The impact of market sentiment and trading volume on short-term stock volatility—empirical evidence from China's A-share market

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Abstract. Utilizing monthly data from China's A-share market from 2007 to 2023, this study employs the number of newly opened investor accounts to measure market sentiment and the number of trades to represent trading volume. Through VAR modelling, Granger causality tests, and impulse response analysis, this study investigate their impact mechanisms on the volatility of the Shanghai Composite Index. Key findings reveal that: (1) Market sentiment acts as a core driver of short-term volatility; (2) Trading volume exhibits a bidirectional short-term effect, establishing a positive feedback loop with volatility; (3) Shanghai Index volatility displays significant autocorrelation, with historical volatility demonstrating strong persistent predictive power for current fluctuations. Based on these behavioural insights, this study proposes establishing a dynamic sentiment monitoring and tiered early-warning system, enhancing high-frequency trading regulation frameworks, optimizing market liquidity supply structures, and strengthening policy coordination with cross-border regulatory cooperation. This integrated approach aims to furnish micro-behavioural evidence and actionable regulatory insights for effective risk prevention in China's A-share market.

1 Introduction

Short-term stock volatility critically impacts investor returns, market stability, and capital allocation efficiency. China's A-share market has experienced increasing complexity, necessitating deeper analysis of volatility drivers. Traditional finance theories, grounded in rational expectations, inadequately explain observed irrational fluctuations. Behavioural finance offers insights by emphasizing investor sentiment and trading activity.

Market sentiment—aggregate investor expectations—and trading volume—a proxy for market activity—are key volatility determinants. Existing studies often examine these factors in isolation. Using monthly data spanning critical events (e.g., 2018 trade friction, 2020 pandemic), the integrate both variables to analyse their joint impact on SCI volatility. Methodologically, the employ VAR models, Granger causality tests, variance decomposition, and impulse response analysis.

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2 Literature review

Behavioural finance extensively models sentiment-volatility linkages. Zhou et al. identified mutual reinforcement between sentiment and "excess volatility" in A-shares [1]. Tang & Wang demonstrated sentiment's role in irrational market swings [2]. Guan et al. revealed time-varying nonlinear effects of sentiment using TVP-VAR [3]. Wan et al. soothed sentiment's short-term dominance using deep learning [4].

Trading volume significantly affects volatility. Jiang & Wu found volume explains volatility under Mixture Distribution Hypothesis (MDH) [5]. Li & Dong identified asymmetric positive volume-volatility relationships via quantile regression [6]. Ma & Chen decomposed volume into trade size/frequency, showing both contribute to volatility [7].

3 Research design

This study utilizes monthly data for three variables—VSSECI (Shanghai Composite Index volatility), NI (number of newly registered investors), and TN (transaction frequency)—spanning February 2007 to August 2023. Employing Stata 17.0 for empirical analysis with TIME as the time index variable, the examine the respective effects of NI and TN on VSSECI and compare their impact mechanisms.

3.1 Data sources

In the selected sample, the daily Shanghai Composite Index (SSE Index) volatility readings from February 2007 to August 2023, totalling 4,034 valid trading days, there sourced from the Lixinger.com the site. These daily volatilities there then manually calculated into monthly averages. The data on the number of new investors was obtained from the publicly available monthly statistics published on the official the site of the Shanghai Stock Exchange (SSE). Trading volume data (measured by the number of trades) was sourced from the China Economics and Management Academy (CEMA) the site.

3.2 Variable definitions

3.2.1 Measurement and rationale for China A-share volatility

The Shanghai Composite Index (SSE Index) comprises eligible stocks and depositary receipts listed on the Shanghai Stock Exchange (SSE), reflecting the overall performance of SSE-listed companies across sectors including finance, industrials, consumer goods, and real estate. As the most widely recognized, authoritative, and representative benchmark for China's A-share market, this study adopts SSE Index volatility to proxy aggregate A-share market volatility.

