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ECONOMIC CYCLE AND THE LARGE-SCALE ASSET ALLOCATION STRATEGY OF CHINESE NATIONAL SOCIAL SECURITY FUND

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ABSTRACT

Based on the quarterly data of GDP from 1993 to 2018, this paper forecasts that China is in a recession period at present, and the trend of economic cycle in the next ten years is divided into five stages, which can be approximately regarded as a sequential evolution of Juglar-cycle. Combined with the prediction results, the BL model is used to allocate the assets of the three parts of the social security fund: stock, debt and cash. The results show that: 1) when only considering cash, stock and bond, the impact of economic cycle on the allocation of large categories of social security fund assets is not severe, but it has a significant impact on the style and industry rotation of large categories of assets; 2) according to the calculation of the model, the cash assets of social security fund are deposited. In case of over matching, it should be adjusted to the level near the minimum limit of 10%.

Contribution/ Originality: This study contributes to existing literature by establishing a quantitative measurement of economic cycle based on wavelet analysis, and we proposed a new method combining economic cycle, asset allocation and BL-model, we take the investment opinions of Chinese experts into our model and find an improvement in return of Chinese National Social Security Fund.

1. INTRODUCTION

The National Social Security Fund was established in 2000. It is mainly composed of funds allocated by the central government, state-owned assets, and fund income. It is a state reserve dedicated to supplement social security expenditures under the aging population. Starting from the initial 20 billion yuan of financial appropriations, after 16 years of development, the size of the National Social Security Fund has continued to expand. As of the end of 2018, the total assets managed by the National Council of Social Security Funds were 296.3245 billion yuan. On the whole, the process of entering the market for pensions has gone through four stages: conception, piloting, legislation, and implementation. Starting from the Chinese version of the "401K Plan" for the introduction of basic pension insurance into the market by the Securities and Futures Commission in 2011, various legal documents such as the "Administrative Measures for the Investment of Basic Pension Insurance Funds" and the "Regulations on National Social Security Funds" were in place in In November 2016, the management institutions and custodian banks for the investment of pensions in the market were officially announced. At present, the implementation of the investment of basic pensions in China has entered a stage of stable operation.

At present, the scale of pensions in the entire market is about 190 billion yuan. The Social Security Fund Council manages about 70 billion yuan by itself, and 120 billion yuan is entrusted to management agencies. Among them, the stock asset allocation scale is about 15 billion. Social security funds entering the market, while sharing investment income, also means taking on market risks. How to balance benefits with risks and maximize the value preservation and appreciation of national social security fund assets has formed an important proposition for social security funds entering the market. The "Basic Pension Insurance Fund Investment Management Measures" clearly stipulates the asset allocation constraints of social security funds. Based on the current status of the domestic capital market, this article attempts to explore the optimal investment strategy in accordance with the basic investment policy of social security funds in different economic states by dividing the economic cycle.

2. LITERATURE REVIEW

2.1. Basic Theoretical Framework of Asset Allocation

Classic investment theory started with Markowitz (1952) mean variance model. This model believes that in a perfect market, rational investors will measure the return level of securities by expected returns, and measure uncertainty and correlation with variance and correlation coefficience. On this basis, investors choose the maximum return combination with the same variance or the minimum volatility foot combination with the same return. In addition to the perfect market, rational investor assumptions, and the measurement of return risks, this model also implicitly specifies assumptions such as the normality of securities returns, and simplifies market realities such as taxes and transaction costs. These theoretical paradigms constitute the basic framework of traditional portfolio theory. In the past half century, the academic community has made various improvements to the modern portfolio theory from different aspects to make it more suitable for practical market applications. These improvements mainly focus on the improvement of the basic assumptions of the model, the optimization of the objective function, the solution of special conditions to the model, and the reduction of the complexity of variable calculation by upgrading the calculation technology.

First, based on Gauss-Markov assumptions, the standard mean-variance model uses variance to measure risk levels. On this basis, the academic community has made a lot of attempts to improve the measurement of risk to further make the model closer to the market reality. Another typical extension is the application of Value at Risk (VaR) (eg Gaivoronski and Pflug (2013)). Based on VaR, Rockafellar and Uryasev (2002) proposed the concept of CVaR (Conditional Expectation at Value at Risk). Compared with VaR, this concept can achieve a higher consistency risk measurement, making up for the limitations of VaR's sub-additivity and tail risk. CVaR not only improves the limitations of VaR, but is also used to add uncertainty to the mean variance model and improve the quantification of risk aversion coefficient (Chan *et al.*, 2014).

In addition to the variance setting, another important aspect of the mean variance model is the improvement of perfect markets and no transaction costs. Earlier studies such as Arnott and Wagner (1990) proposed that investors required excess returns in order to make up for transaction costs, otherwise it would lead to invalid portfolios. In addition, in terms of the rational person hypothesis of investors, on the one hand, some objective conditions that cause the rational person hypothesis to be broken are considered, mainly the background risks faced by investors in asset allocation (Gollier, 2001) such as housing investment, consumption habits, medical health Background conditions such as the environment will have an impact on the portfolio (eg (Edwards, 2010; Goldman and Maestas, 2013)). Another aspect is the improvement of investor's decision-making mechanism, which mainly includes the “mental accounts” in behavioral finance and other factors into the mean variance model (Das *et al.*, 2010).

