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Three-Dimensional Characteristics of Speculative Capital and Ex Post Stock Price Volatility: The Inverted U-Shaped Divergence and Asymmetry in Daily Price Limits

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Abstract

Using a sample of 14,281 A-share main board "Dragon and Tiger List" events from 2023 to 2024, this paper systematically examines the nonlinear impact of speculative capital involvement characteristics on ex post excess stock price volatility. The results indicate that the three-dimensional characteristics of speculative capital exhibit significantly differentiated effects on ex post volatility. Specifically, the proportion of net buying by speculative capital shows a significant inverted-U relationship with ex post volatility, with volatility peaking in the mild net selling range; moreover, this effect is significant only in samples with high trading intensity. The daily price limit system exerts an asymmetric moderating effect, with the volatility amplification effect being stronger when the upper price limit is triggered in scenarios of net selling by speculative capital. This study employs an ex post window identification strategy, which effectively mitigates counterfactual causal interference during the same period. The findings not only supplement the empirical evidence on the nonlinearity of hot money's volatility effects but also provide a quantitative reference for monitoring abnormal stock price movements and implementing differentiated regulation in the A-share market.

Keywords

Speculative capital; bull-bear divergence; stock price volatility; inverted U-shaped relationship; price limit system.

1. Introduction

In China's A-share market, active speculative capital—represented by the "price-limit-up death squads"—has long been a key driver of short-term abnormal movements in speculative stocks. Stocks where speculative capital is active are often accompanied by a sudden surge in trading volume and sharp price fluctuations; the market typically views such capital as key traders that exacerbate price volatility and create a "fueling both rises and falls" effect. However, in actual trading, the behavioral patterns of speculative capital go far beyond simple inflows and outflows; rather, they constitute a comprehensive set of behaviors that encompass intensity, sentiment, and persistence: trading intensity reflects the magnitude of the order impact they exert on the market; the proportion of net purchases indicates whether there is divergence of views or a high degree of consensus within the speculative capital group; and examining persistence reveals whether speculative capital maintains sustained attention on and repeatedly engages with a particular stock.

Most existing studies capture speculative capital behavior from a single dimension—either examining purchase volume or focusing solely on net flows—with few providing a systematic, multidimensional characterization of their behavior. More importantly, most literature still tends to assume a linear relationship between speculative capital and stock price volatility, yet rarely recognizes that the behavior of speculative capital across different dimensions is likely to influence subsequent stock price performance through various channels—such as order flow shocks, noise trader risk, and information cascades—and that the resulting effects may not be monotonic but may instead exhibit nonlinear patterns such as diminishing returns or an inverted U-shaped structure. Furthermore, the price limit system unique to the A-share market imposes significant constraints and adjustments on such nonlinear relationships, and this influence often exhibits asymmetric characteristics; however, this important institutional context has not yet received sufficient attention in existing research.

In light of this, this paper constructs a three-dimensional framework comprising trading intensity, net buying share, and monitoring continuity to systematically analyze the relationship between speculative capital involvement and the ex post volatility of individual stocks after they appear on the "Dragon and Tiger List." To mitigate endogeneity issues arising from "speculative capital's tendency to actively select high-volatility stocks," this paper adopts an ex post window identification strategy—strictly limiting the measurement of volatility to the 1–5 trading days following the date a stock appears on the "Dragon and Tiger List." High volatility on the day of listing serves only as a prerequisite for sample selection, rather than the dependent variable to be explained in this study. Building on this foundation, this paper focuses on several core questions: How exactly do the three-dimensional hot money characteristics influence ex-post excess volatility? Specifically, does the hot money bull-bear divergence, as characterized by the core explanatory variable—the net buy ratio ( )—exhibit a typical inverted U-shaped relationship? Does this inverted-U pattern undergo an asymmetric adjustment due to the A-share price limit system? Furthermore, do significant heterogeneous differences exist in the aforementioned relationship across stocks with varying free-float market capitalizations and turnover rates?

The marginal contributions of this paper are as follows: First, we construct a three-dimensional system of speculative capital characteristics—comprising "intensity, divergence, and persistence"—which addresses the shortcoming of existing research that often characterizes speculative capital behavior from a single dimension. With the proportion of net purchases as the core, and trading intensity and attention continuity as complementary dimensions, this framework provides a three-dimensional analytical framework for systematically understanding the multiple transmission pathways of speculative capital involvement. Second, we verify the inverted U-shaped relationship between the proportion of net purchases and ex post volatility, along with its conditional nature, thereby supplementing the analysis with a nonlinear perspective and providing new nonlinear evidence for the transmission of noise trader risk within the A-share regulatory environment. Third, we reveal the asymmetric moderating effect of the daily price limit system on the transmission of bull-bear divergence. Price limit-up significantly amplifies ex post volatility, and this effect is more pronounced in scenarios where speculative capital is net sellers; price limit-down, however, does not exhibit a systematic impact. This finding helps reinterpret the actual function of price limit-up in speculative trading—which may serve more to "delay selling pressure" than to "lock in volatility"—and provides a quantitative basis for distinguishing between net buying and net selling states in monitoring abnormal market movements.

2. Literature Review and Research Hypotheses

2.1. Existing Explanations for Stock Price Volatility and Research Gaps

Current academic discussions on the causes of stock price volatility generally follow three lines of inquiry. The first is the macroeconomic fundamentals perspective. Existing research has confirmed that frequent adjustments to economic policies, changes in monetary policy stance, and fluctuations in the macroeconomic cycle all transmit volatility pressures to the stock market (Wang Shaomei, 2013; Cui Xiaotong, 2025).At the firm level, special events such as the surprise level of earnings announcements and major asset restructurings can also trigger idiosyncratic volatility (Chen et al., 2023). The second line of inquiry focuses on market microstructure. The level of liquidity, information asymmetry among traders, and trading rule designs—such as daily price limits—have all been shown to be important factors shaping the patterns of stock price volatility (Wang Danfeng, 2009). The third line of inquiry draws on behavioral finance. Fluctuations in investor sentiment, the tendency toward overconfidence, and psychological biases such as uneven attention allocation often lead to market overreactions or underreactions, thereby generating abnormal volatility (Yu Qingjin and Zhang Bing, 2012 ; Rao Yulei et al., 2010).Prospect theory suggests that price extremes (such as the daily upper limit) become new reference points, anchoring investor expectations and fueling irrational herd behavior (Chun et al., 2024).

However, systematic analysis of hot money as a specific trading entity remains relatively limited; existing studies mostly treat hot money as a homogeneous shock, with little attention paid to internal bullish-bearish divergences, nonlinear changes in the intensity of its involvement, or its persistence. Nevertheless, existing research has largely focused on how the rapid entry and exit of short-term speculative capital exacerbates market volatility (Zhou Fangzhao et al., 2020); some scholars have also demonstrated, using manipulation detection models, that hot money's "pump-and-dump" strategy leads to abnormal fluctuations in excess returns (Li Zhihui et al., 2022).Most of the aforementioned studies treat hot money as a homogeneous shock, paying little attention to internal long-short divergences, nonlinear changes in the intensity of their involvement, and the persistence of their intervention behavior; few have incorporated the constraints of the daily price limit system into their analytical frameworks. To address these gaps, this paper reexamines the mechanism through which hot money intervention affects ex post excess stock price volatility from three dimensions: trading intensity, the proportion of net purchases, and the continuity of .

