A Multi-Factor Quantitative Study of A-Share Stocks Following the Daily Price Limit Using Machine Learning

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ABSTRACT

This study examines A-share Main Board stocks that triggered the daily price limit between 2023 and 2025, comparing the performance of a conventional linear multi-factor framework against a random forest algorithm in short-term trading. Empirical results demonstrate that traditional rule-based screening produces a significantly negative expected return, whereas the random forest model effectively captures nonlinear interactions among micro-level price-volume factors and consecutive-limit-streak features. Under rigorous out-of-sample backtesting, the machine-learning strategy achieves a qualitative improvement in both win rate and Sharpe ratio while substantially reducing maximum drawdown. The present study contributes empirical evidence on microstructural pricing anomalies in the A-share market and provides a high-win-rate reference framework for quantitative short-term trading.

Keywords: Price limit; Machine learning; Multi-factor model; Short-term trading; A-share market

1. INTRODUCTION

1.1 Research Background and Market Microstructure Characteristics

China's A-share market operates under a T+1 settlement mechanism and daily price-limit rules, which collectively impose hard boundaries on daily price fluctuations. Although this institutional design was originally intended to curb excessive speculation and dampen volatility, it has in practice given rise to distinctive microstructural phenomena. Research indicates that when stock prices reach their limit boundaries, markets tend to exhibit overreaction—that is, prices overshoot equilibrium levels in response to major events and subsequently correct in the opposite direction [8].

Moreover, the price-limit mechanism has not succeeded in eliminating volatility; instead, the existence of the limit thresholds generates a pronounced "magnet effect." As stock prices approach the upper limit, investor expectations rapidly converge, accelerating capital inflows and driving prices to hit the limit even faster. Empirical evidence shows that the magnet effect is more pronounced in small-cap stocks, stocks with concentrated tradable-share ownership, or stocks with fewer institutional investors, and that such stocks are more susceptible to price manipulation during upswings [5].

Within this extreme microstructural gaming environment, A-share markets have developed a distinctive short-term trading strategy known as "chasing the limit" and "limit-streak relay". The core logic is that investors expecting to buy at the limit price on Day T—or at the open on Day T+1—can capture excess returns over an extremely short horizon (e.g., Day T+1 or the following two to three days) by riding price momentum toward another consecutive limit or a sharp intraday spike.

1.2 Traditional Short-Term Investment Strategies

Drawing on the strategic evaluation framework of Yuan et al. [9], short-term investors participating in the limit-price game should prioritize the attributes of the limit stock, sector momentum effects, and limit strength, with a preference for leading stocks exhibiting strong "sector linkage" effects, while de-emphasizing fundamental financial metrics or long-cycle technical indicators such as MACD and KDJ. Further empirical work supports the existence of a "leading-stock effect": the short-term price trajectory of stocks with five consecutive up-limit days exerts a significant positive spillover on following stocks, and the excess returns generated by opportunity-type leading stocks during consecutive limit periods are highly heterogeneous, providing a theoretical basis for opportunistic short-term positioning [10].

1.3 Introduction of Machine Learning to Quantitative Stock Selection and Advantages of Random Forests

Traditional linear econometric pricing models are not good at grasping the complex nonlinear relationship between various elements in short-term transactions. Machine learning has great potential in short-term quantitative strategy, because it is not bound by strict distribution assumption and can automatically extract deep features. In the index buying strategy, as shown in Xu [7], the combination of machine learning algorithm and multi-factor model can well correct the shortcomings of appropriate index chasing, and create a quantitative strategy with high Sharpe ratio and low drawdown. In this study, in order to solve the problem of low signal-to-noise ratio of A-share high-frequency data, we chose random forest as the core algorithm. Random forest is not only anti-jamming and robust, but also has the special advantage of “white-box” logic. Using Gini impurity, random forest can accurately express the relative importance of small-level prices and trading volume characteristics by numerical values [11]. Thanks to this nature, this study can clearly find out the successful structure of limit-streak relay strategy and explain the profound economic reasons for the structure with high winning rate.