With the improved mean variance model, it is still difficult to solve the problem of over-sensitive parameters and over-fitting parameters, and the above research has no significant advantage over traditional management-type investment. To this end, Black and Litterman built a Black-Litterman model that takes into account investor perspectives. The model first obtains the equilibrium return rate and its distribution implicit in market information through the CAPM model, further infers its excess returns based on Sharpe's inverse optimization method, and uses the theory of Bayesian decision making The outlook and its likelihood are introduced into the portfolio model to obtain the posterior probability distribution of the rate of return, and the optimization conclusion of the portfolio is improved based on this revised distribution. There are certain problems with the basic setting of the BL model, mainly because the quantification of subjective opinions is limited in many cases. Therefore, it is necessary to incorporate various existing analysis frameworks for asset targets into the subjective judgment of the BL model into the model. Existing research has improved and extended the BL model. Based on the theoretical framework of He and Litterman (1999); Cheung (2013) proposed the Augmented Black-Litterman (ABL) model. Factor analysis was added to the model. Davis and Lleo (2013) further improved the model by improving the viewpoint matrix.

2.2. Combination of Business Cycle and Asset Allocation

Since Merrill Lynch proposed the "investment clock" theory, this theory has become an enduring analysis paradigm in the study of cross-market asset allocation and industry rotation in specific markets. The "investment clock" theory unifies the rotation of large-scale assets and industries in the framework of the economic cycle. It is believed that in different economic cycles, different large-scale assets or industry securities will perform better than others. There are some relatively poor performances that should be avoided. From the theoretical analysis of the "investment clock", the economic cycle changes sequentially from the beginning of prosperity through heat, stagflation, and recession, and the relative cyclical assets in different periods will also be replaced sequentially.

However, the "investment clock" theory often encounters a series of problems in practical analysis: first, the actual business cycle does not follow the order specified in the theory; second, in the securities market, asset allocation, industry rotation There are many different explanations for the motivation of movement; once again, even if it reflects certain characteristics with the economic cycle, the periodicity of its rotation is unstable and difficult to predict. For example, in the Chinese A-share market from the second half of 2015 to the present, the rotation of stock performance in different industries is very fast, which cannot be explained by economic fundamentals. It is vividly described as: The "clock" theory is a typical example of poor performance in the actual analysis of securities. Therefore, whether the cyclical factors of the industry can explain the industry's rotation effect, otherwise what kind of logic should be used to explain this issue remains to be further studied and discussed.

In addition to the theory of “investment clock” that attributes the drivers of large-scale assets and industry allocation to the macroeconomic cycle, related research in the academia on industry cycle rotation drivers has also proposed the monetary environment (Conover *et al.*, 2008) and the leading lag relationship (Kanas and Kouretas, 2001) momentum and inversion. In the traditional analysis of industry factors, scholars often analyze industry rotation by adding industry factors to the Fama-French three-factor model, but in the research results, the systematic risk of market influence factors is always the most significant In different market conditions, there are also different factors showing significant effects, but industry characteristics are often not as obvious as other factors. This makes it necessary to introduce more advanced thinking and analysis tools into the analysis of industry configuration. Recently, some scholars at home and abroad have used various methods to study industry factors (such as Bakhsha *et al.* (2015)) and have obtained results that can be used for reference. Among them, the time-frequency analysis of the time series of the securities market is a major aspect. At present, the typical time-frequency analysis tools in economic research mainly include Box-Jenkins series models and factor models that focus on time-domain analysis, and Fourier transform and wavelet analysis that focus on frequency-domain analysis. Tuning and filtering analysis methods. These models often have non-stationary non-linear data, key parameters that depend on subjective settings (such as the basis function of Fourier analysis and seasonal frequency in seasonal adjustment, etc.), and lack of economic explanatory power (such as some artificial intelligence technologies). Problems, scope of application and effectiveness need to be improved.

3. ECONOMIC CYCLE PREDICTION BASED ON WAVELET ANALYSIS

3.1. Basic Theoretical Framework of Asset Allocation

Wavelet analysis can realize localization in the time and frequency domains. The analysis indicators can be analyzed at multiple levels and angles from far to near, and find the influencing factors of various data generation and performance status. The evolution of various indicators at any scale the analysis of the trajectory infers the future development of the indicator. According to Percival and Walden, if the function satisfies admissibility conditions (Equation 1 means the function is admissible.)

$$\int_0^{\infty} \frac{|\Psi(k)|^2}{k} dk < \infty \qquad (1)$$

Or the Equivalent form of Equation 1:

$$\int_{-\infty}^{\infty} \Psi(t) dt = 0 \qquad (2)$$

The function $\Psi(t)$ is called the wavelet mother function, and the Fourier transform of the function is represented by $\Psi(t)$ to $\Psi(t)$. Equation 2 can express the oscillatory nature of the generating function and its frequency domain characteristics. By translating and scaling the generating function $\Psi(t)$, we can get Equation 3,:

$$\Psi_{\tau,s} = 2^{-\frac{s}{2}} \Psi(2^{-s}t - \tau) \qquad (3)$$

In Equation 3, $s \in Z = \{0, \pm 1, \pm 2, \ldots\}$ is called scale parameter, $\tau \in Z$ is called translation parameters, Equation 3 is the wavelet function.

