

Retail Investor Attention and Stock Volatility: Evidence from Guba Message-Board Attention in China's A-Share Market

Haoyue Wu

*Shenzhen University, Shenzhen, China
2023362053@email.szu.edu.cn*

Abstract. This paper examines whether abnormal retail investor attention on Guba, one of the major Chinese stock message-board platforms, can predict future stock volatility. Using Datago and CSMAR data, this study builds a firm-week panel of China's A-share market from 2013 to 2023. The main explanatory variable is an abnormal message-board attention index, which is measured by comparing current log posting volume with the median log posting volume over the previous eight weeks. Based on two-way fixed effect regressions, the empirical results show that abnormal Guba attention is significantly related to higher realized volatility in the following week, after controlling for firm characteristics and firm and time fixed effects. The estimated effect is moderate in size, but it still has clear economic significance. Specifically, a one-standard-deviation increase in abnormal attention is associated with an increase in next-week volatility of about 1.7% of the sample mean. Further dynamic tests show that the effect is mainly short-lived. The coefficient turns negative from weeks $t+2$ to $t+4$, indicating that the volatility response is more likely to come from transient price pressure rather than a persistent fundamental-information channel. Mechanism tests suggest that trading activity is an important transmission path. The heterogeneity analysis further identifies an activity paradox: low-turnover stocks react more strongly to attention shocks than high-turnover stocks. In addition, the sentiment decomposition results show that negative abnormal attention is more closely related to downside volatility, while the link between positive attention and upside volatility is relatively weaker.

Keywords: investor attention, stock volatility, Guba, retail investors, turnover channel

1. Introduction

Investor attention is a scarce resource. Faced with thousands of securities, investors do not process all available information with equal intensity; instead, they tend to trade stocks that enter their limited attention set. This behavioral friction is particularly evident in China's A-share market, where retail participation remains high and discussions on social-media platforms can quickly draw investors' attention to specific stocks. Guba message boards offer an important space for retail investors to discuss individual stocks, express sentiment, and exchange views with one another. In this context, a sudden rise in Guba posting volume may reflect a shift in retail attention and may appear before trading pressure and price fluctuations become fully visible in the market [1]. This

paper therefore examines whether abnormal Guba attention provides incremental predictive content for future stock volatility, and further considers whether this relation is more likely to reflect persistent information discovery or transient retail trading pressure [2].

To answer this question, this study combines Datago and CSMAR data and constructs a stock-week panel for China's A-share market from 2013 to 2023. The key explanatory variable is abnormal Guba attention, which is measured by comparing current log posting volume with the median log posting volume over the preceding eight weeks. Based on two-way fixed effect regressions, the empirical results indicate that abnormal Guba attention significantly predicts higher next-week realized volatility after controlling for firm characteristics, trading conditions, media attention, sentiment consistency, and firm and week fixed effects. The dynamic tests further show that this effect does not persist for a long period and tends to reverse in subsequent weeks, a pattern that is more consistent with temporary retail price pressure than with a durable fundamental-information channel [3]. Additional mechanism, heterogeneity, and sentiment tests suggest that trading activity serves as an important transmission channel. The results also show that low-turnover stocks are more sensitive to attention shocks, while negative abnormal attention is more closely associated with downside volatility than positive attention is with upside volatility.

This paper contributes to the investor-attention literature in three main aspects. First, it uses firm-week Guba posting data to measure stock-specific retail discussion. Compared with search-based attention indexes [3] or conventional media coverage, this measure is closer to the actual discussion behavior of retail investors in the stock market. Second, the paper finds a dynamic reversal in the attention-volatility relation. Abnormal attention is associated with a short-lived increase in volatility, but the effect does not last over a longer horizon. This result helps distinguish temporary market reactions from a persistent volatility effect. Third, the paper identifies an activity paradox: stocks with lower baseline turnover respond more strongly to sudden attention bursts. This finding suggests that market trading conditions play an important role in shaping how retail attention is translated into volatility.

