

Trend-Enhanced Improved Bollinger Bands Trend-Following High-Frequency Trading Strategy for Futures Market

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Abstract. The application of digital scientific technologies in the global financial markets has become widespread, which has led to the prevalence of the concept of quantitative trading. Among various quantitative trading strategies, high-frequency trading has gained significant popularity. In this study, we propose an improved Bollinger Bands trend-following high-frequency trading strategy based on trend enhancement. Instead of using the simple moving average (SMA), we replace it with the exponential moving average (EMA). Furthermore, we introduce a 3-times average true range (ATR) limit price rebound exit system to achieve timely profit-taking and stop-loss. By incorporating trend measurement indicators such as the average directional index (ADX), moving average convergence divergence (MACD), and commodity channel index (CCI), we determine the futures trend. Subsequently, this study formulates suitable parameters for the high-frequency trading strategy and conduct backtesting on the 2022 CSI 300 stock index futures, resulting in a remarkably high annualized return. These results present a novel approach to high-frequency trading strategy and provide valuable insights for the market.

Keywords: High-frequency trading; trend enhancement; Bollinger bands; futures market.

1. Introduction

In recent years, the widespread application of digital scientific technology in the global financial market has propelled the prevalence of the concept of quantitative trading, exerting a profound influence on the operational mechanisms of the financial market. High-frequency trading is a special type of algorithmic trading that is based on a certain trading strategy. It utilizes high-speed computers to closely monitor relevant information at an extremely high frequency and automatically execute buy and sell orders. High-frequency trading directly links computers with trading platforms in algorithmic trading, processing orders without human interference. Based on pre-set algorithms, computers automatically monitor market data and other relevant information at a high frequency and issue trading instructions within milliseconds. It has the following four main characteristics: firstly, decision-making, order generation, and execution of trading programs are carried out through algorithmic procedures; secondly, it has extremely short latency, aiming to minimize response time; thirdly, trading instructions quickly enter the system and interact with the market through high-speed connections; finally, high-frequency trading generates a large volume of trading activities, resulting in a relatively large amount of information [1].

Chen conducted a comparative analysis of the development of quantitative finance both domestically and internationally [2]. He provided an empirical study on the performance attribution of various quantitative strategies. Fan proposed recommendations for risk management and control of high-frequency trading in the Chinese futures market by examining Japan's regulatory system for high-frequency trading [3]. However, no specific solutions were put forward. In the realm of high-frequency quantitative trading, Li constructed an optimized quantitative model using Bollinger Bands and corresponding financial data, and attempted to apply it to the A-share market [4]. The study yielded a model that can serve as a practical reference, providing feasible solutions for investment

decision-making to investor. Yan presented an improved technical standard and strategic process centered around the Bollinger Band trading rule [5]. Regarding the performance evaluation of high-frequency quantitative trading [6, 7], Shi defined high-frequency trading proxy indicators and employed a vector autoregressive model to study the relationship between algorithmic trading proxy variables and bid-ask spreads [8]. The conclusion drawn was that although high-frequency trading may raise overall risk levels, it does not increase liquidity risk additionally. Zhang conducted a comprehensive analysis of alpha strategies by combining momentum models with fundamental arbitrage models [9]. The study delved into the risks associated with alpha strategies and innovatively proposed a method of hedging beta with stock index futures to mitigate systematic risk, effectively reducing the risk of alpha strategies [10]. However, there are certain flaws in cost control, and there is a lack of sufficient derivative instruments in the Chinese futures market. This article will discuss the application of the trend Bollinger Band strategy in high-frequency trading, optimize and improve the model multiple times based on performance, and thus derive a strategy for Bollinger Band trend tracking in the high-frequency trading market for futures.