1.4 Research Objectives, Sample Selection, and Contributions

Taking the price limit stocks of A-share Main Board from 2023 to 2025 as the research sample, this study uses machine learning to solve the problem of negative expected return of traditional linear strategy in short-term trading. This paper has two contributions. First, on the engineering level, this study controls the “execution-side data leakage”, introduces a new Label-Shuffle mechanism, and eliminates the over-matching of sections. Therefore, the statistical robustness of multi-day forecasting ability is established. Second, the study actually shows that the core determinants of excess returns are the micro K-line model of donations and the ability to absorb funds, not just fundamental factors and a certain index. This study gives a nonlinear empirical result for the abnormal pricing of microstructure of A-shares, and establishes a short-term trading judgment system with high winning rate, which can explain the model logic.

2. DATA SOURCES, SAMPLE SELECTION, AND FACTOR CONSTRUCTION

2.1 Data Sources and Sample Selection

This study draws on daily-bar data, high-frequency call-auction data, and financial indicators, all sourced from the Tushare database. The financial data sample covers January 1, 2023 to December 31, 2025, yielding a total of 39,615 observations. The strategy data sample covers December 1, 2023 to December 31, 2025 (506 trading days), with a total feature sample of 31,943 observations.

The initial factor pool is constructed from stocks that triggered the daily upper price limit. During sample preprocessing, ST-designated stocks, STAR Market and ChiNext stocks, and “locked-limit” stocks—where the stock opens at the up-limit price on Day T+1 with no intraday trading—are strictly excluded based on price-limit and trading-volume constraints.

2.2 Factor Construction

Building on Yuan et al.’s [9] emphasis on sector leading stocks, Liu’s [6] finding that stocks ranked higher among limit-price stocks earn higher subsequent returns, and Zhang et al.’s [10] observation of substantial heterogeneity in the excess returns of opportunity-type leading stocks, this study constructs the Tonghuashun Hot List factor (ths_hot)—derived from the daily hot-stock rankings on the Tonghuashun APP—alongside the sector/concept factor (limit_cpt_list). These factors are combined with the consecutive-limit factor (limit_step), which integrates the number of consecutive up-limit days and the affiliated hot concept sector to identify “leading stocks” as defined above.

In order to support the next part of the timing strategy, this study uses the momentum premium theory of Jegadeesh and Titman [4] to conduct a 20-day relative momentum indicator between CSI 2000 and CSI 300 to identify small-cap speculative cycles. In addition, Referring to the “day-of-week effect” and “holiday effect” in behavioral finance [3] [1], the study was conducted on the trading day before or after the legal holiday.

Table 1 presents the factors used in this study.

Table 1. Factor Variable Definitions

Factor Variable	Factor Name	Type	Construction Description
Turnover	Turnover Rate	Market	Individual stock turnover rate on Day T (%)
Vol_Ratio	Volume Ratio	Market	Ratio of Day T trading volume to recent average volume
Pe	P/E Ratio	Market	Rolling price-to-earnings ratio on Day T
Pb	P/B Ratio	Market	Price-to-book ratio on Day T
Ps	P/S Ratio	Market	Price-to-sales ratio on Day T
Log_Total_Mv	Log Total Market Cap	Market	Natural logarithm of total market capitalization on Day T
Log_Circ_Mv	Log Float Market Cap	Market	Natural logarithm of floating market capitalization on Day T
Close_T	Day T Closing Price	Market	Closing price on Day T (CNY)
Amount_T	Day T Trading Amount	Market	Total trading amount on Day T (CNY)
Fd_Amount	Locked-Limit Order Amount	Market	Volume of locked buy orders at the upper limit on Day T (CNY)
Open_Times	Limit Unlock Count	Market	Number of times the upper limit was broken on Day T
Boards	Consecutive Limit Count	Market/Concept	Number of consecutive up-limit days on Day T; captures streak strength and sector leader status
Auc_Open	Auction Open Price	Market	Opening price from Day T+1 call auction
Auc_High	Auction High Price	Market	Highest execution price in Day T+1 call auction
Auc_Low	Auction Low Price	Market	Lowest execution price in Day T+1 call auction
Auc_Vwap	Auction VWAP	Market	Volume-weighted average price of Day T+1 call auction
Auc_Amount	Auction Trading Amount	Market	Total trading amount in Day T+1 call auction
Auc_Yizi	Auction Locked-Limit Flag	Market	Whether Day T+1 call auction forms a locked up-limit (0/1 dummy)
Gap_Up	Gap-Up Magnitude	Market	Opening price of Day T+1 relative to Day T closing price (%)
Eps	EPS	Financial	Most recently reported quarterly EPS (CNY/share; look-ahead bias prevented)
Roe	ROE	Financial	Most recently reported quarterly return on equity (%)
Roa	ROA	Financial	Most recently reported quarterly return on assets (%)
Npm	Net Profit Margin	Financial	Most recently reported quarterly net profit margin (%)
Gpm	Gross Profit Margin	Financial	Most recently reported quarterly gross profit margin (%)

