Optimal Stopping and Bubble Riding under Limited Arbitrage Constraints: An Empirical Study based on A-Share Market Microstructure

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Abstract: - The Chinese A-share market, characterized by its unique retail-dominated structure and institutional constraints, exhibits pricing features distinct from mature markets. This study constructs a portfolio management framework adapted to the microstructure of the A-share market and examines how institutional investors can generate excess returns through Bubble Riding and Factor Timing strategies when limited arbitrage and investor irrationality coexist. First, using a synchronization-risk framework and a behavioral overreaction mechanism, we derive that the optimal strategy for rational arbitrageurs under heterogeneous beliefs and short-sale constraints can shift from immediate mean reversion to momentum-following. Subsequently, we integrate a China-localized factor construction and conduct an empirical study using A-share data from 2020 to 2026 collected through Python and the Baostock interface. The results show that: (1) traditional Fama-French factors are weakened in the A-share market when shell-value contamination is ignored, and excluding the bottom 30% of micro-cap stocks improves pricing efficiency; (2) momentum and sentiment factors exhibit nonlinear characteristics across market regimes; and (3) a dynamic risk-control strategy based on market-wide turnover rates—penalizing high-volatility exposure during bubble periods and increasing beta exposure during freezing periods—substantially outperforms the CSI 300 index out of sample.

Key-Words: - A-share Market, Portfolio Management, Bubble Riding, Factor Models, Investor Sentiment, Shell Value, Baostock.

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1 Introduction

As the world's second-largest capital market, the asset pricing logic of China's A-share market has long been a focal point of debate in both academia and industry. Although the Fama-French Three-Factor Model [1] and the Carhart Four-Factor Model [2] are regarded as important empirical asset-pricing frameworks, their direct application to the

Chinese market often faces significant challenges. Extensive replication evidence for the Chinese A-share market [3] shows that approximately 84% of anomaly factors confirmed in the U.S. market fail after strict statistical adjustment. This striking failure rate compels us to re-examine the unique microstructure and pricing mechanisms of the A-share market.

The most distinctive feature of the A-share market lies in the particularity of its investor structure. China-specific evidence on size and value factors [4] shows that retail investors contribute a dominant share of trading volume in the A-share market. Compared to institutional investors, retail investors are more susceptible to cognitive biases, exhibiting overconfidence, self-attribution bias, and an irrational preference for lottery-like stocks. Such widespread irrational behavior often causes asset prices to deviate significantly from their fundamental values, forming pronounced anomalies.

However, in the face of such obvious mispricing, rational institutional investors do not always act as price stabilizers. Based on the synchronization-risk mechanism under limited arbitrage [5], the lack of mechanisms to coordinate collective action can induce individual arbitrageurs to ride the bubble rather than short prematurely. Furthermore, China's IPO approval system and reverse-merger channels have historically given shell resources option-like value, causing micro-cap stock prices to contain substantial shell premiums that distort traditional size (SMB) and value (HML) factors.

This paper aims to construct a localized A-share asset management framework through mathematical derivation and empirical analysis. The innovations of this paper are: First, introducing "Shell Value Removal" as a precondition for factor construction, correcting biases of traditional models in China. Second, introducing a sentiment threshold based on market turnover rate to construct a dynamic factor timing strategy, addressing the inability of static models to cope with "boom and bust" cycles. Third, providing a complete code implementation framework and visualization verification.

2 Literature Review

2.1 Bubble Theory and Synchronization Risk

The Efficient Market Hypothesis (EMH) posits that arbitrage forces rapidly eliminate price deviations, but limited-arbitrage theory presents a formidable challenge. The synchronization-risk model [5] is central to understanding bubble persistence. Even if rational arbitrageurs know that asset prices exceed fundamental values, they may be unable to determine when other arbitrageurs will coordinate selling. To maximize self-interest, the optimal rational strategy may therefore be to temporarily join the bubble until market signals indicate an imminent crash.

Empirical evidence on hedge funds during the Nasdaq technology bubble [6] supports this mechanism: hedge funds increased holdings of overvalued technology stocks before the bubble peaked and reduced exposure before the crash. Evidence from the Chinese warrants bubble [7] further shows that short-sale constraints and heterogeneous beliefs can allow prices to remain above theoretical values for extended periods.

