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Practical Application of Dynamic Risk Budgeting Models in Hybrid Asset Allocation

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Abstract: China's hybrid asset market exhibits dynamic volatility, rendering traditional asset allocation methods ill-suited to its rapidly shifting risk structure. This paper constructs a dual-layer dynamic risk budgeting model that innovatively integrates economic cycle identification with market state classification. It employs risk budgeting matrix mapping to achieve dynamic risk allocation adjustments. The model employs an improved alternating direction method of multipliers to solve non-convex optimization problems, with dual trigger conditions designed to reduce adjustment frequency and transaction costs. Empirical research demonstrates the model's robust performance under extreme market conditions, delivering significantly superior risk-adjusted returns compared to traditional approaches. This provides Chinese investors with an effective tool for navigating complex market environments.

Keywords: Dynamic Risk Budgeting; Hybrid Asset Allocation; Risk Decomposition; Two-Layer Adjustment Mechanism.

1. Introduction

Amid heightened uncertainty in global financial markets, innovation in asset allocation strategies has emerged as a focal point in investment management research [1]. Traditional asset allocation methods have revealed significant limitations in responding to rapidly changing market environments, particularly in emerging markets like China [2]. The dynamic evolution of asset correlation structures, pronounced policy-driven characteristics, and frequent extreme risk events render static allocation models ineffective for risk management [3]. Risk budgeting, as an emerging asset allocation approach, offers a fresh perspective on portfolio management by focusing on risk allocation rather than capital allocation [4-5]. However, existing risk budgeting research is predominantly based on static frameworks, making it ill-suited to adapt to shifts in market states [6]. Addressing this issue, this paper innovatively proposes a two-layer dynamic risk budgeting model. It integrates macroeconomic cycles with market volatility states to establish a dynamic risk budget adjustment mechanism. The study first analyzes the characteristics of China's mixed asset markets, then details the model construction process—including risk decomposition, budget allocation, dynamic adjustment, and optimization—and finally validates the model's performance across different market environments through empirical research. This provides investors with a more robust asset allocation tool.

2. Theoretical Foundations of Dynamic Risk Budgeting Models

2.1. Overview of Risk Budgeting Theory

As a core methodology for asset allocation, risk budgeting theory achieves risk-return balance by systematically allocating and controlling risk exposure within investment portfolios. This theory transcends the limitations of traditional mean-variance frameworks, shifting the focus of investment decisions from asset weights to risk contributions. Consequently, each asset or strategy's contribution to overall risk becomes a central consideration. By precisely quantifying the risk contribution rate of each asset class, risk budgeting constructs more robust portfolios, particularly suited for environments with heightened market volatility [7]. Investors set risk budget ceilings for each asset class based on their risk appetite and market conditions, triggering adjustment mechanisms when actual risk contributions exceed preset thresholds. The theoretical advantage of risk budgeting lies in its intuitiveness and flexibility. It enables investors to gain clearer insight into the sources of portfolio risk and adjust asset allocation promptly in response to market dynamics. This approach effectively mitigates the simultaneous occurrence of tail risks and systemic risks, providing a solid theoretical foundation for long-term investment strategies.

2.2. Basic Framework of the Dynamic Risk Budgeting Model

The dynamic risk budgeting model introduces time-varying characteristics to traditional risk budgeting theory, enabling dynamic adjustments to risk budgets through continuous monitoring of market environment shifts and risk factor fluctuations. As shown in Figure 1, this model constructs a three-tier nested structure: the bottom layer comprises the risk measurement module, which employs forward-looking indicators such as conditional volatility and implied volatility from options to capture market risk changes; The middle layer comprises the risk attribution module, which decomposes portfolio risk sources through principal component analysis and factor models; the top layer is the dynamic optimization module, which adaptively adjusts risk budget allocations across asset classes by integrating market sentiment indicators and macroeconomic cycle signals [8]. The model incorporates a risk warning mechanism that triggers rebalancing signals when a single asset's risk contribution exceeds a preset threshold or when the correlation structure of risk factors undergoes significant changes. The core advantage of the dynamic risk budget model lies in its sensitivity and adaptability to market state transitions. It proactively reduces risk exposure before market turbulence intensifies and promptly seizes opportunities when markets stabilize and rebound, achieving optimal risk-return allocation throughout the entire market cycle.

