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Application and Effect Analysis of Financial Engineering Tools in Portfolio Optimization

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Abstract

The purpose of this study is to deeply discuss the application of financial engineering tools (FET) in portfolio optimization, and analyze its effect in detail. Through the comprehensive application of modern investment theory and advanced mathematical modeling technology, this study discusses the potential advantages of FET in improving portfolio efficiency, reducing risks and adapting to market fluctuations. This study focuses on the application of Kalman filtering (KF) algorithm in portfolio optimization. The algorithm provides a powerful and effective tool for investors by estimating and adjusting the market state in real time. The advantage of KF algorithm lies in dealing with noise, missing data and dynamic weight adjustment, thus improving the efficiency of portfolio, especially in the rapidly changing market environment. By adopting advanced risk measurement and model, investors can identify and measure the risk of portfolio more comprehensively and formulate more effective hedging and insurance strategies. This helps to reduce the overall risk level of portfolio and improve the robustness of asset allocation when market volatility increases. The application of FET in portfolio optimization provides investors with more comprehensive and accurate decision support.

Keywords

Financial Engineering Tools, Portfolio Optimization, Kalman Filtering

1. Introduction

In today's rapidly changing financial market environment, investors are facing increasingly complex and evolving challenges. In order to strike a balance between risk and return, portfolio optimization has become a crucial task. With the continuous development and innovation in the field of financial engineering, various advanced tools and technologies have emerged, providing more refined and effective solutions for portfolio management (Silva, Pinheiro, & Poggi, 2017; Ye, Yang, & Feng, 2017).

The purpose of this paper is to deeply discuss the application of financial engineering tools (FET) in portfolio optimization, and analyze its effect in detail. The introduction of FET, such as derivative pricing model, risk measurement method and quantitative trading strategy, provides investors with a more comprehensive and systematic perspective, enabling them to better understand and cope with market fluctuations. Through the analysis of empirical cases, this paper will evaluate the performance of FET in different market environments, and explore its potential in improving portfolio efficiency, reducing risks and coping with market uncertainty. Through this study, we are expected to provide more practical methods for financial decision makers to better adapt to the dynamic financial market.

The remainder of this paper is organized as follows: Section 2 defines financial engineering tools (FET) and their significance in financial markets. Section 3 discusses the basic theory of portfolio optimization, including the foundational concepts of Modern Portfolio Theory (MPT). Section 4 delves into the application of the Kalman filtering (KF) algorithm in portfolio optimization, presenting its principles and advantages. Section 5 provides a case analysis using the SSE Composite Index to illustrate the practical application of the KF algorithm. Finally, Section 6 concludes the paper with a summary of findings and implications for future research.

2. Definition of FET and Comprehensive Literature Review

2.1. The Definition of FET

FET is a series of applications of mathematics, statistics and computer science and technology in the financial field, aiming at solving complex financial problems, improving financial products and optimizing investment portfolio (Ferreira et al., 2018). The application of these tools can improve financial market participants' understanding of the market, reduce risks, increase profits and make financial decisions more effectively.

FET models the behavior of financial assets through mathematical models, such as stochastic process, differential equation and Monte Carlo simulation. These models are widely used in the pricing of financial products, such as options, bonds and other derivatives. Through mathematical modeling, financial practitioners can more accurately understand the dynamics and risks of financial markets (Kallio & Hardoroudi, 2018; Santos-Alamillos et al., 2017). FET plays a key role in risk management. By using risk measures such as value-at-risk (VaR) and conditional value-at-risk (CVaR), financial practitioners can better evaluate the risk exposure of the portfolio and adopt corresponding hedging and insurance strategies to reduce the overall risk of the portfolio (Han & Vinel, 2022; Nasini, Labbé, & Brotcorne, 2022).

FET provides strong support in portfolio optimization. By using modern investment theory methods, such as markowitz's modern portfolio theory and Black-Litterman model, investors can better balance risks and returns, optimize asset allocation, and achieve a more ideal portfolio (Sahamkhadam, Stephan, & Östermark, 2022). FET provides technical support for quantitative trading. By applying mathematical models and algorithms, quantitative trading strategies can automatically execute trading decisions and realize more efficient and faster trading based on a large number of data and signals.

