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Construction of High-order Dynamic Portfolio Models Based on VAR-ICA-MGARCH

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ABSTRACT

The aim of the study is to prove that dynamic portfolios can effectively reflect the temporal dynamics of current risks of a higher order, providing greater reliability and stability compared to traditional portfolios. The subject is the economic imbalance in portfolio models, which occurs when different participants have different level of knowledge about market conditions and the performance of assets. In an environment where traditional portfolios have shown low returns due to the pronounced peaks and sharp declines in financial asset returns, as well as their inability to account for dynamic changes in financial risks. This study incorporates higher-order short-term risks into traditional portfolios in order to mitigate the effects of deviations from the normal distribution. The methodology is based on the concept of multiple financial time series and the VAR-ICA-MGARCH model. This model effectively captures the conditional mean, the covariance matrix, the mutual asymmetry matrix, and the mutual kurtosis matrix, thereby characterizing temporal changes at higher-order moments. Due to the inherent nonlinearities of dynamic portfolio optimization tasks, we use a genetic algorithm to solve the dynamic portfolio model. The results of the study show that dynamic portfolios can effectively reflect the changing dynamics of current higher-order risks, while providing greater reliability and stability than traditional portfolios. Even when exposed to such complex risks, dynamic portfolios perform better. The practical significance of this research lies in determining the time-varying weighting coefficients for the portfolio and conducting both simulation experiments and empirical analysis.

Keywords: AI; high-order dynamic investment portfolio; genetic algorithm; VAR-ICA-MGARCHSK model; CARA utility function

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INTRODUCTION

One of the most important reasons is that financial market variables often violate the normality assumption, failing the traditional Markowitz mean-variance model. Many relevant studies have shown that the yield of financial assets is non-normal, usually showing the characteristics of peaks and thick tails. The investment results obtained by calculating such data using the traditional Markowitz mean-variance model may significantly deviate from the actual situation. In response to this phenomenon, to weaken the impact of non-normality on the outcome of investment decisions, scholars have done many fruitful studies in this regard [1, 2]: consider the skewness of the traditional portfolio and find that the investment portfolio that introduces the skewness considerably deviates from the conventional portfolio results.

It considered financial income data's peak and thick tail phenomenon [3]. It is difficult for the traditional portfolio model to achieve the desired effect and constructs a high-order moment portfolio model considering skewness and kurtosis and then solve this high-order moment portfolio model using the genetic algorithm. Empirical results suggest that the presence of high-order moments has a more significant impact on investment decisions. Based on investor utility, we have constructed a two-tier parameter estimation model of a portfolio with base constraints with the idea of two-tier planning [4]. Then, the algorithm framework for derivative-free optimization was designed, and the algorithm subproblems were solved using ADMM (Alternating Direction Method of Multipliers). This approach better serves the portfolio model with base constraints for investment decisions. The wavelet-high-order moment portfolio model was proposed [5], taking into account that investors have different preferences, combining the considerable overlap of the discrete wavelet transformation method with a high-order portfolio moment. Based on different perspectives, two integration schemes were proposed: high-frequency and full-scale. The model is improved by screening appropriate risk preference characteristics.

Economic asymmetry arises when different market participants possess varying levels or types of knowledge about market conditions, asset performance, or other relevant factors affecting investments. Traditional models often assume that information is evenly distributed among investors, but in reality, this is not always the case. This can lead to inaccuracies in investment decisions, as investors with more information may have an advantage over those with less information.

By using genetic algorithms in a dynamic portfolio context, several advantages emerge regarding handling these asymmetries. Higher-order moment risks captured by frameworks like VAR-ICA-MGARCH provide a richer understanding of volatility clustering, skewness, kurtosis, and the interdependencies between assets. Incorporating these features ensures that the optimization process explicitly takes into account structural shifts caused by changing economic environments or shocks. Unlike traditional methods that require strict assumptions about probability distributions (such as normality), genetic algorithms work directly with raw datasets, allowing for more flexibility in dealing with irregular patterns resulting from heterogeneous investor behaviors [5–7].

It introduced a central regularization algorithm to compensate for the original method's shortcomings and significantly improved its application value by applying L1 norm penalties to the non-diagonal elements of the estimated matrix during the solution process. Using the sensitivity VaR model (SDSVaR), which takes into account state dependence to measure the direction and magnitude of risk spillover effects between industries, This model considered the plate rotation effect and constructed a cross-industry portfolio model. They have analyzed the impact of inter-industry risk spillover and portfolio rotation on asset allocation. The traditional portfolio method is easily affected by outliers, leading to the calculation results that are inconsistent with the actual situation. They improved the traditional portfolio model by combining the robust method and obtained a better portfolio model [8–10].

The authors used a particle swarm optimization algorithm to solve the portfolio model reducing the possibility of falling into local optimization [11–13]. They built a portfolio model based on symmetric triangular fuzzy numbers and compared it with the combination of set empirical mode decomposition and ordinary least squares and the single fuzzy linear regression method. The results indicate that the portfolio model based on set empirical mode decomposition and fuzzy linear regression is superior, which has reference significance for building the optimal portfolios [14–18].

Most existing portfolio models assume that the investment period is fixed [19, 20]. However, with the ongoing in-depth study of the financial market, we have found that there are not only high-order moment risks in the financial market but also time-varying risks. However, the traditional Markowitz mean-variance model does not consider the dynamic relationship between financial asset returns and risks, which is one of the main drawbacks of the conventional Markowitz mean-variance model. Thus, how to effectively construct a dynamic portfolio effectively has become a topic of interest for many researchers. For example, it studied the portfolio problem using the mean end wealth risk-return (EaR) in continuous time and compared it with the traditional mean-variance model. The researchers [21–24] proposed the MGARCHSK model in order to capture the dynamic changes of high-order moments and to conduct empirical research, given the non-normality of the distribution of return on financial assets and the fact that traditional portfolios do not take into account the high-order moment risk or the time variability of financial risk. The empirical results demonstrate time-varying high-order moment risk in the financial market as well as volatility aggregation in these high-order moment risks.

At the same time, the investment effect of a portfolio based on high-order moment risk is also better than that of a traditional portfolio. This was achieved by using interval numbers to measure returns and semi-absolute deviations to measure risks, in order to construct an interval-valued portfolio model. Research shows that investors can choose the investment proportion based on their personal preferences and adjust it depending on the investment environment [25–27]. Finally, the effectiveness and reliability of the dynamic portfolio was demonstrated through empirical analysis. The researchers [28–30] improved the relative robust portfolio optimization (RRPO) model by introducing a dynamic reference point. Their empirical findings suggest that the benefits of aggressive behavior are good, and conservative behavior has reasonable control over the standard deviation and maximum loss value. The goal was to minimize risk taking into account the background risks of investment decisions and the turnover rate of securities as constraints. A fuzzy portfolio model was then constructed. The empirical results support the general principle of "high yield, high risk". It proposes an investment decision-making model with a flexible time horizon that considers consumption and bankruptcy management. The researchers built an optimal portfolio model considering inflation and an uncertain time horizon. They evaluated the portfolio problems of varied projects, stocks, and risk-free assets; and constructed a mixed portfolio optimization model with a flexible time horizon aimed at the maximizing net present value of final wealth. Empirical research shows that the hybrid portfolio strategy, which allows for a flexible time horizon is more effective than the existing project portfolio strategy with a flexible time frame [31–34].