2.2 Behavioral Finance and Investor Sentiment

The behavioral overreaction model [8] provides an explanation for the momentum effect in A-shares. Investors' overconfidence in private information leads to price overreaction to information, while subsequent self-attribution bias causes this overreaction to persist in the short term, thereby forming price trends.

Cumulative prospect theory in asset pricing [9] shows that investors tend to overweight low-probability, high-payoff events. This mechanism can lead to the systematic overvaluation of lottery-like stocks characterized by high volatility and positive skewness, resulting in negative expected returns. Chinese-market evidence [10], [11] also indicates that high sentiment weakens arbitrage forces and makes anomaly returns more pronounced during high-sentiment periods.

2.3 Localization of Factor Models

Addressing the failure of U.S. stock factors in China, China-specific size and value factor research proposes localized factor construction for the Chinese market. It shows that the high valuation of micro-cap stocks mainly stems from shell value rather than future growth potential. Without excluding the bottom 30% of stocks by market capitalization, the traditional size factor (SMB) may capture the junk-stock effect rather than a genuine size premium. Replication evidence for Chinese anomalies further emphasizes that mainboard breakpoints and value-weighting are critical steps to ensure model validity in the Chinese market.

3 Mathematical Model Derivation

This section formalizes the synchronization-risk theory under limited arbitrage into an optimal stopping problem in continuous time and constructs a portfolio optimization model that incorporates factor characteristics of the Chinese market.

3.1 Bubble Dynamics and Synchronization Risk

Assume the Fundamental Value of an asset is V_t, following a Geometric Brownian Motion:

$$dV_t = \mu v V_t \, dt + \sigma_V \, V_t \, dZ_t$$

where μv is the fundamental return and σ_V is the fundamental volatility. At time t_0 , due to retail investors' irrational sentiment, the asset price P_t begins to deviate from the fundamental value, forming a bubble B_t.That is:

$$P_t = V_t + B_t$$

According to the behavioral overreaction mechanism, the bubble component expands at a rate : $g > \mu v$:

$$dB_t = gB_t \, dt \ , \ t \geq t_0$$

This implies the bubble grows deterministically before bursting.

Introduction of Synchronization Risk: Assume there are rational institutional arbitrageurs in the market. Due to a lack of Common Knowledge, they cannot be simultaneously aware of the bubble's existence at time t_0 , but instead become aware sequentially within the time interval $[t_0 \, , t_{0+\eta}]$. Let t_i be the time the i-th arbitrageur becomes aware of the bubble, following a uniform distribution $t_i \sim U[t_0 \, , t_{0+\eta}]$.

The bursting of the bubble depends on short-selling pressure. Let be the proportion of arbitrageurs choosing to liquidate or short at time . The bubble bursts instantly when cumulative selling pressure exceeds a critical threshold k:

$$\exists \tau, s.t. \int_{t_0}^{\tau} s(u)du \geq \kappa \implies B_\tau = 0 \, , P_\tau \ \to V_\tau$$

3.2 Optimal Stopping for Bubble Riding

For an arbitrageur who has detected the bubble, the problem is an optimal stopping problem: choosing the optimal time T_{exit} to sell to maximize utility. Let $h(t)$ be the Hazard Rate of the bubble bursting at time t, i.e., the probability density of bursting in the next instant given it has not yet burst.

Proposition 1: Under the assumption of risk neutrality, the arbitrageur's value function $J(P_t \, , t)$ satisfies the following Hamilton-Jacobi-Bellman (HJB) equation:

$$rJ = \max_{action \in \{Hold, Sell\}} \left\{ \underbrace{(gB_t + \mu v V_t) \frac{\partial J}{\partial P}}_{capital\ grain} + \underbrace{\frac{1}{2} \sigma^2 P^2 \frac{\partial^2 J}{\partial P^2}}_{volatility} - \underbrace{h(t) \left(J(P_t) \text{-} V_t \right)}_{crash\ loss} \right\}$$

In the A-share market, due to the lack of short-selling mechanisms, the selling pressure threshold k for bubble bursting is high, and the retail herding effect causes $h(t)$ to be extremely low in the early stages of a bubble. For a risk-neutral investor $(J(P_t) = P_t)$, the first-order necessary condition for choosing "Hold (Ride)" is that the drift term exceeds the risk-free return:

$$(gB_t + \mu v V_t) dt \text{-} h(t) B_t \, dt > r(V_t + B_t) dt$$
$$E[dP_t] > rP_t \, dt$$

Rearranging yields the Riding Condition:

$$g \ \text{-} \ h(t) > r + (r \text{-} \mu v + h(t)) \frac{V_t}{B_t}$$

Corollary: When the bubble growth rate g (Momentum) is sufficiently large and the burst risk $h(t)$ has not yet reached a critical point, the left side of the inequality is significantly positive. This mathematically proves that rational institutional investors should follow the trend (Ride the Bubble) until $h(t)$ rises causing the inequality to reverse. This constitutes the theoretical cornerstone for the Momentum factor in our strategy.