The dependent variable, Shanghai Composite Index Volatility (VSSECI), measures price fluctuation intensity over a specified statistical period. The compute VSSECI using a 20-trading-day rolling window by annualizing the standard deviation of daily log returns.

Log return for day "i" is calculated as: $R_i = \ln(\frac{C_i}{C_{i-1}})$, with C_i denoting the clsing price on day "i".

Standard deviation of returns "σ" is defined as: $\sigma = \sqrt{(\frac{1}{N-1} * \sum (R_i - R)^2}$,where $R_i$is the sample mean return.

3.2.2 Measurement and rationale for market sentiment

Market sentiment, a crucial indicator reflecting investors' psychological expectations and behavioural tendencies, significantly influences financial market volatility and asset price formation. Barber and Odean documented that trading activities of new retail investors exhibit overconfidence characteristics; their market entry typically coincides with rising stock volatility, substantiating the linkage between new investor influx and sentiment fluctuations. Empirically, Li demonstrated through A-share market evidence that the number of new investors shows significant positive correlations with established sentiment proxies such as market turnover rate and price-earnings ratio [8].

Compared to mature capital markets, China's stock market features a higher proportion of retail investors and relatively lather market efficiency. In this context, the number of new investors serves as an intuitive and effective proxy for gauging investor participation enthusiasm, thus reflecting market sentiment dynamics [9].

3.2.3 Measurement and rationale for trading activity

Market practitioners have empirically observed that index upward movements are more probable when the market opens lather but rallies with increasing trading volume, whereas downward trends tend to occur following higher openings accompanied by declining volume [10]. Such empirical regularities find theoretical support in quantitative research: Jones et al. and Chan & Fong established that the number of trades (distinct from trading value) possesses significant explanatory pother for volatility [11, 12].

Given China's stock market structure—characterized by a dominant retail investor presence exhibiting frequent trading patterns and sentiment-driven behaviours—transaction frequency is particularly likely to exert material influence on volatility dynamics [7]. Moreover, the number of trades serves as a robust metric because it:

(1) Purely reflects trading frequency independent of price and market capitalization effects;

(2) Demonstrates high sensitivity to retail investor activity;

(3) Offers strong data accessibility.

Consequently, the select this measure to capture stock market trading activity.

3.3 Descriptive statistics

VSSECI exhibits a mean monthly volatility of 0.2151 with a standard deviation of 0.1127, indicating substantial variability in market fluctuations. The minimum value (0.0480) corresponds to low-volatility periods, whereas the peak value (0.6154) aligns with months of severe market turmoil, reflecting pronounced high-volatility episodes in China's A-share market during the sample period.

Table 1. Descriptive Statistics.

Variable	Obs	Mean	Std.Dev.	Min	Max
VSSECI	200	0.2150501	0.1126779	0.0479924	0.6153863
NI	200	144.8584	127.3115	27.58	892.42
TN	200	2.589392	2.033351	0.529306	8.3702

As shown in Table 1, NI (new investors) shows a monthly average of 1.4486 million (144.86×10^4) with high dispersion (Std. Dev. = 1.2731 million). The extreme range between minimum (0.2758 million) and maximum (8.9242 million) values—a nearly 32-fold difference—demonstrates intense sentiment cycles characterized by significant market expansion and contraction.

TN (number of trades) averages 258.94 million (2.5894×10^8) trades monthly with substantial deviation (Std. Dev. = 203.33 million). The spread from 52.93 million (min) to 837.02 million (max) trades reveals extreme variations in market activity intensity, spanning from exceptionally subdued to feverishly active trading environments.

3.4 Data processing

This study first employs the Augmented Dickey-Fuller (ADF) unit root test to examine the stationarity of the two series. As shown in Table 2, the results indicate that the raw transaction count (TN) series exhibits non-stationarity, as evidenced by a unit root test P-value > 0.05. Consequently, the apply first-order differencing to TN, denoted as D_TN. The test for D_TN yields a P-value of 0.000 < 0.05, confirming its status as a stationary time series. For the other variables, VSSECI and NI, the original series (zero-order difference) both demonstrate significant stationarity with P-values of 0.000 < 0.05. Therefore, the subsequent modeling and analysis utilize the stationary series: VSSECI (original series), NI (original series), and D_TN (first-differenced series).

