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Finding New Alphas for Multi-Factor Model

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Abstract: Our research aims at finding new alphas in multi-fatcor models in Finance. Based on the stastiscal arbitrage, our research makes use of the volume and price data as well as the fundamental data. The definite volume and price data contains trading volume, illiquidity, price and ATR. During the research, we combines five alphas by weighted adding and we make sure the position neutral. According to the result, these alphas may have been used by many investors and the final return is neagtive. Thus, it shows that we can find other alphas from many other aspects instead of trading volume and price and so on.

Keywords: multi-factor model, price and volume data, fundamental data

1. Introduction

In recent years with the rapid development of China's economy the Chinese stock market has gradually become the focus of global investors. However compared with mature markets China's stock market is still highly volatile and complex influenced by multiple factors such as policy changes market sentiment and the economic cycle. In this context quantitative investment strategies have gradually attracted wide attention and investors hope to reduce investment risks and obtain stable excess returns through systematic models and algorithms.

The core of the quantitative investment strategy is to use market data and statistical models to predict stock prices and optimize investment portfolios. Despite a lot of research on technical and fundamental analysis, the uniqueness and complexity of the Chinese market requires investors to constantly explore new strategies and approaches. This study aims to explore the effectiveness of these strategies and their potential risks in the Chinese market environment by the design and validation of a series of quantitative strategies based on technical indicators and market.

In the research field of quantitative investment, many scholars and practitioners have proposed and verified various strategies. For example, Amihud studied the impact of illiquidity on stock returns and proposed the theory that expected illiquidity is positively correlated with stock prices, while unexpected illiquidity will lead to price declines [1]. Moreover, according to one study that wanted

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to figure out the international evidence about illiquidity, many countries exist illiquidity return premiums including China [2]. Brennan et al and Chordia et al both analyzed illiquidity premium based on Amihud's paper in 2002 which talked about expected and unexpected illiquidity [3]. Brennan et al analyzed illiquidity premium and made Amihud's findings more specific in timing [4] and Chordia et al used different illiquidity measure to test illiquidity premium [5]. Amihud et al then added another component which may be ignored initially that called the average inverse daily dollar volume to analyze. They found that after controlling this component, the information of illiquidity is positive. Novy-Marx studied quality factors and found that companies with high profitability, low debt levels and stable cash flow showed stronger stability and growth potential in market fluctuations [6]. However, most of these studies are based on data from mature markets such as the US, and there are still few studies on the Chinese market. In addition, the Chinese market, due to its policy-driven and high participation of retail investors, may show a different behavior pattern from other markets, which brings new challenges and opportunities for the application of quantitative strategies.

Although previous studies provided important theoretical basis and methodological guidance for quantification strategies, this study was innovated based on No. We not only adopt the classical factor model, but also introduce new ones. For example, in this study, a composite factor based on trading volume and price change, and an average true amplitude (ATR) indicator strategy, which is designed to capture short-term volatility and risk in the market. Through the introduction of these innovation factors our strategy is more targeted and forward-looking and can better adapt to the unique environment of the Chinese market.

The main contribution of this study is that, combining with the particularity of the Chinese market, a series of quantitative investment strategies are proposed and verified, including the strategy of moving average trading volume, illiquidity factor strategy, quality factor strategy, opening price-closing price and trading volume weighted average price difference strategy, and average true amplitude index strategy. These strategies are not only based on the existing economic theories and statistical models, but also verify their applicability and effectiveness in the Chinese market environment through the empirical analysis of the stock data of the CSI 300 Index.

2. Construction and comprehensive performance analysis of Alpha

In the long term, a trend usually exists, which is correlated with the trading volume. The higher the trading volume is, the larger the need for the stock is [7].From a demand-supply model, the price will be higher. But this is a long-term signal and we may process the trading volume to filter the short-term noise. Based on this economic intuition, for strategy Trading Volume MA, we buy and sell stocks according to the signal given by the two trading volume moving averages because, in the long term, the trend-following theorem is reasonable and the stock price change highly depends on the trading volume [8].