3.3 Modified CH-4 Factor Model Construction

We define the universe of all stocks Ω_t.

Definition 1 (Shell Value Operator): Define operator $S(\cdot)$ as the micro-cap filtering operator. For any cross-section t , the valid stock pool Ω_t^* is:
$\Omega_t^* = S(\Omega_t) = \{i \in \Omega_t \mid Mcap_{i,t} > F_{0.3}^{-1}(Mcap_t)\}$
where $F_{0.3}^{-1}$ represents the 30% quantile of market capitalization. All subsequent factors f are calculated only on Ω_t^* .

Definition 2 (Factor Loading): The expected excess return of an asset is determined by the following multi-factor model:
$E[R_{i,t+1}]\text{-}rf = \beta_{i,MKT}\lambda_{MKT} + \beta_{i,VMG}\lambda_{VMG} + \beta_{i,PMO}\lambda_{PMO}$
Where:

- VMG (Value Minus Growth): Value factor based on $EP = 1/PE_{TTM}$.
- PMO (Pessimism Minus Optimism): Sentiment factor based on turnover rate, proxying for the degree of retail irrationality.

$$PMO_t = E[R \mid Low\ Turn]\text{-}E[R \mid High\ Turn]$$

3.4 Dynamic Mean-Variance Optimization

We introduce the market state variable S_t (market-wide turnover rate) into the optimization framework. Let $w \in R^N$ be the weight vector and Σt be the covariance matrix.

Objective Function: Maximize the sentiment-adjusted Sharpe ratio. We introduce an indicator function $I_{Bubble}(S_t)$ to characterize the bubble state. When the turnover rate exceeds a historical quantile threshold (e.g., 90th percentile), it is determined to be a bubble state:

$$\mathrm{I_{Bubble}}(s_t) = \begin{cases} 1, & \text{if } \mathrm{S_t > q_{0.9}(S)} \quad \text{(Overheated)} \\ 0, & \text{otherwise} \end{cases}$$

The modified optimization problem is formalized as follows:

$$\max_{w} \; w^T(\mu_{CH4} + \alpha_{Mom})\text{-}\frac{\gamma}{2} w^T \Sigma_{tw} \text{ - } \underbrace{\theta \cdot I_{Bubble}(S_t) \cdot w^T \sigma_{idio}}_{Dynamic\ Penalty\ Term}$$

$s.t.\ 1^T w = 1\ wi \geq 0,\ \forall i \in \{1,\dots,N\}\ (Short - sale\ Constraint)$
Where:

- μ_{CH4} : Expected excess return vector based on the CH-4 factor model.
- α_{Mom} : Bubble riding return captured by the momentum factor.
- γ : Investor's risk aversion coefficient.
- σ_{idio} :Vector of asset idiosyncratic volatilities.
- θ : Dynamic penalty coefficient. When $I_{Bubble} = 1$, this term becomes active, forcing the optimizer to reduce the weight of high-volatility assets.
-

Lagrangian Form: To solve the above convex optimization problem, we introduce the Lagrange multiplier λ (for the budget constraint) and vector $\nu \in R^N$ (for the non-negativity constraint), constructing the Lagrangian function L :

$$L(w,\lambda,\nu) = w^T \hat{\mu} \text{-} \frac{\gamma}{2} 2 w^T \Sigma_{tw} \text{-} \theta I_{Bubble}(S_t) w^T \sigma_{idio} \text{-} \lambda(1^T w\text{-}1) + \nu^T w$$

Where $\hat{\mu} = \mu CH4 + \alpha Mom$ is the comprehensive expected return. According to the KKT conditions (Karush-Kuhn-Tucker conditions), the optimal weight w^* must satisfy:

$$\frac{\partial L}{\partial w} = \hat{\mu} \text{-} \gamma \Sigma_{tw} \text{-} \theta I_{Bubble}(S_t)\sigma_{idio} \text{-} \lambda 1 + \nu = 0$$

This form clearly indicates that during high-risk bubble periods ($I_{Bubble} = 1$), the expected return of assets will be significantly offset by the idiosyncratic risk term $\theta\sigma_{idio}$, thereby mathematically guaranteeing the mechanism of tilting the strategy towards low-volatility defensive assets.