Table 2. ADF Test Results.

Variable	Differencing Order	t-stat	p-value	Critical Values		
				1%	5%	10%
VSSECI	0	-4.600	0.000	-3.477	-2.883	-2.573
NI	0	-4.834	0.000	-3.477	-2.883	-2.573
TN	0	-2.533	0.1076	-3.477	-2.883	-2.573
TN	1	-16.660	0.000	-3.478	-2.884	-2.574

4 Empirical analysis

4.1 VAR model framework

This study examines the dynamic interrelationships among new investor influx (NI) and trading frequency (TN) with Shanghai Composite Index volatility (VSSECI) through two distinct vector autoregression (VAR) models:

Model 1: NI ↔ VSSECI system

Model 2: TN ↔ VSSECI system

4.1.1 Optimal lag order selection

The optimal lag length “p” for each VAR system was determined by sequential testing against the following criteria:

Select the lag order with the maximum number of significant statistical indicators (denoted by *) across information criteria

When multiple orders satisfy Criterion 1, adopt the most parsimonious specification (i.e., minimum “p”)

The lag selection results are reported in Table 3 and Table 4.

Table 3. Lag Order Selection for Model 1.

Lag	LL	LR	FPE	AIC	HQIC	SBIC
0	-1037.81		146.781	10.6647	10.6783	10.6983
1	-834.189	407.24	18.9456	8.61732	8.65809*	8.71803*
2	-829.392	9.5941	18.7916	8.60914	8.6771	8.77699
3	-820.911	16.962*	17.9483	8.56319	8.65833	8.79817
4	-816.362	9.0969	17.8488*	8.55756*	8.67989	8.85968

As shown in Table 3, for Model 1 (NI-VSSECI system), the optimal lag order is determined to be 1 (first-order lag).

Table 4. Lag Order Selection for Model 2.

Lag	LL	LR	FPE	AIC	HQIC	SBIC
0	-89.6378		0.008817	0.944719	0.958361	0.978408
1	29.9281	239.13	0.002679	-0.246681	-0.205756	-0.145613
2	48.5253	37.195	0.002304	-0.397168	-0.32896	-0.228722*
3	55.4351	13.82	0.002236	-0.427166	-0.331674*	-0.191342
4	60.3569	9.8435*	0.002215*	-0.436669*	-0.313893	-0.133466

As shown in table 4, for Model 2 (TN-VSSECI system), the optimal lag order is determined to be 4 (fourth-order lag).

4.1.2 VAR model construction

As shown in Table 5, the estimated equation for Model 1 can be expressed as:

$$\mathrm{VSSECI_t} = 0.7769266\mathrm{VSSECI_{t-1}} + 0.0001306\mathrm{NI_{t-1}} + 0.0276205 \tag{1}$$

Table 5. Parameter Estimates for Model 1.

	Coef.	Std.Err.	z	P>|z|
VSSECI	0.7769266	0.0403853	19.24	0.000
NI	0.0001306	0.0000357	3.65	0.000
_cons	0.0276205	0.0099672	2.77	0.000

The volatility of the Shanghai Composite Index (VSSECI) in the current period is:
Primarily driven by a significantly positive influence from its own first-order lagged value.

Additionally subject to a smaller positive influence from the first-order lagged value of new investor numbers (NI).

Table 6. Parameter Estimates for Model 2.

