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Article

A Study on the Suitability of Grid Trading Strategies for Quantitative Investment Services Targeting High-Net-Worth Clients at Banks in China—A Framework Analysis Based on Multi-Market Backtesting

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Abstract: In the context of the constantly changing global economic landscape and the long-term volatility of the financial market, how to find an investment method that can effectively cope with stock market fluctuations and avoid risks is a topic worthy of study. Therefore, this article selects the quantitative investment data of Bank of China in the A-share market as a case, and selects suitable ETFs for constructing grid trading investment targets from a large number of A-share ETFs. The grid trading method constructed in this article is subjected to backtesting analysis, and its defects are improved. Further, the traditional grid trading and the improved grid trading strategies are backtested and compared and analyzed. The research results show that both grid trading strategies have excellent profitability when investing in the A-share market. Compared with the traditional grid trading strategy, although the improved grid trading strategy lacks a little stability, its income capacity has been significantly improved.

Keywords: Grid trading; Securities investment; ETF; Backtesting; Investment

1. Introduction

At present, the number of high-net-worth individuals in China has exceeded 2 million. Based on the current situation analysis, high-net-worth groups will become the main force of China's investment groups. According to the data released by the People's Bank of China in 2025 regarding the financial account funds stock, by the end of 2024, the total personal investable assets in China reached the second place in the world, with a total amount exceeding 300 trillion yuan [1]. Among them, the total investable assets of high-net-worth families accounted for about 40% of all investable assets. Although the overall wealth growth rate of high-net-worth individuals has declined in the macroeconomic environment, the relevant data predict that it will still maintain a growth rate of around 15% from 2019 to 2025, accompanied by huge development opportunities for banking and other financial services [2].

The idea of grid trading strategy originated from the stock market investment experience of Shannon, the father of information theory, and some investors believe that it was invented by mathematician James Simons [3]. The grid trading strategy is to set a trading range under market fluctuations, for financial products with higher volatility, when the price drops, buy, and when the price rises, sell, dividing the funds into several parts, setting the buying and selling prices for each part of the funds before the transaction, and the buying price of each part of the funds is the selling price of the previous part of the funds, connected end to end, like weaving a large net. No matter how the price fluctuates, the profits can be collected in the net. As long as it is strictly executed, each part of the funds can buy low and sell high to obtain profits [4-5]. Regarding the research on grid trading strategy, Rundo et al. believe that the grid trading strategy is a method to obtain profits by reasonably setting the time intervals of buy and sell orders, taking advantage of the market trend of the underlying financial instrument. Its advantage lies in its financial sustainability algorithm, providing a stable way to control losses in financial transactions [6]. Cheevirot et al. introduced the drawdown ratio (DDR = maximum equity drawdown / maximum balance drawdown) as a scalar indicator to measure risk, and constructed an enhanced grid trading strategy [7]. Yeh et al. proposed a new flexible grid trading model, which combines a simplified group optimization algorithm to optimize the input parameters in different market situations and uses fully connected neural networks (FNN) and long short-term memory (LSTM) models to train quantitative trading models [8].

Regarding the research on quantitative investment services for high-net-worth individuals of banks, Tan focuses on the risk management and investment strategy analysis of high-net-worth individual asset allocation, discusses the investment risks faced by this group, and proposes specific strategies for asset allocation, including investment diversification, implementation of financial innovation measures, and dynamic adjustment of the investment portfolio [9]. Assaf et al. identified the constraints affecting bank wealth management service marketing, including internal company factors and external environmental factors; banks can adopt marketing strategies such as multi-channel distribution and expanding strategic partnerships to increase the number of high-net-worth clients [10]. De Smet et al. focused on the composition of the actual customer group's service portfolio; the research found that in the context of financial services, the existence of specific customer types is a necessary and sufficient condition for achieving core service innovation [11]. Roberts, through the theoretical perspective of behavioral finance, studied the choice support bias, decision-making methods, and risk tolerance of high-net-worth individuals, and discovered that people tend to attribute positive evaluations to their own choices and decisions, while often attributing negative characteristics to the unselected options or decisions [12]. Yadav believes that for high-net-worth individuals, they are often the influencers in investment decisions, and high-net-worth investors are further adopting value-based screening mechanisms, leveraging AI-driven tools to reinforce this concept [13]. Kaarlep and Alavi believe that the number of high-net-worth individuals is constantly increasing, and the wealth of high-net-worth individuals is also rapidly growing. Private foundations are an effective way to achieve this goal [14].

