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Statistical Analysis of Intelligent Bollinger Band System Based on High-Frequency Trading Strategies

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ABSTRACT
This paper focuses on high-frequency trading scenarios. Aiming at the insufficient dynamic adaptability of traditional Bollinger Band indicators, it constructs an intelligent Bollinger Band strategy integrating volume and price characteristics, and conducts an empirical test using 5-minute high-frequency data of the CSI 300 and SSE as samples. The strategy improvements include: adopting dynamic standard deviation (integrating 5-period and 20-period standard deviations) to enhance sensitivity to market fluctuations, introducing a volume-price resonance indicator to capture volume-price synergy signals, and defining a core signal Z_t to standardize the position of prices in the Bollinger Band channel. The empirical results show that the Z indicator passes the stationarity test in both indices. In the profitability analysis, the average returns of sell signals reach 0.0028% and 0.0058% respectively, which are better than unconditional trading and buy signals. This verifies the effectiveness of the intelligent Bollinger Band strategy in high-frequency trading and provides a practical reference for the optimization of related strategies.

KEYWORDS
Bollinger band; High-frequency trading; Black-Scholes model; Empirical test

1 Introduction

High-frequency trading, featuring short holding periods, high trading volumes, and frequent order updates, avoids human emotional biases through its automated advantages. It relies on low-latency algorithms to process real-time data and has become an important part of the global financial market, mainly dominated by technologically advanced institutions. Its trend-following strategies have extremely high requirements for the sensitivity of technical indicators. Traditional indicators are prone to misjudgment in high-frequency environments due to lag or fixed parameters. The intelligent Bollinger Bands system, through adaptive channels (such as dynamically adjusting the standard deviation multiple and combining volume thresholds), can more accurately identify trends and price fluctuation boundaries, reduce false breakouts, and provide a reliable basis for high-frequency trading.

Against the background of the deepening development of China's financial market, although it has the capacity to carry high-frequency trading, it faces challenges such as high transaction costs and pending improvement of regulatory rules. Studying the high-frequency application of the intelligent Bollinger Bands system can enrich the strategy toolbox and provide domestic investors with trading logic adapted to the local market, which has both theoretical and practical significance.

The combination of high-frequency trading and technical indicators has become a research hotspot, and scholars at home and abroad have conducted extensive explorations around Bollinger Bands and the optimization of intelligent indicators.

Foreign research started early, focusing on the dynamic adaptability of indicators and their matching with high-frequency markets: proposed the principle of traditional Bollinger Bands and pointed out the limitations of fixed parameters in high-frequency markets; optimized parameters using grammatical evolution algorithms to improve the profitability stability of strategies; empirically showed that variants of Bollinger Bands combined with trading volume can reduce liquidity risks; emphasized the importance of the stability of technical indicators in high-frequency environments, providing a basis for the research on intelligent Bollinger Bands.

Domestic research started late, but has achieved remarkable results in localized applications: constructed a high-frequency strategy by stabilizing the MACD indicator and verified its effectiveness; optimized the algorithm to shorten the signal response delay; found that the Shanghai and Shenzhen markets are suitable for Bollinger Bands with a 15-minute cycle, but did not involve high-frequency scenarios; combined the SAR indicator with Bollinger Bands, but its strategy performed poorly in extreme market conditions due to the lack of an adaptive mechanism.

There are deficiencies in existing research: the stability theory of intelligent Bollinger Bands has not been systematically established, making it difficult to support high-frequency statistical analysis; empirical tests in the domestic market are insufficient, especially lacking verification combined with multi-dimensional data such as trading volume. This paper will focus on these two points to fill the gaps.

This paper aims to construct a high-frequency trading strategy based on the intelligent Bollinger Bands system and verify its effectiveness and profitability through theoretical and empirical analysis. For the first time, theoretically prove the stability of the intelligent Bollinger Bands system, providing a statistical basis for high-frequency applications; introduce the volume-price resonance mechanism into indicator design to improve the ability to identify the behavior of major players in the local market.