Equation 4 is the frequency response of the wavelet generating function.

$$\Psi(k) \begin{cases} 1 & |k| \in (\pi, 2\pi) \\ 0 & else. \end{cases} \qquad (4)$$

Therefore, Equation 5 is the frequency response of the expanded wavelet function.

$$\Psi_{\tau,s}(k) \begin{cases} 2^{s/2} & |k| \in (2^{-s}\pi, 2^{-s+1}\pi) \\ 0 & else. \end{cases} \qquad (5)$$

And $f(t)$'s wavelet is transformed as Equation 6:

$$C_{\tau,s} = \int f(t) \psi_{\tau,s}(t) dt \qquad (6)$$

In Equation 6, $C_{\tau,s}$ contains $f(t)$'s time range $[s_t + \tau - \Delta s, s_t + \tau + \Delta s]$ and its information. In the meantime, $f(t)$ contains information during frequency range $[{}^{\omega}/_{s} - {}^{\Delta\omega}/_{s}, {}^{\omega}/_{s} + {}^{\Delta\omega}/_{s}]$:

$$[s_t + \tau - \Delta s, s_t + \tau + \Delta s] \times [\omega/_s - \Delta\omega/_s, \omega/_s + \Delta\omega/_s] \quad (7)$$

In Equation 7, the area of function's "time and frequency window" is $4\Delta t\Delta\omega$. The scaling of wavelet analysis comes from the adjustment of s. A smaller s value corresponds to a short-time window and a high-frequency analysis frame, whereas a larger s corresponds to a low-frequency long-term analysis.

Wavelet analysis can analyze and predict time series in both time and frequency domain space. Compared with time series analysis in pure time domain, it can provide new perspective and feature robustness for prediction. Compared with the traditional Fourier decomposition technique, wavelet analysis has the advantages of locality without global data, and disorderly setting of specific data structures. Therefore, this paper selects wavelet analysis for analysis and prediction based on the non-stationary and nonlinear characteristics of macro data.

3.2. Empirical Results and Analysis

3.2.1. Selection of Economic Data and General Fluctuation Trends

China's business cycle research is mainly achieved by analyzing the growth rate. This is because China has been in an economic growth state since the 1980s, and only the growth rate fluctuated. Among the macroeconomic growth indicators, the level of GDP growth is the most commonly used and explained variable, and it is one of the core variables to measure economic level fluctuations (Stock and Watson, 1999). Based on the analysis of the statistical data of the national economy in this article, it is found that after China's reform and opening up, there were five rounds of growth cycles, of which the third round (1987-1990) ended in 1990. Therefore, this paper uses China 's actual GDP growth rate as an indicator, and its sample interval is from the fourth quarter of 1993 to the fourth quarter of 2018. A total of 100 data are used to construct a univariate wavelet prediction model.

3.2.2. Data Decomposition Using Wavelet Model

Since the GDP fluctuation data can be layered, we thought of using the wavelet model to split the GDP sequence into sub-sequences of different fluctuation patterns. This article uses Python to implement the db (4) filter to decompose the sample sequence. This filter has good performance and interpretability. After the decomposition is realized, further regression analysis is performed on each subsequence by R software to determine the parameters to be determined. The smoothing methods such as wavelet transform and traditional seasonal adjustment need to set the wave pattern manually. Its decomposition algorithm is adaptive and is a data-driven process. Under wavelet decomposition, the original sequence will be decomposed into components of different power periods of 2, and by observing component subsequences of different scales, the constituent elements of the time-frequency characteristics of the original sequence can be discussed:

$$\text{Data} = cA5+cD5+cD4+cD3+cD2+cD1$$

cA5: Long-term trend of wavelet decomposition extraction sequence, fluctuation or oscillating part in cD1-cD5 window. cD1, cD2 are higher frequency components and the fluctuation frequency is faster than one year. Through this simple economic logic, cD1 and cD2 can be combined to obtain a high-frequency fluctuation pattern, and then cD3, cD4, and cD5 can be synthesized to obtain a medium-term fluctuation trend. CA5 represents a long-term fluctuation trend.

Using the wavelet transform, the GDP growth rate can be decomposed into a long-term trend term (cA1) above 32 quarters, a low-frequency fluctuation term (cD3-cD5) over one year, and a high-frequency fluctuation term (cD1 and cD2) under one year. Using the ARIMA model to fit and refer to the literature, we can see the following fluctuation trend equation.