Table 1. (continued) Factor Variable Definitions

Factor Variable	Factor Name	Type	Construction Description
Or_Yoy	Revenue YoY Growth	Financial	Most recently reported revenue year-over-year growth (%)
Tr_Yoy	Total Revenue YoY	Financial	Most recently reported total revenue year-over-year growth (%)
Np_Yoy	Net Profit YoY	Financial	Most recently reported net profit year-over-year growth (%)
Debt	Debt-to-Asset Ratio	Financial	Most recently reported total liabilities / total assets (%)
Cr	Current Ratio	Financial	Most recently reported current assets / current liabilities
Qr	Quick Ratio	Financial	Most recently reported (current assets − inventory) / current liabilities
Q_Roe	Single-Quarter ROE	Financial	Most recently reported single-quarter return on equity (%)
Bps	Book Value per Share	Financial	Most recently reported book value per share (CNY/share)
Peg	PEG Ratio	Financial	P/E ratio divided by net profit growth rate
Holiday_Flag	Holiday Window Flag	Timing	Whether the trading day falls within the pre/post statutory holiday window (0/1)
Bad_Day_Flag	Day-of-Week Anomaly	Timing	Whether the trading day is Monday, Thursday, or Friday (0/1)

3. STRATEGY DESIGN AND RESULTS

3.1 Sample Selection and Trading Mechanism Constraints

The core backtesting window spans from December 1, 2023 to December 31, 2025 (506 trading days). The target is the non-ST Main Board brand, focusing on the products with the up-limit of 1 to 5 times in a row. In order to imitate the actual trading environment as correctly as possible, this study has formulated strict rules for the trading executors of the strategy.

First of all, the old mode of "limit-chase", that is, the moment when the stock reaches the upper limit price, will be replaced by the new mode of "limit-streak relay". Because the time priority matching mechanism of A-share order book can hardly allow individual investors to buy at the upper limit price at the moment, this study determines the time to start buying as a specific time after the end of the transaction with the Day T limit close. Specifically, it is 09:30, 09:32 or 09:36 on Day T+1.

Secondly, carry out strict transaction-cost deduction. Slippage and commission with a purchase price of 0.5% (i.e. 50 basis points for one way) are always used when the purchase order is entered on call-auction of Day T+1 or early-session high-frequency K-line entries. This is a comprehensive impact cost, which is used to absorb the price deviation in reality when placing an order.

Third, use the mechanism of exit at the closing price of Day T+2. Because of A-share's T+1 settlement rules, ultra-short-term funds generally make a profit the next day. The reason why the closing price is chosen as the exit point instead of the closing price of Day T+2 is because the price fluctuates greatly during the opening period and it is difficult to set the price. However, the closing price contains all the information of the day and is more liquid, which can more accurately reflect the real risk status and profit status of the strategy.

3.2 Testing the Linear Explanatory Power of the Traditional Multi-Factor Framework

Before describing the complex machine learning model, this study first established a general multi-factor system consisting of 35 variables, and employs ordinary least squares (OLS) regression to explain the short-term (Day T+1 to T+2) net-of-cost return of Day-T limit stocks. The purpose of realizing the step of day is to confirm whether the traditional factor has linear persuasiveness to the short-term momentum premia, and to set a benchmark for the experiment of nonlinear models mentioned later. The variables used in the description are: micro market-and-capital factors (19 variables), fundamental financial factors (14), timing-and-anomaly factors (2 variables, comprising the holiday window and the day-of-week anomaly). The relevant results of each candidate factor and the single factor of the return rate are recorded in Table 2 below.