FET has played a key role in promoting the innovation of financial engineering. From emerging markets to digital assets, FET continues to evolve, providing new solutions for the financial industry (Faia et al., 2021). For example, the application of emerging technologies such as blockchain technology, artificial intelligence and machine learning in financial engineering is an important direction of financial innovation. FET provides powerful analysis and decision support for the financial field, enabling financial practitioners to better understand the market, optimize investment portfolio and manage risks, so as to cope with the ever-changing financial environment more effectively.

2.2. Comprehensive Literature Review

The literature on financial engineering tools (FET) in portfolio optimization is extensive and multifaceted. Previous studies have explored various aspects of FET, including derivative pricing models, risk measurement methods, and quantitative trading strategies (Bouchaud & Potters, 2003; Buehler, Gonon, Teichmann, & Wood, 2019). However, there remains a gap in the literature regarding the real-time application of these tools in rapidly changing markets and the integration of advanced algorithms such as Kalman filtering (KF) for dynamic portfolio management.

This research aims to fill this gap by providing a detailed analysis of the application and effects of FET, with a particular focus on the KF algorithm, in portfolio optimization. By doing so, it extends the current understanding of FET's role in enhancing portfolio efficiency and adapting to market fluctuations.

3. Basic Theory of Portfolio Optimization

Portfolio optimization is an important branch of modern financial theory, which is devoted to finding an optimal portfolio allocation to maximize the expected return at a given risk level or minimize the risk at a given expected return. Based on the basic framework of Modern Portfolio Theory (MPT), portfolio optimization enables investors to make wise choices between different risks and return levels through the construction of effective boundaries.

Markowitz put forward MPT in 1952. The core point of this theory is that investors should not only consider the expected return of a single asset, but also consider the covariance and standard deviation between assets when building a portfolio. The main achievement of MPT is to construct the effective boundary of portfolio, which is a series of highest expected returns that can be achieved at a given risk level.

The point on the efficient boundary is called the efficient frontier, which represents the best combination of risk and return that investors can achieve. Under the framework of MPT, investors can make decisions by choosing the portfolio that best suits their risk preference on the effective frontier. The indifference curve shows investors' preference for risk under a given expected return level. Capital market line is another key concept in portfolio theory, which combines risk-free assets with effective frontier to form a full-market portfolio that investors can choose. By introducing risk-free assets, investors can achieve more flexible allocation under different risk levels, and the tangent of the indifference curve is the capital market line.

Besides MPT, some extension theories have also been widely used in portfolio optimization. Risk parity investment is one of them, which advocates the equal distribution of risks in the portfolio to various assets in order to achieve a more balanced return (Shaverdi & Yaghoubi, 2021).

The basic theory of portfolio optimization provides a systematic method for investors to make rational asset allocation decisions under different risk and return levels. However, these theories also face some assumptions and limitations, such as the normal assumption of market stability and asset income distribution, so they still need to be carefully considered in practical application.

4. Application of FET in Portfolio Optimization

4.1. Principle of KF Algorithm

Kalman filtering (KF) is a recursive algorithm, which is used to estimate the state of dynamic systems from a series of incomplete and noisy observation data. The algorithm was first proposed by Rudolf E. Kálmán in 1960, and is widely used in control system, signal processing, navigation and financial fields.

The core principle of KF is based on Bayesian filtering theory, which includes two main steps: prediction and update. The prediction step is used to predict the next state of the system according to the previous state estimation and the dynamic model of the system. Using the state transition matrix of the system, the current state estimation is mapped to the next moment. Predict the uncertainty of system state and consider the process noise. The updating step is used to compare the actual observation data with the prediction, and then correct the system state according to the measured value. The KF algorithm flow is shown in **Figure 1**.

Kalman gain calculation calculates the Kalman gain through the estimated state covariance and observation noise covariance. Kalman gain reflects the trade-off between observation data and prediction. State update uses Kalman gain to correct the predicted state to be closer to the actual state. Covariance update updates the uncertainty of state through Kalman gain.

