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Research on the Control of Uncertainty Risks in Investment Decision-making by Financial Modeling

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Abstract: With the increasing uncertainty of the financial market, the accuracy and efficiency of investment decision-making are severely challenged. This paper takes financial modeling technology to deal with uncertain risks in financial market as the core, studies several common financial modeling strategies and the impact of their risk factors, and then deeply discusses model selection, data pre-processing, risk assessment, etc., and puts forward the impact of these methods in the practical application of investment decision-making. The results show that the suitable model has great advantages in improving decision accuracy and reducing risk, and shows good practicability and flexibility.

1. Introduction

Faced with the complex development of the financial market and the impact of market fluctuations, policy changes and external macroeconomic influences, it is often impossible to use traditional means to solve problems. Therefore, it is necessary to adopt more accurate modeling methods and risk measurement methods to guide decision-making. As an important quantitative analysis method, financial modeling provides strong support for investment decisions through model construction. By establishing a flexible mathematical model, it can reveal, measure and manage the uncertain risks in the investment process, thus speeding up the processing progress of investment decisions and reducing the investment risks brought by uncertainty. This paper will discuss the application of financial modeling in investment decision making and its practical effect on uncertainty risk control.

2. Financial modeling and uncertainty risk analysis

2.1 Common financial modeling methods

The common financial modeling methods mainly include time series model, regression analysis model, Monte Carlo simulation model, Black-Scholes option pricing model and so on. Based on different financial market characteristics and data types, these methods help investors predict market trends and assess asset risks from different angles.

Time series model: Using arima (autoregressive integral moving average) model and other methods to analyze the past evolution of financial assets, so as to predict the future evolution, which is suitable for the prediction of financial markets with certain rules.

Regression analysis model: Establish a regression model based on the relationship between various factors to predict the relationship between stock prices and other factors (such as interest rates, macroeconomic variables, etc.). The main methods are linear regression method and logistic regression method.

Monte Carlo simulation model: Through random sampling, it simulates the possible fluctuation range of asset prices, carries out risk assessment and decision optimization. This model is suitable for complex market situations and can evaluate the risk under multiple variables and scenarios.

Hae-scholes option pricing model: mainly used in the pricing of financial derivatives, it calculates the theoretical price of options by assuming that the market is frictionless and the price of the underlying asset is subject to geometric Brownian motion and other assumptions, and is widely used in option pricing and risk control.

Each model has different application scenarios in investment decision-making. Investors choose the most appropriate modeling method according to market characteristics, asset types and their own needs to achieve the goal of maximizing returns and risk control.

2.2 Source and classification of uncertainty risk

Uncertainty risk refers to the risk factors that cannot be completely predicted and controlled in investment decisions. It comes from a variety of sources, which can be roughly divided into market risk, credit risk, operational risk and liquidity risk. The following table shows the main sources and classifications of these risks:

Table 1. Main sources and classifications of risks

Risk type	Source	Description
Market risk	Economic fluctuations, political changes, changes in market demand	Fluctuations in market prices, such as unpredictable changes in stocks, exchange rates, commodity prices, etc.
Credit risk	Debt defaults and corporate credit ratings downgrades	Loss of funds caused by the failure of the investor or counterparty to perform the contract.
Operational risk	System failure, personnel error, internal control failure	Loss due to administrative, technical or human error.
Liquidity risk	Market depth is insufficient and capital liquidity is insufficient	The risk of not being able to quickly trade an asset at a reasonable price when it is urgently needed to liquidate the asset.

Environmental impact from external factors, market changes, internal business management and many other factors may lead to the occurrence of risks. However, it is difficult for enterprises to fully predict and eliminate or avoid all uncertain risks when making investment decisions. In the process of investment decision-making, it is particularly important to use financial modeling to predict and control the occurrence of risks. It can correctly identify, classify and control unpredictable risks through data research, model calculation and other methods to help investors make correct investment decisions to a certain extent.