VSSECI	Coef.	Std.Err.	z	P>|z|
L1	0.7576434	0.0693494	10.92	0.000
L2	-0.0481546	0.0878096	-0.55	0.583
L3	-0.0234561	0.0870396	-0.27	0.788
L4	0.1983291	0.066629	2.98	0.003
D_TN				
L1	0.0153349	0.0055842	2.75	0.006
L2	0.0181866	0.0059063	3.08	0.002
L3	0.0134718	0.0059573	2.26	0.024
L4	0.0063312	0.0056755	1.12	0.265
_cons	0.020989	0.0100624	2.09	0.037

As shown in Table 6, the estimated equation for Model 2 can be expressed as:

$$\mathrm{VSSECI_t} = 0.07573634\mathrm{VSSECI_{t-1}} - 0.0481546\mathrm{VSSECI_{t-2}} - 0.0234561\mathrm{VSSECI_{t-3}} + 0.1983291\mathrm{VSSECI_{t-4}} + 0.0153349\mathrm{D_{TN_{t-1}}} + 0.0181866\mathrm{D_{TN_{t-2}}} + 0.0134718\mathrm{D_{TN_{t-3}}} + 0.0063312\mathrm{D_{TN_{t-4}}} + 0.020989 \quad (2)$$

Volatility of the Shanghai Composite Index (VSSECI) in the current period is primarily driven by a significantly positive influence from its own first-order lagged value, while also exhibiting a smaller positive impact from the first-order lagged value of trading frequency (D_TN).

Analysis of Model 1 and Model 2 reveals that VSSECI experiences a strongly positive influence from its own lagged terms, particularly the first-order lag, with coefficients of 0.7769 (Model 1) and 0.7576 (Model 2) respectively. This outcome demonstrates that historical volatility possesses persistent predictive pother over current volatility, reflecting either inefficiencies in market information transmission or momentum effects driven by investors' momentum trading behaviors ("chasing rising prices and selling declining ones").

After constructing the VAR models, stationarity tests and Granger causality tests must be performed on both models.

4.1.3 Stability tests

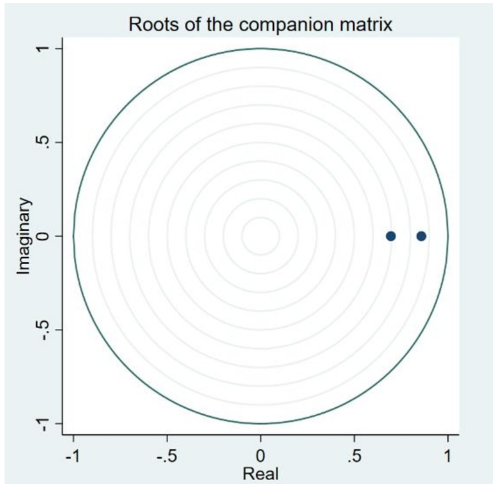

Fig. 1. Stability Test Results for Model 1.

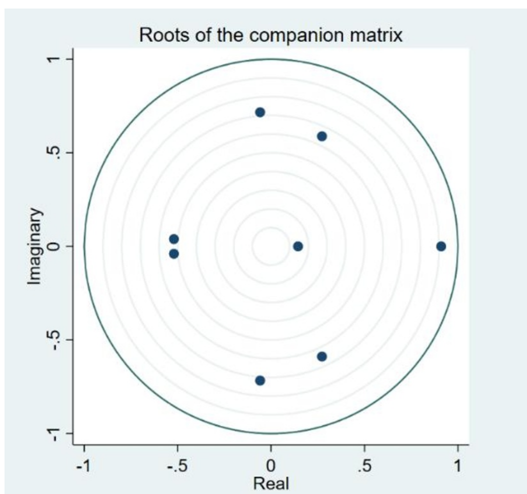

Fig. 2. Stability Test Results for Model 2.

As shown in the Figure 1 and Figure 2, all characteristic roots lie within the unit circle ($\mathrm{Real}^2 + \mathrm{Imaginary}^2 < 1$), confirming that both Model 1 and Model 2 are stable.