2.2. Construction of the Three-Dimensional Speculative Capital Variables

1. Speculative Capital and Trading Intensity

The fundamental characteristics of hot money lie in its short-term nature, high liquidity, and high sensitivity to information. While short-term speculative capital injects liquidity into the market, its characteristics of "abnormal flow" and "severe volatility" amplify stock price fluctuations (Gaston et al., 2021; Xue Yaowen et al., 2016).Speculative capital actively screens for individual stocks with specific themes, low prices, and small market capitalization for concentrated investment (Xu Rong et al., 2025); at the micro level, this concentrated buying behavior manifests as large-order-flow shocks. Kyle's (1985) order-flow shock model indicates that large orders are interpreted by the market as signals of informational advantage, and the magnitude of the shock is positively correlated with the ratio of the order size to the market's normal trading volume.Therefore, trading intensity serves as a direct proxy for measuring the magnitude of speculative shocks caused by hot money.

From the perspective of micro-level transmission mechanisms, the intensity of speculative trading not only characterizes the scale of order flow shocks but also reflects the degree of concentrated transfer of shares: high-intensity intervention implies that a large number of shares are concentrated in the hands of speculators from their original holders within a short period. Subsequently, once information disruptions or profit-taking pressure arise, the sell-off of these concentrated shares or the relay-style price rally will trigger sharp price adjustments, forming the "concentration of shares effect."

2. Heterogeneous Beliefs and the Proportion of Net Purchases

Heterogeneous beliefs are a key driver of stock anomalies (Li Linbo et al., 2024). As the group exhibiting the strongest heterogeneity of beliefs, the degree of internal divergence between bullish and bearish positions among speculative capital directly influences stock price volatility.

When bullish and bearish forces are balanced within the speculative capital group, divergence is intense, leading to amplified volatility; when a high degree of consensus is formed, divergence converges, and volatility decreases (Liu Yunting et al., 2021).In the A-share market, where short selling is restricted, the sign and absolute value of the net buying ratio can capture the degree of consensus and divergence within speculative capital, making it a core variable for measuring the structure of heterogeneous beliefs.

Under the A-share market's daily price limit system, the volatility effect of the net buying ratio is further subject to institutional adjustments: extreme net buying is often accompanied by a price limit up, and the lock-in effect compresses the release of intraday volatility;extreme net selling is often accompanied by a price limit down, and liquidity shortages suppress trading activity; whereas the range of moderate net selling—where there are no price limit-induced lock-in effects but significant divergence between long and short positions—exhibits the most intense price tug-of-war ex post, making it the interval where volatility peaks are concentrated.

3. Focus on Continuity

The Information Cascade Theory (Bikhchandani et al., 1992) suggests that when subsequent decision-makers observe the action sequences of pioneers, they rationally infer that the pioneers possess private information and choose to follow suit.In speculative trading, the first appearance on the list sends a "pioneer signal"; consecutive appearances serve as repeated validation of this signal, with each appearance extending the information cascade chain and attracting a new wave of speculative capital to follow suit. Therefore, monitoring continuity (the number of consecutive days on the list) serves as a direct proxy for measuring the strength of the information cascade.

2.3. Theoretical Inferences and Research Hypotheses

1. Large-Order-Flow Shock Pathways

The large-order-flow shock model (Kyle, 1985) indicates that the magnitude of the price impact caused by informed traders' large orders is determined by the proportion of these orders relative to normal market trading volume. At the micro level, concentrated buying by speculative capital manifests as a large-order-flow shock ( ). When the amount purchased by speculative capital accounts for a high proportion of a stock's daily trading volume, the market perceives significant buying pressure.This signal may be interpreted by other market participants (especially retail investors) as "capital with an information advantage is entering the market," thereby triggering herd buying behavior. The influx of herd trading further amplifies the effect of the initial order flow shock, leading to more significant price fluctuations on subsequent trading days. Under the A-share price limit system, the buying behavior of high-intensity speculative capital is more likely to push stock prices up to the daily upper price limit.

Furthermore, the daily price limit has a dual effect. On the one hand, it captures the limited attention of retail investors—since hitting the limit is viewed as a strong signal, retail investors often overlook the specific balance of buying and selling forces and tend to follow the herd; on the other hand, the limit prevents the stock price from rising further, suppressing some buying demand and creating potential follow-on buying pressure. Once the limit is broken on subsequent trading days or market sentiment shifts, this suppressed demand may be released all at once, further exacerbating volatility.High trading intensity also implies that speculative capital ranks high among the top buyers on the Dragon and Tiger List, which enhances the signal's transparency and visibility, attracting more investor attention. Conversely, speculative capital with low trading intensity places smaller buy orders; their order flow is easily absorbed by normal market volume, making it difficult to generate significant price impacts or effectively trigger the price limit-up mechanism and attention-capturing effect.Therefore, there is a positive correlation between speculative capital trading intensity and ex post excess volatility. Based on this, we propose:

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H1: Speculative trading intensity is positively correlated with ex post excess volatility, but the marginal effect diminishes (the coefficient for the low-intensity group is greater than that for the high-intensity group).

2. Risk Pathways of Noise Traders

The noise trader model (De Long et al., 1990) indicates that the greater the divergence in beliefs, the higher the risk for noise traders and the more volatile the market becomes. Accordingly, in the absence of trading regime constraints, ex post excess volatility should be highest when the proportion of net buying by speculative capital approaches zero (indicating maximum divergence between long and short positions); as the proportion of net buying moves toward the positive and negative extremes (indicating increased consensus), volatility should gradually decline, exhibiting an inverted U-shaped relationship peaking at zero.

However, the daily price limit system in the A-share market may alter the specific location of this peak. When the proportion of net buying is exactly zero—representing a complete standoff between bulls and bears—stock prices tend to fluctuate repeatedly near the upper price limit. On the one hand, the upper price limit attracts retail investors' attention and drives herd buying; on the other hand, it prevents short sellers from immediately liquidating their positions, resulting in delayed selling pressure. However, precisely because bulls and bears are evenly matched, the upper price limit is often difficult to sustain and may be repeatedly breached, thereby allowing some of the market divergence to be released intraday and relatively alleviating volatility pressure afterward.