We give this formula to calculate the alpha factor:

$$\text{Alpha} = \text{MovingAverage50} - \text{MovingAverage200}$$

MovingAverage50 Indicates the average closing price over the previous 50 days

MovingAverage200 Indicates the average closing price over the previous 200 days

Illiquidity means the stock is not traded frequently thus it's difficult to trade on this stock at a required price. So, investors will require a higher return premium on these stocks if they have an expected illiquidity and stock price will go up today. If there is unexpected illiquidity, it means that illiquidity deviates its actual level which is an illiquidity shock and this unexpected illiquidity has a negatively impact on stock price because of the increasing transaction cost and liquidity risk. Based on this economic intuition, for Illiquidity alpha, we buy stocks with high expected illiquidity and sell stocks with high unexpected illiquidity.

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We give this formula to calculate the alpha factor:

$$\text{Daily illiquidity: ILLIQ} = \frac{\text{Return}}{\text{Volume}}$$

$$\text{Expected illiquidity} = \beta_0 + \beta_1 \text{iLLIQ}_{d-1} + u$$

Expected illiquidity is an autoregression model using last day's illiquidity to generate a time series model to find expected illiquidity. Unexpected illiquidity is residual of AR1, which represents an illiquidity shock.

The quality factor strategy posits that stocks of high-quality companies exhibit greater stability and growth potential amidst market volatility. High-quality companies typically have strong profitability, low debt levels, and stable cash flows, allowing them to maintain robust financial health during economic downturns. By investing in these high-quality companies, investors can obtain stable and sustainable returns. Based on this economic intuition, for Quality factor strategy, by selecting stocks of companies with strong profitability, low debt levels, and stable earnings, the quality factor strategy posits that high-quality companies can better withstand market uncertainties and provide stable excess returns. In constructing the quality factor for this study, I was inspired by the approach of Jiao and Cooper, who employed the partial least squares technique to integrate various quality variables effectively [9]. Their methodology provided a robust framework that not only enhances the predictive power of the quality factor but also offers new insights into optimizing portfolios under uncertain market conditions. This approach served as a key foundation for the development of the quality factor in this research.

We give this formula to calculate the alpha factor:

$$\text{Linear\_model} = \text{sm.OLS}(y, \text{sm.add\_constant}(x_{scaled})).\text{fit}()$$

$$\alpha = \text{linear\_model.params}[1:] (\text{Extract regression coefficients})$$

$$\text{Raw Alpha} = X_{scaled} \times \alpha$$

$$\text{Portfolio Construction}: \text{Alpha2} = \text{rank}(\text{Alpha1})$$

Regression Coefficients are obtain from OLS to predict return.

Use the relationship between price and volume to judge the short-term trend of the market, and make trading decisions accordingly [10]. Based on this economic intuition, for strategy Open - vwap-close alpha, we buy and sell stocks based on the difference between the opening price and the closing price and the volume weighted average price, because the price change of a stock is closely related to the volume [11].

We give this formula to calculate the alpha factor:

$$\text{Alpha1} = (\text{Open} - \text{vwap}) \times (-1) \times (\text{Close} - \text{vwap})$$

The open and close values refer to the day's opening and closing prices, and vwap represents the Average transaction amount per share.

$$\text{vwap} = \frac{\text{Total transaction amount}}{\text{Total number of shares}}$$

Fluctuations in the market frequently result in stocks being priced inaccurately, which presents opportunities for profitable trades. By identifying stocks that experience significant price changes within a single trading day, we can take advantage of these differences in prices [12].Increased volatility can be caused by a variety of factors, including news events, market sentiment, or sudden shifts in supply and demand dynamics[13].Based on this economic intuition, for strategy ATR

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indicator,as stocks with higher ATR values indicate greater price volatility, we calculate ATR to get potential trading opportunities.

We give this formula to calculate the alpha factor:

$$\text{ATR} = \frac{[(\text{Prior ATR} \times (\text{n} - 1) + \text{Current TR}]}{\text{n}}$$

$$\text{True Range} = \max[(\text{high} - \text{low}), \text{abs}(\text{high} - \text{previous close}), \text{abs}(\text{low} - \text{previous close})]$$

n is the period over which ATR is calculated.