Long-term fluctuation trend:

$$VGDP_t^L = 9.603 + 2.389VGDP_{t-1}^L - 1.808VGDP_{t-2}^L + 0.414VGDP_{t-3}^L + \varepsilon_t$$

Mid-term fluctuation trend:

$$\Delta VGDP_t^S = 1.490\Delta VGDP_{t-1}^S - 0.581\Delta VGDP_{t-2}^S + u_t - 0.995u_{t-2}$$

Short-term fluctuation trend:

$$VGDP_t = -0.543VGDP_{t-1}^I - 0.383VGDP_{t-3}^I + \sigma_t - 0.978\sigma_{t-2}$$

Prediction model:

$$VGDP_t = VGDP_t^L + VGDP_t^S + VGDP_t^I$$

Based on the analysis of the fluctuation characteristics of the above model, this article chooses the Juglar-cycle with a duration of 10 years as China's economic cycle. It is assumed that 2017Q2 is the trough of the economic cycle and is in the recession phase. From 2018Q1 to 2020Q2, it is a recovery, and 2020Q3-2022Q4 is overheating. 2023Q1-2024Q4 is a stagflation, after which a second phase of decline has occurred.

4. LARGE ASSET ALLOCATION OF SOCIAL SECURITY FUNDS BASED ON THE BL MODEL

4.1. Black-Litterman Model

The Black-Litterman (BL) model uses the market equilibrium returns of CAPM and its distribution as a prior hypothesis, adds the posterior information of the Investor Views portfolio, and inversely optimizes the excess A posteriori distribution of returns. This method is widely used in investment practice because of its high practical value.

The basic framework of the BL model is as follows:

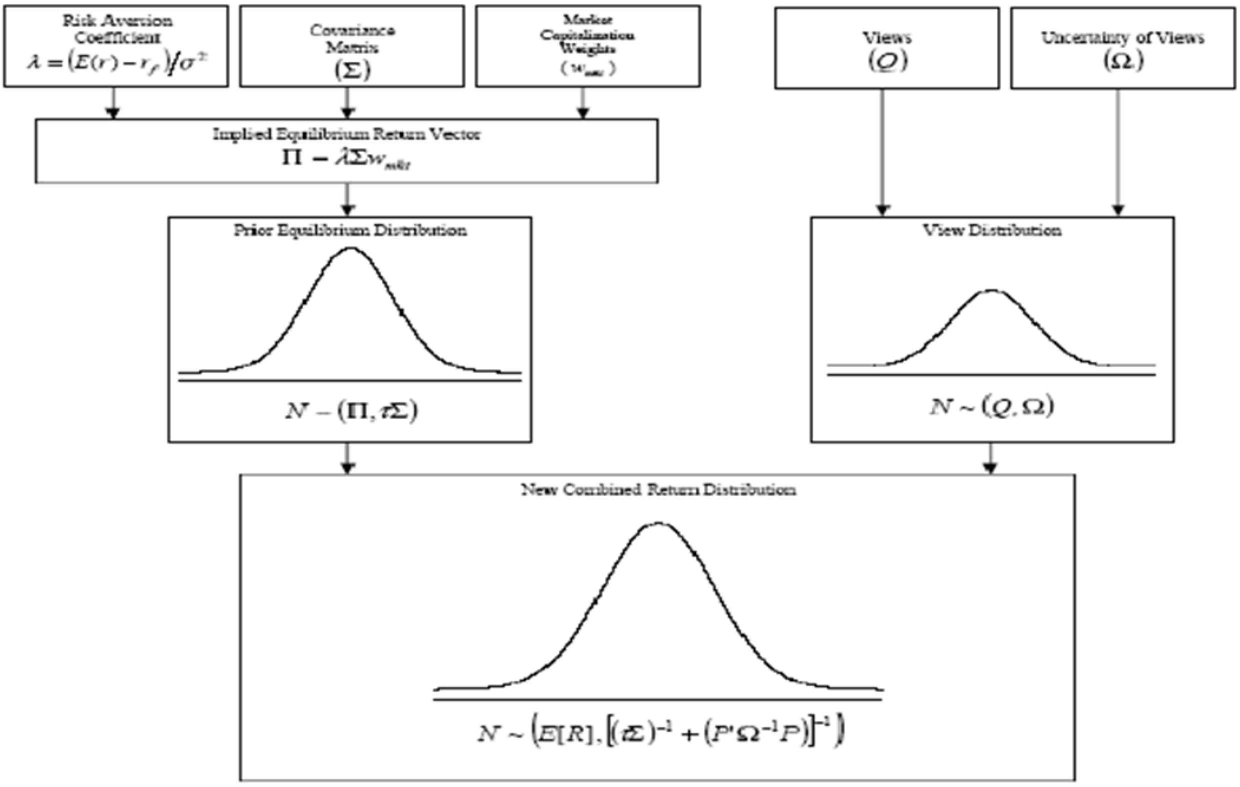

Figure-1. BL model basic framework.

Where:

n: Number of assets.

k: Number of Perspectives ($k \leq n$).

λ: Risk aversion coefficient.

E(R): Posterior vector of return ($n\times1$).

τ: Scalar.

$\sum$: Covariance matrix of n asset returns($n\times n$).