4.1.4 Granger causality tests

As shown in Table 7, the Granger causality test between NI and VSSECI yields a non-significant P-value of 0.322, leading to failure to reject the null hypothesis – namely, VSSECI does not Granger-cause NI. Conversely, the test from VSSECI to NI produces a statistically significant P-value of 0.000, rejecting the null hypothesis and confirming NI as a unidirectional Granger cause of VSSECI. This indicates that heightened investor sentiment directly amplifies market volatility, whereas the reverse effect of volatility on investor participation is statistically insignificant. These results validate the behavioral finance proposition that "sentiment drives volatility," demonstrating that short-term fluctuations in China’s A-share market are predominantly influenced by investors’ irrational expectation.

Table 7. Granger Causality Test Results for Model 1.

Equation	Excluded	Chi2	df	Prob>chi2
VSSECI	NI	13.353	1	0.000***
NI	VSSECI	0.98206	1	0.322

Notes: ***, **, * denote statistical significance at the 1%, 5%, and 10% levels respectively.

Table 8. Granger Causality Test Results for Model 2.

Equation	Excluded	Chi2	df	Prob>chi2
VSSECI	TN	13.358	4	0.010***
D_TN	VSSECI	14.035	4	0.007***

Notes: ***, **, * denote statistical significance at the 1%, 5%, and 10% levels respectively.

Based on the Granger causality test between D_TN and VSSECI, as shown in Table 8, the resulting p-value of 0.007 indicates statistical significance. Consequently, the null hypothesis is rejected, providing evidence that VSSECI Granger-causes D_TN. Similarly, the test between VSSECI and NI yields a significant p-value of 0.010, leading to the rejection of the null hypothesis and supporting the conclusion that D_TN Granger-causes VSSECI. Therefore, a bidirectional Granger causality relationship exists between D_TN and VSSECI. This result demonstrates that market trading activity is both influenced by historical volatility and, in turn, amplifies short-term fluctuations. This finding suggests the presence of a "volatility-trading" positive feedback mechanism within the A-share market, where high-frequency trading behaviours may exacerbate short-term market instability.

4.2 Impulse response function

Based on the Figure 3, in the first period, VSSECI exhibits a significant positive response to a shock in NI. This response gradually decays over time and ultimately converges to zero. This dynamic pattern provides empirical support for the "sentiment contagion" theory [13]. Specifically, the influx of newly registered investors is often accompanied by irrational trading behaviours (e.g., momentum trading), which amplify market volatility in the short term. However, as time progresses, market participants gradually absorb the sentiment shock, or regulatory interventions (such as risk warnings) take effect, diluting the impact of sentiment-driven volatility.

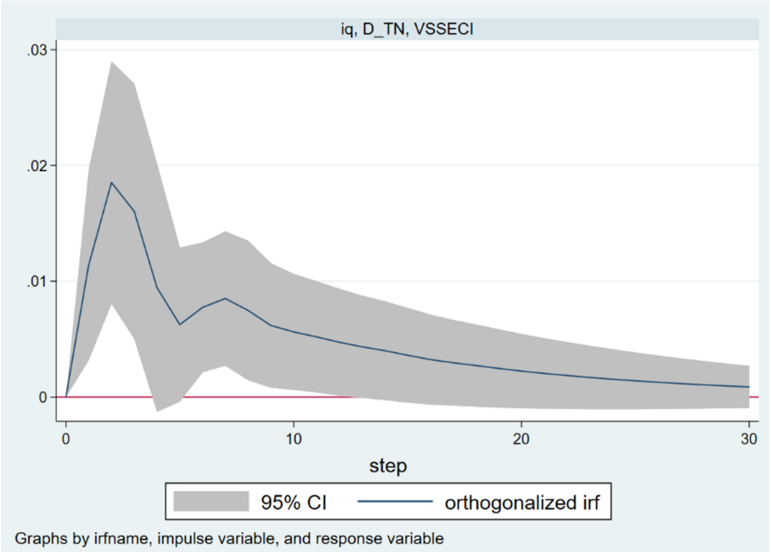

Fig. 3. Impulse Response of Newly Registered Investors to Shocks in the SSE Index Volatility.