When the net buying ratio shows a slight net selling position, the bulls still have enough strength to push the stock price to the daily limit up, while bearish selling pressure is insufficient to immediately break through the limit up. At this point, the limit up is more likely to remain intact, maximizing its "delayed selling pressure" and "attention-driven bandwagon buying" effects: selling pressure is forced to the future, while buying interest continues to pour in, drawn by the limit up signal. The conflict between bulls and bears cannot be resolved within the trading day and accumulates entirely for subsequent trading days. Once the price limit is breached, the concentrated release of selling pressure and the reversal of market sentiment will trigger even more severe price volatility. From the perspective of micro-level behavioral mechanisms, this range corresponds precisely to the state of "most intense tug-of-war between bulls and bears" among speculative capital: the bulls use the price limit up to send a strong signal to attract retail investors to follow the trend and take over positions, while the bears take advantage of the liquidity after the price limit is sealed to unload their positions in batches, with both sides repeatedly engaging in a game of brinkmanship at the price limit level. The daily price limit system artificially interrupts this price discovery process, preventing information on the divergence between bulls and bears from being fully released within the trading day; instead, it is deferred to subsequent trading days. Meanwhile, the attention of retail investors captured by the price limit further amplifies price volatility. Irrational bandwagon traders, unable to discern the true extent of internal divergence among speculative capital, chase rallies and sell off during declines driven by sentiment. Once the logic behind the price limit is disrupted, the severity of the price reversal far exceeds that observed when there is clear consensus between bulls and bears. This transmission mechanism also aligns with the theory of attention-driven trading: extreme price signals capture investors' limited attention first, triggering emotional trading and thereby amplifying subsequent volatility. Consequently, the peak of ex-post volatility may not occur at the zero point but may shift toward the side of mild net selling.

When the net buying ratio shifts further toward extreme net selling, speculative capital exhibits a high degree of bearish consensus, and the stock price often hits the daily limit down; in this case, the depletion of liquidity actually suppresses ex-post volatility. Conversely, during periods of extreme net buying, shares are locked up and consensus is strong, resulting in lower ex-post

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volatility. In summary, the net buying ratio and ex-post excess volatility should exhibit an inverted U-shaped relationship, with the peak occurring in the mild net selling range.

Furthermore, this inverted U-shaped relationship requires sufficiently high trading intensity to manifest. This is because the order sizes of low-intensity speculative capital are limited; their signals of bullish-bearish divergence struggle to penetrate market noise, generate effective price shocks, or capture market attention, and thus fail to trigger the aforementioned "tug-of-war—delay—release" transmission chain. Based on this, we propose:

H2: The proportion of net buying by speculative capital exhibits an inverted U-shaped relationship with ex post excess volatility, peaking in the mild net selling range, and this relationship is primarily driven by speculative capital with high trading intensity.

3. Information Cascade Path

Information cascade theory (Bikhchandani et al., 1992) posits that when subsequent decision-makers observe the action sequences of early movers, they rationally infer that the latter possess private information and choose to follow, thereby forming a self-reinforcing information cascade. In the context of speculative trading, a stock's first appearance on the "Dragon and Tiger List" sends an early signal that "a party with a capital advantage has entered the market." The credibility of this signal depends on whether it is validated by subsequent actions. If a stock appears on the list for only a single day and there are no records of new speculative capital entering the market afterward, the market may view this as a one-time transaction rather than a sustained information advantage, resulting in relatively limited follow-on trading. However, if a stock appears on the list consecutively over subsequent trading days, this serves as repeated validation of the initial signal—each appearance conveys to the market that "speculative capital is still monitoring and trading this stock," thereby extending the chain of the information cascade.

Specifically, consecutive appearances have a cumulative effect: the first appearance attracts an initial wave of attention; the second indicates that speculative capital's interest in the stock is not coincidental, thereby drawing in more followers; and the third and subsequent appearances create a positive feedback loop, where new investors make similar buying decisions based on the actions of those who came before them. Under the daily price limit system, consecutive appearances on the list are often accompanied by multiple instances of hitting the daily price limit, which repeatedly captures investors' attention—the more frequently the price limit is hit, the higher the exposure, the more heated the discussions on social media and investment forums, and the faster sentiment spreads. The more consecutive days a stock appears on the list, the larger the scale of the information cascade, the stronger the cumulative effect of bandwagon trading, and the more likely price volatility in subsequent trading days is to be amplified. Conversely, for stocks that appear on the list only once, the information cascade chain is shorter, subsequent bandwagon trading is relatively limited, and ex post volatility is smaller. Therefore, there is a positive correlation between the continuity of speculative capital attention and ex post excess volatility. Based on this, we propose:

H3: There is a positive correlation between the continuity of speculative capital attention and ex post excess volatility, and this effect is stronger in the high-trading-intensity group .

3. Research Design

3.1. Data Sources

This paper focuses on companies listed on the A-share Main Board, with a sample period ranging from January 1, 2023, to December 31, 2024.Daily stock trading data, financial data, and top trader ranking data were obtained from East Money, the CSMAR database, and the WIND database. To ensure consistency in the daily price limit system, stocks listed on the STAR

Market and the ChiNext Board (with a daily price fluctuation limit of 20%) were excluded, retaining only those on the Main Board (with a daily price fluctuation limit of 10%).Additionally, companies that were delisted, designated as "ST," or "*ST" during the study period were excluded, as were samples with missing financial or trading data during the ranking period. Observations with fewer than 10 valid trading days in the pre-event normal volatility estimation window (60 to 6 trading days prior to the event date) were also excluded.

Table 1 Distribution of the Number of Times a Brokerage Branch Appeared on the List

<10	10–49	50–99	100–149	150–199	200–249
7,015	1,550	173	45	32	27

As shown in Table 1, The identification of speculative trading branches is based on the power-law distribution of the number of times branches appear on the Dragon and Tiger List. An analysis of 8,842 branches and 81,015 listings throughout 2024 revealed that branches appearing 10 times or fewer accounted for 79.33%, those appearing 50 times or fewer accounted for 96.87%, and those appearing 100 times or fewer accounted for 98.82%.Only about 1.18% of brokerage branches appeared on the list 100 times or more, and the top 1% of branches (approximately 88) all appeared more than 100 times. This distribution exhibits typical power-law characteristics, with the top 1% of branches located at the breakpoint at the tail of the distribution. Therefore, this paper defines the top 1% of brokerage branches by the number of appearances on the list each year as active speculative trading seats.

Based on this, we screened the listed events involving the aforementioned brokerage branches and further required the individual stocks to meet one of the following conditions: (1) Non-ST stocks whose cumulative deviation in closing price from the corresponding industry index reached ±20% over three consecutive trading days;(2) Stocks disclosed on the Dragon and Tiger List due to abnormal trading conditions, such as a daily price deviation of ±7% or a daily turnover rate of 20%. Ultimately, 14,281 valid listed events were identified, involving 2,049 stocks.

3.2. Variable Definitions

1. Ex Post Excess Volatility

This study uses the Garman-Klass volatility estimator to measure the daily volatility of individual stocks. This metric comprehensively utilizes the opening price, high, low, and closing price, making it more sensitive to intraday price fluctuations.For each stock, using the event date (t=0) as the baseline, we select a window of [-60, -6] trading days prior to the event and calculate the mean of the Garman-Klass volatility within that window as the normal volatility level$\overline{\sigma}_{normal}$; we then select a window of [1, 5] trading days following the event and calculate the mean within that window as the ex-post volatility level$\overline{\sigma}_{post}$. Ex-post excess volatility is defined as the difference between the two:

$$ExVol = \overline{\sigma}_{post} - \overline{\sigma}_{normal} \tag{1}$$

A positive value for this indicator indicates amplified volatility, while a negative value indicates suppressed volatility.

