Dynamic Financial Asset Allocation Strategy Based on Particle Swarm Optimization Algorithm

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Abstract—With the continuous improvement and development of the financial market, the allocation of financing assets has become a hot topic. In the financial market, the imbalance of capital supply and demand is very common. Therefore, in order to grasp the financial dynamics in time, it is necessary to conduct relevant analysis on its asset allocation. In order to improve the accuracy of calculation, this paper proposes the application of particle swarm optimization algorithm. This paper mainly uses digital modeling and data comparison to study the dynamic financial asset allocation strategy. The experimental results show that the TSVL-DPM model has the strongest ability to predict asset allocation, and the minimum error is 2.01.

Keywords- Particle Swarm Optimization, Dynamic Finance, Asset Placement, Optimization Strategy

1. Introduction

The role of financial assets in economic development is becoming increasingly prominent. With the acceleration of interest rate liberalization reform process, the continuous enrichment of financial instruments and the progress of Internet technology, a variety of innovative and highly practical investment and financing platforms have appeared in China's capital market. But it also faces various risks. Due to the imperfect domestic financial system and inflexible interest rate mechanism, a large amount of funds cannot be effectively used, resulting in idle waste and serious losses. Therefore, it is necessary to reasonably allocate the funds in the financial market.

The research on particle swarm optimization is a commonplace topic, while the research on dynamic financial asset allocation strategy is rare, but there are also some theoretical results. For example, some scholars propose that the two objective optimization model using Kelly cvar function can maximize value gain and minimize risk, and adopt multi-objective particle swarm optimization algorithm for empirical analysis [1-2]. Other experts believe that particle swarm optimization (PSO) is a new optimization technology, whose core idea is to simulate the intelligent effects of fish and birds [3-4]. Some experts pointed out that Bayesian allocation strategy can significantly reduce investment risk, improve the return on investment portfolio, and significantly improve the return on investment [5-6]. Therefore, this paper studies the allocation of financial assets from the perspective of particle swarm optimization algorithm, which is a combination of practical problems and practical means, and has reference significance.

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The main work of this paper includes the following aspects: First, the theory of financial asset allocation is systematically studied. On this basis, three new mathematical models, FCM, PFG technology and game theory based on particle swarm optimization algorithm, are proposed to build a dynamic financial trading platform. Through the analysis of the data obtained by these different modeling methods, relevant conclusions are drawn.

2. Dynamic Financial Asset Allocation Strategy Based on Particle Swarm Optimization

2.1 Convergence of Particle Swarm Optimization Algorithm

PSO algorithm is very fast, simple and easy to understand and implement. It also has few parameters to adjust. PSO finds the best value through particle interaction, but when the search space is very high, its convergence speed becomes very slow near the global optimal value. In this paper, PSO convergence related analysis is divided into four categories: particle motion stability analysis, particle motion trajectory analysis, algorithm local convergence analysis and expected time analysis of the first hit [7-8].

One of the earliest convergence analysis of stochastic optimization algorithm. The iterative stochastic optimization algorithm converges to the search space with probability. The formula is met (2):

$$\forall \ell \succ 0, \lim_{s\to\infty} G(|a_s - A| \prec \ell) = 1 \tag{1}$$

Where, G is a probability measure, is a solution generated by s. There are two possibilities: the first is when A is an arbitrary point in the search space. The second possibility is when A is the local optimal value of the objective function in the search space [9-10].

In the standard particle swarm algorithm, the particle velocity vector leaves the search space and moves to infinity. The analysis of the particle behavior reveals the reason why the resulting solution sequence does not converge. This is known as a stability analysis. The purpose of the analysis is to determine the limits of inertial weights and acceleration coefficients so that particle positions converge to a point in the search space. Deterministic model stability analysis, first order stability analysis, and second order stability analysis. First-order stability analysis verifies the expected values of particle positions, and second-order stability analysis verifies the variance of particle positions. To simplify the development of the update rules, the random components are omitted from the system. The particle position converges to a stable point. If the formula is met (2):

$$A = \frac{2\mathrm{j}}{\left|2 - d - \sqrt{d^2 - 4d}\right|} \tag{2}$$

Where A is the coefficient of the contraction factor, and, j is the interval (0,1]. The greater the value of j, the slower the convergence to a fixed point.

