A General Quantitative Investment Theory and Fundamental Value Technical System Based on Multi-factor Models in Chinese Stock Selection

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Abstract

Along with the continuous development of capital markets and intelligent finance technologies, quantitative investment is entering into the most critical and challenging area fundamental quantitative investment. So far, quantitative investment has been focused on automation of technical analysis and trading, while fundamental investment has been large discretionary. This paper provides an overview of quantitative investment and fundamental investment towards a fundamental quantitative investment theory and technical system based on multi-factor models. We start with reviewing relevant literature on modern financial quantitative investment and fundamental investment. Then we cover the theoretical basis and development of multi-factor models and their applications for stock selection, involving linear and non-linear relationships, machine learning, deep learning with neural networks, random forests, and Support Vector Machines (SVMs). We explore the frontiers of fundamental quantitative investment and shed light on the future research prospects.

KEYWORDS: fundamental quantitative investment, value technical system, multi-factor models, stock selection.

1 INTRODUCTION

Since Benjamin Graham (1934) proposed his methodology of value investment, stating that the value of a stock depends on its fundamental factors , research on fundamental analysis in academia has followed up and never stopped. Fundamental analysis can separate value from price, explain the economic laws behind economic phenomena such as colossal trading volume, and guide investors to choose high-quality stocks through case-by-case analysis of quantitative factors and financial data. The investment community widely recognizes Graham's thoughts. However, with the development of modern information technology and the continuous development of financial theories, the constant enrichment of information has increased the difficulty of fundamental analysis, and fundamental research has been challenged.

The excellent processing ability of the quantitative investment to massive and complex information has attracted the attention of academia and industry. Using modern quantitative tools to analyze relevant factors can effectively compensate for the lack of fundamental analysis, and fundamental quantitative investment came into being.

This paper discusses the theoretical development of fundamental investment, quantitative investment, and multi-factor models. Then the paper introduces the theoretical basis of multi-factor analysis of quantitative investments, its technical route in stock selection. finally gives an outlook on future research work.

2 EVOLUTION OF MODERN FINANCE, QUANTITATIVE INVESTMENT, FUNDAMENTAL QUANTITATIVE INVESTMENT

2.1 Header, Footer, Page Numbering Portfolio Theory A Foundation of Modern Finance

Harry Markowitz(1952) put forward the portfolio theory , which laid the foundation of modern portfolio theory in 1952, the starting point of modern financial theory. Based on Markowitz's research, William Sharpe put forward the capital asset pricing model (CAPM) in 1964 and proposed a single factor model to deal with the disadvantages of CAPM. Eugene Fama established the efficient market hypothesis (EMH)in 1970 . Stephen Ross optimized CAPM and established Arbitrage Pricing Theory (APT) in 1976 . These theories form the theoretical foundation of modern financial theories, and they are shown in Figure 1.

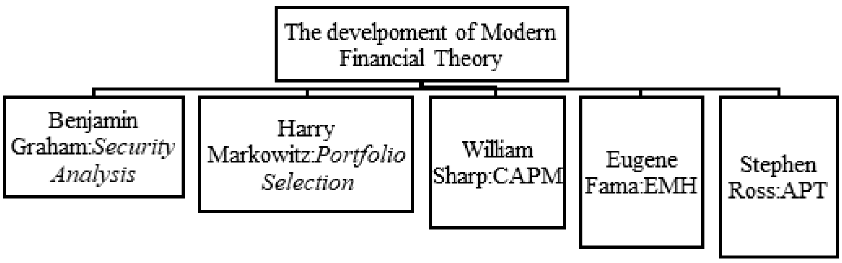

Figure 1: *The Development of Modern Financial Theory*

2.2 Quantitative Investment Based On Portfolio Theory

Quantitative investment uses mathematical models to select a specific stock portfolio, predicting asset returns and risks. The "stock portfolio" is generally called quantitative stock selection, and "predicting asset returns and risks" means quantitative analysis. The combination of computer-driven quantitative and human-driven value investment is a relatively cutting-edge intelligent quantitative investment method in recent years.