2. Basic Bollinger Band Strategy

BOLL (Bollinger Bands) is the United States stock market analyst John Bollinger in the last century eighty years up to the principle of standard deviation according to statistics designed a very simple and practical technical analysis indicators, mainly used to analyze the stock, foreign exchange, commodities and other financial markets, price trends, and provide traders with entry and exit signals. It uses the mean and standard deviation to portray the range of fluctuations in stock prices and future trends of technical indicators, in general, the movement of stock prices is always around a certain value pivot (such as averages, cost lines, etc.) within a certain range of changes, Bollinger Bands indicator indicator is precisely on the basis of the conditions described above, the introduction of the concept of "stock channel", which is believed to be The width of the stock price channel changes with the magnitude of stock price fluctuations, and the stock price channel has variability, it will automatically adjust with the changes in the stock price. It is because of its flexibility, intuition and trend characteristics, BOLL indicator gradually become investors widely used in the market popular indicators due to its need to show the range of values, so by the composition of the three lines: the upper rail, the middle rail and the lower rail, and therefore also known as the Bollinger Band. The classic Bollinger Band strategy suggests that when the price touches or breaks the upper line, it may be an overbought signal and traders may consider selling; when the price touches or breaks the lower line, it may be an oversold signal and traders may consider buying.

Bollinger bands strategy in the channel consists of the upper rail line and the lower rail line, its intrinsic mathematical basis is based on the probability density of the standard normal distribution: the standard normal distribution is 0 for the mean, 1 for the standard deviation of the normal distribution, notated as $N(0, 1)$. The standard deviation determines the bandwidth of the Bollinger Band channel. When the stock price fluctuates more, the larger the standard deviation, the larger the bandwidth of the Bollinger Band; when the stock price fluctuates less, the smaller the standard deviation, the narrower the bandwidth of the Bollinger Band.

Bollinger band channel calculation formula is as follows. We set x_1, x_2, \dots, x_n indicates the stock price in the previous n days, then on the n th day, the Bollinger band's center rail line u_n is calculated as follows:

$$u_n = \frac{1}{n} \sum_{i=1}^n x_i \quad (1)$$

The value of the upper rail of the Bollinger band is denoted by \bar{B} which is calculated by the following formula.

$$\bar{B} = u_n + a\sigma_n \quad (2)$$

The value of the lower rail of the Bollinger band is denoted by \underline{B} which is calculated by the following formula:

$$\underline{B} = u_n - a\sigma_n \tag{3}$$

In the above formula σ_n represents the standard deviation of stock prices, which is calculated as:

$$\sigma_n = \sqrt{\frac{1}{n} \sum_{i=1}^n (p_i - u_n)^2} \tag{4}$$

Where a indicates a multiple of the standard deviation, generally take the value of 2, the bandwidth that is the difference between the upper rail line and the lower rail line. In this paper, the five-minute trading frequency is selected for study.

3. The Center Line Part

In the traditional Bollinger band strategy generally use SMA (Simple Moving Average) that is, simple moving average as the indicator of the middle line. The principle is to use the moving average of the time series, in short, the current moment of the first n observations to predict the value of the next period. The moving average removes short-term fluctuations from the time series and smoothes the data, making it easier to see the trend characteristics of the series, so the principle is usually used in the direction of forecasting, smoothing the fluctuations of the series and revealing the trend characteristics of the time series. The formula for calculating the Medium SMA used in the classic Bollinger Band strategy is as follows. Given a time series $\{X_t\}$, the sequence of observations is x_1, x_2, \dots, x_t :

$$SMA_t(n) = \frac{1}{n} \sum_{i=t-n+1}^t x_i \tag{5}$$

where n is the window size and SMA_t is the moving average at time t . In Bollinger band strategy this indicator can be defined as:

$$SMA(N) = \frac{1}{N} \sum_{i=1}^N close(i) \tag{6}$$

where N is the set period parameter, i represents the first i K-lines of the current K-line, and $close(i)$ represents the closing price. In this study, the improved strategy uses EMA (Exponential Moving Average), which is the exponential moving average, as the center line. Its calculation formula is as follows:

$$EMA_t = \frac{x_t + (1-\alpha)x_{t-1} + (1-\alpha)^2 x_{t-2} + \dots + (1-\alpha)^t x_0}{1 + (1-\alpha) + (1-\alpha)^2 + \dots + (1-\alpha)^t} \tag{7}$$