Selecting a coefficient value within the convergence boundary prevents particles from moving indefinitely. However, it cannot be guaranteed that the particle convergence point is locally optimal. If the individual of the particle can best ensure the convergence to the local optimum, then it is said that the particle is locally convergent. If a PSO method is guaranteed to converge to the local optimum, the PSO method is considered to be locally convergent [11-12].

2.2 Dynamic Asset Allocation

In practice, we divide asset allocation management into three levels according to different levels: strategic asset allocation, also known as asset category allocation. This goal aims to achieve asset allocation in various financial markets. Strategic asset allocation is based on long-term forecasts of expected returns, standard deviation and covariance of major asset classes. The goal is to determine the portfolio that best meets the investor's risk return objectives. Dynamic Asset Allocation (DFA) is used to dynamically manage asset allocation ratios after determining strategic asset allocations. Tactical asset allocation (TAA) is a prediction of the risk return rate of short-term assets, which aims to increase the profit opportunities of the portfolio and reflect the short-term investment decisions of enterprises [13-14]. The hierarchy of asset allocation decisions is shown in Figure 1:

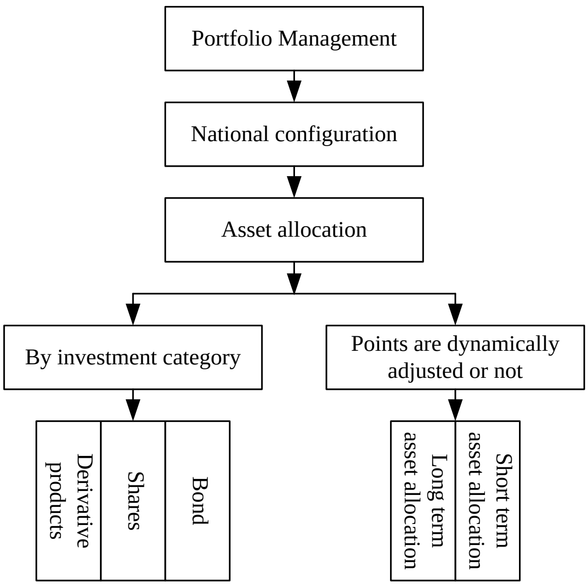

Figure 1. The Hierarchy of Asset Allocation Decisions

Strategic asset allocation is considered from the overall situation of the company, mainly based on the company's investment policy, investment scope and investment period. The investment policies of the Company are mainly divided into two categories: the pursuit of long-term capital growth and the pursuit of current capital income. The Company's investment scope is mainly various securities, such as bonds, stocks, futures, options, warrants and other financial derivatives, precious metals and real estate. Open ended enterprises also hold a certain proportion of cash or short-term bills with strong ability to maintain the liquidity of assets.

Different types of investment have their specific investment scope. To standardize the development of Chinese enterprises, Chinese companies can only invest in stocks, bonds and cash assets. The investment period of strategic asset allocation is mainly from a long-term perspective, and also varies according to different investment policies. The long-term can reach 20 to 30 years, which runs through the entire duration. The company's strategic asset allocation process mainly includes four basic elements: determining the scope of investment, determining the expected return and risk level of appropriate assets, using portfolio theory, using investment theory, using portfolio theory, using portfolio theory, using portfolio theory, and using portfolio theory. Based on the asset allocation optimization model and corresponding software, select the portfolio that can achieve the highest return below the tolerable risk level [15-16].

According to the characteristics of asset managers and the nature of investors, asset allocation shows diversified styles, and there are certain differences in its basis for action, risk and return conditions. Dynamic asset allocation refers to whether and how the fund company adjusts the mixed shares of different asset classes for a long time. According to the different basis of asset allocation adjustment, dynamic asset allocation can be divided into three main strategies: buy and hold strategy, continuous mixed strategy and portfolio assurance strategy.

2.3 Risk Analysis of Dynamic Portfolio

In recent years, the most important revolutionary issue in the financial and financial circles is the birth of the value at risk method, which greatly revised the concept of evaluating performance only by profit figures in the past, and clearly provided quantitative figures as the standard for appropriate capital reserves and profit adjustment. Through the value at risk, investors and managers can better grasp the risk of positions, thus stimulating more active financial commodity markets. Generally, there are three types of indicators to measure risk, but they are still unreasonable for information users or risk managers. Risk evaluation methods include partial evaluation method and full evaluation method [17-18].