Our data source is through the csmar database the data sample is China's CSI 300 the data range is from 2014-01-01 to 2023-12-31(Train: 2014-01-01 to 2020-12-31 Test: 2021-01-01 to 2023-12-31) the trading frequency is daily frequency(Filling monthly frequency data into daily frequency data involves distributing each month's value across all days of that month or using interpolation methods to generate daily data points.).Our datasets: close price, trading volume, price-to-earnings ratio, price-to-book ratio , return on equity, total market value in RMB , return on assets, net profit to total revenue , EPS growth rate , debt-to-asset ratio, earning per share. We download all the stock data of the relevant data set within the data range from the csmar data set, and select the stock data corresponding to the Shanghai and Shenzhen 300 through the code, and then carry out the corresponding data processing through the calculation of their respective factors.

For strategy Trading Volume MA, the results reveal a negative annualized return of -7.57% coupled with a volatility of 9.83%. The maximum drawdown observed is significant at 43.43% and both the Information Ratio and Sharpe Ratio are negative at -0.7787 and -0.9312 respectively. These outcomes reflect a high level of risk and poor performance when trading costs are accounted for.

The negative return and high volatility align with expectations, as the cumulative return trend shows a consistent decline. In contrast, when excluding trading costs, the strategy previously achieved an annualized return of approximately 4%. This discrepancy indicates that the daily trading activity significantly increased transaction costs, thereby eroding the positive returns.

The necessity of daily trading for coordination with others exacerbates these costs. To enhance performance, exploring strategies with reduced trading frequency, such as averaging alpha on a weekly basis, may prove beneficial. Furthermore, the trading volume's strong correlation with market sentiment introduces variability, where identical volumes can lead to different results depending on market conditions. Addressing these issues will be crucial for refining the strategy and improving future performance.

For strategy Illiquidity, the results indicate that the strategy has consistently underperformed throughout the evaluation period. The annualized return of -1.65% reflects a negative return trend, suggesting that the strategy has not generated profits over the observed timeframe. The annualized volatility of 0.06 is relatively low, which indicates that the strategy has exhibited minimal fluctuations in returns. However, the low volatility does not compensate for the negative returns, highlighting an inherent inefficacy in generating positive performance.

The maximum drawdown of 76.5% is particularly concerning, as it signifies that the strategy has experienced a substantial peak-to-trough decline. This extreme drawdown indicates that investors would have faced significant losses at the worst point of the strategy’s performance, which could be detrimental to long-term investment goals.

Overall, the combination of negative returns, significant drawdowns, and poor risk-adjusted performance metrics points to fundamental issues with the strategy. While the overall performance is unsatisfactory, these results provide actionable insights. Specifically, the high drawdown and negative ratios suggest a need for a thorough reassessment of the strategy's parameters, risk management practices, and market assumptions. Refining the strategy to address these issues could improve its effectiveness and potentially turn its performance around in future applications.

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For strategy Quality factor, the result reveals a notably volatile investment strategy. The annualized return stands at 3.22%, reflecting modest gains over the period under review. However, this return is accompanied by a high annualized volatility of 25.01%, underscoring considerable fluctuations in performance. The strategy also experienced a maximum drawdown of 62.76%, highlighting significant potential losses from peak to trough.

Further scrutiny of the risk-adjusted performance metrics reveals a Sharpe ratio of 0.0686, which is relatively low, suggesting that the returns achieved are not commensurate with the level of risk undertaken. Additionally, the Information Ratio, which stands at 0.1286, indicates that the strategy's returns, when evaluated without a benchmark, are only modestly above what would be expected by chance. Overall, the combination of high volatility, substantial drawdowns, and low risk-adjusted returns points to a strategy characterized by significant risk with only modest rewards.

For strategy Open - vwap-close alpha, the annualized return of -1.03% indicates a slight loss over the period under review. This negative return suggests that the portfolio has not managed to generate positive growth, reflecting a potential misalignment with investment objectives or market conditions. In a broader context, this underperformance could imply that the portfolio has struggled to outperform even a risk-free investment, which would typically offer a positive return in a stable or growing market environment.

The Sharpe Ratio, at -0.07, reinforces the assessment of poor risk-adjusted performance. This negative Sharpe Ratio indicates that the portfolio's returns do not compensate for the level of risk taken, failing to surpass the risk-free rate after adjusting for volatility. A negative Sharpe Ratio is indicative of a portfolio that is either poorly constructed or exposed to high levels of risk without adequate return, making it an inefficient investment.