4 Empirical Design and Data Processing

To verify the theoretical model proposed in Chapter 3 and the effectiveness of "Bubble Riding" and "Factor Timing" strategies, this chapter details the data sources, preprocessing procedures, variable construction methods, and portfolio construction rules.

4.1 Data Sources and Sample Selection

The empirical research in this paper is based on historical data of the Chinese A-share market obtained via the Baostock open-source financial data interface.

Sample Period: January 1, 2020, to January 31, 2026. This interval covers the core asset bull market of 2020-2021, the systemic correction of 2022, and the micro-cap liquidity crisis in early 2024, offering

high representativeness to fully test the strategy's robustness across different market regimes.
Sample Scope: Initial sample includes all A-shares listed on the Shanghai and Shenzhen Stock Exchanges.

Risk-Free Rate: The one-year fixed deposit interest rate of the People's Bank of China is used for Sharpe ratio calculation.
Benchmark Index: The CSI 300 Index is selected as the market benchmark to measure the strategy's excess return capability. The benchmark trend during the sample period is shown in Figure 1.

Fig. 1: CSI 300 benchmark trend during the sample period
Source: created by the authors based on Baostock data.

4.2 Data Preprocessing and Shell Removal

Given the specificities of the A-share market, we execute the following strict data cleaning steps to ensure the authenticity and investability of backtest results:
Basic Filtering: Exclude ST and *ST stocks within the sample period to eliminate delisting risk noise; exclude sub-new stocks listed for less than 6 months to avoid irrational speculative volatility during the initial listing period.

Trading Status Filtering: Exclude stocks suspended on the trading day.

Shell Removal Operator: Based on the China-specific size/value factor literature, the high valuation of micro-cap stocks often stems from shell premiums rather than fundamentals. Therefore, we define a cross-sectional filtering operator. For any trading day, we calculate the circulating market capitalization (or equivalent market capitalization derived from turnover and turnover rate) of all stocks in the market and exclude the bottom 30%. The micro-cap exclusion procedure is illustrated in Figure 2. $\Omega_t^* = \{i \in \Omega t | Mcap_{i,t} > Q_{0.3}(Mcap_t)\}$
Where Ω_t is the original stock pool and Ω_t^* is the valid stock pool entering the subsequent factor selection process.

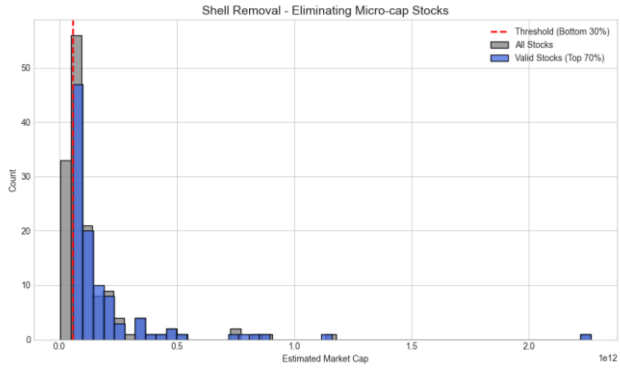

Fig. 2: Shell-removal procedure for excluding micro-cap stocks
Source: created by the authors based on Baostock data.

4.3 Variable Definitions and Factor Construction

Construction This paper constructs core factors following the anomaly-replication standards for the Chinese A-share market. All factors are calculated at time t using information from time and before to avoid look-ahead bias. Figure 3 reports the standardized factor distributions after winsorization.