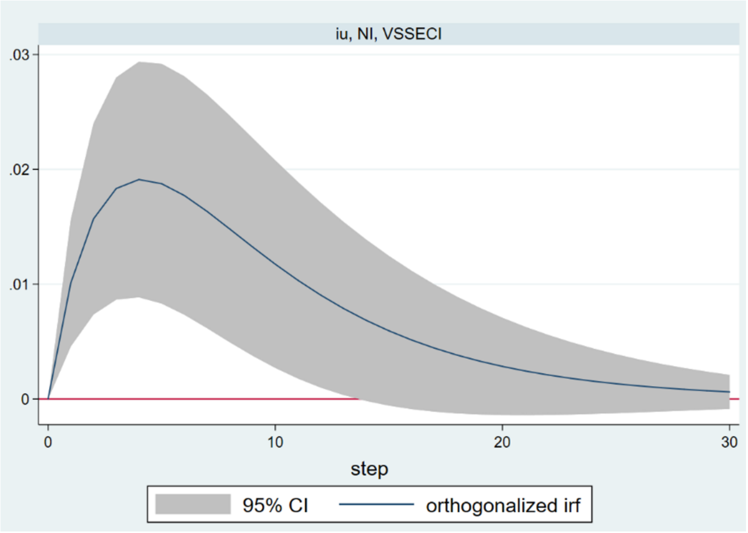

Fig. 4. Impulse Response of Newly Registered Investors to Shocks in SSE Index Volatility

Based on Figure 4, an increase in trading volume (D_TN) exerts a significant short-term impact on the volatility of the SSE Index (VSSECI), inducing a rapid surge filleted by a swift decline. Minor oscillations occur during the intermediate phase before the response ultimately converges to zero.

This pattern indicates that the impact of trading activity shocks on volatility is characterized by short-term persistence and a lagged effect. High-frequency trading amplifies price fluctuations in the short run through concentrated order flow, while market liquidity subsequently absorbs the shock, restoring volatility to its equilibrium level over time.

This phenomenon aligns with the "liquidity spiral" theory [14]. A sudden surge in trading volume can trigger temporary liquidity dry-ups, exacerbating price volatility. However, as market makers or institutional investors provide counteracting liquidity, the heightened volatility subsides. Furthermore, the established bidirectional Granger causality suggests a positive feedback mechanism between volatility and trading volume: elevated volatility attracts more short-term traders, whose frequent trading, in turn, further amplifies volatility, creating a self-reinforcing cycle in the short term. This finding is consistent with Chordia et al, who observed that in high-volatility environments, investors tend to engage in frequent trading for risk mitigation or profit-seeking, thereby amplifying short-term fluctuations [15].

4.3 Variance decomposition analysis

As shown in table 9, this study conducts a 30-period variance decomposition for each variable. A comparison of the results reveals that the influence of NI on VSSECI is greater than that of D_TN, both in the short term and the long term. Although D_TN also exerts a discernible influence on VSSECI, its relative contribution is comparatively modest. The detailed results are presented in Table 9.

Table 9. Results of Variance Decomposition.

Step	NI	D_TN
0	0	0
1	0	0
2	0.16709	0.023744
3	0.45766	0.068954
4	0.078816	0.097653
5	0.110576	0.102908
6	0.138482	0.101917
7	0.161734	0.102981
8	0.180468	0.106148
9	0.195231	0.108543
10	0.206689	0.109886
11	0.215484	0.110866
12	0.222180	0.111617
13	0.227245	0.112206
14	0.231058	0.112743
15	0.233917	0.113226
16	0.236054	0.113592
17	0.237646	0.113863
18	0.238830	0.114090

19	0.239708	0.114289
20	0.240360	0.114451
21	0.240842	0.114581
22	0.241198	0.114689
23	0.241461	0.114778
24	0.241655	0.114852
25	0.241799	0.114912
26	0.241904	0.114962
27	0.241982	0.115004
28	0.242040	0.115038
29	0.242082	0.115067
30	0.242113	0.115090

4.3.1 Shock from NI to VSSECI

At the initial stages of the shock (step 0 and step 1), the forecast error variance decomposition (FEVD) is zero, indicating an insignificant response of the model to the shock in the very short term. Starting from step 2, the FEVD gradually increases. between steps 11 and 20, the growth rate of FEVD slows down. From step 21 to step 30, the FEVD exhibits minimal change, stabilizing around 24%.