where, t is the window size, α is the smoothing factor ($0 < \alpha < 1$, generally $2/(t+1)$ can also be defined), $(1 - \alpha)^i$ is the exponentially increasing weight, the closer the period is to the prediction moment, the greater the weight. In Bollinger Band Strategy this indicator is defined as:

$$EMA(N) = \alpha close(N) + (1 - \alpha)EMA(N - 1) \tag{8}$$

where $close(N)$ represents the closing price of the N th cycle, α is the weight value, usually $2/(N+1)$ or $1/(1+decay)$, where $decay$ is the decay factor.

Comparison of the two, the SMA moving average is the average of historical prices (to the price of equal weight way to sum) in each real-time K line before the implementation of a price, as a guide to the subsequent trading behavior, the average of these prices to the curve to connect, to get a relatively smooth price curve. The curve can reflect the general trend of the price in a certain period, but also can be used to determine some of the current trend, is one of the most basic analysis methods. Exponential Moving Average EMA (Exponential Moving Average) can be seen as a special kind of weighted moving average, sometimes also known as the exponentially weighted moving average (EWMA). It is similar to the Weighted Moving Average WMA (Weighted Moving Average), but it

assigns a series of fixed exponentially decreasing weights, known as weighting factors, to previous values that decrease exponentially over time. Compared to the SMA and WMA the EMA provides a more visible indicator that reflects recent price trends more quickly. Compared to the SMA, the EMA usually reacts faster to price because the weights decay exponentially, the further away the K-line the lower the weight, and the exponential decay is much faster than the linear decay.

Nevertheless, EMA also has shortcomings, for this study for high-frequency trading compared to the SMA has a greater improvement, but for longer periods of trading is not as good as the SMA prediction effect. Because the longer the moving average, the slower it reacts to price movements, the EMA will track price more closely than the SMA in short-term high-frequency trades, but because the EMA will move with price earlier than the SMA, it is often lagged, making it less suited to triggering entries and exits on longer-period charting timeframes (e.g., daily or weekly). The SMA, on the other hand, lags slower and tends to smooth out price action over time, making it a better trend indicator.

4. A Multiple ATR Limit Price Rollback Closing System

The Average True Range (ATR) is a technical analysis indicator developed by Welles Wilder, which represents the average trading range after taking the exponential moving average of N days. The concept of ATR volatility can reflect the expectations and enthusiasm of traders. A significant or increasing ATR volatility indicates that traders may be prepared to continue buying or selling stocks on that day. For the calculation of ATR, please refer to the following formula, where TR (True Range) represents the price range of a certain k-line relative to the closing price of the previous k-line. Simply put, it is the difference between the highest and lowest points of a single k-line, excluding any gaps:

$$ATR_t = \frac{ATR_{t-1} \times (n-1) + TR_t}{n} \quad (9)$$

This article employs a five-fold ATR limit price rollback closing system, where the fixed multiple for the ATR stop-loss method is set at five. This means that the position will be forcibly closed when the price deviates from the opening direction by five times the ATR. In terms of selecting the multiplier, the sample chosen for this article is the CSI 300, which exhibits significant volatility. A multiplier of three for the ATR would result in premature position closure. Based on multiple backtesting results, it has been determined that a multiplier of five is a more suitable parameter for the ATR stop-loss, as it helps avoid excessive sensitivity to parameters. The implementation of the five-fold ATR limit price rollback closing system has resulted in a positive improvement in backtesting performance compared to previous results.

5. Trend Measurement Indicators

The Average Directional Index (ADX) is a technical indicator used for trend analysis. It does not determine the direction of the market, but it indicates the strength of the trend. ADX can assess the likelihood of the market continuing or reversing its current trend. ADX is calculated using two directional indicators, namely the positive directional indicator (+DI) and the negative directional indicator (-DI). These indicators are derived from the Directional Movement Indicator (DMI). The ADX value is calculated by taking the difference and sum of +DI and -DI. After dividing the difference by the sum and multiplying by 100, the result is called the Directional Index or DX. The final ADX indicator is obtained by taking the moving average of DX, typically over a period of 14 days (although any number of periods can be used).