The key advantage of KF is that it can deal with system dynamic changes and observation errors, and update the state estimation in real time by recursive

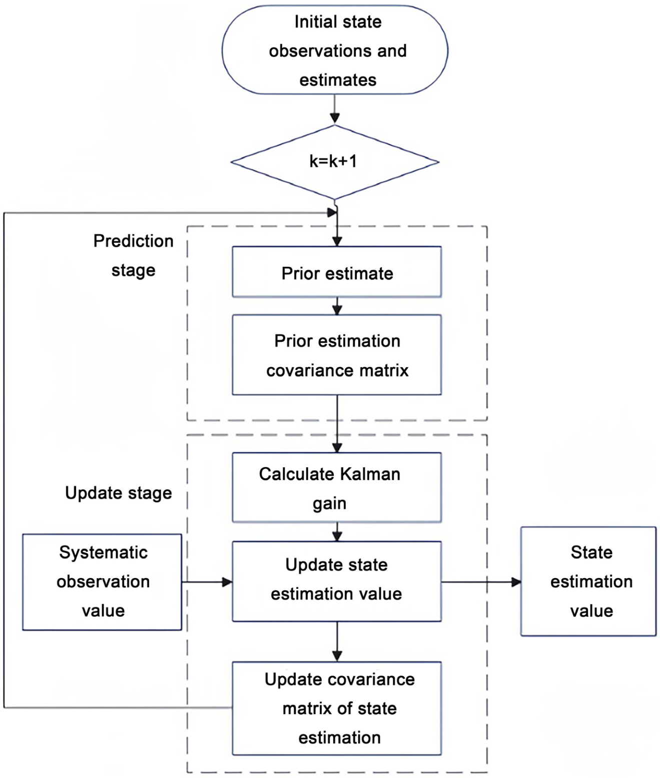

Figure 1. KF algorithm flow.

method. This makes KF especially suitable for systems that need real-time estimation, such as navigation system and time series analysis in financial field.

In the financial field, KF is often used for stock price prediction, volatility estimation and portfolio optimization. Through the dynamic modeling of market fluctuation and price change, KF is helpful to improve the understanding of financial market and make more accurate decisions in the changing market environment.

4.2. Application of KF Algorithm in Portfolio Optimization

With the continuous evolution and complexity of the financial market, investors are facing great challenges in building and managing their portfolios. In order to adapt to the dynamic changes and noise of the market more effectively, KF algorithm, as a recursive and real-time estimation tool, has gradually attracted the attention in the field of portfolio optimization. This paper will discuss the application principle of KF algorithm in portfolio optimization, and analyze its potential advantages in improving portfolio efficiency, reducing risks and adapting to market fluctuations.

KF algorithm can capture the actual performance of each asset in the portfolio more accurately by dynamically estimating the market state. Through state prediction, the algorithm can consider the dynamic changes of the market, so that investors can adjust their configuration more flexibly to adapt to the changing market conditions. In the financial field, volatility is a key parameter in portfolio optimization. KF algorithm can provide more accurate volatility estimation by estimating the observed data in real time. This helps investors to evaluate the risk of assets more accurately, so as to build a portfolio with an appropriate risk-return balance more effectively.

Because of the recursive nature of KF, investors can dynamically adjust their portfolios based on the latest market information at every time point. This ability to adjust the weights in real time enables investors to respond to changes in the market more quickly, thus maximizing the efficiency of the portfolio. KF algorithm performs well in dealing with missing data and noise. In the financial market, due to information asymmetry and market fluctuation, data may be noisy and missing. KF can deal with these challenges more steadily through elegant processing of observation data.

Define state variables, usually including the weight of each asset in the portfolio, the expected rate of return of assets, etc. Determine the observation matrix, which is used to map state variables to observed values, reflecting the relationship between market observation data and state.

State prediction:

$$\hat{x}_t = A \cdot \hat{x}_{t-1} + B \cdot u_t \tag{1}$$

where $\hat{x}_t$ is the predicted value of the state at time t, A is the state transition matrix, $\hat{x}_{t-1}$ is the estimated value of the state at time $t-1$, B is the external input matrix, and u_t is the external input (for example, market factors).

Covariance prediction:

$$P_t = A \cdot P_{t-1} \cdot A^{\mathrm{T}} + Q \tag{2}$$

where P_t is the predicted value of state covariance at time t, P_{t-1} is the estimated value of state covariance at time $t-1$, and Q is the process noise covariance matrix.

