A Study on the Combination Strategy of Quantitative Investment Trend Tracking EMA Triple Averages

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Abstract. In this paper, we use python to code implementation of the classic moving average double mean model in quantitative investment strategies and improve the original model. The improved algorithm generates trading signals on specific breakouts of the EMA triple averages for automatic trading and sets floating stop-loss and take-profit points. The experimental results show that taking CSI 300 as an example, the moving average model can achieve 150% excess return in the decade from 2010 to 2020, and the improved triple-mean model can achieve 555% excess return, which has great investment potential in the experimental sense.

Keywords: Formatting · Style · Styling · Insert (Key Words) Python · Moving Average · EMA Triple Moving Average

1 Introduction

Technical analysis focuses on predicting future price movements by examining the past prices of an asset. With the development of computer programming, passive quantitative investment based on technical analysis is gradually emerging. Technical analysis can be traced back to the 19th century. Before financial information related to company fundamentals was fully disclosed and publicly known, technical analysis played a pivotal role in market analysis. Technical analysis indicator methods can be divided into two main categories: trend following and oscillator capture. All markets have only two states, either an oscillating market or a unilateral trending market, and the corresponding technical analysis methods mainly revolve around these two categories. Although technical analysis has been widely used in trading in the investment world, there is still a large debate in the academic community about the validity of technical analysis. Scholars in different countries have applied different methods to their respective securities markets to test the profitability of technical analysis and have reached different conclusions, which provides more room for research on the effectiveness of technical analysis. In this paper, we consider the shortcomings of the existing technical analysis, improve the classic moving average double average model and study the corresponding quantitative investment strategy based on it [1, 4].

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2 The Basic Mathematical Logic of the Moving Average Model

Rather than using past values of the predictor variables in a regression, moving average models use past prediction errors in a regression-like model. The model is defined as follows [2, 3, 5]:

If there is a univariate time-series data $\{y_t; t = 1, 2, \cdots, t\}$, so we can get

$$\begin{aligned} y_t &= \omega_t + \beta_1\omega_{t-1} + \cdots + \beta_p\omega_{t-p} \\ &= \omega_t + \sum_{t=1}^{p} \beta_i\omega_{t-i} \end{aligned} \tag{1}$$

The moving average model treats returns as a linear combination of historical white noise. The sliding average model models "random noise" in addition to the drift rate, which is interpreted as new interest rates or shocks that affect returns at different moments. The "noise" is modeled to predict the "noise" at the current moment t, which is then combined with the drift rate to predict the return at moment t. In addition, the moving average model must satisfy the smoothness that its series mean is 0 and its autocorrelation coefficient for each interval k satisfies.

$$\rho_k = \begin{cases} 1 \quad , & if \quad k = 0 \\ \dfrac{\sum_{i=0}^{q-k} \beta_i\beta_{i+k}}{\sum_{i=0}^{q} \beta_i^2}, & if \quad k = 1, \cdots, q \\ 0 \quad , & if \quad k > q \end{cases} \tag{2}$$

From the mathematical logic of the moving average model, we can infer from a certain point of view that when the average makes a crossing, the selected target series will have a continuing trend. In simple terms, when a short-term SMA breaks through a long-term SMA, we have reason to believe that the target series will remain in an uptrend for a certain period of time.

3 Algorithm Implementation of Moving Average Double Mean Model

We crawl the stock data of HS 300 from 2010 to 2021 through tushare and find out the 10-day and 60-day closing price averages, after which we will use the stock data of HS 300 to represent the overall performance of the whole market. Figure 1 gives a visualization of the HS 300 and the closing 10-day and 60-day averages. Figure 2 gives an image of the trading signal visualization. The sequential returns of HS 300 are

Fig. 1. Visual image of the SMA.

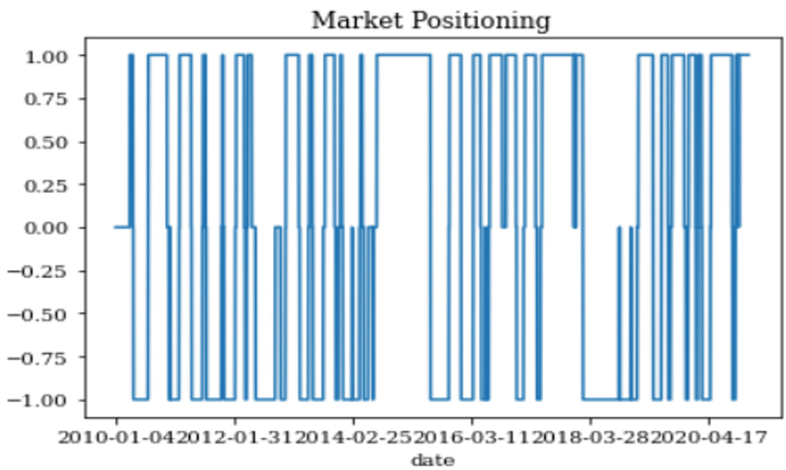

Fig. 2. Image of the trading signal visualization.

then calculated. In order to avoid future functions, the previous day's trading signals are therefore used to multiply with the day's returns, and the returns of the strategy clearly outperform the broad market as seen in Fig. 3.