The MACD indicator, belonging to the category of major trend indicators, is comprised of five components: the long-term moving average MACD, the short-term line DIF, the red energy column (representing bullishness), the green energy column (representing bearishness), and the O-axis (the boundary between bullish and bearish). It utilizes the crossover between the short-term moving

average DIF and the long-term line MACD as a signal. The crossover signals generated by the MACD indicator exhibit a certain degree of sluggishness, yet they prove to be highly effective when employed for the formulation of corresponding trading strategies:

$$MACD = EMA12 - EMA26 \quad (10)$$

$$signal\ line = EMA9(MACD) \quad (11)$$

In the aforementioned equation, EMA12 refers to the 12-day exponential moving average, EMA26 refers to the 26-day exponential moving average, and EMA9 refers to the 9-day exponential moving average. The exponential moving average is a weighted average that assigns higher importance to recent prices. The Commodity Channel Index (CCI) is an indicator developed by Donald Lambert in 1980. It measures the volatility of stock prices by comparing the current price with its 20-day moving average. The CCI is calculated by dividing the difference between the stock price and its 20-day moving average by 0.015 times the mean absolute deviation (MD). The CCI value typically fluctuates between -100 and +100, where +100 indicates that the price is above the 20-day moving average and -100 indicates that the price is below the 20-day moving average:

$$CCI(N\ days) = \frac{TP - MA}{0.015MD} \quad (12)$$

$$TP = \frac{\text{highest price} + \text{lowest price} + \text{closing price}}{3} \quad (13)$$

$$MA = \frac{1}{N} \sum_{i=1}^N \text{closing prices} \quad (14)$$

$$MD = \frac{1}{n} \sum_{i=1}^N (MA - \text{closing prices}) \quad (15)$$

Here, 0.015 represents the calculation coefficient, N represents the calculation period. In this study, ADX and other factors such as MACD and reverse CCI are used to assess trends. When a trend is present, the opening logic is modified (lowering the k-value of the Bollinger Bands) and the position weight for trend opening is increased. Comparing the backtesting performance before and after these changes, there is a significant improvement.

6. Paramter Setups

In order to enhance the strategy's responsiveness to the market and capture subtle arbitrage opportunities, this paper adjusts the parameters as follows. The paper selects EMA lines with periods of 30 and 34, along with a 10-period indicator. These shorter periods provide more recent price data, allowing the system to focus on capturing short-term price movements, tracking and predicting changes in market trends more quickly, and making more timely trading decisions. Within the trend bands, the paper chooses a smaller threshold value of 0.1. The purpose of this choice is to create more trading opportunities. A smaller threshold value means easier triggering of trading signals, allowing the system to trade even in situations with smaller price fluctuations. By increasing the number of trading signals, the strategy can actively participate in the market and increase profit opportunities. The ATR multiplier is set to 5, and an 8-period window is used. This adjustment enables the system to capture small price fluctuations. A smaller ATR multiplier means that smaller price ranges are considered valid trading signals, resulting in more frequent entries and exits. By quickly adjusting positions, the strategy can capitalize on small price movements in the market. The ADX value is set to 27 to establish a lenient trend identification criterion. A lower ADX value allows the system to generate trading signals in relatively weaker trends. This is done to capture more trading opportunities. By combining frequent indicator outputs, the strategy can capture more trend changes in the market and trade accordingly. SMA periods of 1, 3, and 5 are selected as color indicators for bull and bear markets. These ultra-short periods can more quickly reflect minor price fluctuations. By using these ultra-short SMA periods, the strategy can identify and track short-term trend changes in the market earlier, enabling timely actions. A 10-period analysis is used to observe the price behavior of

indicators such as CCI and ADX. The shorter period allows the strategy to closely monitor price fluctuations and trend changes in the market. This fine-grained time analysis helps to better understand short-term market trends and make trading decisions based on them.