This paper introduces skewness and kurtosis risks into the traditional portfolio, combining them with previous literature research and considering the non-normal distribution of financial asset returns and the characteristics of peaks and thick tails. It constructs a high-order moment portfolio to weaken the impact of deviations from the basic assumptions. At the same time, given the time-varying nature of the return rates of financial assets and their risks, this paper utilizes the VAR-ICA-MGARCHSK model to capture the time-varying of conditional mean, covariance matrix, CO-skewness matrix, and CO-kurtosis matrix. Finally, a genetic algorithm is used to solve high-order portfolio solutions' nonconvex and nonlinear problems to obtain the optimal investment weight and construct a dynamic portfolio model. To demonstrate that the dynamic portfolio is more advantageous than the traditional portfolio, this paper provides further explanation based on simulation and empirical analysis. Simulation and empirical analysis results indicate that the VAR-ICA-MGARCHSK model can effectively capture the financial high-order moment risk and find that the financial high-order moment has significant time variability. Compared with the traditional portfolio, the dynamic portfolio model's investment selection results based on the VAR-ICA-MGARCHSK model more closely align with the actual market conditions, and the investment effects are better than a traditional portfolio.

1. PRINCIPLES OF HIGH-LEVEL DYNAMIC PORTFOLIOS

1.1. Principles and Pitfalls of Traditional Portfolios

Traditional mean-variance models (i.e., traditional portfolio models) include the First Type Mean-Variance Model and the Second Type Mean-Variance Model. Taking the First Type of Mean-Variance Model as an example, (assuming that there are *n* securities in the portfolio), a specific principle is shown in Equation (1).

$$\min \sigma_p^2 = W^T \Sigma W$$
$$s.t \begin{cases} \mu_p = W^T \mu \geq r \\ \sum_{i=1}^{n} w_i = 1 \\ w_i \geq 0 \quad i = 1, 2, \cdots, n, \end{cases} \tag{1}$$

where W represents the weight vector, Σ represents a covariance matrix, μ represents the mean vector, and *r* represents a given expected rate of return.

Traditional portfolio models often achieve superior results by satisfying basic assumptions, but as financial markets continue to evolve, the model's flaws are becoming apparent. First, in practice, the volatility of financial markets and the impact of external events, etc., will make it difficult to meet the basic assumptions of the traditional Markowitz mean-variance model. The most important of which is that normality is difficult to satisfy. Secondly, the Traditional portfolio model assumes that the mean and variance are time-varying, that is, only statically consider the relationship between investment returns and risks, and does not consider the fact that investment returns and risks are dynamically changing in actual situations. This makes it challenging to make effective dynamic investment decisions in practice. Therefore, given the problem that normality is challenging to satisfy, this paper introduces high-order moment risk. The VAR-ICA-M GARCHSK model captures the dynamic changes in investment returns, covariance matrix, covariance matrix, and co-kurtosis matrix. Therefore, by considering non-normality and time-varying, this paper improves upon the traditional portfolio model.

1.2. VAR-ICA-MGARCHSK the Principle of the Model

This paper introduces the VAR-MGARCHSK model, which illustrates the existence of high-order financial moment risk and captures the time variability of investment returns and risks. The main expressions of the VAR-MGARCHSK model are shown in Equation (2).

$$\begin{cases} Y_t = \sum_{i=1}^{q_0} \Phi_i Y_{t-i} + \varepsilon_t \\ \eta_t = H_t^{-1/2} \varepsilon_t \\ vech(H_t) = B_0 + \sum_{i=1}^{q_1} B_{1,i} vech\left(\eta_{t-i}\eta_{t-i}^T\right) + \sum_{j=1}^{p_1} B_{2,j} vech\left(H_{t-j}\right) \\ vech(S_t) = \Gamma_0 + \sum_{i=1}^{q_2} \Gamma_{1,i} vech\left(\left(\eta_{t-i}\eta_{t-i}^T\right) \otimes \eta_{t-i}^T\right) + \sum_{j=1}^{p_2} \Gamma_{2,j} vech\left(S_{t-j}\right) \\ vech(K_t) = \delta_0 + \sum_{i=1}^{q_3} \delta_{1,i} vech\left(\left(\eta_{t-i}\eta_{t-i}^T\right) \otimes \eta_{t-i}^T \otimes \eta_{t-i}^T\right) + \sum_{j=1}^{p_3} \delta_{2,j} vech\left(K_{t-j}\right) \end{cases} \tag{2}$$

Among them, Y_t represents the yield series, Φ_i represents the autoregressive vector coefficient represents the VAR model used to capture the dynamic investment return, η_t refers to the vector after the standardization of the ε_t random error vector. H_t, S_t and K_t represents conditional covariance matrix, conditional co skewness matrix and conditional co kurtosis matrix, respectively. $\otimes$ represents Kronercker product. However, the MGARCHSK model is not widely used in practice because as the number of variables and the order of lag increase, the parameters estimated by the MGARCHSK model also increase significantly. The main principles of the ICA-MGARCHSK model are:

$IC_t = (IC_{1t}, IC_{2t}, \cdots, IC_{nt})^T$ *n* independent components Y_t called yield sequences, such as IC_{it} and IC_{jt} $(i \neq j)$ are independent, and there is a reversible matrix *U* (or transformation matrix) such as:

$$IC_t = UY_t. \tag{3}$$

The conditional variance of formula (3), the conditional skewness, and the conditional kurtosis can be obtained, respectively:

$$\begin{cases} \operatorname{var}(IC_t \mid I_{t-1}) = UH_t U^T \\ skew(IC_t \mid I_{t-1}) = US_t\left(U^T \otimes U^T\right) \\ kurt(IC_t \mid I_{t-1}) = UK_t\left(U^T \otimes U^T \otimes U^T\right) \end{cases}, \tag{4}$$

where $\operatorname{var}()$ $skew()$ $kurt()$ represent the variance, skewness, and kurtosis, respectively. After obtaining Y_t the independent components of the yield series IC_t, you can use the unary GARCHSK model to model them separately IC_t, then the unary GARCHSK model is as follows (5):

$$\begin{cases} \xi_{lt}^H = w^H + \sum_{i=1}^{q_1} \alpha_{li}^H (\eta_{l,t-i}^H)^2 + \sum_{j=1}^{p_1} \beta_{lj}^H \xi_{l,t-j}^H \\ \xi_{lt}^S = w^S + \sum_{i=1}^{q_2} \alpha_{li}^S (\eta_{l,t-i}^S)^3 + \sum_{j=1}^{p_2} \beta_{lj}^S \xi_{l,t-j}^S \\ \xi_{lt}^K = w^K + \sum_{i=1}^{q_3} \alpha_{li}^K (\eta_{l,t-i}^K)^4 + \sum_{j=1}^{p_3} \beta_{lj}^K \xi_{l,t-j}^K \end{cases}, \tag{5}$$

where l $\left(l = 1, 2, \ldots, n\right)$ represents the *lth* independent component. ξ_{lt}^H, ξ_{lt}^S and ξ_{lt}^K represents the conditional variance, conditional skewness, and conditional kurtosis of the l independent component, respectively (6).

$$\begin{cases} H_t = U^{-1}\Xi^H (U^T)^{-1} \\ S_t = U^{-1}\Xi^S (U^T \otimes U^T)^{-1} \\ K_t = U^{-1}\Xi^K (U^T \otimes U^T \otimes U^T)^{-1} \end{cases}. \tag{6}$$

Among them $\Xi_t^H = diag\left(\xi_{1t}^H, \xi_{2t}^H, \cdots, \xi_{nt}^H\right)$ $\Xi_t^S = diag\left(\xi_{1t}^S, \xi_{2t}^S, \cdots, \xi_{nt}^S\right)$ and $\Xi_t^K = diag\left(\xi_{1t}^K, \xi_{2t}^K, \cdots, \xi_{nt}^K\right)$ the conditional covariance matrix, the conditional co-skewness matrix and the conditional co-kurtosis matrix represent the independent components, respectively (6).

