Improving the Fama-French Model Based on Technical Indicators: Evidence from the Financial Industry

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Abstract: As a matter of fact, Fama-French models are commonly applied in financial fields, which is an upgrading model for CAPM. Contemporarily, plenty of proposals for adding indicators to improve the performances for the model are demonstrated. With this in mind, this paper deeply and comprehensively discusses the improvement of the Fama-French model based on technical indicators. To be specific, it elaborates on the principles and methods of improvement in detail and systematically expounds its application in the financial industry. By sorting out and analysing relevant research, it reveals the significant advantages and potential problems of the improved model and conducts a forward-looking outlook on future research directions. According to the analysis, the current limitations and prospects are proposed at the same time. Overall, this provides a new perspective for the expansion of financial asset pricing theory and also provides a valuable reference basis for practical operations in the financial industry.

1 INTRODUCTION

With the increasing complexity and uncertainty of financial markets, asset pricing is facing severe challenges. As an important cornerstone of asset pricing, the Fama-French model gradually exposes limitations in the new environment, especially in dealing with short-term fluctuations, emerging industry characteristics, and investor sentiment (Carhart, 1997; Fama & French, 1993; Fama & French, 2015). This study aims to use technical indicators to improve the Fama-French model to enhance the accuracy and practical value of asset pricing.

First, this study will deeply analyse the principle and limitations of the Fama-French model, and clarify its way of explaining stock return differences and the current problems it faces. Then this study will sort out technical indicators suitable for improvement, and analyse the calculation methods, data requirements, application scenarios, and advantages of common technical indicators such as moving averages, relative strength indicators, and Bollinger Bands. Then explore the integration method of technical indicators and the Fama-French model, including incorporating technical indicators as supplementary factors into the original model and dynamically adjusting the factor weights of the original model according to the real-time signals of technical indicators. Finally, through application cases in the financial industry, such as portfolio management, asset allocation decisions, and risk management, show the application process of the improved model, and use quantitative analysis to compare with traditional models to verify its superiority in asset pricing, risk measurement, and investment performance.

This study has important theoretical and practical significance. In theory, it injects new vitality into asset pricing theory, promotes method integration and innovation, fills the gap in research on the combination of technical indicators and traditional models, and perfects the methodological system. In practice, it provides more accurate decision support for investors, helping them choose assets, seize opportunities, and optimize portfolios; it provides powerful tools for financial institutions in risk management, product development, etc., and enhances competitiveness and service levels.

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2 DESCRIPTIONS OF THE IMPROVED FAMA-FRENCH MODEL

As an important theoretical framework in the field of asset pricing, the Fama-French model is constructed based on market factors, size factors, and value factors. The market factor occupies a fundamental position in the model. It mainly reflects the extensive influence of the systemic risk of the entire financial market on stock returns. In practical calculations, usually the part of a representative market index, such as the S&P 500 index exceeding the risk-free interest rate, is used to quantify the market factor (Jegadeesh & Titman, 1993; Barberis et al., 1998). This indicator aims to capture the overall market trend of rise and fall and its general influence on the returns of various stocks.

The size factor focuses on capturing the return differences caused by the size of companies. By carefully constructing small-cap stock portfolios and large-cap stock portfolios and calculating the return difference between the two, the size factor can reveal the significant differences in risk and return characteristics between small companies and large companies (Cochrane, 2001). This difference not only reflects the unique challenges and opportunities faced by small companies in market competition but also reflects the differences in risk preferences and expected returns of investors for companies of different sizes (Hong & Stein, 1999).

The construction of the value factor is based on the book-to-market ratio of companies. By rigorously comparing the stock return differences between companies with high book-to-market ratios and companies with low book-to-market ratios, the value factor can effectively reflect the key influence of the company's intrinsic value attributes on stock returns (Lo & MacKinlay, 1999). This factor helps investors identify companies that are undervalued or overvalued by the market, thereby making more informed investment decisions (Campbell, 2000).