Table 2. Single-Factor Pearson Correlation Test Between Each Factor and Return Rate (yield_rate)

Factor	Correlation	t-statistic	p-value	N	Type	Sig.
Turnover	-0.0068	-1.354	0.1758	39,580	Market	
Vol_Ratio	-0.0586	-11.668	0.0000	39,543	Market	***
Pe	-0.0179	-2.952	0.0032	27,038	Market	***
Pb	0.0095	1.883	0.0597	39,400	Market	*
Ps	-0.0049	-0.969	0.3324	39,568	Market	
Log_Total_Mv	-0.0475	-9.455	0.0000	39,580	Market	***
Log_Circ_Mv	-0.0498	-9.912	0.0000	39,580	Market	***
Close_T	-0.0188	-3.740	0.0002	39,536	Market	***
Amount_T	-0.0331	-6.588	0.0000	39,615	Market	***
Fd_Amount	-0.2013	-40.912	0.0000	39,615	Market	***
Open_Times	-0.0790	-15.776	0.0000	39,615	Market	***
Boards	-0.5579	-133.796	0.0000	39,615	Market	***
Auc_Open	-0.0170	-3.353	0.0008	38,836	Market	***
Auc_High	-0.0167	-3.290	0.0010	38,836	Market	***
Auc_Low	-0.0166	-3.264	0.0011	38,836	Market	***
Auc_Vwap	-0.0170	-3.351	0.0008	38,836	Market	***
Auc_Amount	-0.2539	-52.240	0.0000	39,615	Market	***
Auc_Yizi	-0.1442	-29.005	0.0000	39,615	Market	***
Gap_Up	-0.0292	-5.812	0.0000	39,536	Market	***
Eps	0.0124	2.444	0.0145	39,016	Financial	**
Roe	-0.0033	-0.658	0.5108	39,467	Financial	
Roa	0.0096	1.897	0.0579	39,185	Financial	*
Npm	-0.0009	-0.188	0.8508	39,547	Financial	
Gpm	-0.0141	-2.799	0.0051	39,148	Financial	***
Or_Yoy	0.0000	0.003	0.9973	39,429	Financial	
Tr_Yoy	0.0001	0.027	0.9784	39,442	Financial	
Np_Yoy	0.0018	0.348	0.7279	39,445	Financial	

Table 2. (continued) Single-Factor Pearson Correlation Test Between Each Factor and Return Rate (yield_rate)

Factor	Correlation	t-statistic	p-value	N	Type	Sig.
Debt	0.0052	1.039	0.2987	39,424	Financial	
Cr	-0.0106	-2.099	0.0358	39,131	Financial	**
Qr	-0.0105	-2.086	0.0370	39,131	Financial	**
Q_Roe	-0.0018	-0.362	0.7172	39,423	Financial	
Bps	-0.0017	-0.343	0.7316	39,388	Financial	
Peg	0.0088	0.978	0.3279	12,396	Financial	
Holiday_Flag	-0.0866	-17.301	0.0000	39,615	Timing	***
Bad_Day_Flag	0.0763	15.238	0.0000	39,615	Timing	***

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

3.3 Baseline Strategies (A, B, and C) and Behavioral Finance Hypotheses

To establish performance benchmarks for the backtests, this study constructs three traditional rule-based strategies that do not use machine learning.

Strategy A (Highest-Streak Benchmark): On Day T, the stock with the highest consecutive up-limit count across the entire market is selected and bought blindly at the 09:30 open on Day T+1.

Strategy B (Highest-Streak + Attention Effect): Building on Strategy A, the selected stock must additionally appear in the top 20 of the Tonghuashun hot-stock list or the strongest sector/concept ranking. This strategy incorporates the "attention effect" from behavioral finance. The seminal work of Barber and Odean [2] established that individual investors face substantial search costs and therefore tend to purchase stocks that have recently attracted attention; however, the concentrated buying driven by this attention effect often leads to severe short-term overvaluation followed by return reversal. This strategy is used to test whether retail over-attention in A-share limit-price dynamics acts as a momentum catalyst or a liquidity trap at elevated price levels.

Strategy C (Strategy B + Calendar Effects and Style Rotation): Building on Strategy B, this strategy introduces large-/small-cap rotation timing and eliminates entry signals around statutory holiday windows. The strategy posits that risk-averse capital outflows before extended holidays, combined with policy uncertainty over weekends, make short-term sentiment particularly prone to retreat during holiday windows.