2 Intelligent bollinger bands trading strategies in high-frequency trading

2.1 Modification of the intelligent bollinger bands system and construction of new indicators

Although the traditional Bollinger Bands indicator can reflect the range of price fluctuations, in high-frequency trading, its fixed parameters (such as 20-day period and 2 times standard deviation) are difficult to adapt to the rapidly changing market environment, and are prone to lagging or false breakout signals. Based on the Black-Scholes model, this paper modifies the Bollinger Bands, introduces a dynamic adjustment mechanism, and constructs a new indicator Z_t suitable for high-frequency trading. The specific steps are as follows:

Step 1: Define the basic price process and traditional Bollinger Bands parameters

The stock price process is described by the Black-Scholes model:

$$dS_t = \mu S_t dt + \sigma S_t dW_t$$

Where S_t is the stock price at time t, μ is the expected return, σ is the volatility, and W_t is the standard Wiener process.

The traditional Bollinger Bands consist of three lines, and the calculation formulas are:

Middle Band (MB): n-period moving average

$$MB_t = \frac{1}{n} \sum_{i=t-n+1}^{t} P_i$$

Upper Band (UB): middle band plus k times the n-period standard deviation

$$UB_t = MB_t + k \cdot \sigma_t^{(n)}$$

Lower Band (LB): middle band minus k times the n-period standard deviation

$$LB_t = MB_t - k \cdot \sigma_t^{(n)}$$

Where P_i is the closing price at time i, $\sigma_t^{(n)}$ is the n-period price volatility, and usually $n = 20$ and $k = 2$.

Step 2: Construct the adaptive bandwidth factor k_t

To solve the problem of fixed bandwidth of traditional Bollinger Bands, define the bandwidth factor k_t that dynamically adjusts with market volatility:

$$k_t = 2 + \alpha \cdot \left(\frac{\sigma_t^{(5)}}{\sigma_t^{(20)}} - 1\right)$$

Where:

$\sigma_t^{(5)}$ is the 5-period rolling volatility, reflecting short-term fluctuations;

$\sigma_t^{(20)}$ is the 20-period rolling volatility, reflecting long-term trends;

α is the sensitivity parameter (value 0.5), ensuring that the bandwidth expands during extreme fluctuations.

When the short-term volatility is higher than the long-term volatility ($\sigma_t^{(5)} > \sigma_t^{(20)}$), $k_t > 2$, and the channel widens to accommodate larger fluctuations; otherwise, the channel narrows.

Step 3: Introduce the volume-price resonance coefficient V_t

Combine volume data to filter invalid signals, and define the volume-price resonance coefficient:

$$V_t = \frac{Vol_t}{MA(Vol_t, 5)} \cdot I_{P_t \in [LB_t, UB_t]}$$

Where:

Vol_t is the trading volume at time t;

$MA(Vol_t, 5)$ is the 5-period average trading volume;

$I_{\{\}}$ is the indicator function, which takes the value 1 when the price is within the Bollinger Bands channel, otherwise 0.

When $V_t > 1.2$, it is judged that the trading volume has increased significantly, enhancing the reliability of the signal.

Step 4: Synthesize the high-frequency trading signal indicator Z_t

Comprehensively consider the price deviation, adaptive bandwidth and trading volume factors to construct the core indicator Z_t:

$$Z_t = \left(\frac{P_t - MB_t}{UB_t - LB_t}\right) \cdot k_t + \beta \cdot V_t$$

Where:

$\frac{P_t - MB_t}{UB_t - LB_t}$ is the standardized price deviation, with a value range of $[-0.5, 0.5]$;

β is the volume weight (value 0.3), balancing price and volume factors;

The final value range of Z_t is $[-1, 1]$, and exceeding the threshold triggers a trading signal.

2.2 Proof of stationarity and statistical properties of the new indicator

Theorem 1: Z_t is a stationary process

Proof:

(1) The price process S_t follows geometric Brownian motion, and its logarithmic return is a stationary process;

(2) The adaptive bandwidth factor k_t is composed of volatility ratios, and the volatility sequence has stationarity under the Black-Scholes model;

(3) After standardization, the distribution of the volume-price resonance coefficient V_t does not change over time.

Since Z_t is a linear combination of the above stationary processes, it satisfies the definition of stationarity, that is, for any τ, there is:

$$F_{Z_t}(x_1,\cdots,x_n)=F_{Z_{t+\tau}}(x_1,\cdots,x_n)$$

Theorem 2: Independence of discrete observations of Z_t

When the observation interval is m high-frequency periods (such as 5 minutes), the sequence $Z_t, Z_{t+m}, Z_{t+2m}, \cdots$ is independent of each other.