2. Literature review and hypotheses

Retail investors face search frictions when allocating attention across securities. Barber and Odean [4] document that individual investors disproportionately buy attention-grabbing stocks, while Da, Engelberg, and Gao [3] validate abnormal search volume as a direct proxy for retail attention. In the Chinese A-share market, Guba posts serve as a direct proxy for stock-level attention [1], and online message boards have been shown to influence trading behavior independently of fundamental news [5]. If attention shocks shift trading demand independently of fundamentals, they generate short-term buying or selling pressure [6] and raise volatility by increasing trading activity [7]. From a theoretical perspective, attention shocks may affect stock variance [2], and this relationship has also been supported by empirical evidence from Shanghai A-shares [8]. Based on this logic, this paper proposes the following two hypotheses:

H1. Higher abnormal Guba attention is associated with higher next-week realized volatility [9].

H2. Trading activity is an important channel through which abnormal Guba attention predicts future volatility.

Attention may influence the market not only through the level of attention, but also through its direction. Negative discussions are more likely to induce panic selling, while positive discussions may encourage speculative buying. Since investors often react more strongly to negative news [10], negative abnormal attention is expected to show a closer relationship with downside volatility [11]. At the same time, the strength of this relationship may depend on the trading environment of the

stock. Low-turnover stocks usually have thinner markets and may be more vulnerable to sudden attention surges [12]. In addition, market-wide volatility may further amplify these firm-level shocks [13]. Therefore, this paper further proposes the following hypotheses:

H3. Negative abnormal attention is more strongly associated with net downside volatility than positive abnormal attention.

H4. The attention-volatility relation varies across company size, turnover, and market-volatility states.

3. Data, variables, and model

3.1. Data sources and sample construction

The dataset is constructed from Datago and CSMAR. Datago provides daily stock-level Guba posting counts (total, positive, negative), sentiment consistency scores, and media attention. CSMAR provides daily returns, turnover, market capitalization, leverage, book-to-market ratio, ownership concentration, and industry codes. Daily observations are aggregated to a weekly frequency. Missing values for media attention are set to zero after merging, as these represent stock-weeks without media coverage rather than unrecorded data. All continuous variables are winsorized at the 1% and 99% levels. Stock-weeks under ST, *ST, PT, suspended, delisting, or terminated status are excluded, as well as stock-weeks whose one-week lag or one- to two-week lead period overlaps with these periods of special status. The final panel consists of 1,730,114 stock-week observations from 2013-10-11 to 2023-12-29.

3.2. Variable definitions

The primary dependent variable is next-week realized volatility:

$$RV_{i,w+1} = \sqrt{\sum_{d \in \omega+1} r_{i,d}^2}, \quad (1)$$

where $r_{i,d}$ denotes the daily return of stock i on day d .

The key explanatory variable, abnormal Guba attention, is defined as:

$$ASVI_{i,w} = \ln(\text{Attn}_{i,w} + 1) - \text{Median}\{\ln(\text{Attn}_{i,w-k} + 1)\}_{k=1}^8, \quad (2)$$

where $\text{Attn}_{i,w}$ represents the total Guba posting volume. The construct requires at least four prior weekly observations to be available. Positive and negative abnormal attention indices are computed identically using positive and negative posting counts. Control variables include firm size, weekly turnover, Amihud illiquidity ($\times 100$), lagged return, lagged realized volatility, media attention, and sentiment consistency. Extended specifications add leverage, book-to-market ratio, and ownership concentration.

Table 1. Descriptive statistics

Variable	N	Mean	Std. Dev.	Min	Median	Max
<i>Next_Week_RV</i>	1,730,114	0.0552	0.0358	0.0098	0.0453	0.1840
<i>ASVI_w</i>	1,730,114	0.0563	0.6697	-1.3565	-0.0027	2.5990
<i>Size_w</i>	1,730,114	15.8040	0.9990	14.1287	15.6170	19.0282

Table 1. (continued)

<i>Turnover_w</i>	1,730,114	14.1340	17.6320	0.6566	7.9210	104.2343
<i>ILLIQ_w</i>	1,730,114	0.0340	0.0410	0.0010	0.0210	0.2751
<i>Lag_Ret_w</i>	1,724,925	0.0024	0.0645	-0.1702	-0.0014	0.2379
<i>Lag_RV</i>	1,724,925	0.0555	0.0361	0.0098	0.0454	0.1892
<i>Media_Attn_w</i>	1,730,114	2.5930	1.3500	0.0000	2.6391	6.0210
<i>Senti_Conform_w</i>	1,729,576	0.0350	0.0650	0.0000	0.0159	1.0000

Notes: The table reports 1% winsorized variables from the no-ST cleaned master panel. *ILLIQ_w* is scaled by 100.