To mitigate reverse causality and self-selection biases arising from speculative capital's tendency to actively select high-volatility stocks, the identification strategy for the ex-post window adopted in this paper strictly limits the volatility measurement to the 1 to 5 trading days following the date a stock appears on the "Dragon and Tiger List." High volatility on the day of listing serves only as a prerequisite for sample selection, not as the dependent

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variable.This design fundamentally avoids the issue of reverse causality—where high volatility attracts speculative capital—during the same period.

2. Three-Dimensional Variables of Speculative Capital

The Net Buy Ratio (NetBuy) is defined as the net purchase amount by speculative trading seats on the event day—that is, the purchase amount minus the sale amount, divided by the total trading volume of the stock on that day. The sign and absolute value of NetBuy reflect the bullish and bearish positions within the speculative trading community and the degree of divergence: a value approaching 0 indicates a stalemate between bulls and bears and maximum divergence; a large absolute value indicates a high degree of consensus.To capture the inverted U-shaped relationship, both the first-order term and the squared term ($NetBuy^2$) of NetBuy were included in the regression. The NetBuy ratio is the core variable of this study, used to test the nonlinear relationship between the degree of divergence and ex post volatility, as well as the asymmetric moderation of price limit movements.

Trading intensity and attention continuity are characterized by the following two variables: Speculative Capital Trading Intensity (Intensity), defined as the ratio of the purchase amount by speculative capital seats on the event day to the stock's total daily trading volume, reflecting the relative scale of speculative capital order flow; and Speculative Capital Attention Continuity (Continuity), defined as the cumulative number of days the stock appeared on the Dragon and Tiger List during the five trading days preceding the event day (excluding the event day itself), characterizing the persistence of speculative capital involvement.

These three variables collectively form a three-dimensional framework characterizing speculative capital involvement: trading intensity captures the intensity of involvement, the proportion of net purchases reflects the degree of divergence between bulls and bears, and attention continuity illustrates the persistence of involvement. Among these, the proportion of net purchases serves as the core explanatory variable in this study, while the other two dimensions function as core feature variables for supplementary analysis.

3. Control Variables

The main control variables used in this empirical study include: market return (Rm), one-period lagged stock return (LRi), logarithm of closing price (LnP), logarithm of free-float market capitalization (LnSize), turnover rate (Turn), book-to-market ratio (BM), and cumulative return over the five days prior to the event (RET5).In addition, the number of days between listings (Gap) and the first-listing indicator (First) are included to control for the interference of event overlap and first-time listing effects. As shown in Table 2

Table 2: Variable Definitions

Variable Type	Variable Name	Variable Symbol	Calculation Method	Research Hypotheses
Dependent Variable	Post-hoc Mean Excess Volatility	ExVol	For each trading day within the post-event window (t+1 to t+5), calculated based on the Garman-Klass daily volatility, then averaged over the window	
Core Explanatory Variable	Speculative Trading Intensity	Intensity	On the event day (the day the stock was listed), the sum of purchase amounts by all listed speculative trading seats for the sample stock, divided by the stock's total trading volume for	+

Variable Type	Variable Name	Variable Symbol	Calculation Method	Research Hypotheses
			that day	
	Net Speculative Capital Buy Share	NetBuy	On the event date, the net purchase amount (purchases minus sales) from all listed speculative trading seats for the sample stock, divided by the stock's total trading volume for that day	Inverted U
		NetBuy2	The square of NetBuy	
	Speculative Capital Attention Continuity	Continuity	The cumulative number of days a sample stock appeared on the Dragon and Tiger List within the 5 trading days prior to the event date	+
Control Variables	Price Limit Up Dummy Variable	Limit_up	Set to 1 if the stock closed at the daily price limit on the event day; otherwise, 0	
	Virtual Variable for Daily Price Limit Down	Limit_down	Sets to 1 if the stock closes at the daily limit-down on the event day; otherwise, 0	
	Market Return	Rm	Daily Return of the CSI 300 Index	
	Daily Stock Return	LRi	Daily stock returns with cash dividends reinvested one period behind	
	Logarithm of the closing price	LnP	Logarithm of the stock's closing price on the given day	
	Turnover Rate	Turn	Daily Trading Volume of an Individual Stock / Floating Stock	
	Book-to-Market Ratio	BM	Net Asset Value per Share / Stock Closing Price; quarterly data adjusted to daily frequency	
	Cumulative Return Over the 5 Days	RET5	Cumulative Return of Listed Stocks in the 5 Days Prior to the Event	

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Variable Type	Variable Name	Variable Symbol	Calculation Method	Research Hypotheses
	Prior to the Event			
	Logarithm of Market Capitalization	LnSize	Free-float × closing price on the day, taken as the natural logarithm	
	Days Between Listings	Gap	The difference in calendar days between a stock's current listing and its previous listing.	
	First Listing Indicator	First	Indicates that this is the first time the security has appeared on the Dragon and Tiger List during the sample period; otherwise, the value is 0	

(3) Model Specification

To test the inverted U-shaped relationship between the net buying ratio and ex post excess volatility, a panel two-way fixed-effects model is established:

$$ExVol_{i,e} = \alpha + \beta_1 Intensity_{i,e} + \beta_2 NetBuy_{i,e} + \beta_3 NetBuy_{i,e}^2 + \beta_4 Continuity_{i,e} + \gamma X_{i,e} + \mu_i + \lambda_{t(e)} + \varepsilon_{i,e} \quad (2)$$

where i denotes a stock; e denotes a Dragon and Tiger List event (listing date);$ExVol_{i,e}$ is the ex post mean excess volatility of stock i following event e;$Intensity_{i,e}$ is the speculative trading intensity, measuring the scale of speculative capital involvement;$NetBuy_{i,e}$ is the proportion of net buying by speculative capital, measuring the direction of speculative capital involvement; together with $NetBuy_{i,e}^2$, these variables are used to test the inverted-U hypothesis of H2; $Continuity_{i,e}$ represents the continuity of speculative capital attention, measuring the persistence of speculative capital involvement; $X_{i,e}$ constitutes the set of control variables, covering individual stock trading characteristics and fundamental characteristics;μ_i represents individual fixed effects for each stock, used to account for individual heterogeneity that does not change over time;$\lambda_{t(e)}$ represents time fixed effects, used to control for systematic common shocks that change over time, such as market conditions and macroeconomic policies; $\varepsilon_{i,e}$ represents the random disturbance term.

In addition, the number of days between listings (Gap) and the first-listing indicator (First) were included as supplementary control variables to eliminate potential interference on the conclusions caused by overlapping event windows and the specific nature of the first listing. If the coefficients of these two variables are not significant and the estimates of the core variables are unaffected, they will be excluded from subsequent analyses to maintain model parsimony.