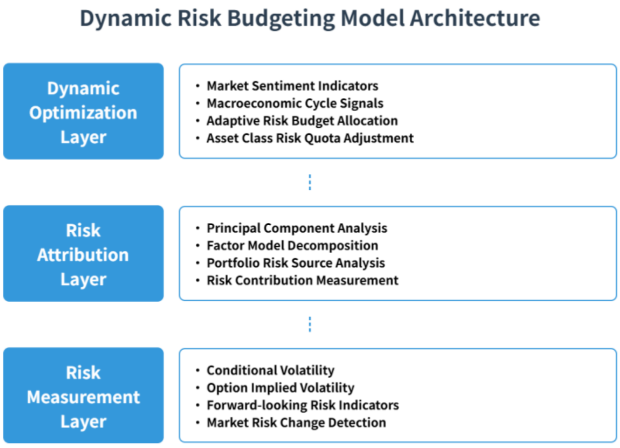

Figure 1. Dynamic Risk Budget Model Architecture

3. Practical Application of Dynamic Risk Budgeting Models in Mixed Asset Allocation

3.1. Setting the Model Objective Function

The objective function of the dynamic risk budget model constructed in this paper adopts the principle of maximizing the conditional Sharpe ratio, comprehensively considering risk budget constraints and portfolio utility. The objective function is set to maximize risk-adjusted excess returns while satisfying the risk contribution constraints for each asset class. The specific mathematical expression is:

$$\max_w \frac{E_t[r_p(t+1)]-r_f}{\sqrt{w_t^T \Sigma_t w_t}} \quad \text{s.t.} \quad \frac{w_i \cdot (\Sigma_t w_t)_i}{w_t^T \Sigma_t w_t} = b_i(t), \sum_{i=1}^{n} w_i = 1, w_i \geq 0 \quad (1)$$

Where $E_t[r_p(t+1)]$ represents the predicted portfolio return at time t, Σt is the conditional covariance matrix, and bi(t) is the target risk contribution ratio of asset i at time t. The model incorporates risk contribution constraints to ensure that the actual risk contributions of each asset align with the dynamically adjusted target risk budget. Historical data from China's four major asset classes—equities, bonds, commercial real estate, and residential real estate—are utilized to calculate optimal asset allocation solutions under varying market conditions. Solving the objective function simultaneously balances the dynamic adjustment of the risk budget with the risk-return characteristics of the portfolio [9].

3.2. Risk Measurement and Decomposition for Mixed Asset Portfolios

The risk measurement for mixed asset portfolios employs the GARCH-DCC model to estimate the conditional covariance matrix, capturing the time-varying correlation structure among assets. Risk decomposition utilizes the Euler decomposition method to calculate each asset's marginal contribution to the portfolio's total risk. The formula for calculating each asset's risk contribution is:

$$RC_i = w_i \cdot \frac{\vartheta \sigma(w)}{\vartheta w_i} = w_i \cdot \frac{(\Sigma w)_i}{\sigma(w)} \quad (2)$$