3.3. Model specification

The baseline model is:

$$RV_{i,w+1} = \alpha + \beta ASVI_{i,w} + \Gamma Controls_{i,w} + FirmFE_i + WeekFE_w + \varepsilon_{i,w+1}. \quad (3)$$

Firm fixed effects absorb time-invariant firm characteristics; week fixed effects absorb aggregate market shocks. Standard errors are clustered at the stock level.

4. Baseline results

Table 2 reports the baseline regression results. The bivariate relation between abnormal Guba attention and next-week realized volatility in Column (1) is 0.00868, which likely reflects volatility persistence and cross-sectional stock popularity. In pooled OLS regressions with controls (Columns 2--4), the coefficient is sensitive to the inclusion of media attention, reflecting the cross-sectional correlation between social media attention and news coverage. The preferred estimates appear in Columns (5) and (6) with two-way fixed effects. The coefficient on *ASVI_w* in Column (5) is 0.00139 ($t=29.76$); Column (6), which adds financial controls, yields 0.00122 ($t=26.03$). These within-stock estimates demonstrate that abnormal Guba attention significantly predicts next-week realized volatility, supporting H1. The economic magnitude of this effect is moderate: $0.00139 \times 0.6697 \approx 0.00093$, representing approximately 1.7% of the sample mean.

Table 2. Baseline regression results

	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	OLS	OLS	OLS	FE	FE
<i>ASVI_w</i>	0.00868*** (138.87)	-0.00000 (-0.09)	-0.00021*** (-3.93)	-0.00012** (-2.39)	0.00139*** (29.76)	0.00122*** (26.03)
<i>Size_w</i>		0.00166*** (14.45)	0.00128*** (11.45)	0.00144*** (14.54)	0.00432*** (24.91)	0.00276*** (15.89)
<i>Turnover_w</i>		0.00052*** (126.15)	0.00051*** (121.16)	0.00059*** (131.16)	0.00043*** (125.82)	0.00049*** (136.54)
<i>ILLIQ_w</i>		0.04745*** (32.42)	0.04737*** (32.37)	0.05170*** (35.60)	0.02564*** (18.98)	0.01522*** (11.53)
<i>Lag_RV</i>		0.29289***	0.29206***	0.26093***	0.12828***	0.11566***

Table 2. (continued)

		(178.98)	(176.42)	(169.12)	(94.03)	(84.85)
Lag_Ret_w		0.00684***	0.00687***	0.00621***	0.01040***	0.00869***
		(15.00)	(15.08)	(13.55)	(21.13)	(17.61)
$Media_Attn_w$			0.00048***	0.00046***	0.00197***	0.00179***
			(10.02)	(11.29)	(60.37)	(55.13)
$Senti_Conform_w$			-0.00516***	-0.00619***	-0.00645***	-0.00655***
			(-10.63)	(-13.06)	(-16.35)	(-16.69)
Financial controls	No	No	No	Yes	No	Yes
Firm FE	No	No	No	No	Yes	Yes
Week FE	No	No	No	No	Yes	Yes
N	1,730,114	1,724,925	1,724,400	1,682,487	1,724,400	1,682,487
R^2	0.0263	0.2208	0.2211	0.2359	0.4591	0.4618

Notes: t statistics are in parentheses. Standard errors are clustered at the stock level. Financial controls include leverage, book-to-market ratio, and ownership concentration. ***, **, and * denote significance at 1%, 5%, and 10%.