Through the above review, it is found that grid trading strategies are usually retail or high-frequency quantitative strategies, rarely associated with high-net-worth customers of banks, and as a state-owned commercial bank, the investment services of the Bank of China are strictly regulated, favoring traditional trusts, fixed income and structured investment products rather than programmatic grid trading. Therefore, the current academic community has not established a study on the applicability of grid trading strategies for quantitative investment services of high-net-worth customers of banks, and lacks a framework analysis of multi-market backtesting.

This paper first elaborates on the construction method of grid trading, based on the characteristics of grid trading and designing trading programs. Selecting fund data from June 17, 2020 to June 22, 2024 in the A-share market, through the introduction of valuation analysis indicators and volatility indicators, conducting a comparative analysis of A-share ETFs. Selecting suitable investment targets for constructing grid trading among a large number of ETFs in the A-share market. On this basis, in view of the shortcomings of traditional grid trading methods such as low capital utilization rate, the grid is improved and an optimized grid trading strategy for the "A-share market" is established. Using historical trading data to conduct backtesting and comparative analysis of the traditional grid trading strategy and the improved grid trading strategy, verifying the effectiveness and applicability of grid trading.

2. Research Design

The grid trading strategy makes profits by using the grid to eliminate the grid. It generates compound interest through multiple short-term profits over a long period. It uses time to increase the returns for ordinary investors. This is how the grid trading strategy works. This method discards the emotional judgment of individual investors regarding the market and conducts trading solely based on data. The trading process is quantifiable and highly operable.

2.1. Construction of Grid Trading Method

When the price increase triggers the preset selling point, the buying point immediately changes to below that price, while when the price decreases triggering the preset buying point, the selling point immediately changes to above that price. When the market price fluctuates within the grid range, it is possible to achieve selling at a high price and buying at a low price, thereby earning profits. The steps for constructing the grid are as follows:

Step 1: Determine the initial positioning price. Generally, the closing price of the previous trading day is used as the starting price, and the initial holding ratio (X) (i.e., the percentage of the initial purchase amount in the total funds) also needs to be determined.

Step 2: Determine the range of the grid trading (R), expressed as a percentage. Determine the top of the grid trading model, the top price (T) = intermediate price / ($1-R$), and the bottom of the grid trading model, the bottom price (D) = intermediate price * ($1-R$). Traders usually determine this parameter value by estimating the changes in the future price range. This study will optimize this parameter through simulation training.

Step 3: Determine the grid space (M), expressed as a percentage, to determine the interval between each layer's sell order and each layer's buy order. This value should be as small as possible to increase grid density and improve the probability of profitable trading. This study will optimize this parameter through simulation training.

Step 4: Calculate the number of grid layers (N), which is the estimated number of sell and buy orders. The more layers, the higher the grid density. In this study, the calculation method for the number of grid layers (N) is to calculate the number of buy orders (N) that can be placed between the first buy order ($b1$) and the bottom price (D); and calculate the number of buy orders that can be placed between the first sell order ($s1$) and the highest price (T). This study will optimize this parameter through simulation training.

Step 5: The order quantity (Q) is the preset trading volume when placing orders in each grid. The order quantity on each grid layer can be set to be the same or different. This study adopts the average allocation method to set the order quantity (Q) based on the number of grid layers (N), and determines the order quantity according to the proportional amount, ensuring that the quantity of each buy and sell order is consistent.

2.2. Transaction Procedure

When conducting grid trading, the Bank of China can follow the following procedures for quantitative investment targeting high-net-worth clients:

Step 1: Establish the base position: In actual operation, the Bank of China usually has a large amount of funds and cannot hold all positions at once. The Bank of China should gradually build the position when the market price is lower than the historical average level, in order to gradually spread the costs and reduce the risk of holding positions.

Step 2: Initial setting: The sell order is "S (s1) = starting price / (1 - M)"; the default buy order is "B (b1) = starting price * (1 - M)".

Step 3: If the price rises to s1, the transaction ends, and the price of the next sell order is set as "S2 = S1 / (1 - M)"; at the same time, the price of b1 is increased as "B1 = S1 * (1 - M)".

Step 4: If the price continues to rise to the preset selling price in the second step, repeat step 3.