Therefore, the VAR-MGARCHSK and the ICA-MGARCHSK models can be constructed based on the principle of the VAR-ICA-MGACHSK model. That is, the investment income of the yield series Y_t time-varying is captured through the VAR model and then extracted. The residuals of the VAR model are used to construct the ICA-MGARCHSK model to estimate the yield sequence's dynamic high-order moment risk.

1.3. Portfolios Based on Utility Functions

Assuming that the investor's initial wealth at the beginning of the period is 1, and the wealth in the t-period is W_t, the investor gets the maximum effect in the t-period, that is, maximizes $U\left(W_t\right)$. Considering the impact of financial high-order moment risk on the portfolio, the Taylor formula unfolds (Fang et al., 2019) the utility function as shown in Equation (7).

$$U\left(W_t\right) = \sum_{i=0}^{\infty} \frac{U^{(k)}\left(\bar{W}_t\right)\left(W_t - \bar{W}_t\right)}{i!}, \tag{7}$$

where $\bar{W}_t = E\left(W_t\right) = 1 + w_t^T \mu_t$ represents the expected wealth at the end of the *t*-period, represents the conditional expected return vector, takes the expectation of equation μ_t (7), and performs a fourth-order truncation to obtain:

$$\begin{aligned} E(U(W_t)) &= U(\bar{W}_t) + U^{(1)}(\bar{W}_t)E(W_t - \bar{W}_t) + \frac{1}{2!}U^{(2)}(\bar{W}_t)E(W_t - \bar{W}_t)^2 + \\ &+ \frac{1}{3!}U^{(3)}(\bar{W}_t)E(W_t - \bar{W}_t)^3 + \frac{1}{4!}U^{(4)}(\bar{W}_t)E(W_t - \bar{W}_t)^4 + o(W_t^4). \end{aligned} \tag{8}$$

From Equation (8), the conditional utility expects the conditional high-order moment risk of the available portfolio to be approximated, i.e.:

$$E\left(U\left(W_t\right)\right) \approx U\left(\bar{W}_t\right)+\frac{1}{2}U^{(2)}\left(\bar{W}_t\right)\sigma_{p,t}^2+\frac{1}{3!}U^{(3)}\left(\bar{W}_t\right)s_{p,t}^3+\frac{1}{4!}U^{(4)}\left(\bar{W}_t\right)k_{p,t}^4, \tag{9}$$

where $\mu_{p,t}$, $\sigma_{p,t}^2$, $s_{p,t}^3$ and $k_{p,t}^4$ represent the total return, total variance, total skewness, and total kurtosis of the t-day of the dynamic portfolio, respectively. The calculation is shown in Equation (10).

$$\begin{cases} \mu_{p,t} = W_t^T R_t \\ \sigma_{p,t}^2 = W_t^T H_t W_t \\ s_{p,t}^3 = W_t^T S_t \left(W_t \otimes W_t\right) \\ k_{p,t}^4 = W_t^T K_t \left(W_t \otimes W_t \otimes W_t\right), \end{cases} \tag{10}$$

where R_t, H_t, S_t and K_t represent income vector, covariance matrix, CO skewness matrix, and CO kurtosis matrix, respectively.

This article uses the constant absolute risk aversion effect function (CARA), which is $U\left(W_t\right) = -e^{\rho W_t}$. The ρ parameter represents the investor's constant absolute risk aversion parameter, which is taken as 1. Thus, the optimization problem of a dynamic portfolio model based on utility functions can be expressed in Equation (11).

$$\begin{cases} \max E_{t-1}\left(U\left(W_t\right)\right) = -e^{-\rho\left(1+\mu_{p,t}\right)}\left(1+\frac{\rho^2}{2}\sigma_{p,t}^2-\frac{\rho^3}{6}s_{p,t}^3+\frac{\rho^4}{24}k_{p,t}^4\right) \\ s.t. \quad W_{t-1}^T I = 1 \\ \qquad w_{i,t} \geq 0 \end{cases} \tag{11}$$

Next, using the Lagrange multiplier method, we can find the optimal weight of Equation (11), and obtain Equation (12):

$$\left(\mu_t - R_{0,t}\right) - \psi_1\left(w_t\right)H_t w_t + \psi_2\left(w_t\right)S_t\left(w_t \otimes w_t\right) - \psi_3\left(w_t\right)K_t\left(w_t \otimes w_t \otimes w_t\right) = 0, \tag{12}$$

where $\psi_i\left(w_t\right) = \frac{\rho^i}{i!}(1+\frac{\rho^2}{2!}\sigma_{p,t}^2-\frac{\rho^3}{3!}s_{p,t}^3+\frac{\rho^4}{4!}k_{p,t}^4)^{-1}$ Equation (12) is a nonlinear function of the weight vector *Wt*. Therefore, considering the nonlinear nature of Equation (12), this paper employs the genetic algorithm with the non-dominated sorting and the elite strategy to obtain the optimal weight to obtain the time-varying dynamic investment weight W_t, and then create the dynamic portfolio.

1.4. Construction of High-order Dynamic Portfolio Models

In summary, according to the principles of the VAR-ICA-M GARCHSK model and the utility function-based portfolio model, as well as the genetic algorithm, this paper develops a high-order dynamic portfolio model. The specific algorithm is illustrated in the flowchart in *Fig. 1*.

(1) Capture of the yield series using the VAR-ICA-M GARCHSK model;

(2) Construction of a high-order dynamic portfolio model using a portfolio model based on utility function;

(3) Adoption of a genetic algorithm with an elite strategy of a non-dominant ranking to obtain high-order dynamic investment weights;

(4) The effectiveness and feasibility of the high-order dynamic portfolio models are explained according to simulation experiments and empirical analysis.

2. SIMULATION EXPERIMENTS

This paper first verifies that high-order dynamic portfolios are more effective than traditional portfolios based on simulation experiments to prove the effectiveness of high-order dynamic portfolios. Firstly, a 4-dimensional MGARCHSK model with 1000 samples was simulated using R software. An independent principal component analysis was then used to obtain each independent component (6). Finally, the high-order dynamic investment weights were obtained using a genetic algorithm. The investment utility and high-order dynamic investment weights for the first 100 days obtained from the VAR-ICA-MGARCHSK model are shown in *Fig. 2*.

Where CL represents the average dynamic portfolio utility value, UCL represents the upper three-sigma limit of the dynamic portfolio's utility value, and LCL represents the lower three-sigma limit of the dynamic portfolio utility value. As can be seen in *Fig. 2*, the investment utility obtained by the traditional portfolio is –0.4783, the average investment utility of dynamic portfolios is –0.4197. The daily investment return of dynamic portfolios is therefore higher than that of the traditional ones. In contrast, the investment value of dynamic portfolios is basically stable within the Six Sigma range. Therefore, the investment benefit obtained from using dynamic portfolios is relatively stable, and the investment effectiveness of dynamic portfolios is consistently greater than that of traditional portfolios (see *Table 1*).

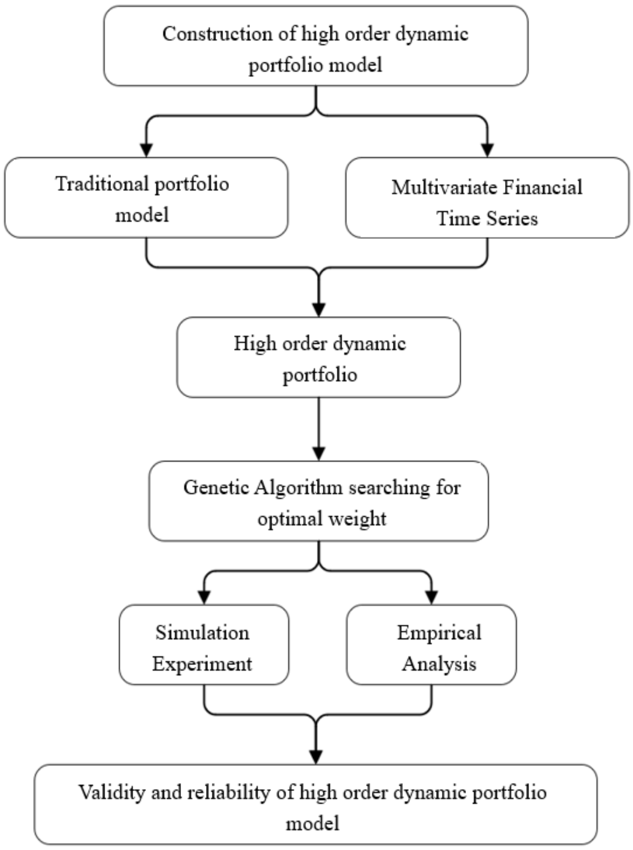

Fig. 1. **Flowchart of the Construction of a Dynamic Portfolio Model**

Source: Compiled by the authors.