3. Application of financial modeling in investment decision-making

3.1 Data collection and preprocessing methods

Data collection is the primary preparation step for financial modeling and an important prerequisite for determining whether financial models can be used. We often use various data such as market conditions, economic indicators, and company financial indicators in investment decisions. This information can be based on different data sources, such as financial information providers (such as Bloomberg, Reuters), government statistics, and industry research institutes. In order to ensure data quality, we need to clean and preprocess the obtained information.

Data preprocessing usually involves the following steps:

1. Missing value processing: If the data is missing, the average filling method, nearest neighbor method and interpolation method are used to fill the missing value.

2. Outlier detection: Use z-score method or boxplot method to identify and eliminate outliers. After the outlier is found, it can be treated by correction or deletion method.

3. Data standardization and normalization: For the differences between different values, it is necessary to standardize or unify them, and the commonly used normalization methods include z-score standardization and min-max unification.

4. Data stabilization: Especially for time series data, it is necessary to apply differential method and other means to process the data smoothly before modeling, so as to ensure the stability and effectiveness of the formed model.

3.2 Modeling method and algorithm selection

When choosing the financial modeling method, it should be based on the specific investment decision scenario and data characteristics. Common modeling methods include statistical models, machine learning models, and deep learning models. Statistical models, such as ARIMA model (autoregressive integral moving average model) and GARCH model (generalized autoregressive conditional heteroscedasticity model), are mainly used to describe the change trend and volatility of time series data, and are suitable for processing more traditional financial market data. ARIMA models can be modeled using the following formula:

$$Y_t = \alpha + \sum_{i=1}^{p} \beta_i Y_{t-i} + \sum_{j=1}^{q} \gamma_j \varepsilon_{t-j} + \varepsilon_t \tag{1}$$

Where, Y_t is the observed value at the current time point, ε_t is the random error term, p and q are the order of autoregressive and moving average terms, respectively. For more complex market volatility, the GARCH model describes the accumulation of volatility by the following formula:

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 \tag{2}$$

Where, σ_t^2 is the conditional variance, α_0 is the constant term, α_i and β_j is the model parameter, ε_{t-i} is the lag error term.

In addition, with the wide application of big data and artificial intelligence, the application of machine learning models (such as random forests, support vector machines) and deep learning models (such as LSTM, convolutional neural networks) in financial modeling is gradually increasing. These methods can capture complex nonlinear relationships, process high-dimensional data, and show good results in high-frequency trading and other scenarios.

3.3 Quantitative analysis of uncertainty risk

Quantification of uncertainty risk is one of the most important applications in financial modeling.

Common quantitative analysis methods include value at risk (VaR) and conditional value at risk (CVaR). VaR is used to measure the maximum possible loss of an asset or portfolio over a certain period of time in the future with a certain degree of confidence. Its calculation formula is as follows:

$$VaR_{\alpha}(X) = -(\mu_X + z_{\alpha} \cdot \sigma_X) \tag{3}$$

Where, μ_X represents the expected return of the asset, σ_X is the standard deviation of the asset, z_{α} is the quantile of the standard normal distribution at confidence level α . VaR provides investors with the worst possible loss at a certain level of confidence and is a common tool to measure investment risk.

However, VaR does not reflect the level at which the maximum loss is to be found, so it does not capture tail risk. Conditional value at Risk (CVaR) was created to capture tail risk more adequately. CVaR refers to the average loss that may be encountered when the loss exceeds VaR, and the formula is as follows:

$$CVaR_{\alpha}(X) = \mathrm{IE}[X \mid X < VaR_{\alpha}(X)] \tag{4}$$

Where, $CVaR_{\alpha}(X)$ is the average loss under conditions exceeding VaR, and IE represents the conditional expectation.

In addition, volatility modeling methods, including the GARCH model, can accurately capture the volatility and unpredictability of financial markets, helping investors to more fully understand and measure changes in risk. In the unpredictable market, this quantitative analysis tool provides investors with a set of practical risk control means, so that they can adjust their investment strategy portfolio according to different risk situations to reduce potential losses.

4. Analysis of the actual control effect of financial modeling on uncertain risks

4.1 Evaluation of model accuracy and risk control effect

Financial modeling is mainly used to suppress market volatility for investors with the help of accurate pricing power. In order to evaluate the performance of the model, its accuracy and risk management effectiveness are the two most important evaluation indicators. In practice, many error indexes are usually used to test the performance of the model, among which the indices such as mean square error (MSE), mean absolute error (MAE) and determination coefficient are commonly used. These indicators allow investors to see how the model fits into the market data to give accurate results.