Step 5: If the price drops to b1, the price of the next buy order is reduced to "b2 = b1 * (1 - M)", and the price of S1 is reduced to "S1 = S1 * (1 - M)".

Step 6: If the price continues to drop to the preset price in step five, repeat step five; to explain the trading process more intuitively, the following part assumes that the data is replaced by the above trading steps and simulates the market fluctuations and calculates the results.

Assuming the parameters of the grid model are: grid space (M) is 2%, the initial price is 100 yuan, and each order transaction volume is 1. (1) The initial setting of the first sell order is 100 / (1 - 2%) = 102.04, and the price of the first buy order is set at 100 * (1 - 2%) = 98; (2) When the price rises to 102.04, sell the first grid, and increase the next sell order as 102.04 / (1 - 2%) = 104.12, and the next buy order as 98 / (1 - 2%) = 100. (3) When the price rises to 104.12, sell the second grid, increase the next sell order as 104.12 / (1 - 2%) = 106.24, and generate the next buy order as 100 / (1 - 2%) = 102.04. (4) When the price drops to 102.04, buy the first grid, and reduce the next sell order to 106.24 * (1 - 2%) = 104.12, and reduce the next buy order to 102.04 * (1 - 2%) = 100. (5) When the price drops to 100, buy the second grid, and reduce the next sell order to 104.12 * (1 - 2%) = 102.03, and reduce the next buy order to 100 * (1 - 2%) = 98...

2.3. Profitability Analysis

Based on the detailed introduction of the grid trading method provided above, we can observe that as long as the price fluctuates within the range of the highest price (T) and the lowest price (B), and the fluctuation range is greater than $(1-M)$^2, at least one buy or sell transaction will be triggered and profits will be earned.

The grid trading diagram is shown in Figure 1. The price first rises, triggering three sell points (s1, s2, s3). When the sell orders end, the preset buy orders simultaneously rise to (b1^, b2^, b3^). When the price drops and triggers three purchase conditions, this is when the preset conditions are met after the previous sell order was triggered. Therefore, during this process of rising first and then falling, there are a total of three pairs of sell and buy transactions that end in profit. Therefore, the key to analyzing the effectiveness of the grid trading method in this study is: (1) The position change ratio (R), which is the percentage of each time the grid trading is triggered for a transaction out of the total position. It should be set and ensured to be basically consistent with the amplitude of future price fluctuations. Too small or too large values will reduce the efficiency of grid trading. (2) The setting of the grid space (M). (3) The calculation of the initial position building ratio (X).

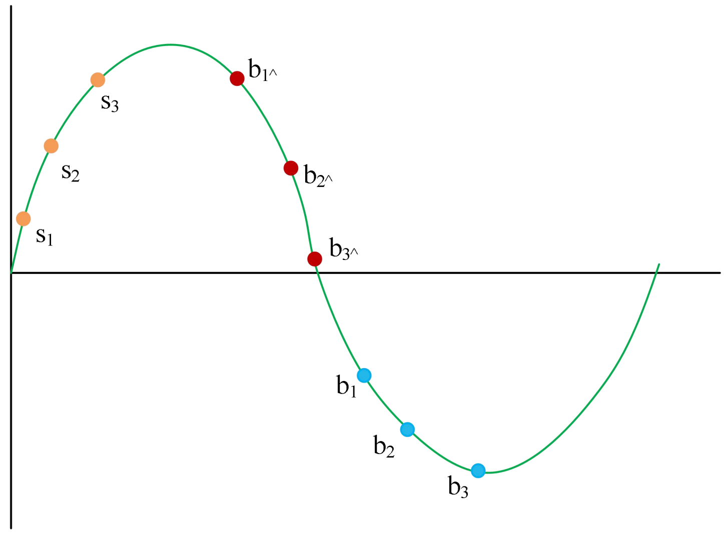

Figure 1. Grid Process Derivation Simplified Diagram

2.4. Evaluation Indicators for Effectiveness in Simulated Trading

(1) Rate of return indicator

(a) Total rate of return

$$R = \frac{V_Y - V_X}{V_X} \tag{1}$$

V_Y represents the total value of the capital holdings at the end of the period, while V_X represents the initial total value.

(b) Annualized compound return rate

$$R_n = \left(\frac{V_Y}{V_X}\right)^{\frac{1}{n}} - 1 \tag{2}$$

The time spans of different strategies vary. Simply looking at the total return rate does not reveal the actual performance. Therefore, it is necessary to evaluate through the annualized return rate. The annualized compound return rate is calculated by averaging the results.