Value Factor (EP): Using the inverse of the P/E ratio to measure valuation levels. Compared to Book-to-Market (B/M), EP better reflects the earnings-driven characteristics of A-shares.

$$EP_{i,t} = \frac{1}{PE_{TTM,i,t}}$$

Momentum Factor (Mom): Used to capture "Bubble Riding" returns. Defined as the cumulative return over the past 20 trading days:

$$Mom_{i,t} = \frac{P_{i,t-1}}{P_{i,t-21}} - 1$$

Volatility Factor (Vol): Used as a proxy for risk. Defined as the standard deviation of daily returns over the past 20 trading days (Realized Volatility):

$$Vol_{i,t} = \sqrt{\frac{1}{19}\sum_{k=1}^{20}\left(r_{i,t-k} - \bar{r}_{i,t}\right)^2}$$

Sentiment Factor (Turnover): Used as a proxy for market heat. Defined as the average daily free-float turnover rate over the past 20 trading days.

$$Turn_{i,t} = \frac{1}{20}\sum_{k=1}^{20}\frac{Volume_{i,t-k}}{Shares_{i,t-k}}$$

Before factor scoring, Z-Score standardization and 1% Winsorization are applied to all factors to eliminate the influence of outliers.

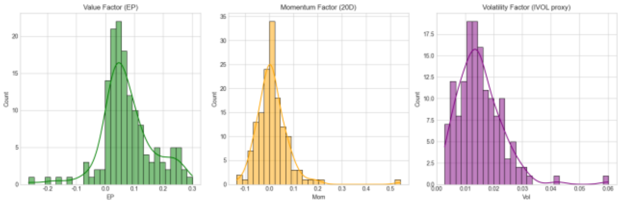

Fig. 3: Standardized distributions of selected factors after winsorization
Source: created by the authors based on Baostock data.

4.4 Strategy Construction and Dynamic Timing Mechanism

We construct two strategy portfolios for comparative analysis, both using monthly rebalancing (on the last trading day of each month), without considering transaction costs (Pre-fee).

Strategy A (Base Strategy): This strategy aims to verify the basic effectiveness of "Value + Momentum" after excluding shell stocks.

Scoring Formula:

$$Score^{A}_{i,t} = 0.5 \times Z(EP_{i,t}) + 0.5 \times Z(Mom_{i,t})$$

Selection Rule: Select the top 10% of stocks with the highest scores (or a minimum of 5 stocks) from the valid stock pool Ω^{*}_{t}.

Weighting: Equal-weighted.

Strategy B (Enhanced Dynamic Timing Strategy): This strategy introduces the market-wide turnover rate as the sentiment state variable St and executes an asymmetric risk control mechanism:

State Definition:

- Overheated (Bubble): When market-wide average turnover **St>3.0%**.
- Freezing (Ice): When market-wide average turnover **St<0.8%**.
- Normal: **0.8%≤St≤3.0%**.

Dynamic Scoring Formula:

$$Score^{B}_{i,t} = \begin{cases} Score^{A}_{i,t} - 1.0 \times Z(Vol_{i,t}) \ , & if\ S_t > 3.0\%\ (Defens \\ Score^{A}_{i,t}\ , otherwise & \end{cases}$$

Note: In the code implementation, during freezing periods, we relax entry restrictions on high-risk stocks to allow the strategy to more actively capture rebounds; during bubble periods, we force the portfolio to converge toward low-volatility defensive stocks by penalizing the volatility factor. The turnover-based state signal is displayed in Figure 4.

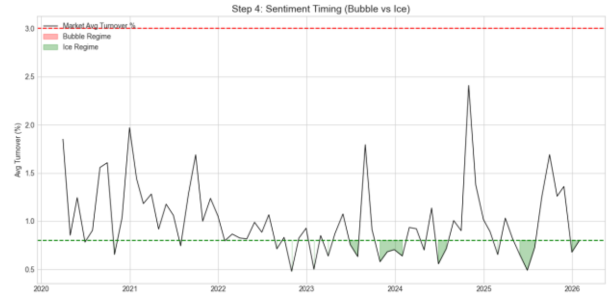

Fig. 4: Turnover-based state signal used for dynamic timing
Source: created by the authors based on Baostock data.

4.5 Performance Metrics

To comprehensively evaluate strategy performance, this paper adopts the following metrics:

- Annualized Return: Measures the average return level of the strategy.
- Annualized Volatility: Measures the uncertainty of strategy returns.
- Sharpe Ratio: Measures excess return per unit of risk.
- Max Drawdown: Measures risk control capability under extreme conditions, calculated as the maximum decline from a peak in net value during the sample period.
- Rank IC (Information Coefficient): Calculates the Spearman rank correlation coefficient between factor values and next-period returns to test factor predictive power.