Kalman gain calculation:

$$K_t = P_t^- \cdot H^{\mathrm{T}} \cdot \left(H \cdot P_t^- \cdot H^{\mathrm{T}} + R\right)^{-1} \tag{3}$$

where K_t is the Kalman gain at time t, H is the observation matrix, and R is the covariance matrix of the observation noise.

Status update:

$$\hat{x}_t = \hat{x}_t^- + K_t \cdot \left(z_t - H \cdot \hat{x}_t^-\right) \tag{4}$$

where $\hat{x}_t$ is the estimated state value at time t and z_t is the observed value at time t.

Covariance update:

$$P_t = \left(I - K_t \cdot H\right) \cdot P_t^- \tag{5}$$

where I is identity matrix.

According to the final state estimate, adjust the weight of each asset in the portfolio to achieve the optimization goal of the portfolio, such as maximizing the income or minimizing the risk. Repeat the forecasting and updating steps, and recursively update the state estimation and covariance of the portfolio to adapt to the dynamic changes of the market.

In the above formula, Q, R is the covariance matrix of the preset process noise and observation noise, which reflect the uncertainty of the system and observation. The performance and effect of the algorithm are affected by the selection of these noise matrices, which need to be adjusted according to the specific application and market situation.

While this paper focuses on the Kalman filtering (KF) algorithm due to its unique real-time estimation capabilities, it is important to acknowledge the breadth of financial engineering tools available for portfolio optimization. These tools include, but are not limited to, derivative pricing models, risk measurement methods such as VaR and CVaR, and quantitative trading strategies. Each of these tools plays a critical role in the broader context of financial engineering and portfolio management. Future research may explore these tools in further detail to provide a more comprehensive overview of FET in portfolio optimization.

5. Case Analysis

The dataset spanning from January 1, 2018, to December 31, 2022, serves as the training set for the Kalman Filter (KF) model. Subsequently, this trained model is employed to forecast the performance of the SSE (Shanghai Composite Index) from January 1 to December 31, 2023.

To provide a clearer understanding of the dataset used in this study, the following Table 1 presents the descriptive statistics of the main variable, the SSE Composite Index, for the period from January 1, 2018, to December 31, 2022.

The forecasts are meticulously compared against the actual performance of the SSE Composite Index during this identical timeframe. The outcomes of this comparison are meticulously illustrated in Figure 2.

Figure 2 presents a comparative trend analysis between the actual SSE Composite Index values and the forecasted values generated by the Kalman Filter (KF) model for the year 2023. The x-axis delineates the months from January 2023 to December 2023, providing a month-by-month visualization of the index's performance. The actual index values are depicted by a solid blue line, showcasing the real-world fluctuations of the SSE Composite Index throughout the year. In contrast, the forecasted values are represented by a dashed red line, indicating the predictive insights derived from the Kalman Filter model. This visual comparison highlights the model's forecasting accuracy and effectiveness in capturing the underlying trends of the market index over the specified period. Notably, the figure demonstrates the model's capacity to approximate market movements, offering valuable insights into its potential utility for financial analysis and decision-making.

Figure 2 illustrates the close alignment between the actual SSE Composite Index values and the KF model's forecasts, highlighting the model's capability to

Table 1. Descriptive Statistics of the SSE Composite Index for the period from January 1, 2018, to December 31, 2022.

Statistic	Mean	Standard Deviation	Min	Max
SSE Composite Index	3250.98	276.80	2464.359863	3731.686035