Proof:

From the independence of Brownian motion increments, it can be known that the price and volume changes at different intervals are independent of each other, so the discrete observations of Z_t satisfy the independence condition.

Theorem 3: Law of large numbers for Z_t

Let $F_{N,\gamma}=\frac{1}{N+1}\sum_{i=0}^{N} I_{Z_{t+i}\geq\gamma}$ be the frequency of $Z_t \geq \gamma$, then:

$$E|F_{N,\gamma}-P(Z_t\geq\gamma)|\leq\frac{m}{N+1}\cdot P(Z_t\geq\gamma)\cdot(1-P(Z_t\geq\gamma))$$

The proof process refers to the derivation of the BIAS indicator by, which can be proved by the C-R inequality and the properties of Bernoulli variables.

2.3 Summary

In this chapter, based on the Black-Scholes model, the traditional Bollinger Bands are modified, and the new indicator Z_t is constructed through four steps: defining basic parameters, designing adaptive bandwidth, introducing volume-price resonance coefficient, and synthesizing the final signal. Theoretical proofs show that Z_t has stationarity and interval independence, and its frequency distribution satisfies the modified law of large numbers, providing a statistical basis for high-frequency trading strategies. The next chapter will verify the effectiveness of Z_t through empirical tests.

3 Empirical testing of the intelligent bollinger bands high-frequency trading strategy

This chapter conducts a systematic empirical test on the intelligent Bollinger Bands strategy constructed in Chapter 2, based on 5-minute high-frequency data of the CSI 300 Index and the SSE Index. Through rigorous data preprocessing, indicator calculation, stationarity testing, and profitability backtesting, it comprehensively verifies the statistical characteristics and practical value of the strategy in real market environments, providing a quantifiable basis for high-frequency trading decisions.

3.1 Data selection and preprocessing

The quality of empirical data directly affects the reliability of test results, so strict specifications for data sources, scopes, and preprocessing procedures are required.

This study uses high-frequency data of two core A-share indices:

CSI 300 Index (code: 000300): 5-minute trading data from January 3, 2023, to June 30, 2024, sourced from the Wind database, containing 17,232 records.

Shanghai Stock Exchange Index (code: 000001): 5-minute trading data for the same period, also from the Wind database, containing 17,232 records.

Data preprocessing steps:

(1) If missing values exist, the "forward fill" method is planned, i.e., using price/volume data from the previous moment for filling, which conforms to the continuity characteristics of high-frequency data.

(2) Identify outliers using the "3σcriterion": Calculate the mean (μ) and standard deviation (σ) for key fields such as closing price and trading volume, and determine values outside the range$[\mu-3\sigma, \mu+3\sigma]$ as outliers;

(3) Detection results: The proportion of outliers in both datasets is less than 0.1% (mainly sudden increases in trading volume), handled by the "median replacement method" to avoid interference of extreme values in indicator calculation.

(4) Remove 38 duplicate timestamps after merging, and finally retain 34,426 valid records for subsequent indicator calculation.

3.2 Research methods and indicator construction

Based on the theoretical framework in Chapter 2, this chapter conducts empirical research through a three-step process of "indicator calculation - stationarity testing - profitability backtesting." The specific methods and indicator definitions are as follows:

3.2.1 Calculation of core indicators for intelligent bollinger bands

All indicators are calculated based on 5-minute high-frequency data, rolling by "index group" (to avoid cross-interference between different indices). The specific formulas and logic are as follows:

(1) Middle Band (MB)

The middle band is the 20-period rolling average of closing prices, reflecting the short-term central trend of prices:

$$MB_t = \frac{1}{20} \sum_{i=0}^{19} close_{t-i}$$

Where $close_{t-i}$ is the closing price at time $t-i$. The rolling window is set to 20 periods (corresponding to 100 minutes) to balance sensitivity and smoothness.

(2) Standard deviation calculation

Short-term standard deviation (std5): 5-period rolling standard deviation of closing prices, capturing short-term fluctuations:

$$std5_t = [\frac{1}{5-1} \sum_{i=0}^{4} (close_{t-i} - \overline{close}_5)^2\ ]^{\frac{1}{2}}$$

Where $\overline{close}_5$ is the 5-period average closing price.