4. Empirical Results and Analysis

4.1. Descriptive Statistics

Table 3: Descriptive Statistics

	count	mean	SD	min
ExVol	14,281	.0164746	.015997	-.0450023
Intensity	14,281	.1451494	.1245753	.0370257
Net Buy	14,281	.0088797	.1103706	-0.8711454
NetBuy2	14,281	.0122597	.048642	0
Continuity	14281	1.200966	1.474034	0
Rm	14,281	.0005376	.0108697	-.068006
LRi	14281	.0316781	.0671148	-.10241
LnP	14281	2.489101	.8079789	0
LnSize	14281	22.22008	1.009938	19.70587
Turn	14,281	17.06124	13.86945	.0009
Limit_up	14,281	.3833065	.486209	0
Limit_down	14,281	.1284224	.3345712	0
BM	14281	.6011471	.2654064	.050455
RET5	14,281	.1213194	.1813661	-.409775
Gap	14,281	36.58994	81.7598	0
First	14281	.1638541	.3701561	0

Note: Figures in parentheses represent cluster-robust standard errors at the stock level; *p<0.10, **p<0.05, ***p<0.01; Limit_up and Limit_down are dummy variables for the upper and lower price limits, respectively.

As shown in Table 3, the mean of ex-post excess volatility (ExVol) is 0.0165, with a standard deviation of 0.0160. This indicates that the average volatility of the listed stocks during the ex-post window is approximately 1.65 percentage points higher than under normal conditions, and there is significant variation among individual stocks.The mean value of NetBuy is 0.0089, which is close to zero, but the range of values is quite wide, spanning from approximately -0.87 to 0.88, reflecting significant differences in the degree of divergence among short-term speculative funds across different listed events.The sample mean for Limit_up is 0.3833, and the mean for Limit_down is 0.1284, indicating that more than one-third of the listed events were accompanied by a price limit up, while approximately one-eighth were accompanied by a price limit down. The distributions of the remaining control variables are all within reasonable ranges.

4.2. Benchmark Regression

Table 4. Benchmark Regression Table

	(1) Basic	(2) U-shape	(3) Full
Intensity	0.00202	0.00740***	0.00740***
	(0.0020)	(0.0020)	(0.0020)
NetBuy	-0.00725***	-0.00581***	-0.00583***
	(0.0020)	(0.0019)	(0.0019)
Continuity	0.000666***	0.000667***	0.000667***
	(0.0002)	(0.0002)	(0.0002)
Rm	0.0390***	0.0382***	0.0382***
	(0.0133)	(0.0133)	(0.0133)
LRi	0.0159***	0.0162***	0.0162***

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	(0.0024)	(0.0024)	(0.0024)
LnP	-0.00575***	-0.00574***	-0.00575***
	(0.0014)	(0.0014)	(0.0014)
LnSize	0.000110	0.0000991	0.0000945
	(0.0010)	(0.0010)	(0.0010)
Turn	0.000156***	0.000154***	0.000154***
	(0.0000)	(0.0000)	(0.0000)
Limit_up	0.00786***	0.00765***	0.00765***
	(0.0004)	(0.0004)	(0.0004)
Limit_down	-0.000646	-0.000353	-0.000362
	(0.0005)	(0.0005)	(0.0005)
BM	0.0173***	0.0173***	0.0173***
	(0.0032)	(0.0032)	(0.0032)
RET5	0.00971***	0.00964***	0.00965***
	(0.0017)	(0.0016)	(0.0016)
NetBuy2		-0.0266***	-0.0266***
		(0.0047)	(0.0047)
Gap			0.00000113
			(0.0000)
First			0.000278
			(0.0004)
_cons	0.00963	0.00943	0.00947
	(0.0206)	(0.0206)	(0.0205)

Note: Figures in parentheses represent cluster-robust standard errors at the stock level; *p<0.10, **p<0.05, ***p<0.01; Limit_up and Limit_down are dummy variables for the upper and lower price limits, respectively.

As shown inTable 4. To examine the relationship between the proportion of net buying and ex post excess volatility, this study employs a panel two-way fixed-effects model for estimation, with the results shown in Table 4. Column (1) includes only the first-order term of NetBuy, while controlling for other variables but excluding squared terms.In this case, the coefficient of NetBuy is -0.00725 ($p < 0.01$), indicating a negative correlation between the proportion of net buying and ex post volatility from a linear perspective. However, this linear fit cannot capture potential nonlinear patterns. Meanwhile, the coefficient for trading intensity (Intensity) is 0.00202, which does not pass the significance test.

After adding the $NetBuy^2$ term to Column (2), the model estimates changed significantly. The coefficient of the NetBuy linear term is -0.00581 ($p < 0.01$), and the coefficient of the $NetBuy^2$ term is -0.0266 ($p < 0.01$).According to the vertex formula for quadratic functions, the extreme point is located at NetBuy ≈ -0.109, which falls within the range of mild net selling. This implies that as the proportion of net buying moves from extremely negative values toward -0.109, ex post excess volatility gradually increases; after passing the peak, the proportion of net buying continues to rise, and ex post volatility begins to decline, exhibiting a clear inverted U-shaped pattern.At the same time, the coefficient for Intensity jumps to 0.00740 and is significant at the 1% level, indicating that the independent effect of trading intensity becomes apparent after controlling for the nonlinear structure of net buying.

Column (3) further includes the number of days between listings (Gap) and the “First” indicator for the first listing. The direction, significance, and magnitude of the core coefficients all remain stable, indicating that the conclusions are not affected by event window overlap or first-time effects. Subsequent analyses exclude Gap and First to maintain model parsimony.

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4.3. Grouped Regression of Speculative Trading Intensity

To test the diminishing marginal returns predicted by H1 and the conditional nature of the "high trading intensity drives" hypothesis in H2 and H3, this study divides the entire sample into low-intensity and high-intensity groups using the median of speculative capital trading intensity as the cutoff, and conducts panel two-way fixed-effects regressions for each group. The results are shown in Table 5.

Table 5. Regression Results by Median Speculative Trading Intensity

	(1) Low Intensity	(2) High Intensity
Intensity	0.0459***	0.00464**
	(0.0158)	(0.0023)
NetBuy	0.00214	-0.00827***
	(0.0070)	(0.0022)
NetBuy2	-0.00389	-0.0208***
	(0.0186)	(0.0046)
Continuity	0.000748***	0.00105***
	(0.0002)	(0.0003)
Rm	0.00947	0.0464**
	(0.0183)	(0.0205)
LRi	0.0173***	0.00814**
	(0.0035)	(0.0038)
LnP	-0.00875***	-0.00497**
	(0.0023)	(0.0020)
LnSize	0.00188	-0.000890
	(0.0015)	(0.0017)
Turn	0.000233***	0.0000732**
	(0.0000)	(0.0000)
Limit_up	0.00933***	0.00583***
	(0.0006)	(0.0006)
Limit_down	-0.000186	-0.00112
	(0.0006)	(0.0008)
BM	0.0233***	0.00987**
	(0.0041)	(0.0039)
RET5	0.0113***	0.0128***
	(0.0020)	(0.0023)
_cons	-0.0319	0.0367

Note: Figures in parentheses represent cluster-robust standard errors at the stock level; *p<0.10, **p<0.05, ***p<0.01; Limit_up, , and Limit_down are dummy variables for the upper and lower price limits, respectively.