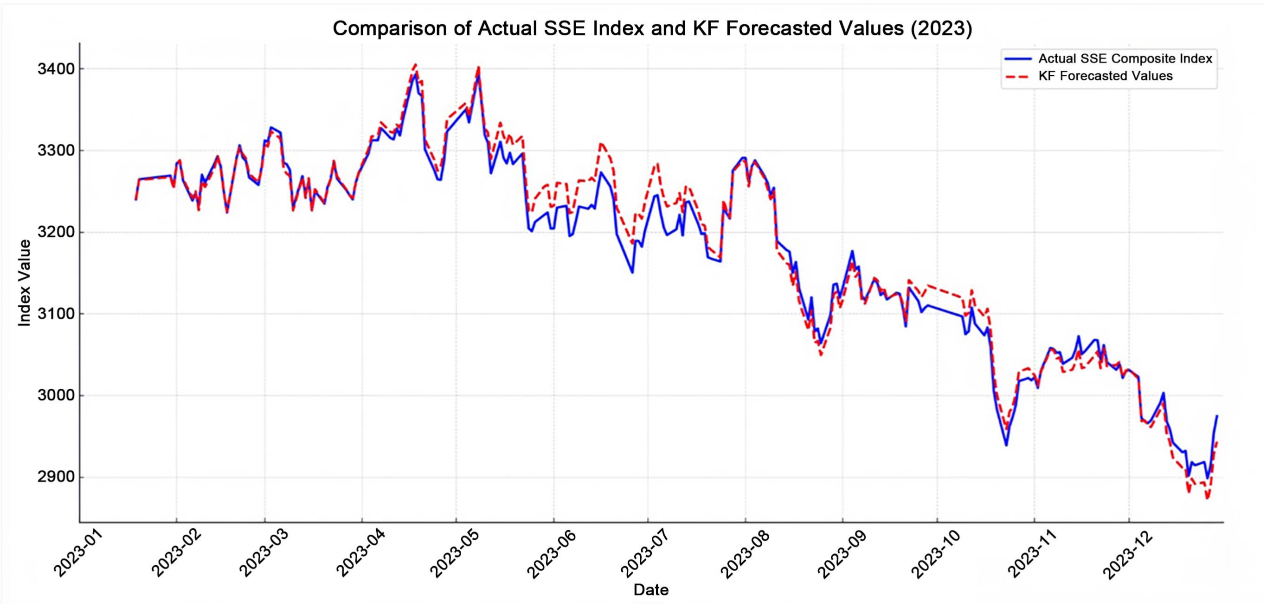

Figure 2. Comparative trend chart: Actual vs KF forecasted SSE composite index (2023).
(Source: http://english.sse.com.cn/markets/indices/overview/).

accurately capture market trends. This precision underscores the potential utility of the KF model in developing trading strategies based on predictive analytics. However, the pure model predictions do not account for the transaction costs associated with implementing these strategies in real markets.

Figure 3 showcases a side-by-side comparison of the original Kalman Filter (KF) model predictions for the SSE Composite Index in 2023 against the adjusted predictions that factor in a 0.15% transaction cost. The original forecasts are represented by a green dashed line, indicating the model's performance without accounting for any trading expenses. Conversely, the purple dotted line illustrates the adjusted forecasts, which deduct a 0.15% transaction cost from each predicted value to simulate the real-world impact of trading fees on investment returns. This figure vividly demonstrates the slight reduction in forecasted index values due to the incorporation of transaction costs, offering a nuanced view of how such costs can influence the profitability of trading strategies based on the model's predictions. The wider lines enhance visibility, ensuring that the comparison between the two sets of predictions is clear and easily discernible.

The introduction of a 0.15% transaction cost in **Figure 3** reveals a perceptible decrease in the forecasted values, emphasizing the importance of considering