The Fama-French model has obvious limitations. First, it is insufficient in responding to short-term market fluctuations and investor sentiment. It mainly relies on the company's long-term fundamental data and historical returns to construct the factor system (Ferson & Harvey, 1991; Banz, 1981). When facing short-term impacts such as sudden major market news, macro policy adjustments, and investor panic, it lacks a rapid incorporation and response mechanism and is difficult to accurately reflect the instantaneous drastic changes in stock prices in a timely manner (Basu, 1977). Second, its explanatory power is limited in specific market environments and emerging industries. In extreme markets such as a frenzied bull market or a desperate bear market, traditional size and value factors are difficult to capture extreme changes in stock returns and are beyond the scope of interpretation of conventional market assumptions (Piotroski, 2000). In emerging industries, which rely on non-traditional assets to create value and are different from traditional industries, the original model is difficult to fully explain its business model and market valuation. Third, there is subjectivity in factor definition and selection. The definitions and calculation methods of size and value factors are not uniform (Novy-Marx, 2013). Different researchers will adjust according to their goals, data, and preferences, leading to inconsistent applications and differences in results. At the same time, factor selection is restricted by data availability and computational complexity, and valuable factors may be ignored, affecting the interpretation and prediction accuracy of specific market phenomena.

3 SELECTION AND CHARACTERISTICS OF TECHNICAL INDICATORS

The moving average is a commonly used basic tool in financial technical analysis. By calculating the arithmetic average of security prices within a specific time period, it smooths short-term random fluctuations and shows long-term trends. It can reduce short-term price noise and make the trend clearer and more coherent, but it has a lag. There is a delay in responding to real-time changes, which may cause missed short-term opportunities. However, it is very valuable in confirming the main price trend. If the price is above the average, it is an uptrend. Conversely, it is a downtrend, which can point the direction for long-term investment (Asness et al., 2019).

The relative strength index is used to measure the relative strength of security price fluctuations. By comparing the sum of rising and falling closing prices within a specific time period, a relative strength value between 0 and 100 is obtained to judge the overbought and oversold states of the market. It is extremely sensitive to short-term price changes and can quickly capture the subtle changes in buying and selling forces, providing timely signals for short-term traders to predict short-term reversals and price adjustments. By setting thresholds, such as when the

RSI value exceeds 70, it is overbought, and when it is below 30, it is oversold, which can prompt investors when prices may reverse and the timing for taking profits or setting stop losses. Moreover, the RSI value fluctuates between 0 and 100, making it convenient and intuitive to compare the relative strength of the market for different securities or time periods.

Bollinger Bands is a technical analysis tool constructed based on statistical principles. It consists of three track lines. The upper and lower limits of price fluctuations and the middle moving average are determined by calculating the standard deviation of security prices. It can intuitively show the volatility of prices. The upper track is usually a resistance level, and the lower track is usually a support level. Observing the relative position of prices to the upper and lower tracks can judge whether the fluctuation is abnormal (Zhang, 2005). When the price touches the upper and lower tracks, it is often an important signal of a possible reversal. If it touches multiple times and then moves in the opposite direction, the signal is more reliable, bringing potential trading opportunities to investors. Besides, the bandwidth of Bollinger Bands will automatically adjust according to the actual market fluctuation. When the market fluctuates violently, the bandwidth expands, and when it is stable, it contracts, maintaining effectiveness and applicability in different market environments.

4 INTEGRATION STRATEGY OF TECHNICAL INDICATORS AND THE FAMA-FRENCH MODEL

4.1 Supplementary Factor

The calculation results of technical indicators are integrated into the Fama-French model as independent factors. For example, the slope or cross signal of the moving average. When it is upward sloping or in a golden cross, the new factor takes a positive value. When it is downward sloping or in a dead cross, it takes a negative value. This introduces price trend and short-term momentum information and enhances the capture of short-term market dynamics. For the relative strength index (RSI), set a threshold. When it is overbought (such as when the RSI value exceeds 70), it is included in the model as an overbought factor and takes a positive value. When it is oversold (such as when it is lower than 30), it is included in the model as an oversold factor and takes a negative value, reflecting the short-term buying and selling status of the market more sensitively and providing timely signals for decision-making.

4.2 Adjusting Factor Weights

Dynamically adjust the weights of each factor in the Fama-French model according to the real-time signals of technical indicators. For example, when the RSI enters the overbought region, reduce the weights of the market and size factors and increase the weight of the value factor to be vigilant against short-term risks and prefer value assets. Conversely, when the RSI enters the oversold region, increase the weights of the market and size factors and reduce the weight of the value factor to capture rebound opportunities.