1. Mean square Error (MSE) : MSE is one of the criteria for measuring the deviation between the predicted value and the actual value, and it evaluates the error of the model by calculating the square of the difference between all the predicted value and the actual value. The specific calculation formula is:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left(Y_i - \hat{Y}_i\right)^2 \tag{5}$$

Where, Y_i is the true value, $\hat{Y}_i$ is the predicted value,nand n is the sample size. The smaller the MSE, the smaller the error and the higher the accuracy of the model.

2. Average Absolute Error (MAE) : MAE measures the average absolute error between the

predicted value and the actual value, reflecting the stability of the model. The formula is:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|Y_i - \hat{Y}_i\right| \tag{6}$$

Compared with MSE, MAE has less influence on outliers, so MAE can more truly reflect the performance of the model when there are extreme fluctuations in the data.

3. Determination coefficient (R^2) : R^2 is used to measure the fit degree of the model, which represents the model's ability to explain the data. The closer to 1, the stronger the model's ability to explain the data; the closer to 0, the weaker the model's ability to predict the data. Its calculation formula is as follows:

$$R^2 = 1 - \frac{\sum_{i=1}^{n}\left(Y_i - \hat{Y}_i\right)^2}{\sum_{i=1}^{n}\left(Y_i - \overline{Y}\right)^2} \tag{7}$$

Where, $\overline{Y}$ is the mean of the actual value, Y_i is the actual value, and $\hat{Y}_i$ is the predicted value.The higher the R^2 value, the better the model fits and more accurately reflects the market data.

Through these error evaluation methods, investors can comprehensively evaluate the prediction accuracy of the investment financial model, and can effectively control the uncertainty risk in the investment process. An accurate model can not only reduce the prediction error, but also help investors to find the risk changes in the market investment in advance, so as to adjust the investment decision.

4.2 Benefit of risk management and effect of decision optimization

In practical application, financial modeling not only helps investors avoid risks, but also provides theoretical guidance for investors to make the best decision. In portfolio optimization, a variety of modeling techniques are commonly used, especially at the intersection of risk management and improved decision making. Based on comparative studies of the effects of its various models, investors can maximize returns on this basis while minimizing risks.

Through the quantitative analysis of risk management benefits and the impact of optimization results, the practical application benefits of financial models can be comprehensively evaluated. In the measurement of risk management benefits, indicators such as VaR and CVaR are commonly used, which can accurately measure the extent of risk exposure. When measuring the impact of optimization results, Sharpe ratio is commonly used to measure the risk-adjusted return, which plays an important role in portfolio optimization. The following table compares the performance of different financial models in terms of risk management benefits and decision optimization effects:

Table 2. Performance of different financial models in risk management benefits and decision optimization effects

Model type	VaR (ten thousand yuan)	CVaR (ten thousand Yuan)	Expected Return Rate (%)	Sharpe Ratio
Traditional statistical model	5000	7000	8	0.85
Machine learning model	4500	6200	12	1.05
Deep learning model	4000	5500	15	1.30

Through the comparative analysis of the data in Table 2, it can be seen that the deep learning model can effectively reduce the risk index (such as VaR and CVaR), and greatly increase the expected return rate and Sharpe index. This shows that the deep learning model can strongly control risks and improve the profitability of investors, providing a more powerful basis for decision-making.

4.3 Analysis of model adaptability and flexibility

The financial market is dynamic, changes in the market environment, fluctuations in the economic cycle, unexpected conditions, etc., can lead to portfolio shocks. Therefore, it is necessary for investors to choose a financial model with strong adaptability and flexibility to create their investment strategy. This highly adaptable model can quickly change its strategy as market conditions change; At the same time, this highly flexible model can self-update and optimize itself based on new information gathered.