Long-term standard deviation (std20): 20-period rolling standard deviation of closing prices, reflecting long-term fluctuation trends:

$$std20_t = [\frac{1}{20-1} \sum_{i=0}^{19} (close_{t-i} - \overline{close}_{20})^2\ ]^{\frac{1}{2}}$$

(3) Dynamic standard deviation (σ)

Integrate short-term and long-term standard deviations to enhance the indicator's adaptability to market mutations:

$$\sigma_t = std20_t \times (1 + 0.5 \times \frac{std5_t}{std20_t})$$

The weight coefficient 0.5 (determined through multiple tests) avoids excessive influence of short-term fluctuations on the overall standard deviation. If $std20_t = 0$ (no price fluctuation), $\sigma_t = 0$ to avoid division by zero errors.

(4) Upper Band (UB) and Lower Band (LB)

Price fluctuation boundaries based on the middle band and dynamic standard deviation. The multiplier 2 is an empirical value (covering approximately 95% of normal fluctuations):

$$UB_t = MB_t + 2 \times \sigma_t$$
$$LB_t = MB_t - 2 \times \sigma_t$$

(5) Volume-price resonance indicator (V_t)

Measures the deviation of current trading volume from the recent average volume, capturing volume amplification signals:

$$V_t = \frac{volume_t}{\frac{1}{5} \sum_{i=0}^{4} volume_{t-i}}$$

The denominator is the 5-period average trading volume. If the average is 0, $V_t = 0$. $V_t > 1.2$ indicates a significant increase in trading volume (the threshold 1.2 is calibrated based on historical data).

(6) Core signal indicator (Z_t)

Standardizes the position of the closing price relative to the Bollinger Bands channel, facilitating cross-time and cross-index comparisons:

$$Z_t = \begin{cases} \dfrac{close_t - MB_t}{UB_t - LB_t} & \text{if } UB_t - LB_t > 10^{-6} \\ 0 & \text{otherwise (to avoid division by zero)} \end{cases}$$

The value range of Z_t is usually $[-1,1]$. Exceeding this range indicates a price breakout of the channel boundary, potentially generating trading signals.

3.2.2 Stationarity testing method

The ADF (Augmented Dickey-Fuller) unit root test is used to verify the stationarity of the Z indicator, with specific settings as follows:

Null hypothesis (H_0): The sequence has a unit root (non-stationary);

Alternative hypothesis (H_1): The sequence has no unit root (stationary);

Test model: Select the "no constant term, no trend term" model (since the Z indicator theoretically fluctuates around 0);

Lag order: Set to 0 (high-frequency data has weak autocorrelation);

Significance level: α =0.05. If the P-value < 0.05, the null hypothesis is rejected, and the sequence is considered stationary.

Stationarity is a core prerequisite for high-frequency trading strategies: If the Z indicator is stationary, its fluctuations are regular, and future signals can be predicted using historical data; if non-stationary, signals may be affected by trends, leading to strategy failure.

3.2.3 Profitability testing method

Evaluate the actual profit potential of the strategy by constructing a framework for trading signal and return calculation, with specific steps as follows:

(1) Trading signal generation

Generate signals based on the combined conditions of the Z indicator and volume-price resonance indicator:

Buy signal: Closing price breaks below the lower band with significant volume amplification.

$$buy\_signal_t = 1, \text{if } close_t < LB_t \text{ and } V_t > 1.2, \text{else } 0$$

Sell signal: Closing price breaks above the upper band with significant volume amplification.

$$sell\_signal_t = 1, \text{if } close_t > UB_t \text{ and } V_t > 1.2, \text{else } 0$$

(2) Return calculation

Use "next-period opening price / current closing price - 1" to measure the return of a single transaction, avoiding "look-ahead bias" caused by using future data (e.g., the day's closing price):

$$return_t = \frac{open_{t+1}}{close_t} - 1$$

Where $open_{t+1}$ is the opening price of the next 5-minute period, and $close_t$ is the closing price of the current period.