4. MACHINE LEARNING HYPERPARAMETER TUNING

4.1 Algorithm Selection: The Transition from Linear to Nonlinear

In order to determine the benefits of feature extraction of nonlinear model, this study first compares logistic regression, random distortion and gradient boosting decision trees (gbdt) in the test set. The test set divides the training data and the test data into 3:7 in chronological order to predict the winning probability (the label is 1 when the profit is greater than 0). The experimental results show that the AUC of logistic regression test set is only 0.6573, while random forest is 0.7170 and GBDT is 0.7479. Therefore, the AUC of the nonlinear model is about 6 %~9% better than that of the linear benchmark model, which shows that the tree algorithm can well grasp the threshold of interaction between features. It should be emphasized here that this static time sequence 3:7 division is only to choose the alternate algorithm of this section. This is to obtain a fast AUC standard, which can be compared among logistic regression, random forest and GBDT. This is not used at all for the reverse testing of the strategy reported in paragraphs 5 to 7. The model training, out-of-sample prediction and performance evaluation of Strategies D1, D2 and D3 all follow the expanding-window rolling scheme introduced in Section 4.3.

4.2 Random Forest Hyperparameter Optimization and Anti-Overfitting Design

In order to adjust hyperparameter, this study uses grid search to find the following important parameter settings according to financial logic: the number of estimators (n_estimators = 200). Increasing the number of subtrees helps to smooth the deviation of a tree; Maximum depth (max_depth = 5). This allows the model to learn only the clearest big pattern, instead of remembering the fluctuations of particularly small values in the past; Then, the minimum number of samples required for a leaf (min_samples_leaf = 20). This means that all leaf nodes must have at least 20 previous transaction records, so that all trading rules retrieved by the model have a large sample of statistical basis.

4.3 Expanding-Window Rolling Time-Series Cross-Validation

Ordinary k-fold cross-validation random mixed time series. This is financial research, which will cause serious look-ahead bias, and use future data to predict previous results. In order to solve this problem, this study uses a strict expanding-window monthly rolling training scheme. Specifically, the model's training start date is December 1, 2023, which is fixed. When forecasting the samples of M month in 2025, all the last past data from December 1, 2023 to M-January will be used as the training set. With the passage of time, the training window is getting bigger and bigger, and the model can firmly remember the new changes in market regimes. This complete out-of-sample prediction mechanism is exactly the same as the information asymmetry state when backtesting environment is used in production.

5. STRATEGY OPTIMIZATION

5.1 Intraday Entry-Time Segmentation: The Machine Learning Strategy Cluster (D1, D2, D3)

To explore the predictive incremental value of short-interval minute-level K-lines for momentum premia, this study derives three distinct random forest strategies from a common sample pool, all of which execute nonlinear decisions at specific time points after the Day T+1 open.

Strategy D3 (Daily/Auction Level): Uses only Day T daily-bar information and the 09:25 call-auction data from Day T+1. The predicted entry point is the 09:30 open on Day T+1, with a transaction cost of opening price + 0.5%.

Strategy D1 (1-Minute K-Line Level): Extends D3's feature set by incorporating the volume and pattern features (e.g., per-minute volume and K-line body direction) of the 09:30 and 09:31 one-minute K-lines on Day T+1. The decision and entry point is set at the 09:32 opening price, with an additional 0.5% impact cost.

Strategy D2 (5-Minute K-Line Level): Introduces micro features derived from the complete five-minute K-line spanning 09:30 to 09:35 on Day T+1 (e.g., maximum instantaneous gain and price amplitude over the first five minutes). The decision entry point is 09:36 (i.e., the close of the five-minute bar), with an additional 0.5% transaction cost.

5.2 Stringent Data Cleansing Mechanism to Prevent Execution-Side Leakage

This study implements an extremely rigorous data cleansing pipeline. For Strategy D1, any sample in which the first limit lock occurs at or before 09:32 is physically removed from both the training and test sets. Moreover, during the early development of Strategy D1, it was found that including the 09:31 closing-price return as a feature induced overfitting on the test set. A deep attribution analysis revealed that the 09:31 closing price and the 09:32 entry price are essentially equivalent in absolute price level. The model was therefore not predicting future price direction; it was performing a tautological back-calculation using "already known current absolute price" information. To sever this covert execution-side leakage, all absolute-price-level factors (e.g., per-minute returns) were removed, retaining only "pattern" and "volume" features within the microstructure. After correcting this leakage, the model's monthly out-of-sample AUC mean reverted to a reasonable yet still excellent value of 0.7926, confirming the authenticity of the return source.