3. EMPIRICAL ANALYSIS

In order to verify the practical application effect of high-order dynamic portfolios, this study selects data from January 03, 2014, to April 19, 2019. The logarithmic yield data for 6 stocks of China Mobile, China Construction Bank, China Telecom, Industrial and Commercial Bank of China, Chinese Life Insurance, and Agricultural Bank of China were used. A total of 1304 samples were recorded as x_1 and x_2, x_3, x_4, x_5, x_6, respectively. The data was obtained from Yingwei Financial, and their yield images are shown in *Fig. 3*.

According to *Fig. 3*, there is a significant volatility aggregation in each stock, but it needs to be further

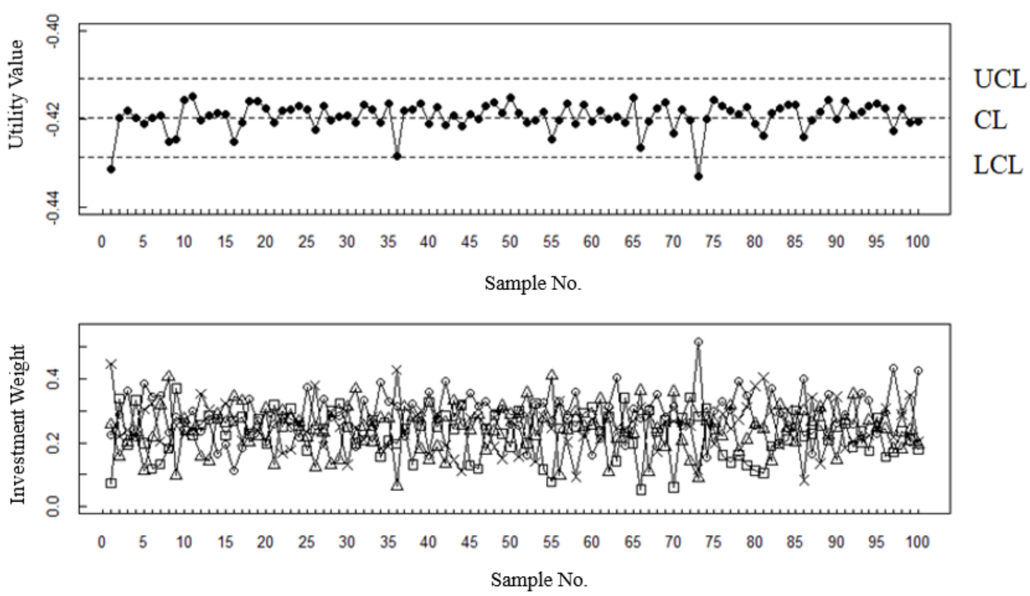

Fig. 2. **Dynamic Portfolio Utility Values for the First 100 Days (Above) and Dynamic Investment Weights (Bottom)**

Source: Compiled by the authors.

Table 1

Comparison of the Effects of High-end Dynamic Portfolios and Traditional Portfolios

Parameter	Utility value	Mean	Variance	Kurtosis	Skewness
Dynamic portfolios	−0.4197	0.0089	0.2618	−0.0018	0.5027
Traditional portfolios	−0.4783	0.0105	0.7922	0.0782	3.1604

Source: Compiled by the authors.

determined whether there is a significant volatility agglomeration at the high-order moment. First, the basic statistical analysis of each stock is carried out to obtain the basic statistical information representing the return series for each stock, as shown in *Table 2*. From *Table 2*, we see that except for the Industrial and Commercial Bank of China and the Agricultural Bank of China, the skewness of the other stock yields is positive, indicating that there is a greater possibility of a decline in ICBC and the Agricultural Bank of China. Except for China Telecom, the peak statistical value is greater than 3. This indicates that China Telecom's yield distribution has a thicker tail than the normal distribution, and other yield distributions have a lighter tail than the normal distribution. At the same time, it can be seen from the JB statistics that each yield series rejects the assumption of following a normal distribution. Therefore, the basic assumptions of the traditional portfolio cannot be satisfied. If at this time only according to the first two-order moment to select the portfolio may have certain limitations, resulting in the investor's choice of a portfolio is not the optimal portfolio. Considering the impact of the high-order moment on the portfolio can help avoid the impact of financial risks better, and choose a more suitable investment weight.

To determine whether the yield series can be used to establish a VAR model, the unit root test is performed on each stock yield series. The specific results are shown in *Table 3.*

According to *Table 3*, each yield sequence is a stationary series. That is, each yield sequence is a 0-order single whole sequence. Based on the AIC criterion, the VAR(1) model is finally selected to fit the yield series, and then the residuals of the VAR(1) model are extracted to establish the ICA-M GARCHSK. The results of the GARCHSK model fitted to each individual component are presented in *Table 4.*

According to *Table 4*, most of the coefficients in the variance equation are very significant, indicating a high level of volatility aggregation in these 6 stocks. At the same time, according to the fitting results of the skewness equation and the kurtosis equation, we can see that these 6 stocks have obvious conditional skew-

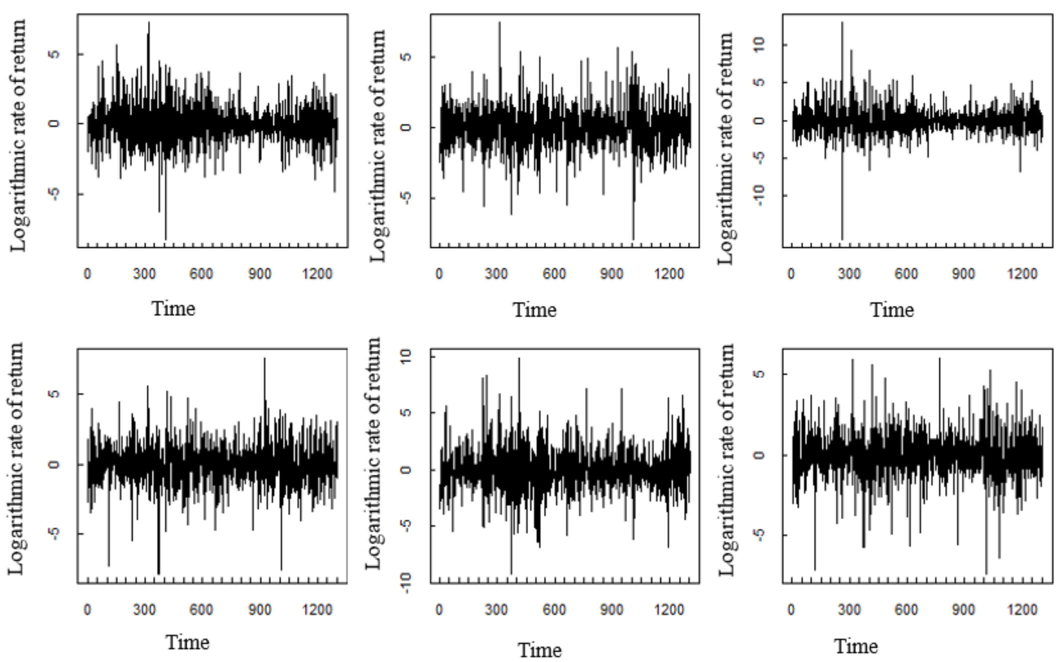

Fig. 3. **6 Stock Closing Price Logarithmic Yield Image**

Source: Compiled by the authors.