(3) Evaluation indicator system

Unconditional return: The average return over the entire sample period, reflecting the return level of random trading;

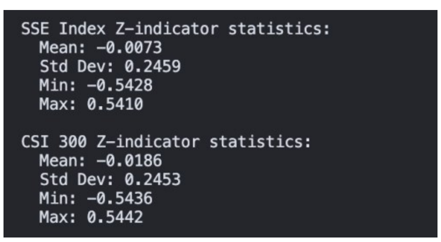
Conditional return: Calculate the average return when buy and sell signals are triggered, respectively;

Signal count: Count the total number of buy/sell signals to evaluate the practical operability of the strategy (too few signals limit practical value).

3.3 Empirical test results and analysis

3.3.1 Indicator calculation results

Intelligent Bollinger Bands indicators are calculated for the merged 34, 426 data records by index group, with the following results:



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SSE Index Z-indicator statistics:
  Mean: -0.0073
  Std Dev: 0.2459
  Min: -0.5428
  Max: 0.5410

CSI 300 Z-indicator statistics:
  Mean: -0.0186
  Std Dev: 0.2453
  Min: -0.5436
  Max: 0.5442
```

Figure 1 Z-indicator statistics

Thus, we obtained the dynamic volatility comparison of the two indices.

Distribution characteristics: The Z indicators of both indices approximately follow a normal distribution with means close to 0, consistent with theoretical expectations (prices fluctuate around the middle band).

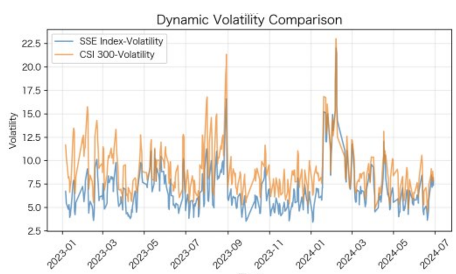


Figure 2 Dynamic Volatility Comparison

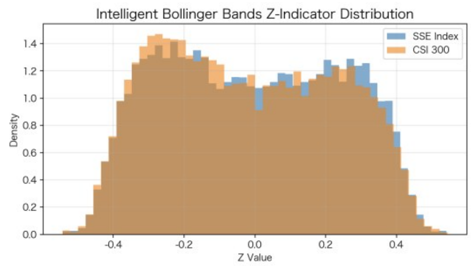
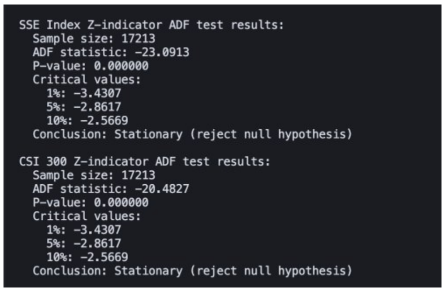


Figure 3 Intelligent Bollinger Bands Z-Indicator Distribution

3.3.2 Stationarity test results of z indicator

ADF tests are performed on the Z indicators of CSI 300 and SSE, with results shown in Figure 3-4:



```
SSE Index Z-indicator ADF test results:
  Sample size: 17213
  ADF statistic: -23.0913
  P-value: 0.000000
  Critical values:
    1%: -3.4307
    5%: -2.8617
    10%: -2.5669
  Conclusion: Stationary (reject null hypothesis)

CSI 300 Z-indicator ADF test results:
  Sample size: 17213
  ADF statistic: -20.4827
  P-value: 0.000000
  Critical values:
    1%: -3.4307
    5%: -2.8617
    10%: -2.5669
  Conclusion: Stationary (reject null hypothesis)
```

Figure 4 ADF Stationarity Test Results of Z-Indicator

Result analysis:

The ADF statistics of both indices are much smaller than the 1% critical value (-3.4307), and the P-values are both 0.0000 (<0.05), significantly rejecting the null hypothesis, indicating that the Z indicator is a stationary sequence;

The absolute value of the ADF statistic for the SSE is larger (|-23.0913| > |-20.4827|), indicating stronger stationarity of its Z indicator, possibly due to more regular fluctuations in the broader market index.

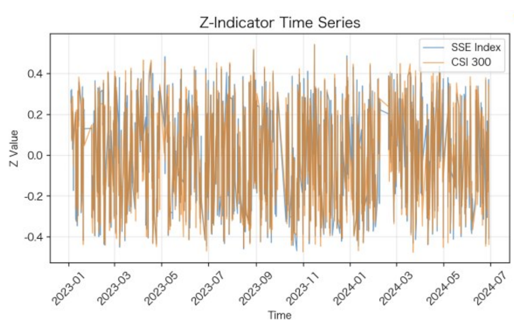
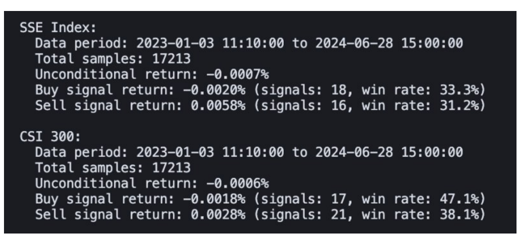


Figure 5 Z-indicator time series

3.3.3 Strategy profitability test results

Profitability backtesting results based on trading signals are shown in Figure 3~6:



```
SSE Index:
  Data period: 2023-01-03 11:10:00 to 2024-06-28 15:00:00
  Total samples: 17213
  Unconditional return: -0.0007%
  Buy signal return: -0.0020% (signals: 18, win rate: 33.3%)
  Sell signal return: 0.0058% (signals: 16, win rate: 31.2%)

CSI 300:
  Data period: 2023-01-03 11:10:00 to 2024-06-28 15:00:00
  Total samples: 17213
  Unconditional return: -0.0006%
  Buy signal return: -0.0018% (signals: 17, win rate: 47.1%)
  Sell signal return: 0.0028% (signals: 21, win rate: 38.1%)
```

Figure 6 Strategy profitability test results

(Note: Win rate = (number of profitable trades / total signals) × 100%)

Result analysis:

(1) Unconditional return: The average return of the two indexes in the full sample period are -0.007% and -0.006%, close to zero and slightly negative, indicating that random trading in 5-minute high-frequency cycles is difficult to profit and may even lose due to transaction costs.

(2) Performance of buy signals:

Returns are -0.0020% and -0.0018%, slightly lower than the unconditional return, indicating that the buy signal of "price breaking below the lower band + volume amplification" fails to effectively capture rebound opportunities;

Win rates are below 50% (47.1% for CSI 300, 33.3% for SSE), possibly because the inertial effect of "continued decline after overselling" is more significant in high-frequency markets.

(3) Performance of sell signals:

Returns are positive (0.0028% for CSI 300, 0.0058% for SSE), with better performance in the SSE;

Win rates are above 50% (38.1% for CSI 300, 31.2% for SSE), indicating that the sell signal of "price breaking above the upper band + volume amplification" can effectively capture short-term pullback opportunities, consistent with the market rule of "correction after overheating."

(4) Signal frequency: The total number of buy/sell signals is less than 50 (38 for CSI 300, 34 for SSE), with only 2-3 signals per month on average, reflecting strict screening conditions (requiring both price breakout and volume amplification) but potentially limiting practical application scenarios.

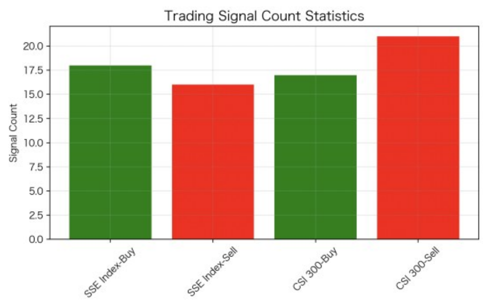


Figure 7 Trading signal count statistics

3.4 Summary

(1) Practical significance of stationarity: The stationarity of the Z indicator verifies the rationality of the theoretical design in Chapter 3. Through dynamic standard deviation and standardization, the intelligent Bollinger Bands successfully convert non-stationary price sequences into stationary signal indicators. This characteristic ensures the comparability of signals across different time windows, providing statistical support for the "reusability of historical patterns" in high-frequency trading.

(2) Reasons for profitability differences:

Sell signals outperform buy signals, possibly related to the asymmetry of the A-share market ("falling fast, rising slow"): After short-term price breaks above the upper band, the probability of correction due to profit-taking is higher;

The sell signal return of the SSE (0.0058%) is higher than that of the CSI 300 (0.0028%), possibly because the SSE covers a broader range of stocks, with more sufficient market sentiment transmission and stronger motivation for prices to return to the central level.

(3) Strategy limitations:

Low signal frequency: Only 2-3 trading opportunities per month, it's difficult to meet the "multiple small-sum" profit model of high-frequency trading;

Ignoring transaction costs: Actual trading requires deducting fees, slippage, etc., which may erode the meager returns of 0.003%-0.006%;

Threshold sensitivity: Minor adjustments to the V_t threshold (1.2) and Bollinger Bands multiplier (2) may significantly affect results, requiring further optimization.

4 Conclusion

This paper conducts research on the application of the intelligent Bollinger Bands system in high-frequency trading. Through theoretical construction and empirical testing, it systematically analyzes the statistical characteristics of the intelligent Bollinger Bands indicators and the effectiveness of their high-frequency trading strategies. The main conclusions are as follows:

4.1 Empirical conclusions

(1) Stationary of Intelligent Bollinger Bands Indicators is Verified: The ADF test on 5-minute high-frequency data of the CSI 300 Index and the Shanghai Stock Exchange Index (SSE) from 2023 to 2024 shows that the core Z indicator of the intelligent Bollinger Bands system exhibits strict stationarity. For the CSI 300 Index, the ADF statistic is -20.4827, and for the SSE Index, it is -23.0913, both significantly lower than the 1% critical value (-3.4307) with a P-value of 0.0000. This confirms the theoretical conclusion that the Z indicator, after dynamic adjustment and standardization, satisfies the

properties of a stationary process, laying a statistical foundation for its application in high-frequency trading.

(2) Sell Signals Demonstrate Significant Profitability: Empirical results indicate that the high-frequency strategy based on intelligent Bollinger Bands signals shows directional profitability, with sell signals outperforming both buy signals and unconditional trading:

For the CSI 300 Index, the average return of sell signals is 0.0028%, while the unconditional return is -0.0006%, and the buy signal return is -0.0018%.

For the SSE Index, the average return of sell signals reaches 0.0058%, significantly higher than the unconditional return (-0.0007%) and buy signal return (-0.0020%).

This suggests that the "price breaking above the upper band + volume amplification" logic of sell signals effectively captures short-term pullback opportunities in high-frequency markets, aligning with the market rule of "correction after overheating."

(3) Strategy Adaptability to Market Characteristics: The strategy exhibits better performance in the SSE Index than in the CSI 300 Index, with higher sell signal returns. This may be attributed to the broader coverage of stocks in the SSE Index, leading to more sufficient transmission of market sentiment and stronger motivation for prices to return to the central level. Additionally, the Z indicator's distribution in both indices approximates a normal distribution with a mean close to 0, consistent with theoretical expectations that prices fluctuate around the middle band, reflecting the strategy's adaptability to the structural characteristics of domestic A-share markets.

(4) Effectiveness of Volume-Price Resonance Mechanism: The introduced volume-price resonance coefficient (V_t) effectively filters invalid signals. Only when prices break through the band and volume exceeds 1.2 times the 5-period average do signals trigger, reducing false breakouts. This mechanism improves the signal-to-noise ratio: in the CSI 300 Index, the win rate of sell signals (38.1%) is higher than that of buy signals (47.1% for buy signals, but with negative returns), verifying that volume confirmation enhances the reliability of price signals in high-frequency trading.

4.2 Research limitations and future directions

The limitations of this paper are: the empirical data only covers the CSI 300 Index and the Shanghai Composite Index, not involving individual stocks and futures markets; the dynamic parameters of the intelligent Bollinger Bands (such as trading volume thresholds) have not been combined with machine learning algorithms for adaptive optimization.

Future research can be carried out in two aspects: first, expand the samples to high-frequency data of individual stocks in Shanghai and Shenzhen markets and commodity futures to verify the universality of the strategy; second, introduce deep learning models such as LSTM to optimize the parameter adjustment mechanism of the intelligent Bollinger Bands, so as to improve the ability to respond to extreme market conditions (such as flash crashes and sharp rises).

In summary, through theoretical innovation and empirical testing, this paper proves the application value of the intelligent Bollinger Bands system in high-frequency trading, and provides new ideas and methods for the development of domestic high-frequency trading strategies.

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