$\prod$: Vector of implied equilibrium return($n\times1$).

W_{mkt}: Weight of market value.

P: Matrix of investor Perspectives($k\times n$, when there is only one perspective, it becomes $1\times n$).

Q: Vector of excess return of Perspectives ($k\times1$).

Ω: Matrix of Confidence level of Perspectives($k\times k$).

BL model framework performs Bayesian analysis based on prior equilibrium income distribution and post-audit investor opinion information:

$$P(A|B) = \frac{P(A)P(B|A)}{P(B)}$$

$P(A)$ represents the expected return distribution of each asset, $P(B|A)$ represents the return distribution of portfolio after the investor's point of view, $P(B)$ is constant, which is given by the researcher. $P(A|B)$ is the optimal solution of BL model. Based on the hypothesis of different distribution of $P(A)$ and $P(B|A)$, different distribution of $P(A|B)$ can be obtained. If both of them are assumed to obey the normal distribution, the distribution of the optimal solution follows the setting in Figure 1.

The initial solution of BL model's asset allocation weight is the optimal solution based on historical data under the assumption of market consistent expectation. Based on this initial solution, the optimal solution considering the subjective concept of investors can be obtained through the reverse optimization of equilibrium income. The main process is as follows:

Firstly, the risk aversion coefficient is obtained through historical data, and then the equilibrium income is obtained:

$$\lambda = \frac{E(r) - r_f}{w_{mkt}^T \Sigma w_{mkt}}$$

$$\Pi = \lambda \Sigma w_{mkt}$$

Where λ is Risk aversion coefficient Π is Equilibrium return.

Then we deduce the formula of return of BL model:

$$E(R) = [(\tau\Sigma)^\wedge(-1) + P'\Omega^\wedge(-1)\ P]^{-1}[(\tau\Sigma)^\wedge(-1)\ \Pi + P'\Omega^\wedge(-1)\ Q]$$

P, Q matrix are respectively the prediction of relative advantage assets and relative excess return in the subjective view of investors:

$$P = \begin{bmatrix} 0 & 1 & \cdots & \ldots 0 \\ \vdots & 0 & 1 & \cdots \vdots \\ 0 & \ldots & 0 & \ldots 1 \end{bmatrix}$$

$$Q = \begin{bmatrix} \pi_1 \\ \vdots \\ \pi_n \end{bmatrix} + \begin{bmatrix} \varepsilon_1 \\ \vdots \\ \varepsilon_n \end{bmatrix}$$

Each row vector of P matrix represents that the investor thinks that the class I of N assets may obtain excess return. For example, in the period of economic recession, if the investor believes in the market law and believes that the bond is a large asset with relative advantage, a row vector with the corresponding bond component of 1 and the other components of 0 represents this view.

Q matrix is n × 1 matrix, which represents investors' judgment on relative excess return of assets. π IUI is the excess return of each asset. The Q-matrix can adjust the solution of the model by adjusting the distribution of the expected disturbance term ε - I. The Ω in the previous section represents the variance covariance matrix of ε IUI. The BL model assumes that the views of investors are independent and there is no guidance relationship, so Ω is a diagonal matrix.

Based on the above settings, the analytical solution of BL model can be obtained:

$$\boldsymbol{\omega}^* = \frac{1}{1+\tau}(\boldsymbol{w}_{mkt} + \boldsymbol{P} \times \Delta)$$

$$\Delta = \frac{\tau\Omega^{-1}Q}{\delta} - A^{-1}P\frac{\Sigma}{1+\tau}\left(w_{mkt} + \tau\Omega^{-1}Q/\delta\right)$$

$$A = \frac{\Omega}{\tau} + P\frac{\Sigma}{1+\tau}P^T$$

$\boldsymbol{\omega}^*$ is the optimal solution of BL model.

Compared with the traditional portfolio method, the advantage of BL model is that it is not sensitive to numerical value, and it also considers historical data and scenario prediction as well as adding heterogeneous expectations. This probability measurement of investors' own subjective evaluation is undoubtedly closer to the actual situation of the portfolio problem.

4.2. Asset Allocation Strategy of Social Security Fund

4.2.1. Analysis of Customer Records of Interviews

First, based on the output gap method mentioned in the previous chapter of the output, this article divides the 2007Q1-2017Q2 economy into four stages of recovery, overheating, stagnation and recession from the two dimensions of output gap and CPI growth. Returns on major assets at various stages and the variance-covariance matrix. The reason for this is: This article assumes that the non-stationarity of the returns on large-scale assets in the market mainly comes from the impact of the economic cycle. If the effect of the economic cycle is stripped, the returns of assets that are about to belong to the same competitive state are stable. Moment estimators can be used in future predictions. Through statistical analysis, we conclude that the characteristics of the major asset returns at each stage are as follows:

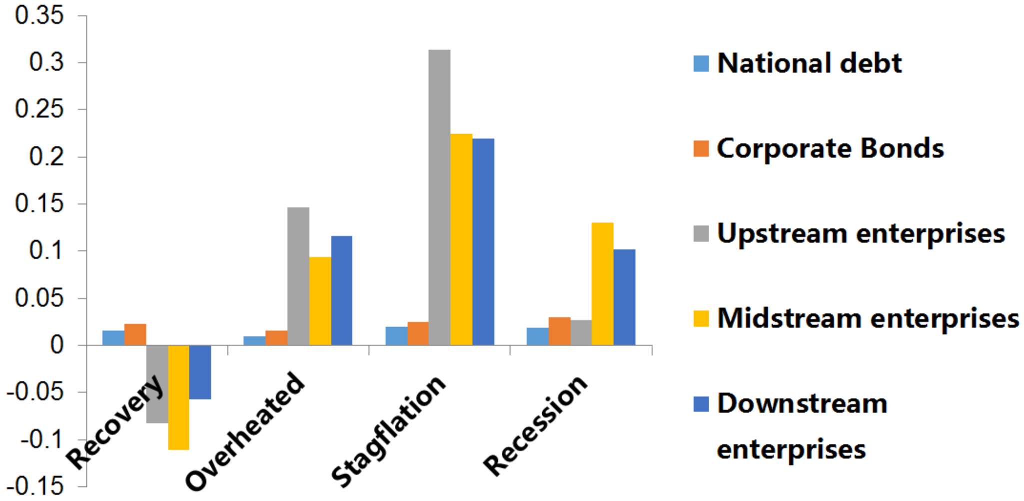

Figure-2. Major asset returns at different stages.

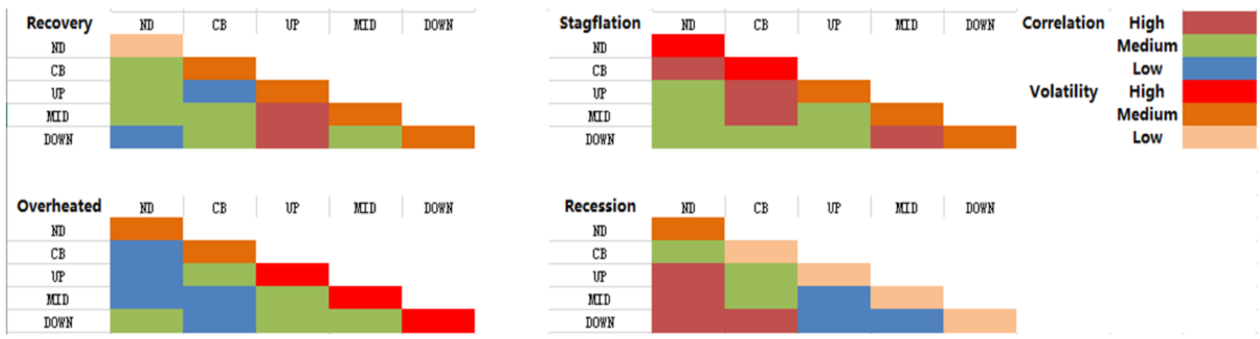

Figure-3. Volatility and correlation of major assets in different stages.

In Figure 3, ND=National Debt, CB=Corporate Bonds, UP= Upstream enterprises, MID= Midstream enterprises, DOWN= Downstream enterprises.

According to the above measurement results of economic cycle, we will apply different posterior data in the prediction of different periods. Because the social security fund has no clear regulations on the rate of return and volatility, this paper no longer considers these two constraints in the model of planning solution, only considers the constraints on asset size. Further, in the first chapter of this paper, it is considered that the scale of social security fund will not have a large withdrawal, so there is no need to stipulate additional rigid positions for cash assets.

4.2.2. Weight Determination of Risk Assets

Based on the basic assumption of the position of social security fund, we set up a nonlinear optimization model with the objective function of maximizing Sharpe index. Based on the historical data, we can get the optimal position proportion of four different stages as follows:

Table-1. Optimal solution without considering subjective point of view $\boldsymbol{w}_{mkt}$.

Asset / Cycle state	ND	CB	UP	Mid	Down
Recovery	82.97%	17.03%	0.00%	0.00%	0.00%
Overheated	24.58%	73.90%	0.16%	0.00%	1.37%
Stagflation	39.94%	53.30%	4.03%	0.00%	2.74%
Recession	48.47%	51.23%	0.00%	0.30%	0.00%

In Table 1, "82.97%" in the second row, second column means we should allocate 82.97% of our total assets to National Debt(ND) when the state of economic cycle is Recovery. It is the optimal proportion. Similarly we should adjust the proportion to the optimal level in different economic cycles.

According to Table 1, we can use the BL model formula mentioned in the previous section to get the implied equilibrium return and investor risk aversion coefficient in different stages of the market:

Table-2. Implied equilibrium return and risk aversion coefficient.