5 MATHEMATICAL EXPRESSION AND THEORETICAL BASIS OF THE IMPROVED MODEL

Supposing that the moving average (MA) and relative strength index (RSI) are introduced. The improved Fama-French model can be expressed as:

$$R_i - R_f = \alpha + \beta_1 MKT + \beta_2 SMB + \beta_3 HML + \beta_4 MA + \beta_5 RSI + \epsilon \tag{1}$$

Here， $R_i - R_f$ represents the excess return of an asset i; α is the intercept term, which reflects the fixed part of the return not explained by other factors in the model. The β series are the coefficients of each factor, and their magnitudes represent the degree of contribution of each factor to the excess return. MKT represents the market factor and reflects the impact of overall market fluctuations on asset returns; SMB is the size factor and reflects the role of company size on returns; HML is the value factor and measures the relationship between the company's value characteristics and returns; MA is the moving average factor and reflects price trend information; RSI is the relative strength index factor and reflects the comparison of market buying and selling forces and short-term momentum; ϵ is the error term and represents the random part that the model cannot explain. The theoretical basis lies in that the improved model combines the advantages of fundamental analysis (Fama-French model) and technical analysis (technical indicators). The Fama-French model starts from the basic financial characteristics of a company, such as size and value, to explain the differences in long-term stock returns, reflecting the intrinsic value of assets and long-term investment logic. This fundamental-based analysis provides a stable and reliable basis for asset pricing, especially suitable for the evaluation and prediction of a company's long-term value.

Technical indicators such as moving averages and relative strength indicators focus on capturing dynamic information such as short-term price trends, investor sentiment, and short-term supply and demand changes in the market. They can quickly respond to immediate changes in the market and provide signals about short-term market momentum and reversal possibilities.

By combining these two analysis methods, the improved model takes into account both the long-term value driving factors of assets and the influence of short-term market dynamics and investor behaviour. This enables the model to explain the formation mechanism of asset prices more comprehensively and accurately and improve the accuracy and adaptability of asset pricing. Under different market conditions, whether it is a long-term trend change or a short-term violent fluctuation, the improved model is expected to provide more reliable pricing and investment decision-making basis.

6 APPLICATION OF THE IMPROVED MODEL IN THE FINANCIAL INDUSTRY

6.1 Investment Strategy Formulation

The improved model provides a more accurate and comprehensive evaluation framework for constructing investment portfolios. By analyzing a large amount of asset historical data and calculating expected returns and risk levels, it can distinguish the potential performance of similar stocks. For example, for stocks in the same industry with similar size and book-to-market ratio, the model can give differentiated evaluations based on moving averages and relative strength indicators, helping investors choose stocks with high short-term upside potential and low risk. At the same time, the model helps to discover undervalued or overvalued assets and provides support for contrarian investment (Hou et al., 2015; Ang et al., 2006).

The integration of technical indicators makes the improved model more sensitive and accurate in investment timing judgment. When the moving average forms a golden cross and the relative strength indicator is oversold, it is usually a buying opportunity; when there is a dead cross and the indicator is overbought, it may be a time to sell or reduce positions. Combined with the Bollinger Bands indicator, when the price breaks through the upper track and trading volume expands, it is time to take profits; when it touches the lower track and stabilizes after a decline, it is time to build positions or add positions.

6.2 Risk Management

Traditional risk measurement methods have limitations. The improved model incorporates technical indicators and can timely reflect short-term abnormal market fluctuations and changes in investor sentiment. For example, changes in relative strength indicators and moving averages can provide early warning signals. Comprehensive analysis can more accurately assess potential losses and provide a more comprehensive and dynamic perspective for risk measurement, helping investors respond in advance.

Based on the risk assessment of the improved model, financial institutions and investors can adjust the structure of their investment portfolios. When market risk rises, reduce the allocation of high-risk assets and increase the proportion of low-risk assets, and use financial derivatives for hedging. The improved model can also help set reasonable stop-loss and take-profit levels and send signals in time to limit losses or lock in gains.

6.3 Case Analysis

E Fund Management Co., Ltd. has long relied on classic asset pricing models to construct investment portfolios in the field of stock investment. However, with the development of the market and the intensification of competition, they found that the traditional Fama-French model performed poorly in responding to rapid market changes and the rise of emerging industries. For example, during the period from 2019 to 2020, the new energy vehicle industry rose rapidly. When the fund company evaluated related enterprises, the evaluation results given by the traditional model based on market factors, size factors, and value factors failed to fully reflect the potential growth value of these enterprises. Therefore, E Fund Management Co., Ltd. decided to introduce technical indicators to improve the Fama-French model (Bali et al., 2011).