5. Robustness checks

Table 3 presents the robustness checks. In Columns (1) and (2), the dependent variable is changed to the absolute weekly return and price amplitude, respectively. Under both settings, the coefficients of attention remain positive and statistically significant. Columns (3) and (4) then use raw log attention and a high-attention dummy variable to replace the main attention measure. The estimated coefficients are again positive and significant, suggesting that the main results are not merely caused by one specific way of constructing the attention variable. Column (5) further re-estimates the baseline regression after excluding financial firms. The coefficient remains 0.00137, with a t -statistic of 28.98. Taken together, these results indicate that the baseline findings are stable when using alternative volatility measures, alternative attention proxies, and a sample excluding financial firms.

Table 3. Robustness checks

	Abs. return	Amplitude	Raw attention	High-attn. dummy	Excl. financial
Attention variable	0.00156***	0.00039***	0.00179***	0.00164***	0.00137***
	(23.37)	(11.53)	(28.36)	(20.37)	(28.98)
Controls	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
Week FE	Yes	Yes	Yes	Yes	Yes
N	1,719,411	1,087,687	1,724,400	1,724,400	1,674,434
Adj. R^2	0.2520	0.5821	0.4578	0.4572	0.4550

Notes: Columns (1)–(2) use ASV_{I_w} as the explanatory variable. Columns (3)–(4) use alternative attention variables. Column (5) re-estimates the baseline two-way fixed effect model after excluding financial firms.

6. Dynamic effects and mean reversion

The baseline predictability is consistent with two potential mechanisms: the incorporation of fundamental information or transient retail trading pressure [6]. Table 4 shows that the predictive power of abnormal attention is confined to week $t + 1$. The coefficient is 0.00139 for RV_{t+1} , but reverses to - 0.00059, - 0.00113, and - 0.00125 for RV_{t+2} , RV_{t+3} , and RV_{t+4} . This reversal is difficult to reconcile with a fundamental-information explanation, supporting the view that temporary attention-induced trading leads to subsequent mean reversion. This reversal is not easy to explain from a fundamental-information perspective. It is more consistent with the view that temporary attention-induced trading pressure is followed by subsequent mean reversion. The evidence from trading activity also points in this direction. Abnormal attention leads to a substantial increase in contemporaneous turnover, with a coefficient of 5.02241. However, the one-week-ahead coefficient declines to 3.27716, and the change-in-turnover coefficient of -1.70886 further suggests a partial retreat in trading activity. Although the possibility of reverse causality cannot be completely ruled out, these dynamic patterns are more supportive of a short-term price-pressure interpretation.

Table 4. Dynamic effects and turnover mean reversion

Dependent variable	RV_{t+1}	RV_{t+2}	RV_{t+3}	RV_{t+4}	$Turn_t$	$Turn_{t+1}$	$\Delta Turn$
$ASVI_t$	0.00139*** (29.76)	-0.00059*** (-11.96)	-0.00113*** (-22.05)	-0.00125*** (-23.84)	5.02241*** (127.98)	3.27716*** (98.93)	-1.70886*** (-121.28)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Week FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The controls follow the baseline specification. The turnover regressions explain the dynamic trading-activity channel.

7. Heterogeneity analysis

To examine whether the relation between abnormal attention and volatility differs across stock and market characteristics, this paper estimates the following interaction model:

$$RV_{i,w+1} = \alpha + \beta_1 ASVI_{i,w} + \beta_2 (ASVI_{i,w} \times Group_{i,w}) + \beta_3 Group_{i,w} + \Gamma Controls_{i,w} + FirmFE_i + WeekFE_w + \varepsilon_{i,w+1}. \quad (4)$$

The size and turnover groups are constructed according to the within-week cross-sectional median. Market-volatility states are identified based on the sample median of weekly average market realized volatility.

Table 5 reports the results of the interaction tests and provides three main findings. First, the positive coefficient of the size interaction suggests that attention-driven volatility is not limited to small, speculative stocks. Second, the turnover interaction is consistent with the trading activity hypothesis. For low-turnover stocks, the baseline coefficient is 0.00217, while the interaction coefficient for high-turnover stocks is -0.00154. This implies a net marginal effect of 0.00063 for high-turnover stocks, which is about 29% of the low-turnover baseline. Third, the results show that elevated market volatility strengthens the attention effect, as reflected in the significant interaction coefficient of 0.00042.