Asset / Cycle state	Implied equilibrium return Π					Risk aversion coefficient λ
	ND	CB	UP	Mid	Down	
Recovery	0.004	0.006	-0.012	-0.012	-0.008	6.175
Overheated	0.003	0.006	0.048	0.044	0.046	1.358
Stagflation	0.015	0.019	0.241	0.188	0.169	1.332
Recession	0.020	0.006	0.114	0.139	0.159	18.649

In Table 2, 0.004 means the implied equilibrium return is 0.4%. Risk aversion coefficient is calculated before, larger the number, more fear of risk the investor is. This paper has obtained data based on historical market data and consensus expectations. Further, by analyzing the impact of investors' subjective views, this paper selects Liu Shijin, former deputy director of the development research center of the State Council and Dr. Ha Jiming, vice chairman and chief investment strategist of Goldman Sachs, as the variables of subjective views. Both experts have long-term research on economic forecasting and asset allocation, and are relatively authoritative in relevant fields. This paper will not make further analysis of its argument, but will translate the main information of the academic report into the viewpoint matrix based on the investment clock theory.

Table-3. Expert opinions and interpretation.

Expert	Perspective	Setting in matrix
Expert1	At the end of 2019, China's GDP growth will reach the bottom, but China is facing many problems such as deleveraging, destocking and the rebound of corporate profits. In particular, when the "bottom of corporate profits" reaches the bottom cannot be determined. If the "bottom of profits" reaches the bottom in time, China's economy can successfully end the recession and contraction and realize recovery, but if it does not reach the bottom, it may fall into "Recession stagflation" cycle.	Before the end of 2019, there will be recession. After 2020, there will be recovery or stagflation. The probability can be simplified by half.
Expert2	China's GDP data is rather wet. According to the analysis of the real economy related data and the trend of RMB devaluation, China's GDP growth rate may actually exceed 6%. It is a regular thing that China's GDP will fall by about 5% in 2022. Both the authorities and the public should face it squarely.	Mainly recession before 2022

Table 3 shows how we take experts' opinions into our matrix. Through the analysis of experts' opinions, it is not difficult to find that there are many differences in experts' study and judgment of economic situation. Take 2017-2020 as an example:

$$P = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}$$

The first and second row vectors represent the argument of expert 2. According to the investment clock theory, bonds are the dominant assets of the recession economy. Therefore, in the corresponding part of the bond's standard 1, other standard 0, the same way, the fourth to sixth lines are: Expert 1 believes that the recovery may occur after the end of 2019 when the economy bottoms out, at this time, stocks are the relatively dominant assets, and in the stagflation period, the monetary dominant assets are not involved here, So the third row vector is all zeroed. It should be noted that expert 1's opinion has two possible prediction directions, each of which has different probability of occurrence. In this paper, this uncertainty is reflected in the specific excess return.

First of all, for the sake of simplicity, we will further predict the excess earnings under the forecast, but assume that the difference between the market equilibrium earnings and the historical data is the possible excess earnings. The same four economic states correspond to four types of excess earnings:

Table-4. Excess return in relative equilibrium (%).

Asset / Cycle state	ND	CB	UP	Mid	Down
Recovery	1.153	1.638	-7.061	-9.862	-4.989
Overheated	0.660	0.965	9.856	5.033	7.024
Stagflation	0.464	0.565	7.247	3.618	5.012
Recession	-0.138	2.407	-8.747	-0.858	-5.754

Table 4 is the excess return in relative equilibrium in different economic cycles. If we interpret the excess return data based on the investment clock, we can find that the excess return of treasury bonds in the recession period is negative, but it has a lot to do with the investor super and does not conflict with the investment clock theory. Generally speaking, the larger excess return assets should increase their positions, and the smaller or even negative ones should be reduced. Further, assuming that the occurrence of each direction of any multi-directional forecast is equal to the possibility, it may be assumed that the expected excess return is the unconditional excess return multiplied by the probability of the occurrence of the predicted economic state.

$$Q = \begin{bmatrix} 0.0038 \\ 0.0054 \\ 0 \\ -0.0235 \\ -0.0328 \\ -0.0166 \end{bmatrix} \qquad Q = \begin{bmatrix} 0.0022 \\ 0.0032 \\ 0 \\ 0.0328 \\ 0.0167 \\ 0.0234 \end{bmatrix} \qquad Q = \begin{bmatrix} -0.0004 \\ 0.0080 \\ 0 \\ -0.0291 \\ -0.0029 \\ -0.0192 \end{bmatrix}$$

Recovery **Overheated** **Recession**

The conclusions given by the first two experts in 2019 are consistent, both of which are recessions. In this model, they are:

$$P = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \end{bmatrix} \qquad Q = \begin{bmatrix} -0.0014 \\ 0.0241 \end{bmatrix}$$

In Table 5, "20'xx'Q'y'" means the yth quarter of year 20xx, for example, during 1st quarter of 2020 to 2nd quarter of 2022, we should allocate 84.59% of our total assets to National Debt. From 2020Q1 to 2022Q2 is recovery, 2022Q3-2024Q4 is overheating, 2025Q1-2026Q4 is stagflation, and then the second recession stage appears.

Table-5. Combined weights adjusted for perspective.