6. STRATEGY RESULTS AND INTERPRETATION

6.1 Core Backtest Performance Evaluation

Table 3 reports the full backtest performance summary for all strategies discussed above, including the rule-based benchmarks (A, B, C) and the machine-learning strategy cluster (D1, D2, D3) under their various probability thresholds.

Table 3. Summary of Backtest Performance Across Strategies (Fixed-Position Portfolio, Accounting for Position Occupancy)

Strategy	Trades	Win Rate	Avg. P&L	Days	Entry	Skip	Portfolio Return	Max DD	Sharpe
Strategy A: Highest-streak only	282	11.70%	-4.50%	227	217	65	-91.45%	-91.45%	-6.07
Strategy B: Highest + hot/concept (top 20)	226	11.95%	-4.26%	187	213	13	-90.38%	-90.38%	-8.80
Strategy C: B + style rotation + holiday	95	7.37%	-4.59%	80	95	0	-43.61%	-43.61%	-11.14
Strategy D1 (ML filter)	2,904	68.80%	+1.09%	235	1,154	1,750	+97.96%	-2.33%	10.15
Strategy D1 (prob > 0.5)	2,904	68.80%	+1.09%	235	1,154	1,750	+97.96%	-2.33%	10.15
Strategy D1 (prob > 0.6)	800	76.50%	+1.35%	197	619	181	+77.96%	-0.74%	10.44
Strategy D1 (prob > 0.7)	34	88.24%	+2.27%	18	34	0	+7.72%	-0.17%	9.12
Strategy D1 (daily top 5, prob > 0.5)	1,154	70.88%	+1.08%	235	1,154	0	+124.85%	-1.48%	11.44
Strategy D2 (ML filter)	2,430	75.31%	+1.41%	236	1,092	1,338	+124.35%	-1.05%	11.91
Strategy D2 (prob > 0.5)	2,430	75.31%	+1.41%	236	1,092	1,338	+124.35%	-1.05%	11.91
Strategy D2 (prob > 0.6)	899	82.20%	+1.82%	212	657	242	+102.40%	-0.61%	11.04
Strategy D2 (prob > 0.7)	105	92.38%	+2.41%	53	101	4	+24.00%	-0.21%	9.01
Strategy D2 (daily top 5, prob > 0.5)	1,092	75.37%	+1.35%	236	1,092	0	+147.02%	-1.14%	12.09
Strategy D3 (ML filter)	324	97.84%	+1.75%	159	320	4	+56.00%	-0.20%	11.38
Strategy D3 (prob > 0.5)	324	97.84%	+1.75%	159	320	4	+56.00%	-0.20%	11.38
Strategy D3 (prob > 0.6)	26	100.00%	+1.30%	21	26	0	+3.37%	0.00%	11.36
Strategy D3 (daily top 5, prob > 0.5)	320	97.81%	+1.77%	159	320	0	+56.66%	-0.20%	11.13

Table 3. (continued) Summary of Backtest Performance Across Strategies (Fixed-Position Portfolio, Accounting for Position Occupancy)

Strategy	Trades	Win Rate	Avg. P&L	Days	Entry	Skip	Portfolio Return	Max DD	Sharpe
Strategy D3-2024(0.5%) (ML filter)	732	70.63%	+0.98%	169	475	257	+57.49%	-3.78%	6.84
Strategy D3-2024(0.5%) (prob > 0.5)	732	70.63%	+0.98%	169	475	257	+57.49%	-3.78%	6.84
Strategy D3-2024(0.5%) (prob > 0.6)	154	88.31%	+1.73%	77	129	25	+22.61%	-0.64%	8.09
Strategy D3-2024(0.5%) (prob > 0.7)	3	100.00%	+1.79%	3	3	0	+0.54%	0.00%	16.09
Strategy D3-2024(0.5%) (daily top 5)	475	80.00%	+1.39%	169	475	0	+66.09%	-1.07%	7.67
D3 – Hot List filter	1,758	32.37%	-1.23%	234	693	1,065	-86.53%	-87.33%	-8.58
D3 – Dragon-Tiger List filter	5,306	28.68%	-1.06%	236	832	4,474	-80.76%	-81.01%	-6.48

Note. For each of Strategies D1, D2, D3, and D3-2024(0.5%), the row labeled “ML filter” and the row labeled “prob > 0.5” report identical figures by construction: the model’s ML filter applies its default binary classification rule of predicted probability > 0.5, so “(ML filter)” and “(prob > 0.5)” denote the same underlying signal. Both labels are retained here only to align with the terminology used in Section 5, where the unqualified “ML filter” strategy is first introduced before its probability threshold is made explicit; the two rows are not independent results.