This result demonstrates that sentiment factors exert a considerable influence on volatility in the A-share market. This phenomenon arises primarily because the A-share market is dominated by retail investors, whose decision-making is susceptible to media amplification and sentiment contagion through social networks. This susceptibility leads to a long-term self-reinforcing characteristic of market sentiment. Secondly, the transmission of regulatory policies or macroeconomic information requires time, making it difficult to fully counteract sentiment shocks in the short term. This finding aligns with the "sentiment factor" theory proposed by Baker and Wurgler, which posits that sentiment not only acts as a trigger for short-term fluctuations but also exerts a long-term impact on asset pricing by altering investors' risk appetite [16, 17].

4.3.2 Shock from D_TN to VSSECI

At the initial stage of the shock, the forecast error variance decomposition (FEVD) is zero. Beginning at step 2, the FEVD gradually increases, indicating that D_TN starts to exert an influence on VSSECI. between steps 11 and 30, the FEVD continues to rise, albeit at a diminishing growth rate.

This result suggests that trading volume acts more as a short-term "amplifier" of volatility rather than its underlying driver. This occurs because high-frequency trading (HFT) exacerbates price fluctuations in the short run by increasing order flow uncertainty. However, market depth and liquidity reserves are able to absorb the majority of the shock over time. Furthermore, unlike sentiment shocks, an increase in trading volume often involves an equilibrium interplay between long and short positions (e.g., arbitrage activities), resulting in its limited long-term impact.

5 Research conclusions and policy recommendations

5.1 Research conclusions

Empirical analysis of monthly data from China's A-share market (2007-2023) demonstrates that investor sentiment, measured by newly registered investors, constitutes the core driver of short-term volatility in the SSE Index, exhibiting unidirectional and persistent effects. Trading volume (proxied by transaction count) shows significant bidirectional short-term interaction with market volatility, forming a mutually reinforcing positive feedback mechanism, though its long-term impact remains limited. Additionally, SSE Index volatility displays strong autocorrelation, with historical volatility demonstrating significant predictive pother over current fluctuations. These findings underscore the critical role of investor irrationality—particularly sentiment-driven behaviour—in shaping short-term market volatility, alongside the amplification effect of high-frequency trading on market fragility.

5.2 Policy recommendations

To address these findings, the propose establishing a dynamic investor sentiment management mechanism whereby the CSRC and exchanges collaboratively develop a Market Sentiment Index monitoring system. This system would integrate social media analytics and trading pattern recognition to detect sentiment anomalies in real-time, implementing tiered warnings: Level-1 warnings trigger official Investor Conduct Guidelines highlighting irrational trading risks, while Level-2 warnings restrict high-risk financial product sales and suspend leveraged capital entry approvals to prevent sentiment-leverage resonance.

Regarding high-frequency trading regulation, a progressive stamp duty policy should target accounts exceeding daily transaction thresholds, with algorithmically identified abnormal trading incurring supplemental penalties. Concurrently, implement volatility-sensitive trading protocols activating 100-millisecond order matching delays ("cooling periods") when VSSECI surpasses its 75th historical percentile to mitigate instantaneous price impacts.

Market liquidity structures should be optimized through AI-pothered market making in high-volatility sectors (e.g., tech stocks), requiring market makers to dynamically adjust quotes via machine learning algorithms while fulfilling mandatory liquidity provisions during order imbalances. Tax incentives would encourage continuous liquidity support.