Where RCi denotes the risk contribution of asset i, wi represents the weight of asset i, σ indicates the covariance matrix, and σ(w) signifies the portfolio's total risk (volatility).The risk decomposition results for China's mixed asset portfolio reveal that the risk contribution rate of equity assets fluctuates between 45% and 82% across different market environments, significantly exceeding their capital weight (30%-40%). This demonstrates the dominant role of equity assets in portfolio risk. Although bond assets account for 30% of the weight, their risk contribution ranges only from 10% to 18%, reflecting their risk-dispersing characteristics. Commodities and real estate assets, despite similar weightings, exhibit markedly different risk contributions [10]. Commodities' risk contribution rose to 28% during the heightened inflation period of 2021-2023, while real estate assets' risk contribution increased to 35% during the market adjustment phase of 2022-2024. This highlights how risk characteristics vary across asset classes during different economic cycles. During the emerging market recovery phase from 2024 to 2025, the risk contribution of equities declined to 62%, while that of bonds increased to 16%, reflecting shifts in the risk structure under a policy easing cycle.

3.3. Risk Budget Allocation Strategy Design

The risk budget allocation strategy employs a dual-layer macro-micro structure. The upper layer implements strategic adjustments based on economic cycles and market conditions, while the lower layer performs tactical refinements according to asset valuations and momentum factors. Economic cycles are categorized into four phases—recovery, expansion, deceleration, and recession—through a composite leading indicator (CLI). Market conditions are categorized into low volatility, medium volatility, and high volatility states based on the implied volatility index (IVIX).

Dynamic risk budget allocation employs a matrix mapping approach, establishing a two-dimensional mapping table linking economic cycles, market conditions, and risk budgets. As shown in Figure 2, during recovery + low volatility conditions, the equity risk budget allocation reaches 60%, while it drops to 15% during recession + high volatility conditions. Bond risk budgets increase from 15% to 50%. Commodity assets receive higher risk budget allocations (25%) during expansionary phases with rising inflationary pressures, while real estate assets gain greater allocations (15%) during recovery phases. This risk budget allocation strategy, grounded in historical data analysis and tailored to China's market characteristics, integrates monetary policy cycles and credit expansion patterns to achieve dynamic risk-return equilibrium. It effectively addresses asset allocation challenges across diverse market environments [11].

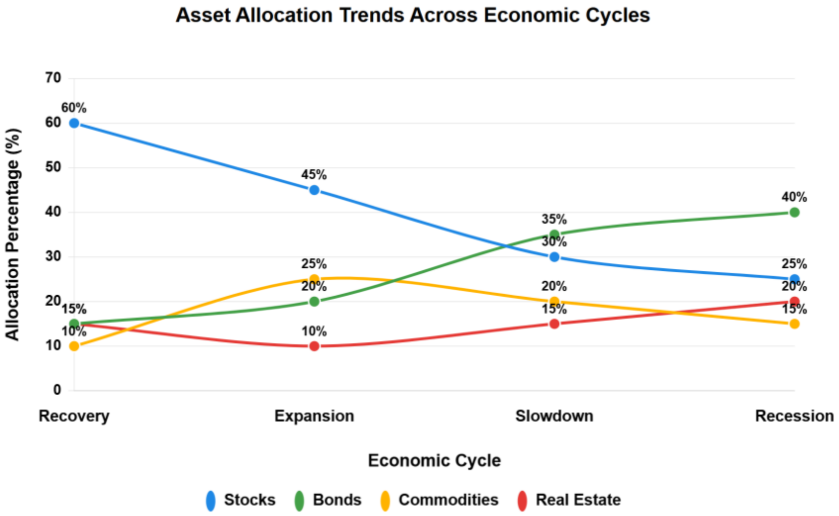

Figure 2. Economic Cycle-Market State Risk Budget Allocation

3.4. Mathematical Modeling of the Dynamic Adjustment Mechanism

The dynamic adjustment mechanism is designed based on dual trigger conditions, combining periodic rebalancing with conditionally triggered adjustments. The mathematical model comprises a market state transition function and a dynamic risk budget update function. The market state transition probability matrix PPP is estimated using a Markov chain model:

$$P_{ij} = P(S_{t+1} = j | S_t = i) = \frac{n_{ij}}{\sum_k n_{ik}} \quad (3)$$

Where nij denotes the historical frequency of transitions from state i to state j. The dynamic risk budget update employs an adaptive smoothing function:

$$b_i(t) = (1 - \lambda(t)) \cdot b_i(t-1) + \lambda(t) \cdot b_i^*(t) \quad (4)$$