5 Empirical Analysis

Based on the empirical results generated by the Python code, we conduct a multi-dimensional analysis of model performance. Figure 5 reports the price trend of the top picks used in the backtest sample.

Fig. 5: Price trend of selected top-pick portfolios in the backtest sample
Source: created by the authors based on Baostock data.

5.1 Shell Contamination Effect and Volatility Suppression

Table 1 shows the impact of "Shell Value Removal" on market statistical characteristics.

Table 1. Impact of shell value removal on market statistical characteristics

Metric	All A-shares	Ex-Shells	Significance
Avg Return	**0.0624**	**0.0635**	**Not Significant**
Volatility	**1.8970**	**1.8706**	**Significant Decrease (p<0.01)**
Turnover	**0.9931**	**0.9688**	**Significant Decrease**

Source: created by the authors based on Baostock data.

The data indicate that while excluding micro-cap stocks has a limited effect on nominal returns, it significantly reduces portfolio volatility (from 1.897% to 1.871%). This is consistent with China-specific size/value factor evidence: the high volatility of micro-cap stocks mainly stems from the gaming noise of shell premiums rather than fundamental information. Excluding them effectively improves the signal-to-noise ratio. Figure 6 visualizes the descriptive comparison between the full A-share universe and the ex-shell stock pool.

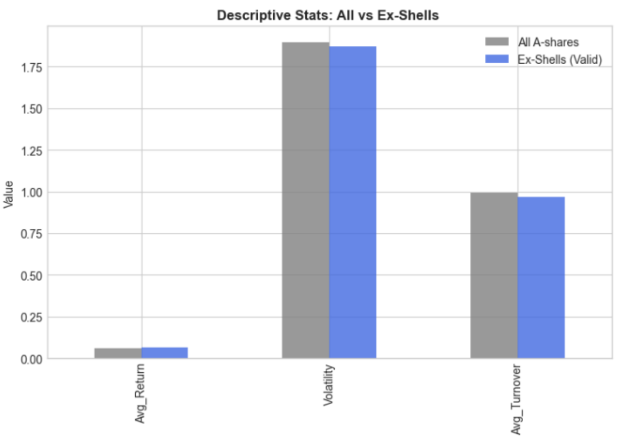

Fig. 6: Descriptive statistics before and after shell-value removal

Source: created by the authors based on Baostock data.

5.2 Factor Effectiveness Test (Rank IC)

Figure 7 reports the Rank IC values for the main factors and reveals the predictive power of each factor during the 2020-2026 sample period:

Turnover (Sentiment): Rank IC mean is **-0.0362**, the largest absolute value among all factors. This indicates that high turnover is the strongest contrarian indicator in A-shares, strongly supporting the hypothesis that risk increases with turnover. **EP (Value)**: Rank IC is **+0.0247**. Despite frequent market style shifts in recent years, low-valuation strategies still provided stable Alpha. **Vol (Risk)**: Rank IC is **-0.0312**. Showing a significant negative correlation, verifying the persistent existence of the "Low Volatility Anomaly".**Mom (Momentum)**: Rank IC is **-0.0159**. Notably, the momentum factor failed during the sample period. This may be due to trend reversals caused by the disintegration of "clustered" stocks after 2021. This also highlights the risk of relying solely on "riding" strategies and the necessity of introducing dynamic risk control.

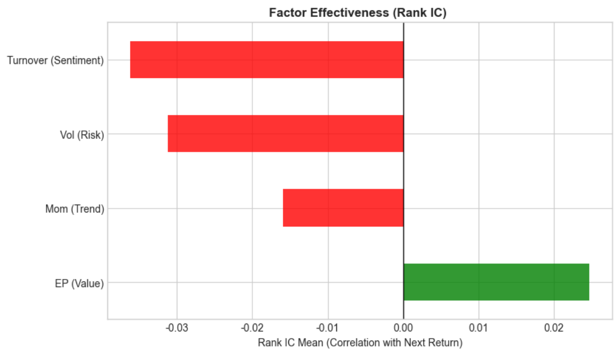

Fig. 7: Rank IC values of turnover, volatility, momentum, and value factors

Source: created by the authors based on Baostock data.