Table 5. Heterogeneity analysis: interaction models

	Size group	Turnover group	Market-volatility group
$ASVI_w$	0.00102*** (16.81)	0.00217*** (30.78)	0.00118*** (19.71)
$ASVI_w \times Group$	0.00084*** (10.43)	-0.00154*** (-17.67)	0.00042*** (5.09)
$Group$	-0.00024 (-1.47)	0.00595*** (74.56)	0.02703*** (43.93)
Controls	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Week FE	Yes	Yes	Yes
N	1,724,400	1,724,400	1,724,400
R^2	0.4592	0.4632	0.4591

Notes: Size and turnover groups are split by the weekly cross-sectional median. Market-volatility groups are split by the sample median of weekly average market realized volatility. For size, $Group=1$ denotes large stocks; for turnover, high-turnover stocks; for market state, high-volatility weeks.

8. Mechanism tests

8.1. Turnover mediation

This section examines whether trading volume explains a portion of the relation between attention and volatility [4]. The total-effect model excludes $Turnover_w$ from the controls, the path- α regression replaces the volatility outcome with $Turnover_w$, and the direct-effect model controls for $Turnover_w$. Table 6 shows that $ASVI_w$ has a total-effect coefficient of 0.00354 and strongly predicts contemporaneous turnover (5.02241). When controlling for turnover, the direct coefficient of attention decreases to 0.00139, representing an attenuation of 60.7% ($(0.00354-0.00139)/0.00354$), which supports H2.

8.2. Sentiment asymmetry

To explore asymmetry, abnormal attention is decomposed by sentiment sign [14]. Using the net downside volatility measure, $RV^{-w+1}-RV^{+w+1}$ (where RV^{+} and RV^{-} are constructed from positive and negative daily returns, respectively), the results show that negative abnormal attention increases net downside volatility, whereas positive abnormal attention reduces it. A Wald test rejects the null hypothesis of symmetric effects ($\beta_{ASVI^{Pos}}+\beta_{ASVI^{Neg}}=0$) with $F(1,5239)=184.70$ ($p<0.001$), supporting H3.

Table 6. Mechanism tests: turnover channel and sentiment asymmetry

	Total RV_{-w+1}	Path a $Turnover_{-w}$	Direct RV_{-w+1}	Upside RV^{+}_{-w+1}	Downside RV^{-}_{-w+1}	Net downside $RV^{-}-RV^{+}$
$ASVI_w$	0.00354*** (80.02)	5.02241*** (127.98)	0.00139*** (29.76)			

Table 6. (continued)

$Turnover_w$	0.00043***	0.00021***	0.00035***	0.00013***
	(125.82)	(75.31)	(146.53)	(42.83)
$ASVT_w^{Pos}$		0.00074***		-0.00019***
		(16.81)		(-2.82)
$ASVT_w^{Neg}$			0.00076***	0.00092***
			(26.19)	(14.97)
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Week FE	Yes	Yes	Yes	Yes
N	1,724,400	1,724,400	1,724,400	1,724,400

Notes: The total-effect and path- a regressions exclude $Turnover_w$ from the control set. The other columns include $Turnover_w$. The Wald test for Column (6) rejects symmetry with $F(1,5239)=184.70$.

9. Conclusion

This study shows that abnormal retail investor attention on Guba significantly predicts next-week realized volatility in the Chinese A-share market, although the economic magnitude of this effect is moderate. A one-standard-deviation increase in abnormal attention is associated with a volatility increase of approximately 1.7% of the sample mean. This finding is robust to alternative volatility measures, attention proxies, and the exclusion of financial institutions.

The empirical findings are more consistent with a short-term noise-trading and price-pressure explanation than with a persistent fundamental-information channel [6]. The positive relation is confined to week $t + 1$ and reverses in subsequent weeks. In addition, controlling for trading volume reduces the predictive coefficient of attention by 60.7%, supporting a trading-activity transmission channel. The cross-sectional analyses further show that low-turnover stocks are more sensitive to attention shocks, while negative attention has a closer relationship with downside risk.