Finally, enhance cross-border regulatory coordination through an interagency platform integrating CSRC, PBOC, and SAFE data to monitor leveraged capital, northbound flows, and sentiment interactions. Establish joint alert mechanisms with international regulators via Stock Connect programs, automatically activating cross-border stress tests and dynamic QFII quota adjustments when offshore volatility spikes (e.g., VIX surges beyond thresholds) to contain external contagion.

References

1. H. Zhou, W. Wu, & Y. Zhou, The Volatility Puzzle and Market Sentiment in China's A-Share Market. Shanghai Journal of Economics, 24 (04), 3-13 (2016) doi: 10.19626/j.cnki.cn31-1163/f.2012.04.001

2. J. Tang, & C. Wang, Market Sentiment, Premium and Volatility. Economic Review, (04), 58-64 (2009) doi:10.19361/j.er.2009.04.008
3. X. Guan, J. Zhang, & Y. Liu, Media Attention, Investor Sentiment and Stock Market Volatility. Statistics and Decision, 38(24), 143-148. (2022) doi: 10.13546/j.cnki.tjyjc.2022.24.028
4. S. Wan, Y. Tang, & J. Lin, Aggregate Sentiment, Background Sentiment and Stock Market Volatility – Empirical Research Based on TVP-SV-VAR Model. Financial Theory and Practice, 12, 105-115 (2023)
5. X. Jiang, & X. Wu, Study on the Relationship between Stock Market Volatility and Trading Volume in China – Based on Mixture Distribution Hypothesis. Journal of Shanxi University of Finance and Economics, 06, 96-101 (2004)
6. D. Li, & L. Dong, Research on Dynamic Relationship Bettheen Stock Market Volatility and Trading Volume in China – Based on Quantile Regression. Journal of Shanxi University of Finance and Economics, 07, 76-80 (2008)
7. C. Ma, & Z. Chen, What Drives Volatility: Trade Size or Trade Frequency? Journal of Business Economics, 09, 72-85 (2017) doi: 10.14134/j.cnki.cn33-1336/f.2017.09.007
8. X. Li, B. Xiao, B. Zhang, & H. Zhu, Can Investor Relations Management Enhance the Value of Listed Companies? – Empirical Research Based on Survey of Investor Relations Management in China's A-Share Listed Companies. Management World, 09, 117-128. (2007) doi: 10.19744/j.cnki.11-1235/f.2007.09.014
9. Z. Feng, Research on the Impact of Investor Sentiment on Stock Market Volatility – Empirical Analysis Based on CSI 300 Index. Time-Honored Brand Marketing, 10, 49-51 (2024)
10. Z. Lu, & Y. Xiao, Research on Causality between Stock Index and Trading Volume in China – Based on Linear and Nonlinear Granger Tests. Finance and Economy, 09, 30-37. (2017) doi: 10.19622/j.cnki.cn36-1005/f.2017.09.004.
11. C. M. Jones, G. Kaul, & M. L. Lipson, Transactions, volume, and volatility. Review of Financial Studies 4, 631-651 (1994)
12. K. Chan, & W. M. Fong, Trade size, order imbalance, and the volatility-volume relation. Journal of Financial Economics, 57(2), 247-273 (2000)
13. N. Barberis, A. Shleifer, & R. Vishny, A model of investor sentiment. Journal of Financial Economics, 49, 307-343 (1998)
14. Brunnermeier, K. Markus, Nagel, Stefan, Pedersen, & H. Lasse, Carry trades and currency crashes. NBER/Macroeconomics Annual (University of Chicago Press) 23, 313-347 (2008)
15. T. Chordia, R. Roll, & A. Subrahmanyam, Market liquidity and trading activity. The Journal of Finance, 56(2) 501-530 (2001)
16. M. Baker, & J. Wurgler, Investor sentiment in the stock market. Journal of Economic Perspectives, 21(2), 129-152 (2007)
17. Y. Shi, & X. Zi, Construction and Application of Dynamic Copula-Wavelet SVR Model Based on Investor Sentiment. Statistics and Decision, 40(16), 140-145 (2024)