Table 2

Basic Descriptive Statistics

Variable	Number of samples	Mean	Variance	Skewness	Kurtosis	JB Statistics
x_1	1303	−0.004	1.374	0.099	2.701	400.963***
x_2	1303	0.015	1.474	0.090	2.304	292.357***
x_3	1303	0.005	1.573	0.080	8.864	4287.536***
x_4	1303	0.011	1.487	−0.204	2.845	451.638***
x_5	1303	−0.007	1.900	0.307	2.453	349.704***
x_6	1303	−0.003	1.415	−0.177	2.835	451.765***

Source: Compiled by the authors.
Note: *** represents passing 1% respectively a Significance test.

ness and conditional kurtosis, and there are significant time-varying features. Therefore, to better avoid risks, investors should take into account the existence of high-order financial risk moments when making investment decisions. Based on this, the construction of a portfolio can better obtain stability and get closer to the desired investment outcome.

The conditional variance, conditional skewness, and conditional kurtosis of each stock are calculated according to the GARCHSK model fitted with each independent component, as shown in *Fig. 4–6*. Based on these *Fig.*, the conditional variance, conditional skewness, and conditional kurtosis have the phenomenon of large fluctuations followed by large fluctuations, and small fluctuations followed by small fluctuations. This also shows that there is also a significant fluctuation aggregation phenomenon of the conditional high-order moment, which further proves that when the portfolio is carried out. The impact of the conditional high-order moment risk on the portfolio cannot be ignored. It should be considered to facilitate investors to make better investment choices.

According to Equation (6), the optimal investment weight for the first 20 days of April 2019 (including April 19, 2019) was obtained using the genetic algorithm, as shown in *Fig. 7.* In the year leading up to April 19, 2019 (including April 2019), each stock's weight change on the 19th is shown in *Fig. 8*.

According to *Fig. 7*, the investment weight of each stock changes with time, and the change of different stock weights over time are also more significant. This also reflects that in the process of building a portfolio, the dynamic changes of risk cannot be ignored to achieve the desired outcome. *Figure 8* demonstrates the change in the weight of each stock at different investment stages. The results show that the dynamic investment weight of each stock varies over time. This

Table 3

Unit Root Test Results

Variable	Statistics	p-value
x_1	−26.556***	<0.01
x_2	−25.589***	<0.01
x_3	−26.429***	<0.01
x_4	−25.977***	<0.01
x_5	−25.473***	<0.01
x_6	−24.2156***	<0.01

Source: Compiled by the authors
Note: *** represents passing 1% respectively a Significance test.

means that the investment situation of investors in each stock daily is inconsistent. In theory, it is necessary to continuously adjust the investment weight according to the different risks faced by different stocks to maintain the expected utility maximization, so the high-order dynamic portfolio is both theoretically and practically more reliable and feasible.

Next, we calculated the investment utility value from April 19, 2024 (including April 19, 2024) to further compare the Dynamic portfolio and the Traditional portfolio. The results are shown in *Table 5*. The change in total utility in the year before April 19, 2024 (including April 19, 2024) is shown in *Fig. 9*, where the red dotted line represents the utility value of the Traditional portfolio.

According to *Table 5*, the average investment utility obtained by the high-order dynamic portfolio is –0.414, while the investment utility of the traditional portfolio is –0.620. At the same time, we can see that the investment return obtained by the high-order dynamic portfolio fluctuates less. In other words, its investment results are relatively stable, and its investment utility is better than the traditional portfolio. This also shows

Table 4

Fitting Results of the CHARTSK Model for Each Independent Component

	Parameter	IC_1	IC_2	IC_3	IC_4	IC_5	IC_6
Equation of variance	w^H	0.0126***	0.2738***	0.1097***	0.1665***	0.0295***	0.0397***
	α_1^H	0.9281***	0.5940***	0.6167***	0.7554***	0.7251***	0.7075***
	β_1^H	0.0447***	0.1242***	0.3833***	0.0595***	0.0429***	0.0522***
Equation of skewness	w^S	0.2145***	0.0278	−0.0468	0.0250	0.2241***	4.0300***
	α_1^S	0.1125	0.2661***	−0.5174	−0.6066***	0.9985***	0.4577***
	β_1^S	0.0161***	−0.0374***	0.0000	0.0016	0.0256***	0.9509***
Kurtosis equation	w^K	0.9165	3.3807***	3.6772***	3.5706***	0.6717***	1.2399***
	α_1^K	0.6659**	0.0356***	0.0000	0.000	0.7336***	0.8743***
	β_1^K	0.0003	0.1838***	0.0003	0.0002	0.1658***	0.0710***

Source: Compiled by the authors.

Note: ***, ** represents passing 1%, 5% respectively a Significance test.

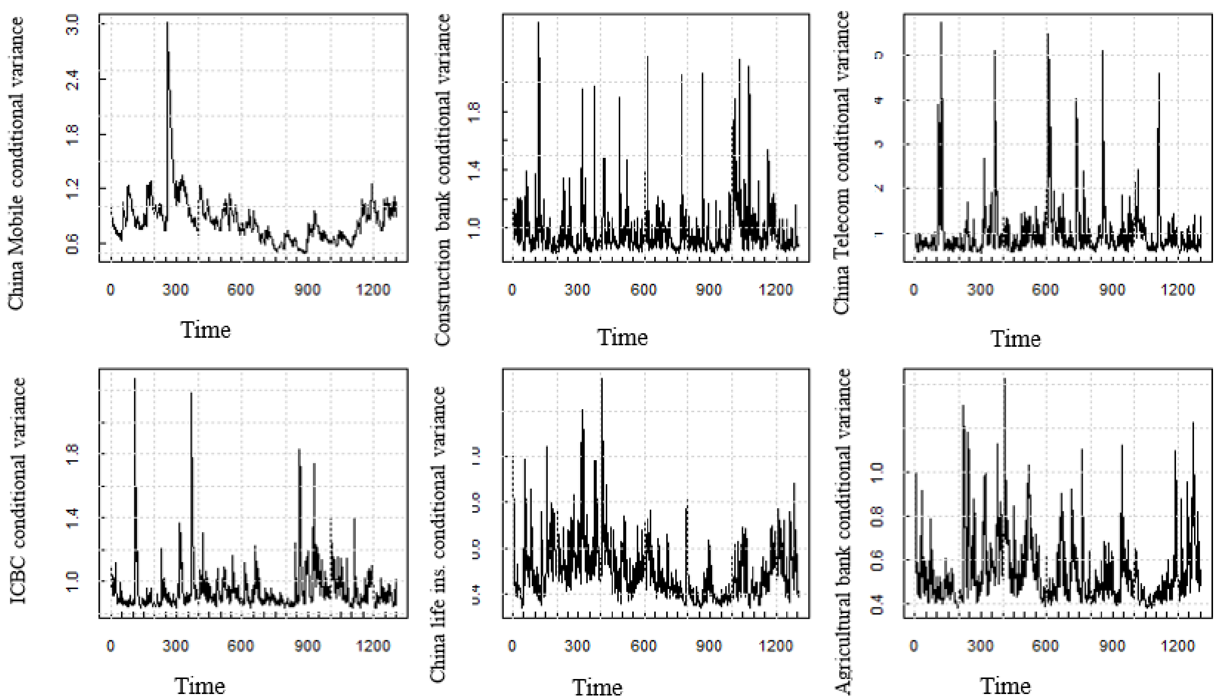

Fig. 4. **Image of the Conditional Variance of Each Stock**

Source: Compiled by the authors.

that if the basic assumptions of the traditional portfolio are not met, only second-order moment risk is considered. It often fails to bring better investment decisions for investors but will misestimate or underestimate the possible risks, resulting in wrong investment decisions. Further, it can be found that the investment weight between different stocks changes with time. That is, the investment weight of different stocks sometimes changes, while the investment weight of each stock in the traditional portfolio remains unchanged. Therefore, ignoring the time-varying risk of different stocks can lead to poor investment results.