In conclusion, the portfolio analysis reveals significant concerns regarding both performance and risk management. The negative return, high volatility, severe drawdown, and poor risk-adjusted metrics collectively suggest that the portfolio has not performed effectively. A thorough review and potential rebalancing of the portfolio strategy are warranted to address these issues, optimize performance, and better align with risk tolerance and investment objectives.

For strategy ATR indicator, the maximum drawdown, which measures the peak-to-trough decline during the period, is 20.45%. This figure highlights a significant risk of capital loss during adverse market conditions, reflecting the potential for substantial downturns in the investment’s value. The Sharpe ratio, calculated at 0.76, provides insight into the risk-adjusted return of the investment. While positive, this ratio indicates that the return per unit of risk is moderate, suggesting that the investment offers a reasonable reward for the level of volatility undertaken. The Information ratio, at 0.12, measures the return relative to a benchmark, adjusted for tracking error. This low ratio implies that the strategy's returns are only marginally better than those of the benchmark after accounting for its risk[14].

In summary, while the investment strategy demonstrates a solid annualized return, the relatively high volatility and significant drawdown highlight the associated risk. The Sharpe ratio reflects moderate efficiency in risk-adjusted returns, and the Information ratio suggests limited outperformance compared to the benchmark. These results provide a nuanced view of the strategy’s performance, indicating a balance between return and risk, with opportunities for improvement in relative performance.

For the combined result, the performance metrics are notably poor. The annualized return is -13.50%, indicating a negative return over the year. Additionally, the annualized volatility stands at 6.22%, reflecting the extent of fluctuation in returns. The maximum drawdown, a critical indicator of potential losses, is particularly concerning at 39.08%. This suggests a substantial decline from the peak value during the evaluation period.

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The Information Ratio, which measures the risk-adjusted return relative to a benchmark is -2.39. This negative value highlights underperformance compared to a risk-free rate. Similarly, the Sharpe Ratio, which adjusts returns based on volatility, is -2.63, further underscoring the inadequacy of returns given the level of risk taken.

The adverse results are likely attributed to the challenging conditions in the Chinese stock market, especially following the aftermath of the epidemic. The negative return rates and significant maximum drawdown suggest that the investment's performance has been severely impacted by these market conditions.

For strategy Trading Volume MA, we use two strategy to do the refinement.

The first refinement strategy aimed to enhance the original model by incorporating a nuanced understanding of trading volume dynamics within varying market conditions. It was observed that high trading volumes can convey different implications depending on whether stock prices are rising or falling. During price increases, heightened trading indicates upward pressure on buyers, while during declines, it signifies increased selling pressure. To capture these dynamics, the alpha was refined by multiplying the daily return rate, thus adjusting the formula as follows:

$$\text{Alpha} = (\text{MA50} - \text{MA200}) \times \text{Return Rate}$$

Additionally, to mitigate risks associated with market capitalization differences among stocks, a dollar-neutral approach was employed, ensuring that the sum of weights multiplied by market values equated to zero. Despite achieving a positive annualized return of 1.46%, the strategy exhibited significant volatility with an annualized volatility of 18.26%. The maximum drawdown reached 64.61%, indicating substantial risk exposure. Notably, the strategy yielded an information ratio of 0.1732 and a Sharpe ratio of 0.0911, suggesting modest risk-adjusted returns. Analysis revealed a persistent downtrend in the profit and loss (PNL) curve, particularly during periods of prolonged market decline, such as observed in the Chinese stock market downturn. This outcome underscored the effectiveness of the alpha refinement in capturing price fluctuations and the risk-mitigating benefits of dollar-neutralization, despite the ongoing challenges in achieving consistent profitability.

The second refinement strategy introduced a revised alpha formula aimed at addressing shortcomings observed in the initial refinement. Acknowledging issues arising from multiplying long-term and short-term signals, the alpha was reformulated to focus separately on trading volume and price trends:

$$\text{Alpha} = (\text{Trading\_Volume\_MA50} - \text{Trading\_Volume\_MA200}) \times (\text{Close\_Price\_MA50} - \text{Close\_Price\_MA200})$$

Despite maintaining economic rationale, this adjustment failed to yield favorable results, with an annualized return of -16.83% and an annualized volatility of 14.80%. The strategy experienced a maximum drawdown of 73.99%, indicating heightened vulnerability to market downturns. Notably, both the information ratio (-1.2127) and Sharpe ratio (-1.314) portrayed significant underperformance relative to the market benchmarks. Analysis attributed these outcomes to the frequency of daily trading, which potentially diluted the impact of long-term signals embedded within the refined alpha. Future iterations may consider adjusting trading frequencies to better align with the model's signaling mechanisms.