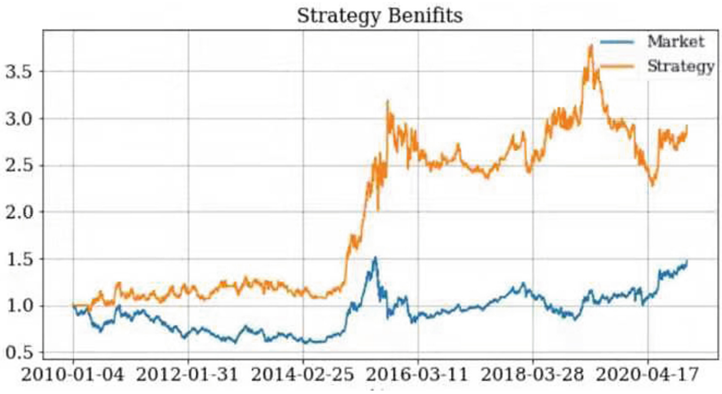

Fig. 3. Strategy Benefits

4 The Overall Assessment of the Strategy and Ideas for Improvement

4.1 Strategy Advantages

From the total return curve, the strategy as a whole outperformed the broad market represented by HS 300, achieving a return of nearly 300% while achieving an excess return of nearly 150%, which shows that to some extent the strategy has a certain degree of feasibility. In addition, the overall logic of the strategy is very simple and can be flexibly adjusted according to different types of stocks or markets. For example, we can use a multi-average model, or we can add factors such as ccl to the overall strategy to set the trigger conditions to make the whole strategy more reliable.

In addition, the strategy can accurately grasp the market, in the whole market is in the overall rise, the average model can well seize the opportunity to generate timely average crossing trading signals, will not miss the bull market dividends.

4.2 Strategy Disadvantages

Due to the underlying logic and realistic operation of the strategy itself model, it is easy to see that this simple model in many cases can not be able to achieve the expected results, categorized can be summarized as the following points.

4.2.1 Can Not Grasp the Consolidation Market

In the consolidation period, the stock price experienced a period of rapid rise or fall, encountered a resistance line or support line, and therefore the stock price fluctuations began to become smaller. In the operation of the strategy, there are many times that the selected averages cross each other several times in the short term, constantly sending out buy and sell signals, resulting in the overall position of the strategy constantly changing. In the case of commission, the loss caused by multiple trades will be huge and will have a great impact on the overall profit of the strategy. In addition, multiple trades during consolidation periods can easily lead to large pullbacks in strategy returns, which is not conducive to maintaining trader confidence and may result in large redemptions of fund products.

4.2.2 Large Price Fluctuations Can Easily Lead to Miss the Big Market

In the case of the double average model, for example, if the overall price of a stock is highly volatile, one of the averages will be above or below the other for a long period of time, and it will not be able to generate trading signals in time to grasp the big trend, so it will lose a large part of the profit or even a loss. This is completely contrary to the underlying idea of the overall strategy, and the overall strategy will lose its edge. Of course, investor confidence will also suffer a big blow, failure to grasp the big market may result in the liquidation of the fund products such as very serious consequences.

4.2.3 Vulnerability to the Characteristics of the Past Data Itself (Whether the Series Mean is 0)

If the data itself is not zero, the underlying mathematical logic of the moving average model will be useless. Although the moving average double mean model is largely based on past stock experience, when the stock data does not satisfy the underlying mathematical structure, the credibility of the resulting decision will be reduced.

5 EMA Three Averages Combination Strategy (Moving Average Double Average Model Improved Version)

5.1 Long-Term Averages Have Both a Booster and a Suppressing Effect on Prices

When the price is below the long-term average, the price is suppressed, the price has a trend of breakthrough, reversing the trend.

When the price is below the long-term average for a long time, the long-term average has a supporting role for the price, there is a tendency to fall below the long-term average (bear market).

5.2 Short-Term, Medium-Term and Long-Term Averages Break Through Each Other Factor

When the medium-term SMA is on the long-term SMA, there is a tendency to turn to a bull market.

When the short-term average breaks through the medium-term average, you can buy (there is an upward trend in the short term, this is the basic logic of the double average model).

When the short-term average falls below the medium-term average, you can sell a small amount (turn bear trend).