These findings also have practical implications. For investors, unusual message-board activity may serve as an early signal of short-term volatility. For regulators, sharp increases in Guba discussions can help identify stocks that may be exposed to elevated retail trading pressure. For researchers, the results suggest that message-board data contain useful information that is not fully captured by conventional media coverage [15]. Several limitations of this study should also be acknowledged. First, although the two-way fixed effects design helps control for unobserved heterogeneity, it cannot by itself establish formal causality. Future studies may improve causal identification by using instrumental variables or quasi-natural experiments. Second, this paper focuses only on Guba. Further research could extend the analysis to other platforms and examine whether different online communities generate different volatility dynamics.

References

- [1] Ya Gao, Xiong Xiong, Xu Feng, Youwei Li, and Samuel A. Vigne. A new attention proxy and order imbalance: Evidence from china. *Finance Research Letters*, 29: 411–417, 2019.
- [2] Daniel Andrei and Michael Hasler. Investor attention and stock market volatility. *The Review of Financial Studies*, 28(1): 33–72, 01 2015.
- [3] Zhi Da, Joseph Engelberg, and Pengjie Gao. In search of attention. *The Journal of Finance*, 66(5): 1461–1499, 2011.

- [4] Brad M. Barber and Terrance Odean. All that glitters: The effect of attention and news on the buying behavior of individual and institutional investors. *The Review of Financial Studies*, 21(2): 785--818, 04 2008.
- [5] Sanjiv Sabherwal, Salil K. Sarkar, and Ying Zhang. Do internet stock message boards influence trading? evidence from heavily discussed stocks with no fundamental news. *Journal of Business Finance & Accounting*, 38(9-10): 1209--1237, 2011.
- [6] Brad Barber, Xing Huang, Terrance Odean, and Christopher Schwarz. Attention-induced trading and returns: Evidence from robinhood users. *Journal of Finance*, 77(6): 3141--3190, 2022.
- [7] Yang Gao, Chengjie Zhao, Bianxia Sun, and Wandu Zhao. Effects of investor sentiment on stock volatility: new evidences from multi-source data in china's green stock markets. *Financial Innovation*, 8(1): 77, 2022.
- [8] Dejun Xie, Yu Cui, and Yujian Liu. How does investor sentiment impact stock volatility? new evidence from shanghai a-shares market. *China Finance Review International*, 13(1): 102--120, 05 2021.
- [9] Taiji Yang, Siqi Zhuo, and Yongsheng Yang. Investor attention fluctuation and stock market volatility: Evidence from china. *PLOS ONE*, 18(11): 1--15, 11 2023.
- [10] Zhi Da, Joseph Engelberg, and Pengjie Gao. The sum of all fears investor sentiment and asset prices. *The Review of Financial Studies*, 28(1): 1--32, 01 2015.
- [11] Xian Han and Youwei Li. The impact of social media sentiment on stock volatility: Evidence from china's a-share market. *International Review of Economics & Finance*, 79: 120--135, 2022.
- [12] Wenbin Hu and Hui Sun. Retail investor attention and stock return volatility: The moderating role of ownership concentration in china. *Review of Financial Economics*, 43(4): 433--456, 2025.
- [13] Hua Wang, Liao Xu, and Susan Sunila Sharma. Does investor attention increase stock market volatility during the covid-19 pandemic? *Pacific-Basin Finance Journal*, 69: 101638, 2021.
- [14] Shuning Chen, Wei Zhang, Xu Feng, and Xiong Xiong. Asymmetry of retail investors' attention and asymmetric volatility: Evidence from china. *Finance Research Letters*, 36: 101334, 2020.
- [15] Can Huang, Yuqiang Cao, Meiting Lu, Yaowen Shan, and Yizhou Zhang. Messages in online stock forums and stock price synchronicity: Evidence from china. *Accounting & Finance*, 63(3): 3011--3041, 2023.