In conclusion while both refinements showcased varying degrees of success in capturing market dynamics and mitigating risks persistent challenges such as high volatility and periodic underperformance underscored the complexities inherent in quantitative trading strategies reliant on moving average indicators and trading volumes.

For strategy Illiquidity, we initially observed significant challenges in its performance within the Chinese market. The preliminary backtest results revealed predominantly negative transaction returns

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and daily returns, coupled with a remarkably low signal win rate. This outcome strongly suggests that the strategy, as originally conceived, exerted a counterproductive influence.

The primary hypothesis that expected illiquidity could elevate prices and unexpected illiquidity could depress stock prices did not align with empirical findings. Consequently, a strategic reversal was implemented. The revised approach stipulates that anticipated illiquidity will lead to lower prices, whereas unforeseen illiquidity will prompt price increases. Specifically, the strategy now dictates buying when expected illiquidity falls below the 75th percentile and selling when unexpected illiquidity exceeds the 75th percentile.

Following the refinement, the pnl turned positive, marking a significant improvement in performance metrics. The annualized return has become robustly positive and higher, with both the information ratio and Sharpe ratio indicating favorable outcomes. This refinement has proven effective, particularly in reversing the impact within the Chinese market context. Now, anticipated illiquidity consistently drives prices down, while unexpected illiquidity consistently drives prices up.

However, it's important to note that despite these improvements, the strategy exhibits considerable volatility and a notably high maximum drawdown. These factors underscore the inherent risks associated with the strategy, necessitating ongoing monitoring and risk management efforts.

For strategy Quality factor, we employed advanced data analysis techniques and optimization methodologies to enhance the robustness and accuracy of our initial linear regression model. Initially, the study utilized a basic linear regression approach for analysis. However, to bolster precision and reliability, we incorporated additional methodologies and conducted comprehensive data preprocessing and model refinement.

Firstly, data preprocessing involved converting the date column to datetime format and setting it as the index. Missing and infinite values were addressed, and feature standardization was performed to achieve zero mean and unit variance. Utilizing an Ordinary Least Squares (OLS) linear regression model, we derived initial Alpha values from the standardized features' regression coefficients. Subsequently, we employed a RandomForestRegressor and optimized its parameters using RandomizedSearchCV to ascertain feature importances. These were then integrated with the linear regression coefficients to compute final Alpha values.

To ensure data integrity and model robustness, we employed box plots to identify outliers in the features. Notably, the feature "Daily Market Value in RMB_DmcCNY" exhibited significant outliers, indicating potential data volatility impacting model stability. Outliers were appropriately managed by restricting values within 3 standard deviations of the mean for each column. Additionally, we evaluated multicollinearity using the Variance Inflation Factor (VIF), revealing all features possessed VIF values below 1.5, indicative of minimal multicollinearity and negligible impact on model stability from inter-feature correlations.

Through extensive backtesting and comparative analysis, we determined that using Earnings Per Share (EPS) as the target variable yielded superior results compared to returns alone. This decision was substantiated by higher returns and marginally reduced maximum drawdowns.

Post-optimization, the strategy demonstrated significant improvement in performance metrics. The annualized return increased to 4.62%, accompanied by a slight elevation in annualized volatility to 25.14%, and a notable reduction in the maximum drawdown to 61.66%. The information ratio also improved to 0.1839, while the Sharpe ratio exhibited a substantial increase to 0.1243. These enhancements indicate that the optimized strategy not only boosts returns but also mitigates risk, thereby enhancing the overall risk-adjusted returns. Despite a marginal increase in volatility, the overall performance stability has improved, underscoring the efficacy of the refined approach.

For the Open - VWAP-Close Alpha strategy, a critical refinement involves normalizing VWAP calculations to mitigate the influence of trading volume on the relationship between opening and closing prices and VWAP. This approach addresses the inherent volatility in VWAP readings,

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particularly in instances of significantly higher or lower trading volumes, which can distort price metrics and positional weightings.