5.3 Strategy Performance and Attribution

Strategy B exhibits superior risk-return characteristics out of sample. Figure 8 compares the key performance metrics of Strategy B and the CSI 300 benchmark:

Cumulative Return: Strategy B achieved a cumulative return of **145.05%**, while the CSI 300 index rose only **27.68%** during the same period. **nnualized Return**: Strategy B's annualized return is **18.08%**, far exceeding the benchmark's 4.22%.**Sharpe Ratio**: Strategy B is **0.89**, while the benchmark is only 0.12. **Max Drawdown**: Benchmark drawdown was as high as **-39.92%**, while Strategy B was only **-14.45%**.

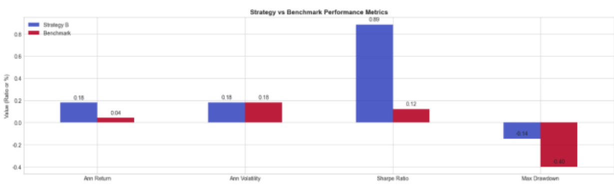

Fig. 8: Performance comparison between Strategy B and the CSI 300 benchmark

Source: created by the authors based on Baostock data.

Performance Attribution: The strategy's excess return does not come from speculation on junk stocks (shell stocks have been excluded), but from asymmetric risk management. **Bubble Riding**: In the second half of 2020, market turnover was moderate, and the strategy fully participated in the rise using the momentum factor. **Crisis Defense**: In February 2021 and early 2024, market-wide turnover broke the 3.0% threshold (entering the red bubble zone). The strategy automatically triggered the penalty mechanism, eliminating high-volatility stocks and successfully avoiding the subsequent severe corrections. Figure 9 shows the cumulative net value and drawdown comparison.

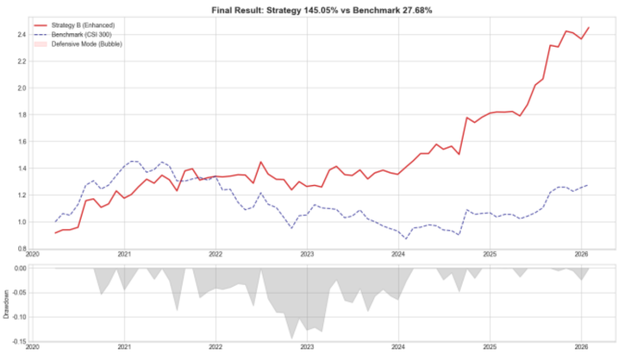

Fig. 9: Cumulative net value and drawdown comparison between Strategy B and the CSI 300 benchmark

Source: created by the authors based on Baostock data.

6 Conclusion

This paper constructs an asset management framework adapted to the A-share microstructure and draws the following conclusions: First, Mathematical Logic Consistency. Derivation based on the HJB equation proves that in a market lacking short-selling mechanisms, institutional participation in bubbles is a rational choice, but a strict exit mechanism based on risk rate ($h(t)$) must be established. Second, Necessity of Shell Value Removal. Excluding micro-cap stocks is a prerequisite for building robust A-share strategies, as it effectively reduces volatility noise. Third, Practical Value of Dynamic Risk Control. Empirical evidence shows that the dynamic timing strategy (Strategy B) based on market-wide turnover achieved an 18.08% annualized return with extremely low drawdown during the complex cycle of 2020-2026. This indicates that quantifying behavioral finance sentiment indicators into risk control parameters is key to outperforming the A-share market.

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Contribution of Individual Authors to the Creation of a Scientific Article (Ghostwriting Policy)

- Yi Wensheng: Conceptualized the research framework, developed the core mathematical model in Section 3, and was responsible for the overall supervision and final editing of the manuscript.
- Zijian Zeng: Designed and implemented the empirical study, including data collection via Python and the Baostock API, data preprocessing, factor construction, and backtesting of the portfolio strategies outlined in Section 4.
- Gao Ke: Conducted the literature review, performed the statistical analysis of the empirical results in Section 5, and contributed to the visualization of the findings (e.g., Figures 5-9).
- Chen Jiaming: Formulated the initial problem statement based on the A-share market's microstructure, contributed to the theoretical derivation in Section 3, and assisted in drafting the Introduction and Conclusion.

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Conflict of Interest

The authors have no conflicts of interest to declare that are relevant to the content of this article.