Asset / Time period	ND	CB	UP	Mid	Down
-2019Q4	36.36%	63.13%	0.00%	0.52%	0.00%
2020Q1-2022Q2	84.59%	15.37%	0.02%	0.00%	0.02%
2022Q3-2024Q4	22.46%	75.00%	0.02%	0.68%	1.84%

In Table 6, 0.4976 means the Sharpe ratio of total assets is 0.4976 when we use Mean-variance model. If we adjust our allocation using B-L model, the Sharpe ratio will be 0.6130. It means returns perform better. It is advisable to compare the performance of the combination under two groups of weights, taking Sharp ratio as an example:

Table-6. Sharpe ratio of different weight combinations.

Models / Time period	Original weight	BL model adjusted weight
-2019Q4	0.4976	0.6130
2020Q1-2022Q2	0.1664	0.2620
2022Q3-2024Q4	0.0904	0.0863

Table 7 shows how we should allocate our assets in different time periods. In the third stage, the sharp ratio of BL model's adjusted portfolio is lower than that of its unadjusted portfolio weight, which shows that the main reason why subjective views are not necessarily effective in a long period of time is that under the assumption of BL model, the greater the divergence of views, the lower the confidence level, and the less the excess return brought by positive prediction. In a short period of time, the forecasting method is relatively perfect, and professional forecasters can use effective tools to make clear judgment on the trend. So in the prediction of this paper. Only the three stages before 2022 are adjusted by intuitive viewpoint, and the viewpoint adjustment is no longer considered in the decision-making of 2022-2029.

Table-7. Portfolio weight of risk assets in each stage.

Asset / Time period	ND	CB	UP	Mid	Down
-2019Q4	36.36%	63.13%	0.00%	0.52%	0.00%
2020Q1-2022Q2	84.59%	15.37%	0.02%	0.00%	0.02%
2022Q3-2024Q4	22.46%	75.00%	0.02%	0.68%	1.84%
2025Q1-2026Q4	39.94%	53.30%	4.03%	0.00%	2.74%
2027Q1-	48.47%	51.23%	0.00%	0.30%	0.00%

4.2.3. Ratio of Risk Assets to Cash

After determining the weight of risk assets, the paper further discusses the ratio of risk assets and cash. According to the separation law of two funds, in the capital market, people use the optimal combination and cash ratio of effective boundary, and use the risk aversion coefficient of investors' personality to determine the optimal ratio:

$$y^* = \frac{E(R) - r_f}{A\sigma^2}$$

According to the calculation, the proportion of risk assets in the five stages should be: 136%, 98%, 98%, 100%, not only all of which can't meet the 10% cash position requirement of social security fund, but also need bank loan and leverage investment sometimes. Therefore, in view of the rigid position requirement of social security fund, the cash in the five stages should be maintained at 10% share, and there is no need to keep more. Table 8 is the weight of different assets when cash is set as 10%.

It can be seen from the comparison that in risk assets, the relative share of stocks and bonds will be relatively stable, while the change of large types of assets mainly occurs in stocks and bonds. The rotation of corporate bonds in bond China exists in every cycle. National bonds can be regarded as defensive assets with insensitive interest rate, while corporate bonds have stronger periodicity than national bonds. In the upstream, middle and downstream allocation of stocks in different periods, the preferences are not the same, which needs to be further studied and found.

Table-8. Portfolio weight of each stage considering cash.

Asset / Time period	CASH	ND	CB	UP	Mid	Down
-2019Q4	10%	27.26%	56.82%	0.00%	0.47%	0.00%
2020Q1-2022Q2	10%	72.51%	13.83%	3.62%	0.00%	0.02%
2022Q3-2024Q4	10%	20.21%	67.50%	0.02%	0.61%	1.66%
2025Q1-2026Q4	10%	35.95%	47.97%	3.63%	0.00%	2.47%
2027Q1-	10%	43.62%	46.11%	0.00%	0.27%	3.29%

Further comparing the current asset allocation of social security fund, we can find that: first, the relative stability of the ratio of stock to debt cash exists in reality, which shows that the current asset allocation of large categories is also relatively stable. The economic cycle mainly affects the specific style of asset allocation. At the same time, we can find that the cash of social security fund is higher than the bottom line requirement of 10%. According to the demonstration in the previous chapter, according to the risk preference of institutional investment, the cash of social security fund is not even needed for 10% in theory. And in reality, a considerable part of the assets of social security fund are treasury bond assets with strong liquidity. Therefore, we believe that the cash of social security fund is over matched and can be replaced by bond assets in subsequent operations to create better investment income.

5. CONCLUSIONS AND SUGGESTIONS

Based on the quarterly data of GDP from 1993 to 2018, this paper forecasts that China is in a recession period at present, and the trend of economic cycle in the next ten years is divided into five stages, which can be approximately regarded as a sequential evolution of Juglar-cycle. Combined with the prediction results, the BL model is used to allocate the assets of the three parts of the social security fund: stock, debt and cash. The results show that: 1) when only considering cash, stock and bond, the impact of economic cycle on the allocation of large categories of social security fund assets is not severe, but it has a significant impact on the style and industry rotation of large categories of assets; 2) according to the calculation of the model, the cash assets of social security fund are deposited In case of over matching, it should be adjusted to the level near the minimum limit of 10%.

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