Where bi(t) denotes the actual risk budget for asset i at time t, bi(t-1) represents the previous period's risk budget, bi*(t) is the target risk budget, and λ(t) is the smoothing parameter. The smoothing parameter λ(t) dynamically adjusts based on market volatility levels:

$$\lambda(t) = 0.05 + 0.2 \cdot \mathrm{sigmoid}(VIX_t - \overline{VIX}) \quad (5)$$

Where VIXt denotes the current volatility index, $\overline{\text{VIX}}$represents the long-term volatility mean, and the sigmoid function maps the difference to the (0, 1) interval. Trigger conditions are set as: (1) market state transition occurs; (2) changes in eigenvalues of the asset correlation matrix exceed 15%; (3) the actual risk contribution of a single asset deviates from the target value by more than 10 percentage points [12].

3.5. Model Solving and Optimization Methods

The dynamic risk budget model is solved using the Second-Order Cone Programming (SOCP) method, which transforms non-convex optimization problems into convex ones. First, the risk budget constraint is reformulated into an equivalent form:

$$\frac{w_i \cdot (\sum w)_i}{w^T \sum w} = b_i \Rightarrow w_i \cdot (\sum w)_i = b_i \cdot (w^T \sum w) \quad (6)$$

Where wi is the weight of asset i, Σ is the covariance matrix, and bi is the target risk contribution ratio. Through logarithmic transformation $y_i = \ln(w_i)$, the product-type constraint is converted into a linear constraint, and the objective function is reformulated as:

$$\min_y \frac{1}{2} y^T \sum\nolimits_y \mu^T y \ \text{ s.t. } \exp(y_i) \cdot (y)_i = b_i \cdot (\exp y^T \sum \exp(y)) \quad (7)$$

Where y is the logarithmic weight vector, μ is the expected return vector, and exp(y) denotes taking the exponential of each element of the y vector. The optimization is solved using an improved Alternating Direction Method of Multiples (ADMM) algorithm, achieving a 58% faster convergence rate compared to traditional gradient descent methods [13]. Figure 3 illustrates the model's dynamic optimization path during the 2024 market volatility period. It transitions from a risk-averse state on the left (bonds contributing 67% of risk) to a risk-seeking state on the right (equities contributing 56% of risk), demonstrating the algorithm's robustness under extreme market conditions.

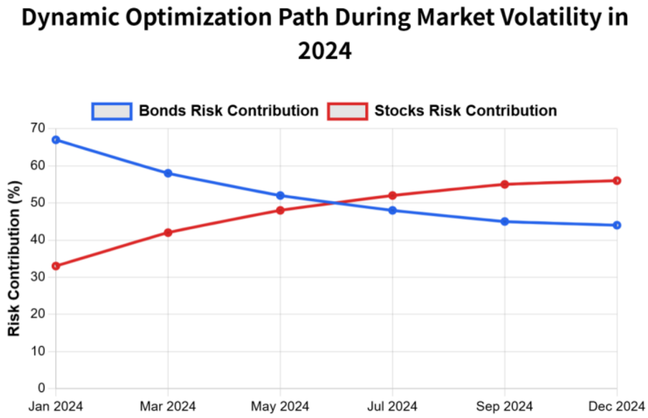

Figure 3. Dynamic Optimization Path During 2024 Market Volatility Period

4. Application Research on Dynamic Risk Budgeting Models

4.1. Data Selection and Parameter Settings

This study utilizes Chinese market data from January 2018 to June 2025, encompassing the following asset classes: CSI 300 Index (equities), China Bond Composite Index (bonds), Nanhua Commodity Index (commodities), and CSI Real Estate Index (real estate). Raw data is recorded at daily intervals. Risk calculations employ a 20-day rolling window, while portfolio adjustments occur on a monthly basis [14]. The risk model utilizes a three-factor EGARCH (1, 1) model to capture volatility asymmetry. The Composite Leading