6.2 Machine Learning Feature Importance Attribution

The top-ten most important features for each model (weighted by out-of-sample observations) are extracted and presented in Tables 4 through 6 below.

Table 4. Top 10 Feature Importance for Strategy D1

Rank	Feature Name	Feature Description	Importance Weight
1	M1_31_bullish	Bullish candlestick dummy variable for the 09:31 1-min K-line	0.4757
2	Gap_up	Call auction gap-up magnitude	0.1375
3	Vol_ratio	Volume ratio	0.0869
4	M1_2bar_range	Price range of the first two 1-min K-lines	0.0668
5	Boards	Consecutive up-limit count	0.0582
6	Auc_amt	Call auction trading amount	0.0218
7	Holiday_flag	Holiday window dummy variable	0.0187
8	Log_circ_mv	Log floating market cap	0.0170
9	M1_31_vol	Volume of the 09:31 1-min K-line	0.0130
10	M1_30_vol	Volume of the 09:30 1-min K-line	0.0129

Table 5. Top 10 Feature Importance for Strategy D2

Rank	Feature Name	Feature Description	Importance Weight
1	Min5_max_gain	Maximum instantaneous gain within the first 5 minutes	0.4037
2	Gap_up	Call auction gap-up magnitude	0.2235
3	Vol_ratio	Volume ratio	0.0896
4	Min5_range	Price range of the first 5-min K-line	0.0654
5	Boards	Consecutive up-limit count	0.0621
6	Auc_amt	Call auction trading amount	0.0219
7	Log_circ_mv	Log floating market cap	0.0208
8	Min5_vol	Volume of the first 5-min K-line	0.0156
9	Holiday_flag	Holiday window dummy variable	0.0150
10	Amount_t	Day T total trading amount	0.0144

Table 6. Top 10 Feature Importance for Strategy D3 (Weighted by OOS Sample)

Rank	Feature Name	Feature Description	Importance Weight
1	Gap_up	Call auction gap-up magnitude	0.1947
2	Vol_ratio	Volume ratio	0.1578
3	Boards	Consecutive up-limit count	0.1461
4	Auc_amt	Call auction trading amount	0.1219
5	Holiday_flag	Holiday window dummy variable	0.0854
6	T_pct_chg	Day T price change rate	0.0559
7	Turnover	Turnover rate	0.0508
8	Fd_amount	Locked-limit order amount	0.0193
9	Amount_t	Day T total trading amount	0.0179
10	Net_amount	Net capital inflow / net buy amount	0.0163

7. ROBUSTNESS CHECKS

7.1 Label-Shuffle Cross-Day Predictive Power Validation

In financial time-series data, multiple stocks that trigger the daily limit on the same day are often driven by common macroeconomic factors or industry betas, leading to cross-sectional correlation in residuals within the same cross-section. To confirm that the excess returns uncovered by the random forest stem from genuine cross-day predictive ability rather than residual cross-sectional data structure from the same day, this study innovatively introduces a label-shuffle control experiment. Before each rolling training iteration, training-set observations are grouped by date, preserving the cross-sectional label distribution for each day but randomly shuffling these “daily label blocks” along the time axis. If the model’s AUC remains high after shuffling, it implies that the model has merely memorized macrostructural contamination in certain cross-sections; if the AUC drops to near-random-coin-flip levels, it inversely confirms that the original model genuinely extracted cross-temporal true alpha. Table 7 reports the true-data versus label-shuffled AUC for each strategy model under this validation scheme.

Table 7. Label-Shuffle Validation Results (OOS Test Set)

Strategy Model	True Data AUC (Mean)	Label-Shuffled AUC (Mean)
Strategy D1 (1-min K-line)	0.7926	0.5133
Strategy D2 (5-min K-line)	0.7996	0.4994
Strategy D3 (Call Auction)	0.7701	0.5023

7.2 Monthly Performance Stability Check

Table 8 presents the month-by-month out-of-sample trade counts, win rates, average P&L, and cumulative returns for Strategies D1 and D3, allowing an assessment of performance stability across the twelve rolling out-of-sample months.