Fig. 4. Accumulated earning

5.3 Selection of Basic Data

Take HS300 as the benchmark for comparison.

Stamp duty rate: 0.1%.

Commission when buying: 0.03%.

Commission when selling: 0.13% (0.1% + 0.03%).

Minimum commission per transaction: $5.

Backtest date: January 1, 2010–January 1, 2021 (11 years, through bulls and bears).

Figure 4 gives an overview of the cumulative returns of the EMA triple average strategy (the blue line is the cumulative return of the strategy and the red line is the cumulative return of HS300). Figure 4 shows that the strategy's return has been significantly ahead of the benchmark curve (HS300) during the 11-year period from 2010 to 2021, and the strategy's cumulative return exploded after 2013, reaching 855.12% by December 31, 2020, while the cumulative return of HS300 was only 45.74% during the same period. Compared to the majority of funds in the current fund market over ten years, the strategy's returns are far ahead and stable and reliable.

Figure 5 shows a visualization of the rolling beta (the orange and purple lines represent the benchmark retracement time in June and December, respectively). From the graph, it is easy to see that the overall beta value shows a trend of large fluctuations, indicating that the strategy is becoming more and more correlated or sensitive to the price movement of the general market. However, it is also easy to see that the overall beta of the strategy is still at a low level, not exceeding 1 for 11 years, and even close to 0 at some moments. This indicates that the strategy has a great flexibility in relation to the general market trend, and to some extent the strategy has the nature of value investment and the potential to cross the bull and bear.

Figure 6 shows a rolling visualization of the sharpe indicator (calculated over a 6-month period). The overall curve of the sharpe ratio fluctuates around 0 and even remains negative for a long period of time, which is somehow contrary to the high returns of the strategy. But when we return to the profitability characteristics of the triple mean strategy (catching the general trend), it is easy to understand. As shown in the chart during 2015, the sharpe ratio exploded, reaching a peak around 17 in the middle of 2015, which

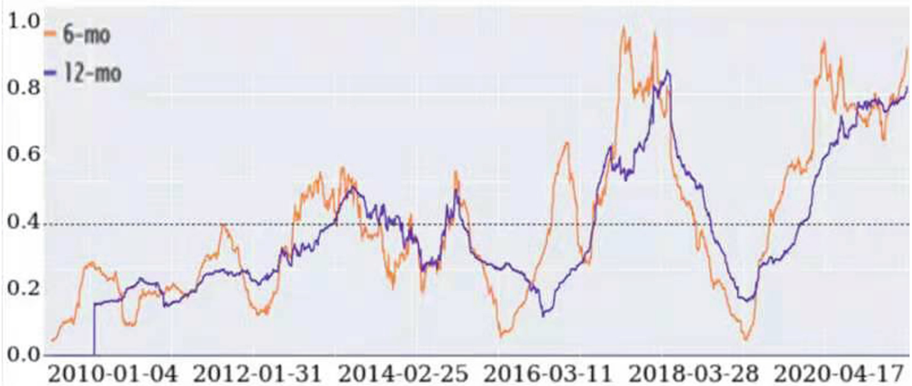

Fig. 5. Rolling Beta Indicator

Fig. 6. Rolling sharpe Indicator

shows that during this period the strategy caught a profitable megatrend. The subsequent decline may be due to factors such as encountering periods of consolidation or high price volatility. Although to some extent this is due to problems brought about by the strategy's own logic, it still cannot hide the fact that the overall sharpe ratio is at a low level and the strategy still needs to make improvements in terms of investment risk-return ratio.

According to the logic of the Brinson model, the excess returns can be decomposed into active allocation contribution (AR), underlying selection contribution (SR), and interaction effect contribution (IR).

The attribution of the tested model shows that the IR return we achieved is much larger than the active allocation AR (timing) return, because this is a model that is always full and not timing, so its AR value is very stable throughout the test. This model factor does not have an enhanced allocation to stocks in sectors with higher gains, so the SR return performs negatively. This reminds us whether we need to allocate to leading stocks in the next iteration to strengthen stock selection within the sector rather than market-wide stock selection, and provides guiding suggestions for the next selection of the strategy's stock pool. In addition, it also reflects the lack of accuracy in this strategy's stock selection and failure to capture companies with large industry gains.

6 Conclusion

The overall strategy was improved from the simplest double-average model to a triple-average model, showing profit potential in indicators such as cumulative returns. However, the risk analysis and position analysis in the later stage still reveal big problems, such as the book-to-market ratio is too large and the Sharpe ratio is small. To further improve the profitability and stability of the strategy, we can try to start from the small market capitalization aspect in the future stock pool selection, and also try to add appropriate signal filters to the strategy.

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