In contrast, traditional statistical models such as ARIMA and GARCH tend to perform better if there are smooth and orderly market conditions. However, for sudden market events, when the market changes greatly, the prediction accuracy of statistical models may decline, such as sudden sharp decline in the stock market, or changes in government policies, which may lead to these traditional statistical models can not work well. On the contrary, machine learning and deep learning models, due to their strong self-adjustment properties, can automatically adjust model parameters according to historical data to automatically adapt to market characteristics in different situations.

This type of deep learning structure, represented by the LSTM(LongShort-Term MmemoryNetwork), can capture and monitor the long-term and short-term movements and cycles of the market. Through its unique gating mechanism, LSTM can selectively store or forget past information, making LSTM very suitable for the study of financial time series data with long-term relevance. Thanks to its flexibility and adaptability, LSTM is able to respond well to unexpected situations and extremely changing market conditions.

4.4 Future trend: The combination of artificial intelligence and big data

With the rapid progress of big data and artificial intelligence technology, financial modeling is moving into a new period of development. In the past, the construction of financial models mostly relied on historical data analysis and statistical methods, however, the integration of AI and big data has brought a more intelligent development path for financial model design. With the help of advanced technologies such as deep learning and augmented learning, artificial intelligence can independently dig out the potential rules of the market from a huge amount of information to achieve more accurate predictions and analytical judgments.

As shown in Figure 1, the framework diagram explains the construction process of financial model by combining artificial intelligence and big data. First, massive financial data and economic data are obtained through the big data platform; second, data is cleaned and standardized for pre-processing; third, the principles of machine learning and deep learning are used to predict market prospects and identify patterns. Finally, through the risk assessment and decision optimization module, the optimal investment plan is designed and the final choice is made. This combination of artificial intelligence and big data enables financial models to more accurately judge market risks, improve portfolio returns and constantly update investment plans in real time, thus improving the accuracy and effectiveness of investment decisions. Relying on the development of artificial intelligence and big data, it will increase computing power and further promote the progress of financial modeling technology to help users make investment judgments more accurately and efficiently.

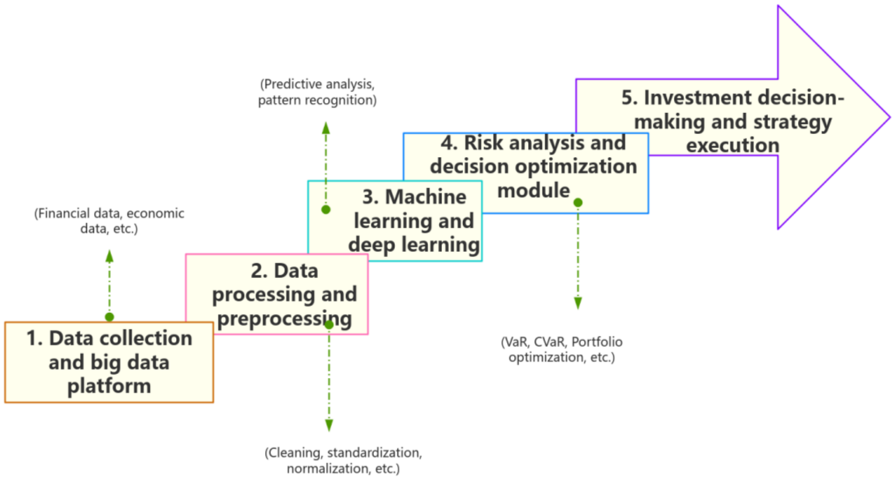

Figure 1. A financial modeling framework combining AI and big data

5. Conclusion

This paper discusses how to effectively solve the problem of uncertain risk management in investment through financial modeling, and analyzes the impact of various modeling strategies and their contributions to risk management and decision optimization. Through the accuracy of quantitative model, the effectiveness of risk management and control, the economic benefits of risk management and control, and the results of decision optimization, it is demonstrated that financial modeling can improve the accuracy of investment decision and effectively control the risk. At the same time, with the development of artificial intelligence and big data technology, the applicability and flexibility of financial modeling will increase, thus helping investors better respond to changes in market conditions. In the long term, financial modeling combined with AI and big data may become the primary method for intelligent investment decisions, thereby improving the stability and efficiency of financial markets.

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