As shown inTable 5. Based on the economic significance and statistical characteristics of the coefficients, the marginal diminishing returns of trading intensity are clearly established.In the low-intensity group, the coefficient for *Intensity* is 0.0459, significant at the 1% level; in the high-intensity group, the coefficient for *Intensity* is 0.00464, significant at the 5% level. The former is approximately 10 times that of the latter, indicating that the volatility amplification effect resulting from a unit increase in trading intensity decreases significantly as investment depth increases, fully supporting research hypothesis H1 regarding the diminishing returns of trading intensity.

The inverted-U effect of the net buying ratio exhibits distinct heterogeneity across levels of market involvement. In the high-trading-intensity group, both the linear and squared terms of

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NetBuy are highly significant, with coefficients of -0.00827 and -0.0208, respectively, both significant at the 1% level. The inverted-U relationship holds robustly, with the peak occurring at NetBuy ≈ -0.199, which still falls within the range of mild net selling;In contrast, in the low-trading-intensity group, neither the coefficient for NetBuy nor that for $NetBuy^2$ passed the significance test, and their economic impact was negligible; thus, no statistically and economically significant inverted-U relationship was observed.When speculative trading intensity is low, the proportion of speculative capital relative to market turnover is limited; signals of internal bullish-bearish divergence are difficult for market participants to detect and are insufficient to drive subsequent price dynamics. Only when speculative capital reaches a sufficient level of involvement do these divergence signals gain market influence, thereby exerting a significant nonlinear effect on ex post excess volatility. Research hypothesis H2 is confirmed.

The positive effect of Continuity was significant in both groups; however, the coefficient for Continuity in the high-intensity group was 0.00105—approximately 1.4 times that of the low-intensity group (0.000748)—indicating that the information cascade effect amplifies in tandem with the depth of intervention, supporting Research Hypothesis H3.

4.4. Asymmetric Moderating Effects of Daily Price Limits

To test the heterogeneous moderating effects of price limit-up and limit-down under different net buying directions, this study divided the sample into a net buying group (NetBuy > 0) and a net selling group (NetBuy < 0) and conducted separate regressions. The results are shown in Table 6 below.

Table 6. Regression Results by Net Buying Direction

	(1) Net Buying Group	(2) Net Selling Group
Intensity	0.00619	0.0157***
	(0.0050)	(0.0060)
NetBuy	0.000588	0.0111*
	(0.0078)	(0.0057)
NetBuy2	-0.0354***	0.0161*
	(0.0111)	(0.0090)
Continuity	0.000971***	0.000560***
	(0.0003)	(0.0002)
Rm	-0.0411*	0.0944***
	(0.0212)	(0.0200)
LRi	0.0194***	0.0136***
	(0.0036)	(0.0037)
LnP	-0.00276	-0.00896***
	(0.0020)	(0.0018)
LnSize	0.0000245	0.000379
	(0.0015)	(0.0012)
Turn	0.000119***	0.000204***
	(0.0000)	(0.0000)
Limit_up	0.00574***	0.00982***
	(0.0006)	(0.0006)
Limit_down	-0.00162*	0.000655
	(0.0009)	(0.0006)
BM	0.0198***	0.0168***
	(0.0039)	(0.0037)
RET5	0.0139***	0.00790***

	(0.0023)	(0.0019)
_cons	0.00330	0.00999
	(0.0310)	(0.0244)
N	7,048	7184

Note: Figures in parentheses represent cluster-robust standard errors at the stock level; *p<0.10, **p<0.05, ***p<0.01; Limit_up and Limit_down are dummy variables for the upper and lower price limits, respectively. The 49 observations where NetBuy=0 were excluded.

As shown inTable 6. In the net buying group, the $NetBuy^2$ coefficient is significantly negative, and an inverted U-shaped relationship holds, indicating that when speculative capital is net buying overall, the divergence between long and short positions can still be fully transmitted to ex post volatility even at the end of mild net selling; as the consensus on net buying strengthens, volatility gradually converges. In contrast, in the net selling group, the $NetBuy^2$ coefficient turns positive and is marginally significant, reversing the pattern.The reason lies in the fact that within the net selling range, stock prices are more likely to hit the lower price limit. The liquidity drought caused by hitting the lower price limit severely suppresses trading activity and the price discovery process, preventing bullish-bearish divergence from being effectively released ex post.This heterogeneity further indicates that the constraints imposed by the daily price limit system on the transmission of disagreements are not symmetrical—the upper limit delays selling pressure and amplifies ex-post volatility, while the lower limit suppresses volatility by freezing trading—thereby shaping distinctly different nonlinear patterns across different net buying directions, consistent with the intrinsic logic of the benchmark theoretical framework.

In terms of the moderating effects of price limits, Limit_up is significantly positive in both groups, but the coefficient is markedly larger in the net selling group than in the net buying group, indicating that the amplification effect of upper price limits on ex-post volatility is more pronounced in net selling scenarios.Limit_down is marginally significant and negative in the net buying group (−0.00162, $p < 0.1$), but is not significant in the net selling group, showing no systematic effect.

To further test the statistical significance of differences between groups, this study employed interaction term regression, introducing a dummy variable for the net selling group and its interaction terms with Limit_up and Limit_down into the full sample. The results are shown in Table 7 below.

Table 7. Test of Differences Between Groups

	Interaction Coefficients	Standard Error	t-value	p-value
H_0: limit_up coefficients are equal	0.00403	0.00065	6.20	0.000
H_0: The coefficients are equal	0.00158	0.00092	1.71	0.087

As shown in Table 7. The between-group difference in Limit_up—calculated by subtracting the net buying group from the net selling group—had an interaction coefficient of 0.00403 (, p-value < 0.001), indicating that the limit-up effect in the net selling group was significantly stronger than that in the net buying group, and the difference between the two groups was highly significant.In contrast, the between-group difference for Limit_down was 0.00158, with a p-value of 0.087, which did not pass the conventional significance level test; there was no significant difference in the limit-down effect between the two groups. This confirms the asymmetry of limit-up and limit-down effects: when speculative capital is net selling (bearish)

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overall, the limit-up effect has a stronger amplifying effect on subsequent volatility; the limit-down effect, however, has no significant impact, and there is no directional asymmetry.

Based on this, it can be inferred that a price limit-up occurring against a backdrop of net buying by speculative capital is likely the result of speculative capital actively driving up the price and locking in the limit-up, accompanied by the concentration and locking of shares, resulting in limited subsequent selling pressure;conversely, price limit-ups occurring against a backdrop of net selling by speculative capital are mostly the passive result of speculative capital pushing prices higher to unload positions. The price limit-up restricts the immediate release of sell orders, forcing selling pressure to be deferred to subsequent trading days; once the price limit-up is broken and liquidity is restored, the concentrated release of sell orders will trigger more severe price volatility.