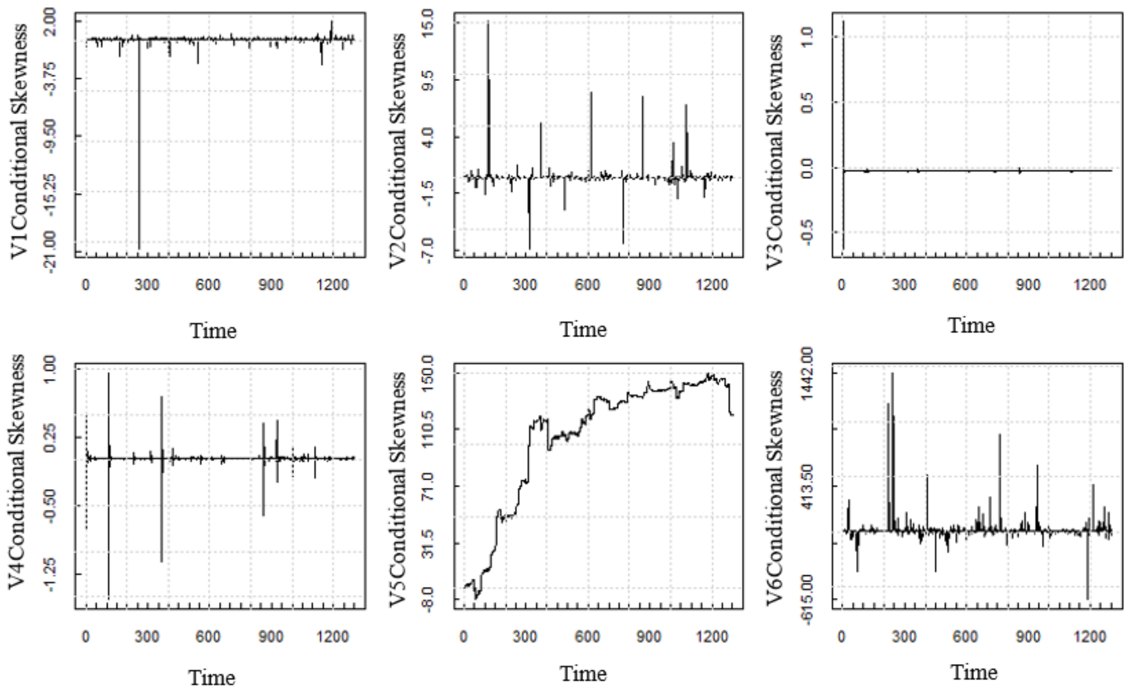

Fig. 5. **Skewness Image of Each Stock Condition**

Source: Compiled by the authors.

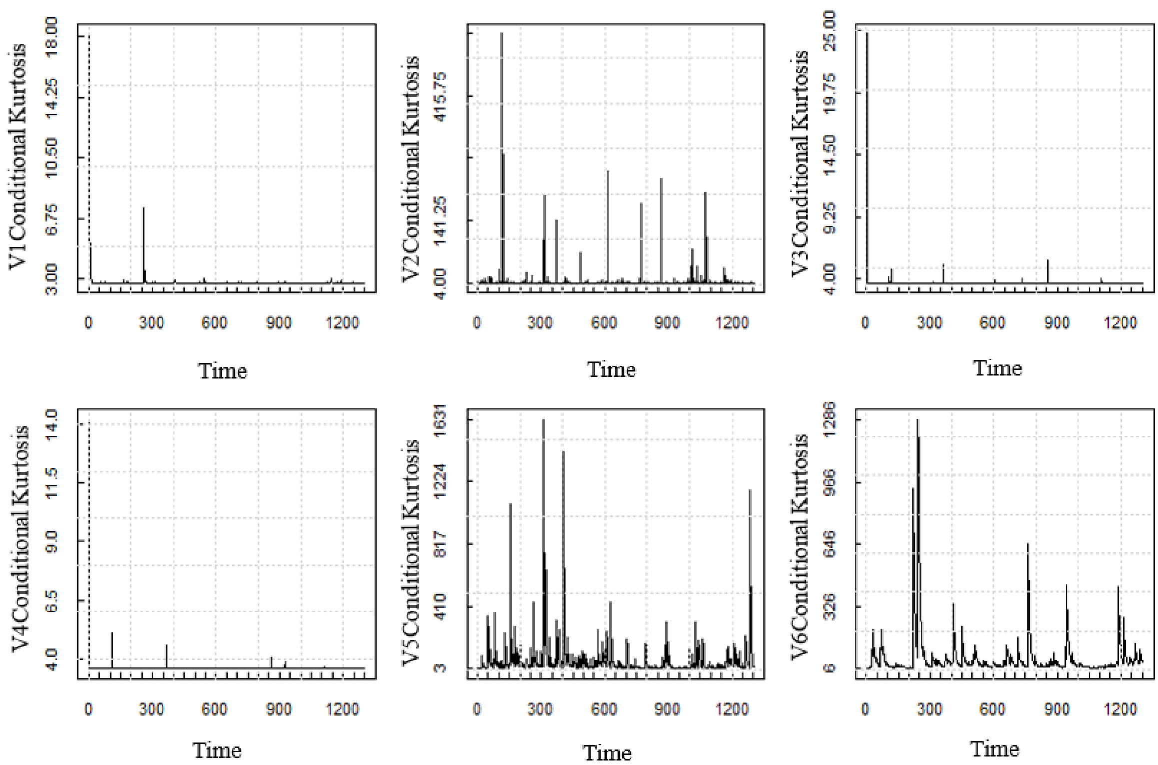

Fig. 6. **Image of the Kurtosis of Each Stock Condition**

Source: Compiled by the authors.

Figure 9 reflects the utility comparison between a high-order dynamic portfolio and a traditional portfolio (where the solid black line represents the utility of a traditional portfolio). The results show that the investment utility of a high-order dynamic portfolio is always higher than that of the utility of traditional portfolio. The investment utility of a high-order dynamic portfolio is relatively stable, which shows the adaptability and reliability of a high-order dynamic portfolio. Therefore, in the ac-

