors trade too much? Am. Econ. Rev. 89, 1279–1298. https://doi.org/10.1257/aer.89.5.1279.

Peng, L., Xiong, W., 2006. Investor attention, overconfidence and category learning. J. Financ. Econ. 80, 563–602. https://doi.org/10.1016/j.jfineco.2005.05.003.

Scharfstein, D.S., Stein, J.C., 1990. Herd behavior and investment. Am. Econ. Rev. 80, 465–479.

Shleifer, A., Summers, L.H., 1990. The noise trader approach to finance. J. Econ. Perspect. 4, 19–33. https://doi.org/10.1257/jep.4.2.19.

Sun, L., Najand, M., Shen, J., 2016. Stock return predictability and investor sentiment: a high-frequency perspective. J. Bank. Financ. 73, 147–164. https://doi.org/10.1016/j.jbankfin.2016.09.010.

Sun, Y., Fu, H., 2025. Economic policy uncertainty and herding behavior in venture capital market: evidence from China. Pac.-Basin Finance J. 92, 102803. https://doi.org/10.1016/j.pacfin.2025.102803.

Tan, L., Chiang, T.C., Mason, J.R., Nelling, E., 2008. Herding behavior in Chinese stock markets: an examination of A and B shares. Pac.-Basin Finance J. 16, 61–77. https://doi.org/10.1016/j.pacfin.2007.04.004.

Wang, X., Kim, M.H., Suardi, S., 2022. Herding and China's market-wide circuit breaker. J. Bank. Financ. 141, 106533. https://doi.org/10.1016/j.jbankfin.2022.106533.

Wu, M.H., Hu, W.T., Weng, P.S., 2023. Herd behaviors in index futures trading: driving factors and impact on market volatility. J. Futures Mark. 43, 1373–1392. https://doi.org/10.1002/fut.22413.

Wu, J.J., Zhang, J.A., 2019. Short selling and market anomalies. J. Financ. Mark. 46, 100502. https://doi.org/10.1002/fut.22413.

Xing, S., Cheng, T., Sun, S., 2024. Do investors herd under global crises? A comparative study between Chinese and the United States stock markets. Finance Res. Lett. 62, 105120. https://doi.org/10.1016/j.frl.2024.105120.

Xing, S., Cheng, T., Qiu, L., Li, X., 2025. The evolution of herding behavior in stock markets: evidence from a smooth time-varying analysis. Pac.-Basin Finance J. 90, 102664. https://doi.org/10.1016/j.pacfin.2025.102664.

Yuan, Y., 2015. Market-wide attention, trading, and stock returns. J. Financ. Econ. 116, 548–564. https://doi.org/10.1016/j.jfineco.2015.03.006.