(2) Risk indicators

(a) Sharpe ratio

The Sharpe ratio compares the return rate of the quantitative strategy's investment portfolio with the risk-free rate of the market. The Sharpe ratio represents the return that investors can obtain for each amount of risk they undertake. Its formula is as follows:

$$SharpeRatio = \frac{E(R_p) - R_f}{\varepsilon_p} \tag{3}$$

Here, $E(R_p)$ represents the expected return rate of the investment portfolio, R_f represents the risk-free rate of return, and ε_p represents the standard deviation of the investment portfolio's excess return rate. Here, the annualized yield of a 10-year government bond starting from the beginning of the backtesting period is taken as the risk-free interest rate. When the Sharpe ratio is greater than 1, it indicates that the investment return rate is higher than the volatility risk; when the Sharpe ratio is less than 1, it indicates that the investment return rate is lower than the volatility risk. The higher the Sharpe ratio, the better.

(b) Maximum Drawdown

Maximum drawdown represents the proportion of the decline in investment return rate from the highest point to the lowest point at any point in the investment period, moving backward from the current point. Maximum drawdown is mainly used to indicate the worst situation of the investment portfolio within a certain period. Its formula is as follows:

$$MD = \max \frac{C_x - C_y}{C_x}, x < y \tag{4}$$

Among them, C_x represents the total account assets at the time of x, and C_y represents the total account assets at the time of y.

(c) Information Ratio

The information ratio measures the risk-adjusted excess return of a certain investment portfolio over a specific index. It is based on Markowitz's diversification model and is used to measure the excess return generated per unit of active risk. Its formula is as follows:

$$IR = \frac{a}{w} \tag{5}$$

Among them, the numerator a represents the difference between the actual expected return and the return calculated by the pricing model. The denominator w represents the residual risk, which is the standard deviation of the residual term. The information ratio describes the risk-adjusted return from an active management perspective. The larger the information ratio, the higher the excess return obtained from tracking errors.

3. Analysis of the Applicability Indicators for Grid Trading

3.1. Volatility Index Analysis

This article selects the fund data of China Bank personnel providing quantitative investment services for clients in the A-share market from June 17, 2020 to June 22, 2024. Among them, index ETF funds have diversified their holdings, reducing the risks of individual stock black swans and smoothing out the abnormal fluctuation curves of individual stocks.

Using the annualized volatility as the volatility indicator, the data source is the East Finance Choice platform. 354 ETFs were selected based on the annualized volatility ≥ 20%. To ensure the liquidity of fund transactions and the validity of data, the screening conditions added a fund size of ≥ 500 million yuan and an establishment period of ≥ 3 years. 15 ETFs were selected as shown in Table 1.

It can be seen that the annualized volatility of ETFs of the securities industry is at the top. The securities industry is a strong cyclical industry, with the profit cycle matching the bull and bear cycles of the securities market. The implied leverage volatility is large. During the bull market, the performance of the securities industry improves, and the valuation and performance simultaneously explode, resulting in a Davis double hit. During the bear market, the valuation and performance of securities simultaneously decline, resulting in a Davis double kill. Starting from the left thinking of grid trading, cyclical stocks should be bought during the industry's trough period. In the volatile market, through grid trading to obtain excess returns, and wait for the arrival of the bull market. Therefore, ETFs of the securities industry are suitable for constructing grids.

Table 1. ETF fluctuation ratio

Order number	Stock code	Volatility (annualized)	Fund Size (in billions of yuan)	Year of Establishment1
1	512900.SH	31.3669	33.6166	3.3973
2	512000.SH	31.1945	115.8949	3.9233
3	512880.SH	30.6787	196.608	4.0192
4	159949.SZ	29.2827	94.7519	4.0904
5	512330.SH	29.2272	12.5635	5.0959
6	159939.SZ	28.3216	17.0208	5.5671
7	512220.SH	28.1157	5.2225	6.0438
8	159928.SZ	27.9929	57.9491	6.9452
9	512660.SH	27.182	21.0391	4.0192
10	512010.SH	27.1057	19.4017	6.8603
11	159948.SZ	26.9881	17.696	4.2219
12	159915.SZ	26.7637	171.5843	8.8712
13	159952.SZ	25.9435	14.0999	3.2712
14	512400.SH	25.2958	7.5739	2.9973
15	159938.SZ	31.3669	33.6166	3.3973