Table 8. Out-of-Sample Monthly Performance Stability for Strategies D1 and D3

Month	D1 Trades	D1 Win%	D1 Avg P&L	D1 Monthly Cum.	D3 Trades	D3 Win%	D3 Avg P&L	D3 Monthly Cum.
2025-01	122	77.87%	+1.81%	+221.31%	25	100.00%	+2.76%	+68.89%
2025-02	77	68.83%	+0.59%	+45.52%	25	92.00%	+2.07%	+51.80%
2025-03	34	76.47%	+1.49%	+50.75%	35	97.14%	+1.29%	+45.23%
2025-04	104	86.54%	+2.73%	+283.67%	36	100.00%	+1.41%	+50.70%
2025-05	56	80.36%	+1.15%	+64.34%	30	93.33%	+1.95%	+58.65%
2025-06	55	78.18%	+1.89%	+104.13%	22	95.45%	+2.37%	+52.24%
2025-07	51	74.51%	+1.18%	+60.23%	24	91.67%	+0.96%	+23.16%
2025-08	43	79.07%	+0.83%	+35.62%	34	100.00%	+1.48%	+50.22%
2025-09	81	87.65%	+1.28%	+103.60%	12	100.00%	+1.25%	+14.96%
2025-10	50	74.00%	+0.94%	+47.24%	18	94.44%	+2.14%	+38.45%
2025-11	51	66.67%	+1.22%	+62.12%	35	100.00%	+1.44%	+50.41%
2025-12	81	80.25%	+1.49%	+120.42%	40	97.50%	+1.33%	+53.34%

8. CONCLUSIONS AND IMPLICATIONS

8.1 Research Conclusions

Using A-share Main Board limit-price stocks from 2023 to 2025 as the sample, and strictly controlling for execution-side data leakage and liquidity constraints, this study compares the efficacy of a traditional linear multi-factor framework and a random forest algorithm in predicting short-term momentum premia. The empirical investigation yields the following core conclusions.

First, traditional linear selection rules centered on fundamental financial indicators and single high-attention metrics (e.g., hot-stock list rankings, Dragon-Tiger board listings) exhibit a significant negative expected return in the extreme short-term limit-price gaming environment of A-shares. The results empirically confirm the behavioral finance “excessive attention trap”: limit-price stocks blindly chased by retail capital driven by search-cost considerations—so-called “high-heat” stocks—have typically already exhausted the next-day premium and become targets of liquidity harvesting.

Second, compared with linear models, the random forest algorithm effectively captures nonlinear interaction thresholds among micro price-volume factors. Following the introduction of Day T+1 opening call-auction and early-session 1-to-5-minute K-line microstructural features, the out-of-sample performance of strategies D1, D2, and D3 achieves a qualitative leap. High-confidence machine learning filter signals (prob > 0.6 or 0.7) can reliably elevate the win rate to between 75% and 90% while substantially reducing maximum drawdown.

Third, Label-Shuffle cross-day predictive validation and feature importance attribution reveal that the core drivers of limit-streak relay win rates are not macro factors or same-day cross-sectional structure, but rather micro trading signals at the open, including bullish K-line patterns, gap-up magnitude, and volume ratios.

8.2 Practical Implications

The results of this study have a simple and clear practical effect on quantitative investment. In the actual short-term trade, investor should abandon the high-risk “leading-streak pursuit” method that has existed since ancient times. market microstructure has a strong magnet effect and strength traps, so the decision on where to use the funds should be re-established on the basis of micro price-volume confirmation after the transaction starts the next day. Using the machine learning model, the locked-limit stock with low liquidity and the spurious momentum stock with loose big position are excluded, and trading starts at the time with sufficient liquidity, such as 09:32 or 09:36.

8.3 Limitations and Future Research Directions

Although this study adopts strict engineering methods to prevent pre-reading deviation and slippage cost management, there are still some shortcomings. In particular, the assumed one-way impact cost of 0.5% may still be too cautious when the transaction volume drops extremely. Future research needs to further incorporate the high-frequency tick data of order-book to dynamically model impact cost.

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