The paper sets the trend score threshold to 4, meaning that more trend confirmations are required to generate a trading signal. By setting a stricter threshold, the strategy can track the formation of price trends carefully and take corresponding trading actions. This paper takes into account the specific requirements of high-frequency trading strategies and adjusts these parameters accordingly. Each adjustment has its unique role, making the strategy more adaptable to the rapidly changing market and small fluctuations. By utilizing these parameter adjustments, the strategy can capture more trading opportunities from the market and generate profits in a fast-paced market environment. Finally, the strategy is backtested to evaluate its performance.

7. Results and Discussion

To examine the effectiveness of the strategy, we conducted a backtest on the CSI 300 stock index futures in 2022. The results of the high-frequency trading strategy based on the Bollinger Bands are presented in Table 1 and Fig. 1. It can be observed that the strategy exhibits a significantly high annualized return and Alpha indicator, while being relatively unaffected by market conditions:

Table 1. The results of strategy

Annualized Return	Sharpe Ratio	Alpha	Beta	Volatility	Maximum Drawdown
123.9%	3.26	117.4%	-0.12	36.9%	13.7%

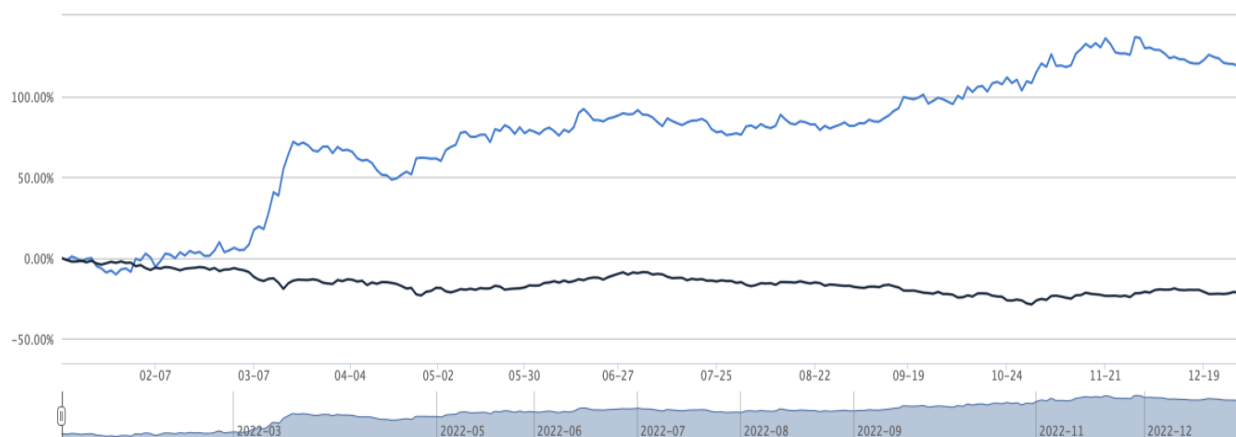


Fig. 1 The results of strategy

Based on the results mentioned above, it is evident that the strategy exhibits a significantly high annualized return, which may indicate potential overfitting of the parameters. To assess the robustness of the strategy, we conducted a sensitivity analysis on important parameters. The analysis results are as follows. The trend Bollinger Bands' k value triggers the opening signal when the price exceeds k times the standard deviation of the Bollinger Bands (seen from Table 2). It reflects the strategy's sensitivity to trend signals. By conducting a sensitivity analysis on the k value of the trend Bollinger Bands, the following results were obtained. As the k value changes, the difficulty of triggering the opening signal increases, leading to a decrease in the Sharpe Ratio and annualized return. This indicates that the strategy can achieve higher returns when it is highly sensitive to the market conditions, which aligns with the findings of this paper.