3.2. Analysis of Valuation Indicators

Valuation refers to the assessment of the value of the grid stocks. The price-to-book ratio (PB) and the price-to-earnings ratio (PE) are two commonly used valuation indicators in the Chinese A-share market. The price-to-earnings ratio (PE) is current market value / net profit. The common calculation methods for three types of price-to-earnings ratios are the trailing price-to-earnings ratio (TTM), the static price-to-earnings ratio, and the dynamic price-to-earnings ratio. The main problem with the static price-to-earnings ratio is its obvious lag, while the main problem with the dynamic price-to-earnings ratio is that it cannot consider the quarterly cyclical nature of the enterprise. The rolling price-to-earnings ratio (TTM) combines the advantages of the static and dynamic methods. The primary condition for using the price-to-earnings ratio indicator is that the enterprise's profit is stable; enterprises with unstable profits are not suitable for the price-to-earnings ratio. The price-to-book ratio (PB) is market value / net assets attributable to the common shareholders of the parent company.

Securities belong to a strong cyclical industry. The analysis of the securities ETF fund (512900.SH), the securities ETF fund (512000.SH), and the securities ETF fund (512880.SH) tracks the index of securities companies (399975) involves the price-to-book ratio (PB) of these index securities companies. As shown in Table 2 and Figures 2 and 3, the current price-to-book ratio (PB) of index securities companies (399975) is 2.01. Calculated based on the market median, the current percentile is 47.33%. The maximum price-to-book ratio (PB) within the interval (from July 15, 2014 to August 21, 2024) is 5.95, the minimum is 1.11, the average is 1.83, the 80th percentile is 2.37, the 50th percentile is 2.01, and the 20th percentile is 1.58.

Table 2. Fluctuation data of the price-to-book ratio for securities companies

Start time	2014-07-15	Terminal time	2024-08-21
Current Price-to-Book Ratio	2.01	Market Median Percentage	47.33%
Maximum Price-to-Book Ratio	5.95 Least value	1.11	Average value 1.83
80% quantile	2.37 50% quantile	2.01	20% quantile 1.58

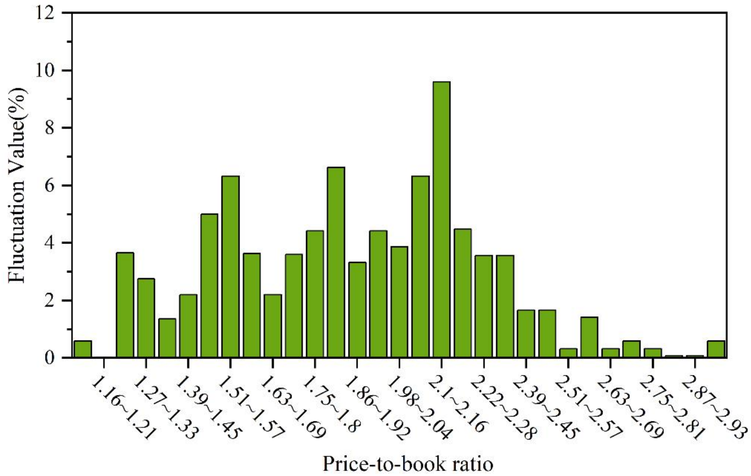

Figure 2. Fluctuation data for the price-to-book ratio of securities companies

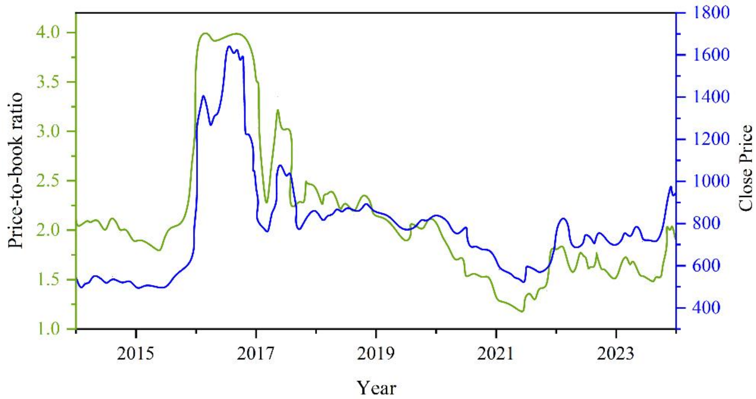

Figure 3. The fluctuation range of the price-to-book ratio for securities companies

3.3. Selection of Grid Marks

By comparing indicators such as volatility (annualized), fund size, establishment years, and return rate (annualized), the securities firm ETF (SH:512000) with the most balanced indicators was selected as the target to construct the grid as shown in Table 3.