The influencing factors of stock prices in different industries are diverse. For example, price-volume factors are more predictive in small-cap stocks; financial-quality factors are more pronounced in value stocks; growth factors favor high-growth industries.

2.3 Fundamental quantitative investment

With an increase in market regulation in financial markets and increasing rationality of investors, quantitative investment has been highly valued, and the valuation of stock prices based on fundamental factors has gained more attention from quantitative investors. The recent analysis method focuses more on the company's operating conditions and related valuation factors, such as profit, operating income, industry status, and other indicators related to company quality, as well as indicators about assets valuation such as P/E ratio . Among these factors, this paper focuses on the analysis of financial factors, which means the fundamental quantitative investment under the influence of financial indicators, and the acquisition of financial factors is closely related to financial statements and financial indicators. The financial factor analysis method can provide a terrific reference for investors , which can be divided into valuation factors and value factors. The residual income model shows that the fundamental quantitative investment based on the valuation and quality dimensions is the concrete embodiment of the value investment concept. Under dimensions of valuation and quality, it is necessary to explore more factors and choose better effective indicators. Fundamental quantification is a top priority . Xuelian Li (2015) established a quantitative investment stock selection model combining fundamentals and technical aspects based on the genetic algorithm of the intelligent algorithm, and trying to eliminate irrational factors in the stock market .

3 THEORETICAL DEVELOPMENT OF QUANTITATIVE INVESTMENT BASED ON MULTI-FACTOR MODEL

Multi-factor model for quantitative investment is the most widely used stock selection model. Its basic principle is to take a few factors as stock selection criteria, then purchase stocks that meet these factors. Otherwise, sell or hold stocks that do not meet the factors.

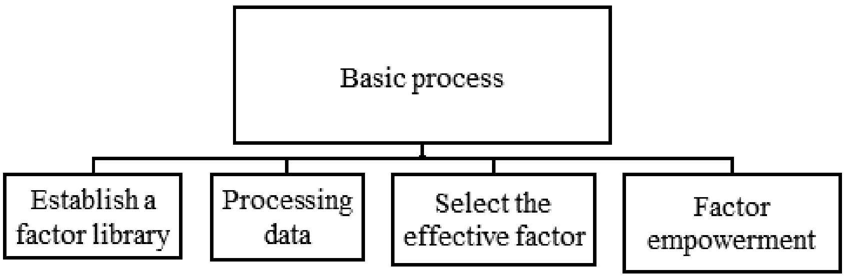

Figure 2: *Basic Process of Stock Selection for Quantitative Investment based on Multi-Factor Model*

A multi-factor model for quantitative investing runs in a process as follows,it is also shown in Figure 2. Firstly, the required factors are selected from the common nine types of factors (size factor, valuation factor, growth factor, profit factor, momentum reversal factor, trading factor, volatility factor, shareholder factor, analyst forecast factor). The collected data is processed to avoid data errors, abnormalities, deletions, inconsistencies in the dimensions, and other issues that adversely affect the objectivity of the research results(common treatments such as outlier treatment, missing value processing, neutralization processing). Then test the validity of the selected factors through the regression or scoring methods. The former can intuitively calculate the expected rate of return, but also can construct a new influential factor, providing a factor basis for the scoring method, but will be affected by extreme values; The latest scores and ranks factors based on the correlation of factor exposure to stock returns, making it more straightforward. Finally, in factor empowerment, many influential factors are scored according to specific empowerment methods so that high-quality stocks can be selected according to the total factor score. The empowerment methods are mainly the information coefficient(IC), weighting, information ratio(IR), and equal weighting methods(EW).