Table 2. Trend Bollinger Bands - k Value

K-Value	0	0.1	0.2	0.3	0.4	0.5	0.6	0.7
Annualized Return	123.7%	123.9%	121.9%	120.5%	118.4%	118.5%	118.4%	108.1%
Sharpe Ratio	3.23	3.26	3.18	3.12	3.06	3.09	3.07	2.78
Maximum Drawdown	13.8%	13.7%	13.8%	13.9%	13%	11.8%	11.9%	12.6%

Table 3. ADX trend threshold

ADX Trend Threshold	5	6	7	8	9	10	11	12
Annualized Return	110.9%	122.8%	122.4%	123.9%	123.3%	123.3%	123.3%	113.6%
Sharpe Ratio	2.97	3.23	3.22	3.26	3.23	3.23	3.23	3.02
Maximum Drawdown	14.5%	13.7%	13.7%	13.7%	13.7%	13.7%	13.7%	14.5

By varying the ADX trend threshold, we can observe the relationship between the strategy's annualized return, Sharpe ratio, and maximum drawdown with respect to changes in the ADX parameter. Based on the provided table, it can be observed that the strategy is relatively insensitive to variations in the ADX trend threshold. The annualized return fluctuates between 123.3% and 123.9%, the Sharpe ratio fluctuates between 3.22 and 3.26, and the maximum drawdown fluctuates between 13.7% and 14.5%. This suggests that within the given range, the strategy's performance remains relatively stable with respect to changes in the ADX trend threshold. Therefore, it does not significantly impact the strategy's overall performance (seen from Table 3).

8. Conclusion

In this study, the classic Bollinger Band strategy is used as the basis for a high-frequency quantitative trading strategy based on a five-minute trading frequency, choosing CSI 300 stock index futures as the underlying asset. This paper innovatively uses Bollinger bands in high-frequency trading and makes targeted improvements to them. This study changed the Bollinger Band midline accounting from SMA to EMA to obtain a faster reaction speed to the price. In addition, we added the ATR stop-loss and take-profit system, further split the Bollinger bands and stop-loss bands with different look-back window periods, and based on this, added the ADX accounting trend enhancement strategy, which uses ADX and various other factors (MACD, reverse CCI, etc.) to determine the trend, and when the trend exists, changed the logic of opening positions (lowering the k-value of the upper and lower Bollinger bands) and increased the trend opening position Weighting .

The parameter optimization and sensitivity analysis for each type of parameter, the final parameter optimization results are: Bollinger bands and the type of closing line (EMA), the two lookback window (30 and 34, respectively), non-trend Bollinger bands opening threshold (k value of 1.3), the trend of Bollinger bands to open a position threshold (k value of 0.1), ATR stop-loss multiplier (5), ATR lookback window (8), ADX thresholds (27), Long/Short Aligned Triple SMA Category (SMA) i.e. Lookback Window (1, 3, 5), Lookback Window for all factors CCI, ADX, etc. (10), Trend Score Threshold (4).

After making targeted optimization of the classic Bollinger Band strategy returns are significantly improved and the results are as follows. In the position opening section, because of the high unit price and high volatility of the CSI 300 stock index futures, it is difficult to use the position control method of the Turtle strategy, and only a fixed lot size is used to open a position. Also because of the characteristics of the CSI 300 stock index futures, it seems that the annualized return of more than

120% is mainly derived from the trend in early March. And basically all parameters were parameter optimized, plus the special point of CSI 300 index futures, so there is a certain parameter overfitting phenomenon - this parameter applied to 2021 to obtain the backtest performance is much lower than the above results (annualized return of 38.1%, Sharpe ratio of 0.79, the maximum retracement of 25.5%), this parameter is applied to different benchmarks to obtain the results of the backtest (annualized return of 38.1%, the Sharpe ratio of 0.79, the maximum retracement of 25.5%).), and the backtested data for the same year for a different underlying rebar is poorer (-1.5% annualized return, Sharpe ratio of -2.15, maximum retracement of 3.0%). However, the main idea of this paper is to present the strategy approach, and the improvement of the Bollinger band trading logic in the paper has brought positive impact on the strategy performance level; although it has caused the parameter overfitting problem, the parameter optimization of all the parameters in this paper is also aimed at the sensitivity analysis.

Author Contribution

All the authors contributed equally and their names were listed in alphabetical order.

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