4.5. Robustness Tests

1. Use of Propensity Score Matching (PSM)

To mitigate self-selection bias caused by high-trading-intensity speculative capital actively selecting highly volatile stocks, the median trading intensity was used as the cutoff. Samples with high trading intensity were designated as the treatment group, and those with low trading intensity as the control group. Free-float market capitalization, turnover rate, ex ante volatility, and cumulative return over the five days prior to the event were selected as covariates for 1:1 nearest-neighbor matching.After matching, the standardized deviations of all covariates fell within 10%, and the balance test was passed.

Table 8. Regression Results After PSM Matching

	(1) PSM Sample
Intensity	0.00743*** (0.0020)
NetBuy	-0.00873*** (0.0021)
NetBuy2	-0.0251*** (0.0047)
Continuity	0.000798*** (0.0002)
Rm	0.0581*** (0.0168)
LRi	0.0156*** (0.0032)
LnP	-0.00528*** (0.0015)
LnSize	-0.000610 (0.0011)
Turn	0.000117*** (0.0000)
Limit_up	0.00705*** (0.0005)
Limit_down	-0.0000875 (0.0006)
BM	0.0136*** (0.0035)
RET5	0.0105*** (0.0019)

_cons	0.0272 (0.0211)
N	9741

Note: Figures in parentheses represent cluster-level robust standard errors; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; Limit_up and Limit_down are dummy variables for the daily price limit up and down, respectively.

As shown in Table 8. The regression results for the matched samples are shown in Table 8. The coefficient for the NetBuy linear term is -0.00873 ($p < 0.01$), and the coefficient for the NetBuy squared term is -0.0251 ($p < 0.01$); the inverted U-shaped pattern remains valid, with the vertex located at NetBuy ≈ -0.174, which still falls within the mild net selling range.The coefficient for Intensity is 0.00743 ($p < 0.01$), and the coefficient for Continuity is 0.000798 ($p < 0.01$); both remain significantly positive.The Limit_up coefficient is 0.00705 ($p < 0.01$), consistent with the direction of the asymmetric difference observed in the baseline regression. The above results indicate that, after controlling for self-selection bias, the core conclusion—that the proportion of net buying exhibits an inverted U-shaped relationship with ex post excess volatility, with the peak located in the mild net selling range—remains robust.

2. Placebo Test

To further rule out the possibility that the core findings are driven by sample-specific characteristics or unobserved variables, this study employs a permutation test to conduct randomized inference on the coefficients of the net buying ratio and its squared term. The correspondence between NetBuy and individual stock events was randomly shuffled; $NetBuy^2$ was then recalculated based on the shuffled NetBuy values, while keeping all other variables constant. The baseline model was re-estimated, and the coefficients of NetBuy and $NetBuy^2$ were recorded, with this process repeated 100 times.

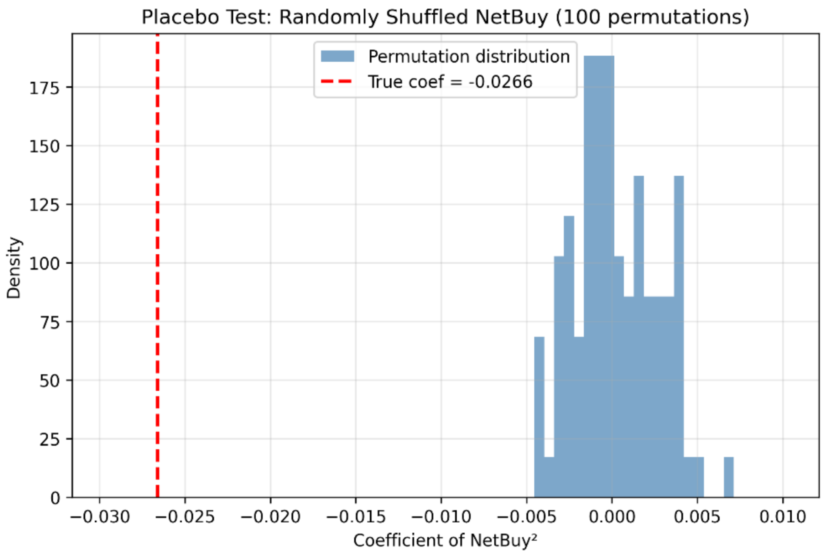

Figure 1. Distribution of $NetBuy^2$ Coefficients After Random Shuffling of NetBuy

As shown in Figure 1, the mean of the randomized coefficients is 0.0002, with a concentration around 0; in contrast, the true regression coefficient is -0.0266, which lies outside the left tail of the randomization distribution, with a two-sided p-value less than 0.001.This indicates that after randomly shuffling the net buying shares, the model fails to reproduce the true inverted U-shaped effect, suggesting that the core conclusion is unlikely to be driven by sample-specific characteristics or omitted variables and thus exhibits good robustness.

3. Window Sensitivity Analysis

To examine whether the core conclusion depends on the choice of key window parameters, this paper conducts sensitivity tests along two dimensions.

First, we replaced the estimation window for the posterior excess volatility.

Table 9: Ex Post Window Sensitivity Analysis

	(1) Ex Post Window [1,3]	(2) Post-event window [1,5]	(3) Post-event window [1,7]
Intensity	0.008***	0.007***	0.007***
	(0.003)	(0.002)	(0.002)
NetBuy	-0.008***	-0.006***	-0.004**
	(0.002)	(0.002)	(0.002)
NetBuy2	-0.036***	-0.027***	-0.023***
	(0.006)	(0.005)	(0.004)
Continuity	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)
Rm	0.034**	0.038***	0.030**
	(0.016)	(0.013)	(0.012)
LRi	0.019***	0.016***	0.017***
	(0.003)	(0.002)	(0.002)
LnP	-0.005***	-0.006***	-0.006***
	(0.002)	(0.001)	(0.001)
LnSize	0.001	0.000	-0.001
	(0.001)	(0.001)	(0.001)
Turn	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)
Limit_up	0.009***	0.008***	0.007***
	(0.000)	(0.000)	(0.000)
Limit_down	0.000	-0.000	-0.001
	(0.001)	(0.000)	(0.000)
BM	0.016***	0.017***	0.019***
	(0.003)	(0.003)	(0.003)
RET5	0.009***	0.010***	0.010***
	(0.002)	(0.002)	(0.002)
_cons	-0.003	0.009	0.023
	(0.023)	(0.021)	(0.021)

Note: Figures in parentheses represent cluster-robust standard errors at the stock level; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$; Limit_up and Limit_down are dummy variables for the upper and lower price limits, respectively.