Based on asset portfolio theory and capital market theory, Sharpe, Lintner, Treynor, and Mossin developed a capital asset pricing model (CAPM) in 1964, which focuses on the relationship between the expected return on assets and risky assets in the securities market and the mechanism of equilibrium price formation, laying the foundation for modern financial market price theory. This CAPM model can be viewed as a single-factor model. Black et al. (1972) derived another version of CAPM under the more realistic assumption of risk-free assets, including two factors, which can be viewed as a two-factor model . Fama-French (1993) published the famous three-factor model, including market capitalization(small market capitalization minus big, SMB), book-to-market ratio(high minus low, HML), and market asset portfolio (the portfolio return minus the risk-free rate of return, it is calculated as Rm-Rf) . Therefore, the quantitative value investment in the narrow sense is mainly expressed as the value factor, starting from Fama. The causes of value factors can be divided into two categories: systematic risk compensation and investor behavior deviation. Lakonishok et al. (1994) gave a behavioral finance explanation for the value factor, suggesting that investors tend to simply extrapolate past performance to evaluate the company's prospects, leading to excessive pessimism about companies that have underperformed in the past, which leads to the value effect .To explain cross-sectional momentum anomalies, Carhart (1997) added a cross-sectional momentum factor to the Fama-French three-factor model . Moreno and Rodriguez (2009) introduced coskewness into the Carhart four-factor model , Naktnasukanjn et al.(2018) added cokurtosis factor making it became six-factor model . Novy Marx (2013) also proposed a four-factor model that reveals the correlation between profitability and future expected returns . Hou, Xue, and Zhang (2015) proposed a four-factor model from the economics of fundamental investment theory, which has become q-theory and reflects the net present value principle in corporate finance . Fama-French (2015) added two factors, earnings, and investment, to the Fama-French three-factor model, resulting in a new five-factor model . AQR Capital(2013) analyzed Buffett's investment performance using six factors, including Fama-French three factors, the momentum factor, the risk factor, and the quality factor . The risk and quality firmly explained Buffett's alpha. Buffett's preference for purchasing safe and high-quality products. Liu et al. (2019) proposed the first multi-factor model of China's A-share market, including three factors: market, value, and scale. The model is more in line with market conditions of China, including avoiding the shell value pollution of A-shares, using the price-earnings ratio (P/E ratio) instead of the book-to-market ratio (BM ratio) as the sorting variable to construct the value factor, using the double sorting of P/E and the market to construct the value factor .

4 MATHEMATICAL EVOLUTION OF MULTI-FACTOR MODELS FOR CAPITAL ASSET PRICING

The foundational work of Markowitz on diversification and modern portfolio theory and subsequent alternative models or improvement such as MADM and BLBM were all built on the market prices. Logically it was natural to consider factors that could drive the dynamics of the asset prices. The universe of factors could include macro-economic indicators, corporate fundamentals, price technicalities, and market sentiment and money flows, as well as fiscal policies and geopolitics.

4.1 Capital Asset Pricing Model (CAPM) the Single Factor Model:

CAPM was introduced by Sharpe (1964), Treynor (1961), Lintner (1965) and Mossin (1966) independently, building on the earlier work of Markowitz mean-variance analysis of modern portfolio theory. CAPM is a model used to determine a theoretically appropriate required rate of return of an asset for making decisions about adding assets to a well- diversified portfolio. For an asset A_i ,the model prices the expected return as a linear function of systematic risk (beta) added to the abnormal return (alpha)

$$R_{it} - R_f = \alpha_i + \beta_i \times (R_{mt} - R_f) + \varepsilon_{it} \tag{1}$$

where R_f is the risk-free rate of interest, $R_m i$ is the return of the market (normally represented by a stock market index) in period t, ε_{it} are the residual (random) returns assumed being i.i.d with mean zero. The expected return is

$$E(R_i) = R_f + \alpha_i + \beta_i \times (E(R_i) - R_f) \tag{2}$$

4.2 The Multi-Factor Model of Rosenberg and Marathe:

After the single-index model CAPM, it was Rosenberg and Marathe who first proposed a general form of multi-factor models. But initially they only came up with a linear model of beta