They selected technical indicators such as moving average (MA), relative strength indicator (RSI), and Bollinger Bands. When evaluating new energy vehicle enterprises, combined with these technical indicators, it was found that although the stock prices of some enterprises fluctuated in the short term, the moving average showed a clear upward trend, and the relative strength indicator showed that it was in a strong area. Based on the signals of these technical indicators, E Fund Management Co., Ltd. increased its investment in these enterprises. After a period of practice, compared with the investment portfolio using the traditional model in the same period, the investment portfolio using the improved model achieved significantly higher investment returns in the field of new energy vehicles, bringing more substantial returns to fund investors. This case shows that the Fama-French model improved based on technical indicators can help fund companies capture market opportunities more sensitively, optimize investment strategies, and improve investment performance (Avramov et al., 2009).

7 LIMITATIONS AND PROSPECTS

The effectiveness of technical indicators depends on market conditions: The effectiveness of different technical indicators varies significantly in different market environments. For example, in a market with obvious trends, trend-following indicators can provide accurate buy and sell signals, but in a volatile or trendless market, they may frequently make mistakes. In addition, technical indicators are easily affected by market manipulation, abnormal trading behaviors, or sudden major news, leading to signal deviations or failures. Increased model complexity: Integrating technical indicators into the Fama-French model increases complexity, which is reflected in the mathematical expressions, the number of parameters, and the increased requirements for data processing and computing power. Complex models are difficult to understand and explain, and are prone to overfitting, losing the ability to predict and generalize to new data, reducing practicability and reliability. Impact of data quality and sample bias: low-quality data and unrepresentative samples can seriously affect the accuracy of model results. Financial market data often has quality problems such as missing values, incorrect records, and asynchronous trading, leading to deviations in technical indicators and model parameters. Sample bias is also common. If the data sample cannot represent market diversity and dynamic changes, the model conclusions may be limited and cannot be widely applied.

In the future, more effective combinations of technical indicators and parameter optimization can be explored. Comprehensively use multiple indicators, combine big data and machine learning algorithms to screen out the optimal combination, and use historical data backtesting to determine the optimal weights and parameters to improve model adaptability and accuracy. For example, fuse common indicators with emerging tools and use intelligent optimization algorithms to determine the best parameter combination to adapt to market changes.

Incorporating investor psychology and behavioral factors into the model to improve the asset pricing mechanism. Behavioral finance shows that investors' irrational behaviors have an important impact on the market. In the future, improved models can quantify these behavioral factors and combine them with technical indicators and Fama-French factors to reflect market laws, explain abnormal phenomena and bubble formation mechanisms, and provide support for investment decisions. For example, introduce relevant indicators, study their synergistic relationship, and construct a pricing model based on behavioral finance.

Real-time monitoring and adaptive adjustment: Developing a dynamic model that responds to market changes in real time is an important trend. As financial market changes accelerate, traditional static models are difficult to adapt. It is necessary to construct a model with self-learning and adaptive adjustment capabilities, monitor data and indicator changes in real time, and adjust parameters and weights. For example, use online learning and reinforcement learning technologies, combined with cloud computing and big data processing technologies, to achieve real-time calculation, rapid decision-making, and provide investment advice and risk warnings.

8 CONCLUSIONS

To sum up, this study focuses on the Fama-French model improved based on technical indicators and conducts a comprehensive and in-depth discussion. It elaborates on its theoretical basis, integration strategy, application fields, potential limitations, and future development directions. The research results clearly show that this model successfully combines the advantages of fundamental analysis and technical analysis. Not only does it build a more comprehensive and in-depth explanatory framework for the asset price formation mechanism at the theoretical level, but also in practical applications, it plays a significant role in key fields such as investment strategy formulation and risk management, providing more accurate and flexible decision-making tools for investors and financial institutions. Looking to the future, it is necessary to further deepen the integration mechanism of technical indicators and the model, actively explore more advanced data analysis methods and optimize the model structure, so as to significantly improve the model's predictive ability and adaptability. At the same time, it is necessary to strengthen empirical research, fully verify the effectiveness of the model with the help of large-scale actual data, and continuously expand the wide application range of the model in different financial markets and asset categories. In addition, closely monitor the innovative development trends of the financial market and changes in regulatory policies, and timely adjust and improve the model to ensure that it always maintains a high degree of practicability and excellent guiding value in the financial field. This research provides a new and extremely valuable perspective and method for financial practitioners, and strongly promotes them to re-examine and optimize existing asset pricing and risk management strategies, which is of great significance for improving the decision-making level and risk management ability of the financial industry.

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