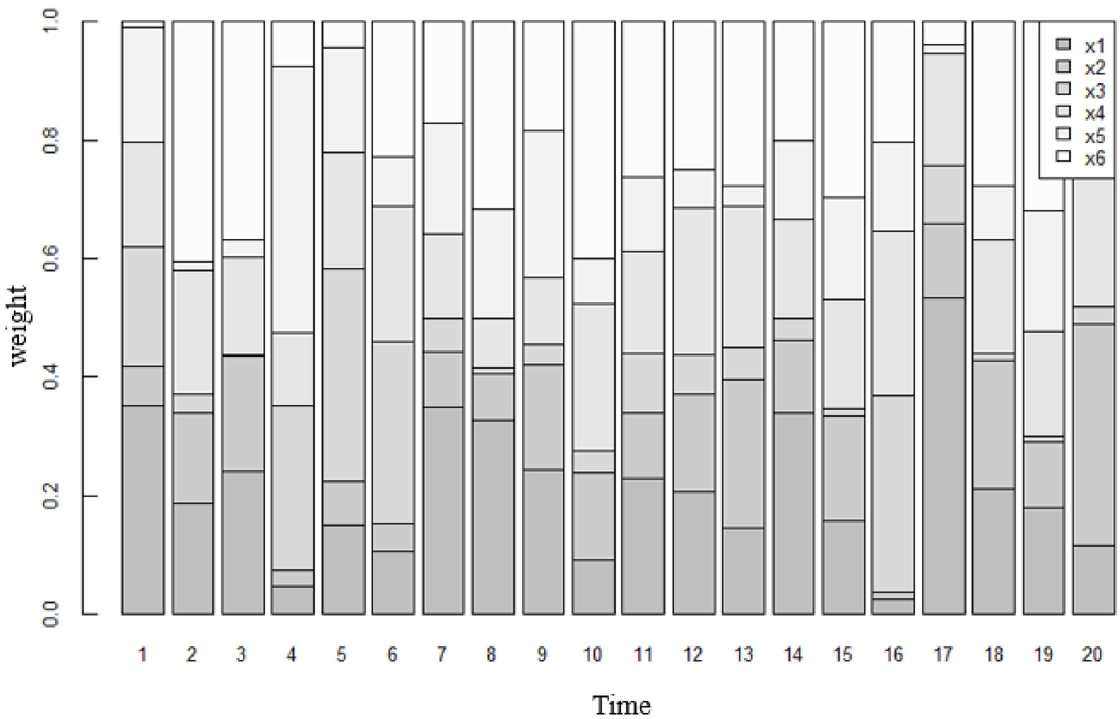

Fig. 7. **Dynamic Weights of a Portfolio**
Source: Compiled by the authors.

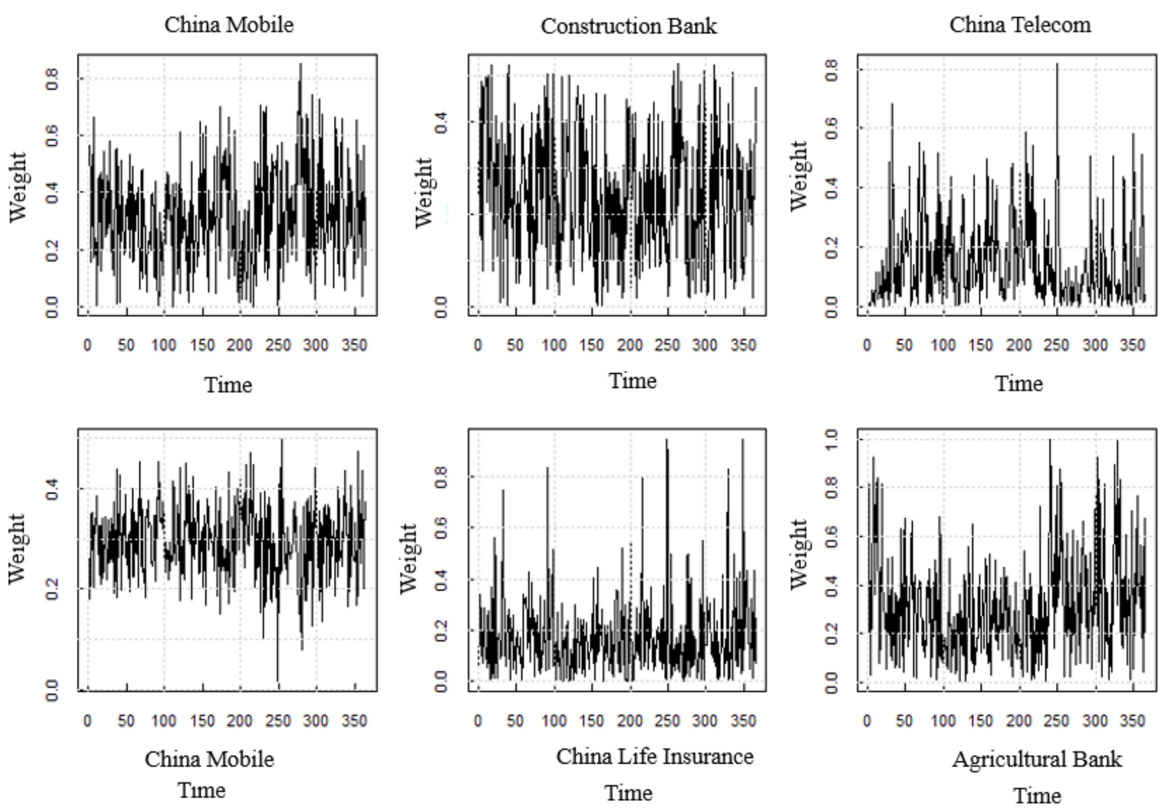

Fig. 8. **Changes in the Investment Weights of Individual Stocks**
Source: Compiled by the authors.

tual investment decision-making process, we should consider the impact of both high-order moment risk and the time-varying risk to make the best possible investment decisions.

Finally, this paper uses the deterministic equivalent losses (CEL%) to compare the specific differences between dynamic and traditional portfolios. This is calculated as:

Table 5

Comparison of Dynamic and Traditional Portfolios

Parameter	Time	x_1	x_2	x_3	x_4	x_5	x_6	Total utility
High-end dynamic portfolios	1	0.35	0.07	0.20	0.18	0.19	0.01	−0.46
	2	0.19	0.15	0.03	0.21	0.02	0.40	−0.37
	3	0.24	0.19	0.00	0.17	0.03	0.37	−0.41
	4	0.05	0.03	0.28	0.12	0.45	0.08	−0.33
	5	0.15	0.07	0.36	0.20	0.18	0.04	−0.35
	6	0.11	0.05	0.31	0.23	0.09	0.23	−0.41
	7	0.35	0.09	0.06	0.14	0.19	0.17	−0.41
	8	0.33	0.08	0.01	0.08	0.18	0.32	−0.36
	9	0.24	0.18	0.03	0.11	0.25	0.18	−0.42
	10	0.09	0.15	0.04	0.25	0.08	0.40	−0.46
	11	0.23	0.11	0.10	0.17	0.13	0.26	−0.40
	12	0.21	0.16	0.07	0.25	0.06	0.25	−0.43
	13	0.15	0.25	0.06	0.24	0.03	0.28	−0.40
	14	0.34	0.12	0.04	0.17	0.13	0.20	−0.44
	15	0.16	0.18	0.01	0.18	0.17	0.30	−0.42
	16	0.02	0.01	0.33	0.28	0.15	0.20	−0.33
	17	0.53	0.13	0.10	0.19	0.01	0.04	−0.45
	18	0.21	0.22	0.01	0.19	0.09	0.28	−0.40
	19	0.18	0.11	0.01	0.18	0.20	0.32	−0.38
	20	0.11	0.37	0.03	0.27	0.06	0.16	−0.42
Traditional portfolios	–	0.44	0.33	0.15	0.07	0.00	0.00	−0.62

Source: Compiled by the authors.

$$\frac{U(V^*)-U(V')}{U(V')}*100\%,$$

where $U(V^*)$ and $U(V')$ sum represent the utility values of a dynamic portfolio and a traditional portfolio, respectively. The greater the deterministic equivalent loss, the better the dynamic portfolio compared to the traditional portfolio, as shown in *Table 6*. The changes in deterministic equivalent CEL% throughout the investment phase are shown in *Fig. 8*.