$$R_{it} - R_f = \alpha_i + \beta_{it}(R_{mt} - R_f) + \varepsilon_{it} \tag{3}$$

$$\beta_{it} = \sum_j W_{ijt} f_{jt} + \varepsilon_{it} \tag{4}$$

where ε_{it} is a market residual return, f_{jt} are the multiple factor returns, W_{ijt} are risk exposure values. This model was reformulated by Rosenberg et al. into a direct model of asset return

$$R_{it} = \sum_j W_{ijt} f_{jt} + \varepsilon_{it} \tag{5}$$

4.3 Arbitrage Pricing Theory(APT):

Ross (1976) developed a general theory of asset pricing that holds that the expected return of an asset can be modeled as a linear function of various factors or theoretical market indices, where sensitivity to changes in each factor is represented by a factor-specific beta coefficient

$$R_{it} = \alpha_i + \sum_j + B_{ijt} + f_{jt} + \varepsilon_{it} \tag{6}$$

where f_{jt} is a systematic factor, β_{ij} is the sensitivity of the i- th asset to the j-th factor, also called factor loading, ε_{it} is the risky assets idiosyncratic random shock with mean zero.

APT states that if asset returns follow a factor structure of (5), then the following relation exists between the expected returns and the factor sensitivities

$$E(R_{it}) = R_f + \sum_j B_{ij} E(f_{jt}) \tag{7}$$

That is, the expected return of an asset is a linear function of the asset sensitivities to the multiple identified factors.

Although theoretically there is no upper limit on the number of factors to be chosen for a multi-factor model as expressed by APT (5)-(6), many academics have attempted to construct multi-factor models preferably with a fairly small number of factors, typically 3-6 factors. The most notable multi-factor models are Fama-French three-factor, Carhart four-factor, and Buffett-Style six-factor models.

4.4 Fama-French Three-Factor Model and Extension:

Based on the CAPM which uses only one factor the market index, Fama and French (1993) added two more factors: small caps (SMB) and high book-to-market ratio (B/P) (HML), to reflect a portfolios exposure to these two classes of stocks

$$E(R) = R_f + \alpha + \beta_m (R_m - R_f) + \beta_s SMB + \beta_h HML \tag{8}$$

where SMB stands for Small [market capitalization] Minus Big and HML for High [book-to-market ratio] Minus Low; they measure the historical excess returns of small caps over big caps and of value stocks over growth stocks.

The Fama-French three-factor model explains over 90% of the diversified portfolio returns, compared with the average 70% given by CAPM (within sample).

In 2015, Fama and French extended their model by adding two more factors: profitability (RMW) and investment (CMA)

$$E(R) = R_f + \alpha + \beta_m (R_m - R_f) + \beta_s SMB + \beta_h HML + \beta_r RMW + \beta_c + CMA \tag{9}$$

where RMW is the difference between the return of firms with robust (high) and weak (low) operating profitability, and CMA is the difference between the returns of firms that invest conservatively and aggressively.

This five-factor model was tested, suggesting that it improves the explanatory power of the returns of stocks relative to the three-factor model.

4.5 Carhart Four-Factor Model:

In 1997, Carhart added a momentum factor to the Fama- French three-factor model

$$E(R) = R_f + \alpha + \beta_m(R_m - R_f) + \beta_s SMB + \beta_h HML + \beta_u UMD \tag{10}$$

where UMD is the monthly premium on winners minus losers.

4.6 Buffett-Style Six-Factor Model:

Frazzini et al. (2018) constructed a six-factor model to reflect the investment style of Warren Buffett by expanding the three factors of Fame and French - market (MKT), scale (SMB) and value (HML) factor and the momentum (UMD) factor of Carhart with 2 more low risk (BAB) and quality (QMJ) factors rather, reward for leveraging cheap, safe, and quality stocks.

$$E(R) = R_f + \alpha + \beta_m(R_m - R_f) + \beta_s SMB + \beta_h HML + \beta_u UMD + \beta_b BAB + \beta_q QMJ \tag{11}$$

5 TECHNICAL SYSTEM IN THE QUANTITATIVE STOCK SELECTION

5.1 Application of linear relationships in the quantitative stock selection

In addition to the multi-factor model of the quantitative investment, the following techniques also involve quantitative investment. As shown in Figure 3.