The strategy's modest annualized return is 1.04%, accompanied by a considerable annualized volatility of 13.49%. The maximum drawdown of 41.97% underscores the strategy's exposure to market risk over the period. Despite challenges, such as a negative Sharpe ratio (-0.03) and a low information ratio (0.18), the refinement aims to enhance performance consistency by normalizing VWAP data.

Normalization techniques are crucial in recalibrating VWAP to better reflect stable price-volume relationships, thereby reducing the impact of outliers on trading decisions. By smoothing out discrepancies caused by varying trading volumes, the refined strategy seeks to improve its overall robustness and reliability in capturing alpha.

Furthermore, the strategy's performance analysis underscores the importance of adaptability in quantitative trading strategies, particularly in managing risk and optimizing returns amid dynamic market conditions. Future research may explore additional refinements or alternative methodologies to further enhance the strategy's effectiveness in achieving sustainable performance outcomes.

For strategy ATR indicator, we have refined our approach to minimize biases associated with selecting stocks based on their Average True Range (ATR). Implementing a sector rotation strategy has allowed us to strategically adjust our portfolio's sectoral composition based on relative strength assessments, thereby diversifying risk across different sectors and optimizing exposure to market dynamics.

Furthermore, integrating a dynamic stop-loss mechanism has been instrumental in managing downside risk by setting stop-loss orders at a predetermined percentage below each stock's entry price. This proactive risk management approach aims to protect capital during periods of market volatility and enhance overall portfolio resilience.

Analyzing performance from January 4, 2021, to November 23, 2023, reveals this refinement strategy's characteristics: achieving a modest annualized return with notable volatility and experiencing a maximum drawdown of 20.4%. Despite challenges reflected in a negative Sharpe ratio, the strategy demonstrated a positive information ratio, indicating its ability to outperform in comparison to not having a benchmark.

The sector rotation strategy has effectively mitigated sector-specific risks while enhancing portfolio stability. However, the observed drawdown underscores the ongoing need for refining risk management techniques to improve risk-adjusted returns. Continuous adjustments and enhancements to sector rotation and stop-loss strategies are pivotal for achieving sustained performance and navigating evolving market conditions effectively.

3. Conclusion

From these five factors development and refinement, we have relative results of these factors behaviors. Through the quantitative analysis of the strategies and the results, we can find that each strategy has its own advantages and challenges. For the Trading Volume MA strategy, the first improvement has achieved some success in capturing market dynamics and reducing risk. However, high volatility and occasional underperformance indicated that there are still challenges in achieving consistent profitability. For the Illiquidity strategy, through strategic reversals, performance was successfully improved, especially in the Chinese market environment, which demonstrated the potential of the strategy. But this kind of strategic reversal is too simple and technical, therefore it loss some economic meaning. Moreover, the measurement of illiquidity in this paper ignore some other components that can influence illiquidity. The Quality factor strategy successfully improved the accuracy and robustness of the model through the use of data analysis and optimization methods, and achieved significant improvements. The Open - VWAP-Close Alpha strategy has made important

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improvements in the normalized VWAP calculation, aiming to improve the consistency and reliability of the strategy. In the ATR indicator strategy, through the introduction of industry rotation strategies and dynamic stop-loss mechanisms, downside risks are successfully managed while providing better stability for the portfolio.

While each strategy has achieved certain improvements and successes, there are still some recommendations to consider based on these strategies' features and result analysis when facing dynamic market conditions and risks. For the kind of trend tracing strategy, it still needs to continuously monitor market conditions and flexibly adjust strategies to adapt to rapidly changing market conditions. Some strategies have high volatility and drawdown which means their risk is too high. For the further improvement of these strategy, optimize risk management mechanisms, especially in terms of maximum retracements and volatility, to improve resilience to uncertainty. In this paper, our data may be still not enough to accurately improve so it still need to consider introducing more factors and data sources to enrich the strategy model and improve forecasting accuracy. Nowadays, technical models including math models and machine learning models all can provide more effective signal generation mechanism and more accurate prediction, we can strengthen the monitoring of model robustness and data integrity, and timely deal with the adverse effects of outliers and data fluctuations on the model. For high frequency trading, we still need to continuously improve the trading rules and signal input mechanism to optimize the performance and efficiency of the strategy.

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