According to *Table 6*, the CEL value is greater than 0, indicating that the effect of the Dynamic portfolio is better than that of the traditional portfolio. This is due to the fact that the Dynamic portfolio can better capture the presence of high-order matrix risk than the Traditional portfolio and effectively avoid the high-order matrix risk, thereby making a more sensible investment decisions. *Figure 10* reflects the change of deterministic equivalents throughout the investment period. The results demonstrate that the investment effect of high-order dynamic portfolios is basically better than that of traditional portfolios [35–37]. High-order dynamic portfolios introduce high-order moment risk into traditional portfolios [38–44]. This not only weakens the impact of not meeting the normality assumption [45–50] but also takes into account the time-varying nature of risk and achieves better investment results, thus demonstrating the

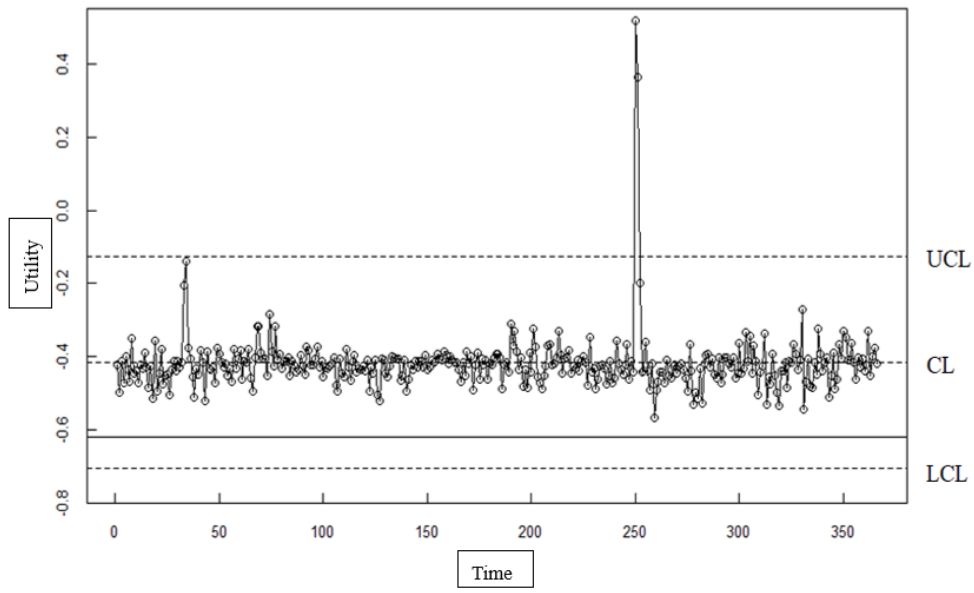

Fig. 9. **Utility Comparison between High-order Dynamic Portfolios and Traditional Portfolios**

Source: Compiled by the authors.

Table 6

Comparison of the Utility Effects of High-Order Dynamic Portfolios and Traditional Portfolios

Days	CEL, %	Days	CEL, %	Days	CEL, %	Days	CEL, %
1	25.66	6	34.13	11	35.11	16	46.58
2	40.75	7	34.15	12	30.86	17	27.28
3	34.64	8	41.23	13	34.70	18	35.91
4	46.83	9	32.76	14	29.52	19	39.38
5	44.13	10	25.85	15	32.02	20	32.71

Source: Compiled by the authors.

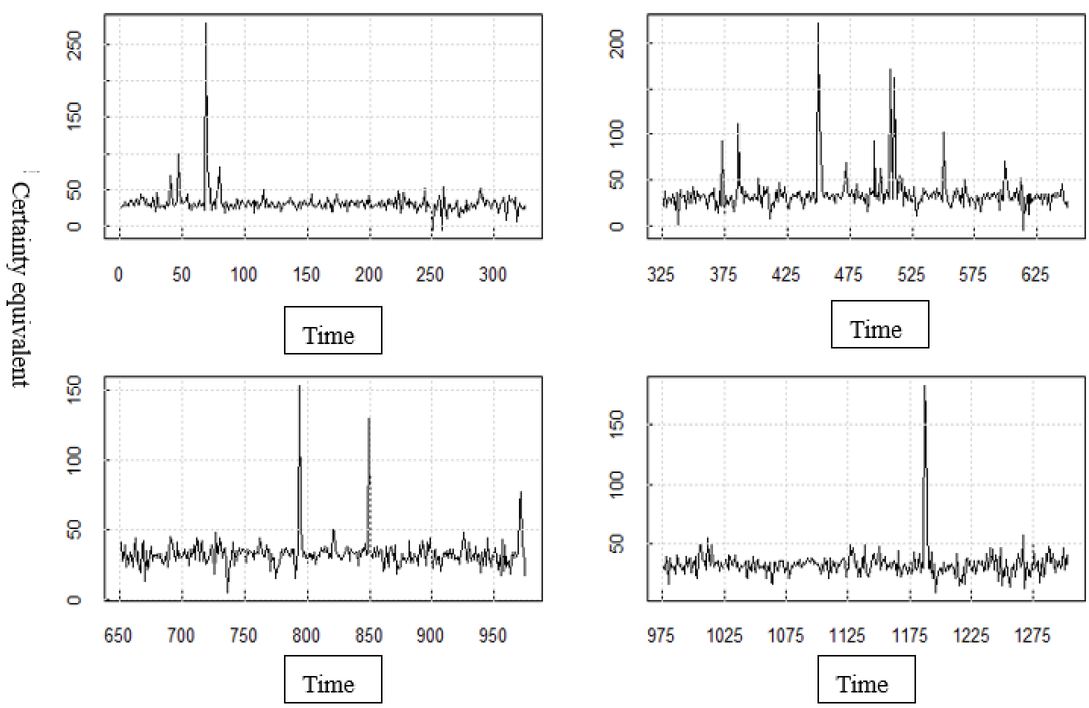

Fig. 10. **Variation in the Loss of Certainty Equivalents (CEL%)**

Source: Compiled by the authors.

robustness and operability of high-order dynamic portfolios [51–55].

CONCLUSION

The Traditional portfolio model requires that the variables obey the assumption of normality. Because of the instability of the financial market, the assumption of normality is often challenging to meet. Therefore, to reduce the impact of violating the normality assumption on the portfolio, skewness, and kurtosis (i.e., high-order moment risk) are also considered in the investment decision-making in order to enhance the reliability of the investment decision-making decisions. At the same time, because the return, covariance matrix, co-skewness matrix, and co-kurtosis matrix of the financial market vary over time, this paper uses the VAR-ICA-MGARCHSK model to capture the temporal variability of returns and risk. Finally, considering the nonlinearity of portfolio solutions based on the utility function, this paper uses the genetic algorithm with an elite strategy to obtain the optimal investment weight to build a dynamic portfolio.

To demonstrate that the effectiveness of the constructed dynamic portfolio is closer to the actual situation, this paper conducts simulation experiments and empirical analysis between the Dynamic portfolio and the Traditional one. The simulation experiment results show that the dynamic portfolio can better consider the existence of high-order moments in the financial market and capture the time variability of high-order moments. At the same time, because the dynamic portfolio takes into account the existence of high-order risks, the dynamic portfolio can obtain better investment results than the traditional portfolio. In the financial market, there is not only a high-order moment risk but also a high-order moment risk that is time-varying, and the high-order moment risk has a significant impact on the portfolio selection. If the high-order moment risk is not considered, it can lead to wrong investment decisions. Therefore, to effectively diversify the risk of financial high-order moments, it is necessary to consider the dynamic investment decisions with high-order moments.

In this paper we consider the possible high-order moment risk in the financial market and pay attention to the dynamic changes in financial risk. However, due to the rapid changes in data in the era of big data, this paper selects the log return data of stocks from January 03, 2014 to April 19, 2024 as a research sample. The data used has a certain lag, which also makes the empirical research of this paper limited to the past development of six stocks of China Mobile, China Construction Bank, China Telecom, Industrial and Commercial Bank of China, China Life Insurance, and Agricultural Bank of China. Therefore, to make the research results more reliable, scholars should try to update the stock return data to the latest date in future research work to make them more timely.

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