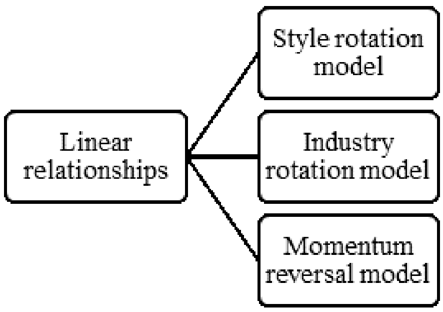

Figure 3: *Linear relationships*

1) Style rotation model: Investment preferences can be diverse in different markets, and it forms the style of the market, and the style also changes with factors. Researched investor sentiment, Qingbin Meng (2015) found the relationship between fund managers' professional

apprehension and investment style, concluding that the stronger the professional apprehension of fund managers, the more conservative their investment style is . Changsheng Hu(2020) found that: 1. the lower the average return in the previous six months, the more likely the extreme sentiment-beta portfolio is to be the current market "hotspot." 2. the switch of "hotspot" in the market is mainly between the high sentiment-beta portfolio and the low sentiment-beta portfolio.

2) Industry rotation model: Industry rotation is an active investment strategy that exploits the market's cyclicality to make different investment decisions based on macroeconomic indicators. Monetary policy and currency cycle are commonly used macroeconomic indicators in the capital market. In low macroeconomic conditions, investments should be made in non-cyclical sectors; when macroeconomic conditions are upward, investments should be made in cyclical sectors.

3) Momentum reversal model: The momentum effect is a quality investment that continues to perform well over time. Conversely, if an investment underperforms for a while and then reverts to the mean in the following period, it is the reversal effect. Xuebin Deng (2021) found the data of China's A-share market from 2007 to 2018 and concluded that the kinetic energy effect of the A-share market was not noticeable, and the stocks with low turnover rates were more evident than the kinetic energy. The reversal effect is pronounced, and the reversal effect is positively correlated with the formation period and the holding period . Hao Wang (2018) used the income decomposition method to find a completely different conclusion: there are significant cross-sectional reversal effects and time-series momentum effects in the A-share market, and the latter outperforms the former.

5.2 Application of non-linear relationships in the quantitative stock selection

In the economic system of financial markets, there must be "uncertainties," and various uncertainties can be brutal to reduce or simply cannot overcome. The complexity of financial markets and economic systems naturally extends well beyond linear (or even non-linear) multi-factor models. The latter pursues the simplicity and intmodel. The world is inherently complex, and interpretable symbolic models cannot fully cope with financial markets and the economic complexity of the system.

For the time being, linear models are still the mainstay of quantitative investing. However, as the value brought by linear models dries up and artificial intelligence technology develops, non-linear models will likely become the main direction of exploration for quantitative models in the future. Several more mature non-linear models have been developed in machine learning with artificial intelligence technology. Technical approaches to quantitative investing in non-linear relationships are shown in Figure 4.

1) Machine learning: Machine learning algorithms can be broadly classified into three categories according to the requirements for labeling the data samples: supervised Learning, Unsupervised Learning, Semi-Supervised Learning, et cetera. Supervised learning requires labels for samples (for example, stock returns), unsupervised learning requires no labels, and semi-supervised learning requires partial labels. In asset return forecasting, return data inherently dictates that the problem is a supervised learning task. Therefore, regression methods in supervised learning are naturally applicable to asset return forecasting studies . In turn,