The partial evaluation method first assumes that the return of a single asset or portfolio of assets follows a given distribution, so as to establish a certain model and evaluate the risk according to certain rules. However, the full amount evaluation method often adopts the simulation method to construct the distribution that the asset return follows, which avoids the risk caused by the wrong assumption of the probability distribution of the asset return.

The multi factor risk model believes that the change of any kind of asset return in its own characteristics (such as different industrial attributes) or external characteristics (such as changes in economic conditions) at different times will lead to different changes in its own volatility characteristics. Although many factors may be considered in the multivariable estimation method, through the multivariable computing technology, the characteristics of a large number of factors can be condensed into a few simple factors, which can also solve the problem of excessive number of factors, heavy computing load, or linear correlation. Although the multi factor risk model conforms to the advantages of intuition and computing, the selection, processing and computing of factors in this model are quite complex, In addition, subjective judgment is an inevitable disadvantage, so the model risk of this method is relatively high.

In order to measure the market risk of transaction portfolio, many banks use internal models based on value at risk. In terms of strategic risk management, the company can simulate the value at risk under various conditions in advance, and provide various departments with effective quantitative solutions for different investment portfolios, including estimating the capital or other resources invested, the possibility of potential losses and the degree of loss, which can be carried by departments. The department's foreseeable losses and the allocation of funds to cover existing risks. At the same time, the concept of VaR can be applied to each counterparty to estimate the credit risk degree and the maximum possible loss of the counterparty. Generally speaking, VAR assessment of potential risks faced by the company from different perspectives can not only provide information for the company's risk management, but also provide a reference for setting the company's position limit conducive to the company's planning resource allocation and measuring the company's performance.

3. Construction and Experiment of Dynamic Asset Allocation Investment Model

3.1 Model Type

Although SV dpm model can effectively describe the deviation and rough tail of the return on assets, it still has some limitations in describing the return on assets. The threshold effect and nonparametric distribution are introduced into the standard SV model, and the following semi parametric threshold stochastic volatility model is established: TSV-DPM model reflects the volatility of financial asset returns.

3.2 Experimental Data

This paper takes the daily returns of China's stock funds, China's bond funds and gold funds as models. All data are from Wanfang database. The data is sampled from January 1, 2022 to July 1, 2022, with the time interval as the investment cycle of the empirical test.

3.3 Experimental Methods

The nonparametric dynamic Bayesian asset allocation model mainly includes the following steps: First, the characteristic portfolio is dynamically constructed according to the changes of investment opportunities during the investment period. That is, with the change of fixed asset yield and asset correlation, new characteristic portfolios are dynamically created. Secondly, the nonparametric Bayesian model is used to fit the return rate of the dynamic portfolio characteristics, predict the expected value and variance of the characteristics and the return rate of the portfolio. Then we use the mean variance method to determine the weight of the characteristic portfolio by maximizing the expected return and minimizing the risk. Finally, the weight of the new feature combination is converted into the weight of the selected asset allocation asset to determine the dynamic asset allocation strategy.

4. Model Effect Comparison

4.1 Model Prediction Effect Evaluation

The mixed threshold stochastic volatility model (TSV-DPM) is extended, based on which the leverage effect is also introduced into the model, the dual leverage and semi-parametric stochastic volatility model (TSVL-DPM) is constructed, and the generation process of the yield of financial risk assets is modeling. The specific model prediction effect is shown in Table 1:

Table 1. Specific Model Prediction Effect

	TSVL-DPM	TSV-DPM	SV-N
LPS	2.23	2.25	2.22
LPTS (0.05)	2.95	2.95	2.94
LPTS (0.01)	4	4.05	4.21

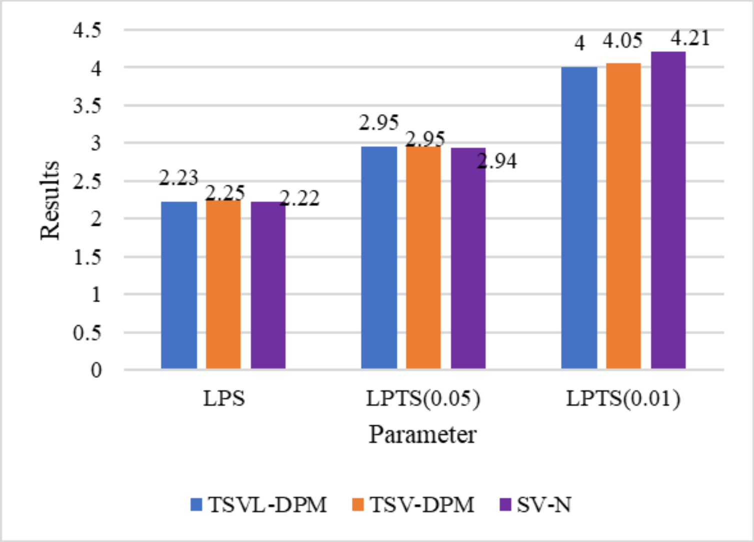

Figure 2. Specific Model Prediction Effect

As shown in Figure 2, we can see that the LPS values are very close, indicating that the model has better predictive power. On the LPTS values, the LPTS value of the TSVL-DPM model is slightly smaller than the LPTS value of the TSV-DPM model, indicating that the TSVL-DPM model is the best predictive power of extreme events.

In order to evaluate the prediction accuracy of different asset return generation models, this paper uses logarithmic prediction score (LPS) and logarithmic prediction tail score (LPTS) evaluation methods to compare the prediction effects of the models. See Table 2 for details:

Table 2. Evaluation of the Model Prediction Effect

	TSVL-DPM	TSV-DPM	SV-N
1	2.01	2.02	2.06
2	2.08	2.12	2.13
3	2.11	2.13	2.14
4	2.07	2.12	2.13

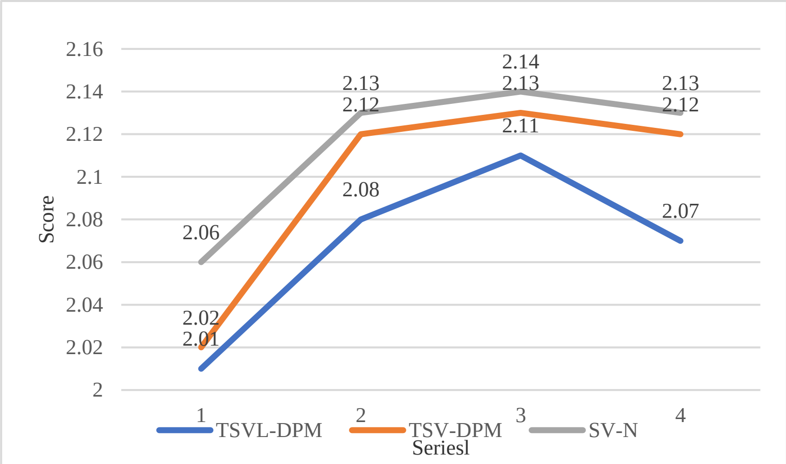

Figure 3. Evaluation of the Model Prediction Effect

As shown in Figure 3, we can see that these models have good fitting effects on sample data. By comparing the logarithmic prediction tail score (LPTS), it is found that the TSVL-DPM model has the lowest score, which is significantly smaller than the SV-N model, indicating that the TSVL-DPM model has the best effect in extreme event prediction.

The main work of this paper is to construct a dynamic asset allocation strategy model based on Bayesian methods under discrete time conditions. In the problem of dynamic asset allocation, due to the time-varying covariance matrix parameter estimation problem, so the Panalysis to solve the parameter estimation problem, in order to capture the asymmetry of FRR volatility and fully depict the typical characteristics of FRR sketail, the threshold effect, leverage effect and Dirichlet process mixed model into the random volatility model, complete the dynamic asset allocation problem of investors with incomplete information.

5. Conclusion

Through theoretical analysis and empirical research, this paper draws some conclusions. The allocation strategy of financial assets is very complex and changeable under the dynamic and gradual characteristics. Because of its complexity and other characteristics. We need to consider that the conditions and characteristics required at different stages are quite different; Moreover, we should also consider the impact of uncertain variables caused by market changes and government policies on decision makers in the stochastic process. Therefore, this paper constructs a mathematical model to predict and analyze the main factors that affect the level of risk management of the system. This paper introduces the advantages of risk analysis and management based on the combination of particle swarm optimization algorithm and dynamic financial asset allocation strategy. In view of the shortcomings of the traditional model, an improved PSO portfolio investment decision-making method is proposed, and its application field, development direction and research status are further discussed.

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