Table 3. Data on ETFs related to the securities industry

Order number	Stock code	Volatility (annualized)	Fund Size (in billions of yuan)	Year of Establishment1	Return (Annualized)
1	512900.SH	31.3669%	33.6166	3.3973	10.87%
2	512000.SH	31.1945%	115.8949	3.9233	9.56%
3	512880.SH	30.6787%	196.608	4.0192	9.25%

4. Evaluation and Analysis of Grid Backtesting Results

4.1. Trade Backtesting

This article conducted a backtesting and analysis of the grid trading method using the brokerage ETF. The backtesting period was from June 17, 2020 to June 22, 2024. Figure 4 shows the backtesting results of Strategy 1's grid trading method. The backtesting data was sourced from the Wind database.

From the backtesting results, it can be observed that the most obvious shortcomings of the current grid trading strategy we have established are two: first, the low utilization of funds and limited returns; second, the grid trading strategy is a trading strategy suitable for volatile market conditions, and cannot exert its advantages in trending market conditions. To address these two shortcomings, the following two improvements will be made when constructing the trading grid:

(1) To address the deficiency of low utilization of funds and limited returns, this article plans to change the equal increase or decrease of positions during the rise and fall phases from equal increments

or decrements to pyramid-style increments or decrements. That is, at the build-up point, when the stock price rises, the number of stocks sold triggered by the grid gradually increases as the stock price grows; when the stock price falls, the number of stocks bought triggered by the grid gradually increases as the stock price declines.

(2) To address the deficiency of the traditional grid trading method in easily missing trending upward market conditions and being involved in trending downward market conditions, this article will add a "lock position" function to the grid trading strategy. That is, when the cumulative increase exceeds the set value within a certain period, the selling operation will be suspended to identify possible upward trend conditions, and then restart the selling according to the program settings when the cumulative increase is less than the set value; when the cumulative decrease exceeds the set value within a certain period, the buying operation will be suspended to identify possible downward trend conditions, and then restart the buying according to the program settings.

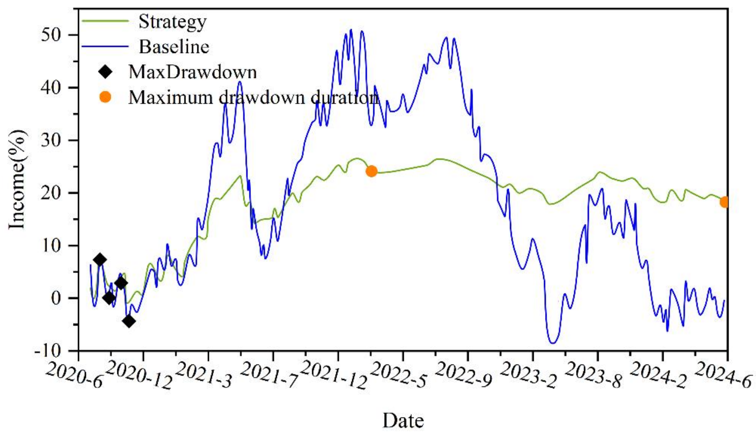

Figure 4. Grid Trading Strategy Backtesting Results

Based on the above analysis, we made the following adjustments to the grid trading strategy to construct Grid Trading Strategy 2:

(1) Change the trading quantity and amount. (2) Add lock-up conditions. (If the cumulative price change within the last three trading days exceeds 6%, stop the buying or selling operation. Wait until the cumulative price change within the next three trading days falls within 6% before resuming. During the lock-up period, any skipped grids will be bought or sold together when the next grid is triggered after resuming trading.)

Use the historical trading data of the "A-share market" to conduct backtesting on the improved strategy 2. Figure 5 shows the backtesting results of Strategy 2, which is the traditional grid trading method. The blue line in the figure is also the backtesting result of the buy-and-hold strategy.