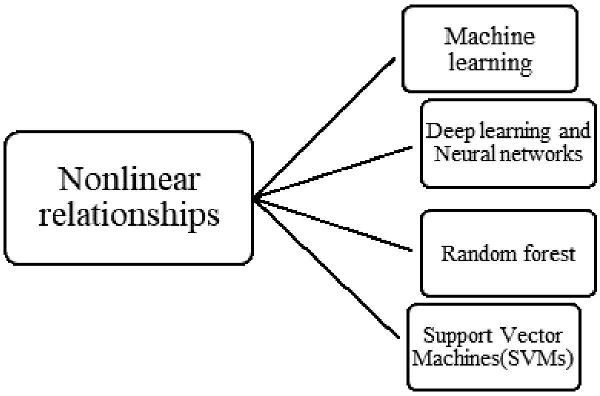

Figure 4: *Non-linear relationships*

they can be classified according to the data set: Logistic regression, Naive Bayes, K-Nearest Neighbors, Decision tree, Support Vector Machines (SVMs). However, some algorithms commonly used in quantitative investing are extensions or variants of the above classification. For example, the random forest algorithm is an extension of decision trees. Moreover, the neural network is a multi-layer non-linear logistic regression with multiple neurons. Some scholars have taken the strengths of each of these algorithms to form integrated algorithms, including parallel (Bagging), serial (Boosting), and tree (Stacking), as representatives of integrated algorithms, with multiple subtle branches.

2) Deep learning and neural networks: Deep learning is based on the in-depth study of neural networks. In finance, commonly used deep models include convolutional neural networks, recurrent neural networks, and long-short term memory neural networks. Furthermore, the above three are widely used in financial text analysis, financial risk assessment, anomaly detection, and portfolio management. Hongke Zhao et al.(2019)proposed the prediction model based on deep neural network fusion hierarchical multi-time series learning, which is effective and robust in forecasting macro-dynamics of the internet financial market. Deep learning shows excellent performance in the control system. The deep learning system can be used to analyze financial investments and learn factor selection models to more accurately select the optimal factors and maximize the profitability of investments.

3) Random forest: The random forest is a supervised learning algorithm with almost the same hyperparameters as decision trees and is widely used in quantitative investment. Shuyan Wang et al. (2016) proposed an eight-factor stock selection model indicator system from Jiao Jian's six-factor model, using indicator correlation analysis methods and a random forest algorithm . Zenan Luo (2021) used the stacking method to combine random forest(RF), gradient boosting decision tree (GBDT) with various machine learning models such as extreme gradient boost (XGBoost) and back propagation(BP) to establish an RXGB-Stacking model to extract potentially practical information, including inventory factors .through the factor importance analysis, Liang Zhou(2021) found that the momentum factors have the most potent role in the random forest model, where the long-term liquidity level is the least important. The non-linear factors represented by the random forest model have some inevitable exposure in the valuation factors, scale factors, and profit factors, where the excess return is undeniable.

4) Support Vector Machines (SVMs): SVMs is a binary classification model whose primary model is a linear classifier that defines a maximum margin on the feature space, which is distinguished from a perceptron; SVMs also include a kernel trick, which makes it a non-linear classifier in nature. In the quantitative investment research, Zhe Zhou (2017) constructed a multi-factor stock selection model based on the SVMs algorithm, taking the Shanghai and Shenzhen 300 index(CSI) 300 constituent stocks as the stock pool and screening out the stocks with investment value through the support vector classification method to construct an investment portfolio. It expects the portfolio can obtain stable excess returns in the future, which not only enriches the construction of multi-factor models but also provide some references for other investors . Xiao Wang (2020) improved the SVMs model by using the naive bayes model, random forest model, and SVMs basic model. Then Wang used the CSI 300 index in a certain period as the primary data for training and analysis. In terms of prediction accuracy and stability, SVMs optimized model and random forest model are efficient.

6 THE CURRENT SITUATION

Except for the quantitative investment based on multi-factor model, there is existing literature on other models, and the research workload is insufficient, especially in the style rotation model, industry rotation model, and momentum reversal model. Research data is relatively scarce. The multi-factor model is time-sensitive, so factors with solid stock selection ability in a certain period may reduce or even lose utility as the market changes. The current research on this phenomenon mainly adopts the reconstruction of multi-factor stock selection. Studies on the market environment, market participants, and supervisors are not included in the main factors considered.