As shown in Table 9. In the robustness analysis, this paper replaces the ex post window with [1, 3] and [1, 7] trading days, respectively, and re-estimates the baseline model. The key results are shown in Table 9 above. Under both the [1, 3] and [1, 7] windows, the coefficients of $NetBuy^2$ are both significantly negative, at -0.0364 and -0.0228, respectively ($p < 0.01$), and the inverted U-shaped pattern remains valid;the inflection points are located at NetBuy ≈ -0.112 and ≈ -0.087, respectively, which still fall within the mild net selling range. The coefficients for Intensity and Continuity also remain consistently positive and significant. Compared with the main window [1,5], the absolute values of the coefficients have changed slightly, but their signs

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and significance levels are entirely consistent, indicating that the core conclusions of this paper do not depend on the specific choice of ex post window length and exhibit good robustness.

Second, we vary the definition window for the Continuity variable.

The baseline regression defines continuity as the cumulative number of days a stock appeared on the list within the 5 trading days prior to the event date. Here, we replace the definition window with the previous 3 trading days and the previous 10 trading days, respectively, recalculate the Continuity variable, and substitute it into the baseline model.

Table 10 Continuity Window Table

	(1) 3-day window	(2) 5-day window (benchmark)	(3) 10-day window
Intensity	0.00752*** (0.0020)	0.00740*** (0.0020)	0.00744*** (0.0020)
NetBuy	-0.00597*** (0.0019)	-0.00581*** (0.0019)	-0.00589*** (0.0019)
NetBuy2	-0.0268*** (0.0047)	-0.0266*** (0.0047)	-0.0265*** (0.0047)
continuity_3	0.000731*** (0.0002)		
Continuity		0.000667*** (0.0002)	
continuity_10			0.000425*** (0.0001)
Rm	0.0380*** (0.0133)	0.0382*** (0.0133)	0.0389*** (0.0133)
LRi	0.0149*** (0.0024)	0.0162*** (0.0024)	0.0148*** (0.0024)
LnP	-0.00539*** (0.0014)	-0.00574*** (0.0014)	-0.00622*** (0.0015)
LnSize	0.000165 (0.0010)	0.0000991 (0.0010)	0.0000162 (0.0010)
Turn	0.000156*** (0.0000)	0.000154*** (0.0000)	0.000156*** (0.0000)
Limit_up	0.00756*** (0.0004)	0.00765*** (0.0004)	0.00769*** (0.0004)
Limit_down	-0.000360 (0.0005)	-0.000353 (0.0005)	-0.000394 (0.0005)
BM	0.0181*** (0.0033)	0.0173*** (0.0032)	0.0166*** (0.0033)
RET5	0.00967*** (0.0017)	0.00964*** (0.0016)	0.0113*** (0.0016)
_cons	0.00684 (0.0205)	0.00943 (0.0206)	0.0128 (0.0208)
N	14,281	14281	14,281

Note: Figures in parentheses represent cluster-robust standard errors at the stock level; * p < 0.10, ** p < 0.05, *** p < 0.01; Limit_up and Limit_down are dummy variables for the upper and lower price limits, respectively.

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As shown in Table 10, the coefficients for both continuity_3 and continuity_10 are positive and significant at the 1% level, at 0.000731 and 0.000425, respectively. This indicates that, regardless of the window definition used, the continuity of speculative capital attention is robustly and positively associated with ex post excess volatility.As the window length increases from 3 days to 10 days, the continuity coefficient decreases, which is intuitive—the longer the window, the more the marginal incremental effect of cumulative days on the list is diluted. More importantly, the sign, significance, and location of the vertex of the inverted U-shaped curve for the core explanatory variables NetBuy and $NetBuy^2$ all fall between -0.11 and -0.12, with no substantial changes observed across different window lengths.These results indicate that the core conclusions of this paper do not depend on the specific choice of continuity window length, and the variable construction is objective.

5. Conclusions and Implications

5.1. Main Conclusions

Based on a sample of A-share Main Board "Dragon and Tiger List" data from 2023–2024, this paper systematically examines the relationship between the characteristics of speculative capital involvement and post-event excess stock price volatility from three dimensions: trading intensity, net purchase share, and continuity of attention. The main conclusions can be summarized as follows:

First, the impact of speculative capital's three-dimensional characteristics on ex-post volatility exhibits a differentiated pattern: trading intensity exerts a marginally diminishing positive effect on ex-post volatility, with the impact of order flow during the initial intervention phase being far greater than that during the deep intervention phase; the proportion of net purchases exhibits a left-skewed inverted U-shaped relationship with ex-post volatility, with volatility peaking in the mild net selling range; and the continuity of attention exhibits a monotonically positive relationship with ex-post volatility, with the effect amplifying in tandem with the depth of intervention.

Second, the inverted U-shaped effect of long-short divergence has a clear threshold for involvement depth; it is robust and significant only in samples with high trading intensity, while divergence signals from low-intensity speculative capital lack independent market influence.

Third, the daily price limit system exerts a significant asymmetric correction on the transmission of divergence-induced volatility: a price limit up significantly amplifies ex-post volatility, and this effect is stronger in scenarios where hot money is net selling; a price limit down has no systematic impact on ex-post volatility . This indicates that the core function of a price limit up is not to lock in volatility, but rather to delay the release of the bull-bear dynamic.

5.2. Practical Implications

For investors, interpreting information from the "Dragon and Tiger List" requires moving beyond a single perspective of net capital flow and instead comprehensively examining participation intensity, bull-bear divergence, and the persistence of listings.Stocks exhibiting intense bull-bear divergence amid high participation intensity—or those in a mild net selling range—face significantly higher subsequent volatility risks; for small-cap, high-turnover stocks that appear consecutively on the list, investors should be wary of sustained volatility risks stemming from speculative capital's relay-style speculation. A price limit up is not the end of volatility; for stocks where a price limit up is accompanied by net selling, investors must guard against the subsequent release of selling pressure.For regulators, a three-dimensional abnormal trading monitoring system can be established to designate listed stocks with high trading intensity, intense divergence, or mild net selling as key monitoring targets; additional liquidity monitoring indicators should be set for price limit-up movements occurring against a backdrop of net selling by speculative capital; and regulatory thresholds should be dynamically adjusted based on market capitalization and turnover rate to enhance the precision of abnormal trading regulation.

5.3. Research Limitations and Future Directions

First, at the mechanism identification level. This paper derives and validates variable associations based on three theoretical pathways; however, due to limitations in publicly available brokerage branch data, direct micro-level testing of transmission pathways has not yet been conducted. Future research could utilize account-level high-frequency data to decompose the independent contributions of different pathways.Second, regarding causal identification. This study mitigated endogeneity issues through ex post window design, PSM, and placebo tests; however, it still cannot completely rule out unobserved confounding factors such as theme popularity and market sentiment. Future research could leverage exogenous shocks—such as the lifting of daily price limits and exchange inquiry letters—to further strengthen causal identification. Third, regarding variable measurement.This study identifies speculative capital based on publicly available "Dragon and Tiger List" trading seats, which fails to capture concealed transactions such as portfolio splitting and multi-seat coordination; the window settings focused on continuity also involve a degree of subjectivity. Future research could further validate the robustness of the conclusions through more granular fund account data and multi-window sensitivity analysis.

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