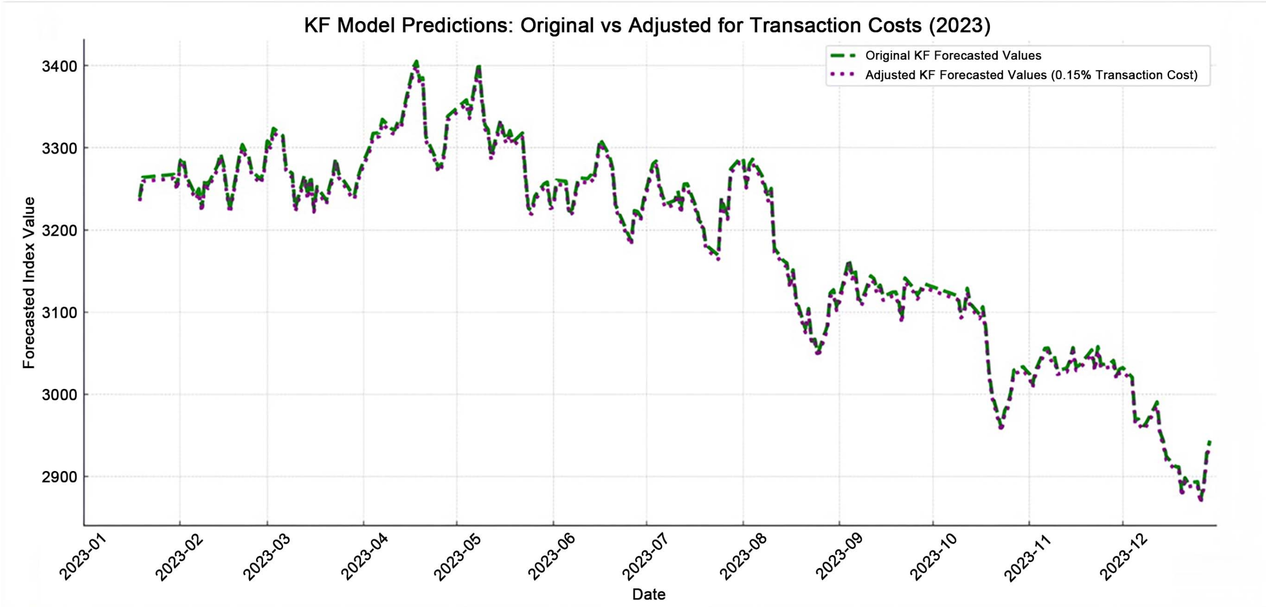

Figure 3. KF model predictions: Original vs adjusted for transaction costs (2023).
(Source: http://english.sse.com.cn/markets/indices/overview/).

trading expenses in financial modeling. This adjustment provides a more realistic assessment of the model's predictive utility and its implications for real-world trading strategies. Although the difference may appear slight, it can significantly affect the overall profitability of a strategy, particularly in high-frequency trading environments or strategies involving frequent portfolio adjustments.

The comparative analysis underscores a crucial aspect of financial modeling: the necessity of incorporating real-world constraints, such as transaction costs, into predictive models. While the KF model demonstrates robust predictive capabilities, the adjustment for transaction costs illustrates the gap between theoretical predictions and practical implementation. This gap highlights the importance of refining predictive models to account for operational costs, thereby enhancing their applicability and effectiveness in guiding real-world trading decisions.

Moreover, the results invite further investigation into the optimization of trading strategies that leverage predictive models like the KF. Specifically, it raises questions about the balance between model accuracy and the cost-effectiveness of trading strategies derived from such models. For instance, how might the model's parameters be adjusted to account for transaction costs upfront? Or, what thresholds of model accuracy and forecast deviation are acceptable when considering the impact of transaction costs on expected returns?

In summary, while the KF model offers promising insights into market behavior and potential future movements of the SSE Composite Index, the incorporation of transaction costs serves as a sobering reminder of the complexities involved in translating theoretical models into practical trading strategies. This analysis not only highlights the model's strengths but also its limitations, providing a foundation for further research aimed at enhancing the model's practical applicability and profitability in the face of real-world trading costs.

6. Conclusion

This study deeply discusses the application of FET in portfolio optimization, and evaluates its effect through empirical analysis. Through the comprehensive application of key concepts such as modern investment theory and KF algorithm. The application of financial engineering tools has significantly improved the dynamic and adaptability of portfolio. Through mathematical modeling, risk management and quantitative analysis, investors can understand the market dynamics more comprehensively and adjust asset allocation in time to cope with changing market conditions. This flexibility helps to optimize portfolio performance, especially in a rapidly changing market environment. The application of KF algorithm in portfolio optimization provides a powerful and effective tool for investors. By estimating and adjusting the market state in real time, KF algorithm can capture the market changes more accurately and improve the efficiency of portfolio. Especially in dealing with noise, missing data and dynamically adjusting weights, KF algorithm shows outstanding advantages. The application of FET in portfolio optimization has a positive impact on improving investment benefits, reducing risks and adapting to market fluctuations. However, it is still necessary to be cautious when applying these tools, and fully consider the possible influence of model assumptions and parameter selection on the results. Future research can further deepen the understanding of FET, improve its operability in actual investment decisions, and better serve investors and financial practitioners. By constantly innovating and improving FET, we are expected to achieve more remarkable results in the field of portfolio management.

Conflicts of Interest

The author declares no conflicts of interest regarding the publication of this paper.

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