Nevertheless, according to a lot of research and news facts, except the company's financial situation, factors like industry prospects, policies, the investors, and other factors, also have an essential influence on the market, so it has considerable research value. For example, investors in China's securities market are generally irrational, and the effect of " sell into corrections " is pronounced. So it is possible to consider incorporating the investor willingness index into a multi-factor model or use the style rotation theory for research.

7 FRONTIER EXPLORATION

From the perspective of the evolution of a larger civilization, both financial investment and economic commerce are complex science. Einstein's theory of relativity inspired us to think that there is no flat space in the physical world. We speculate that the financial market and economic system will not be an absolute "flat space," and the uneven distribution of tremendous wealth value will inevitably lead to "economic Space Bending." Quantum mechanics fundamentally means uncertainty in the microscopic world, making the future unpredictable.

On the connection between big data financial theory and industry practice, Xianzhi Yuan et al. (2020) led the domestic leading Chengdu Digital Brand Company (referred to as "BBD") to innovate and establish support without guarantee and the stochastic dynamic evolution model framework of loan credit risk control for small and micro enterprises without verification, and create a new theory for the unique U-shaped phenomenon of small and micro enterprises, to use online and offline information to build a credit evaluation system for small and micro-enterprises jointly. The pain points of small and micro enterprises that plague the global financial industry are at the top international level in financial technology research and innovation. Based on the perspective of network analysis, Zili Zhang et al.(2019) used the correlation coefficient of stock returns to construct a stock network and described the topological structure of the stock market and the propagation path of systemic risk. Zhang also used network centrality and found that the returns of stock portfolios vary as the portfolio network increases with increasing centrality . Network-based risk measure has significant explanatory power for stock returns, including the systematic risk in asset pricing models and the idiosyncratic risk of individual stocks. Heping Pan (2019) extended innovative finance from quantitative investment transactions in local financial markets to global monitoring, including international financial risks, global economic conditions, global political and environmental crises, while other factors that may affect financial market price trends and volatility.

8 CONCLUSION AND OUTLOOK

As the number of stocks in China's A-share market continues to grow, the contribution of individual stocks to the overall performance of the fund has declined. Coupled with today's flood of information in the market, fundamental data of each company's adequate research has become out of reach. The application of quantitative investment is the optimal solution to these problems. With the continuous expansion of the capital scale of investment institutions, quantitative investment strategies can effectively avoid the influence of irrational factors in the market. They can accurately identify profitable opportunities in the market through scientific and reasonable quantitative models to obtain excess income. China's financial market is also in a stage of continuous development. Due to the launch of margin financing and securities lending, and stock index futures, Chinas market has specific conditions for shorting, and quantitative investment has also ushered in tremendous opportunities.

According to the forecast on the development of quantitative investment in the financial market, we certitude that opportunities and challenges coexist. There is still an inclusive space for the research and application of fundamental quantitative investment based on multi-factor models. Among many factors, whether the stock price can be accurately reflected in the full manifestation of its effectiveness and establishing more quantitative investment models is an essential means to test the effectiveness of the factors. At present, many scholars have conducted detailed exploration and research on the multi-factor quantitative model. The combination of multi-factor models and value investing theory can measure stock prices more reliably and provide investors with practical guidance and methods.

In addition, frontier exploration in finance never stops. Since the multi-factor model in quantitative investment must have insurmountable limitations, it is vital to enter the science of complexity. It seeks the quantification and intelligence of value investment through complex network monitoring and intelligent computing models.

In conclusion, fundamental quantitative investment based on multi-factor models has both opportunities and challenges in financial markets. However, most scholars in academia and industry are optimistic. We believe that domestic and foreign financial markets will continue to improve, and fundamental quantitative research will be more widely used.

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