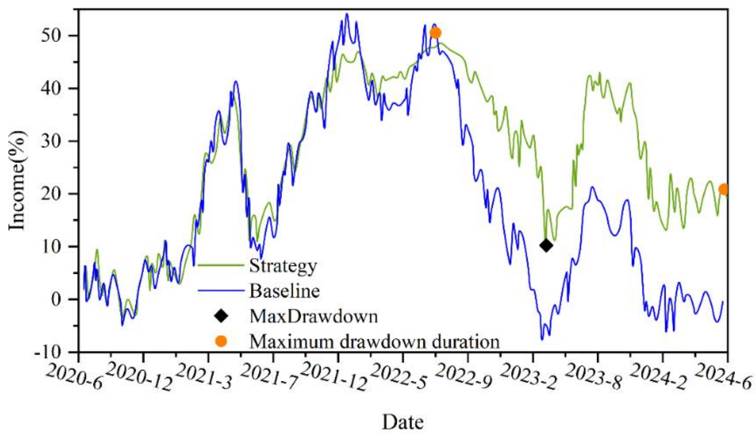

Figure 5. Strategy 2 Backtesting Results

The comparison results of the yield curves for Strategy 1 and Strategy 2 are shown in Figure 6.

Figure 6. Comparison of backtesting results for Strategy 1 and Strategy 2

4.2. Analysis of Backtesting Results

By observing Figure 4, we can find that the return rate of Strategy 2, which is the traditional grid trading strategy, is relatively stable. Although the total return rate and annualized return rate in the testing stage are definitely better than those of the buy-and-hold strategy, in the favorable market conditions, the return rate is very limited. This indicates that the traditional grid trading method indeed has the defects of low capital utilization rate and inability to capture upward trend markets.

By observing Figure 5, we can find that Strategy 1, which is the improved grid trading strategy, has basically the same return rate as the buy-and-hold strategy during favorable market conditions. However, during unfavorable market conditions, the return rate of Strategy 2 is significantly better than that of the buy-and-hold strategy. The final total return rate and annualized return rate in the testing stage are definitely better than those of the buy-and-hold strategy.

Finally, by observing Figure 6, we can find that the improved Strategy 2 has a higher return rate than Strategy 1's grid trading strategy in most cases. The specific parameter statistics of Strategy 1 and Strategy 2 are shown in Table 4.

By analyzing the parameters, we can draw the following conclusions:

(1) In terms of total return rate and annualized return rate, during the backtesting period, the gap between the two strategies is not significant. The initial grid trading strategy was even more outstanding, but this is due to chance and will change with the selected research interval. By observing Figure 6, we can find that in most periods, the improved Strategy 2 has a better return rate.

(2) The Beta of Strategy 1 and Strategy 2 are both greater than 0 and less than 1, and Strategy 2 is much higher than Strategy 1. This indicates that the return rates of both strategies are positively correlated with the index, but Strategy 2 has a better return rate and is also more volatile.

Table 4. Strategy 1 and Strategy 2 Backtesting Results | Parameter Statistics

Backtesting Result Parameters	Strategy 1	Strategy 2
Backtesting Return	19.185%	18.002%
Backtesting Annualized Return	7.62%	6.95%
Base Return	-1.07%	-1.09%
Base Annualized Return	-0.49%	-0.47%
Alpha	0.048	0.059
Beta	0.296	0.775
Sharpe	0.504	0.302
Sortino	0.734	0.436
Information ratio	0.168	0.668
Volitillity	0.12	0.241
MaxDrawdown	9.2%	25.9%
Tracking Error	0.207	0.081
Downside Risk	0.072	0.162

5. Conclusion

This paper takes the quantitative investment data of Bank of China in the A-share market as an example to conduct an empirical study on the grid trading method. The grid trading strategy was used to conduct backtesting analysis on the trading data from June 17, 2020 to June 22, 2024. The deficiencies of the strategy were targetedly improved, and the improved strategy was again subjected to backtesting. The conclusions drawn from the research are as follows:

(1) The market-to-book ratio of the tracking securities company index is 2.01, which is at the median level, with an average of 1.83. The maximum market-to-book ratio from July 15, 2014 to August 21, 2024 is 5.95, and the minimum is 1.11. The valuation is within a reasonable range, that is, neither extreme nor overvalued, providing a safety margin and upward space for the grid.

(2) The traditional grid trading strategy has a greater advantage in the stability of returns, but in terms of profitability, the improved grid trading strategy is higher in most of the backtesting periods. The specific strategy selection can be determined according to the risk-return preference of investors.

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