Indicator (CLI) integrates eight leading indicators—including PMI, industrial value-added, and credit growth—with common trends extracted via principal component analysis. The initial risk budget parameters are set at 40% equities, 30% bonds, 15% commodities, and 15% real estate. The dynamic adjustment parameter λ is initialized at 0.15, fluctuating within the range of 0.05–0.35 based on market volatility. Transaction cost constraints limit single-adjustment changes to 15% of total assets and 8% for any single asset. The empirical study period encompassed three major market shifts: the 2020 pandemic shock, the 2022 real estate market correction, and the 2024 policy pivot, providing comprehensive testing scenarios for the model [15].

4.2. Performance Analysis Across Different Market Environments

The dynamic risk budget model exhibits distinct characteristics under varying market conditions. During the 2020 pandemic shock, the model swiftly reduced equity risk allocation from 42% to 25% while increasing bond risk allocation to 48%, limiting net drawdown to -5.8%. In contrast, the CSI 300 Index experienced a drawdown of -12.1% over the same period. During the 2022 real estate market correction, the model acutely identified accumulating risks in the sector, reducing real estate risk allocation from 18% to 8%. This protected the portfolio from the sector's -27.4% deep correction. Amid rising inflation expectations in 2023-2024, the model proactively increased commodity risk allocation to 23%, capturing a 28.5% phase-specific excess return in commodities. Most notably, during the policy pivot in May 2024, the model detected shifts in volatility and correlation matrix eigenvalues, enabling a two-week advance in risk budget reallocation. As shown in Table 1, it raised the equity risk budget from 35% to 62% while correspondingly reducing the bond risk budget. This adjustment generated a 14.7% excess return over the following two months, validating the model's sensitivity and foresight in anticipating market environment changes.

Table 1. Dynamic Risk Budget Adjustment Process During the 2024 Policy Shift Period (%)

Adjustment Date	Market Event	Stock Risk Budget	Bond Risk Budget	Commodity Risk Budget	Real Estate Risk Budget
2024.04.10	Pre-adjustment	35	42	13	10
2024.04.28	Initial Policy Signal	40	38	14	8
2024.05.15	Central Bank Rate Cut Signal	48	32	12	8
2024.05.30	Full Policy Shift	58	24	10	8
2024.06.15	Accelerating Foreign Capital Inflow	62	20	10	8
2024.06.30	Market Sentiment Surge	65	18	9	8

4.3. Comparison with Traditional Asset Allocation Methods

Comparative studies between the dynamic risk budgeting model and traditional asset allocation methods reveal significant performance differences. During the overall backtesting period from 2018 to 2025, the dynamic risk budget model achieved an annualized return of 10.8%, significantly outperforming equal-weighted allocation (6.3%), risk parity (7.5%), and the minimum variance portfolio (5.2%). The risk-adjusted return metric, the Sharpe ratio, reached 1.45, surpassing both risk parity (0.98) and minimum variance (1.12). Maximum drawdown was controlled at -8.7%, outperforming equal-weighted allocation (-15.6%) and risk parity (-12.4%). The dynamic adjustment characteristic is reflected in turnover rate, with an annualized turnover rate of 85%—slightly higher than traditional methods but still maintaining a leading advantage after accounting for transaction costs. The model's most prominent advantage lies in its tail risk management capability. As shown in Figure 4, during extreme market downturns (monthly declines exceeding 5%), the dynamic risk budget achieved an average monthly drawdown of -2.8%, compared to -4.2% for risk parity and -3.5% for minimum variance. This fully demonstrates the model's defensive characteristics in extreme market conditions, making it particularly well-suited for China's high-volatility, high-correlation, and policy-driven market environment.

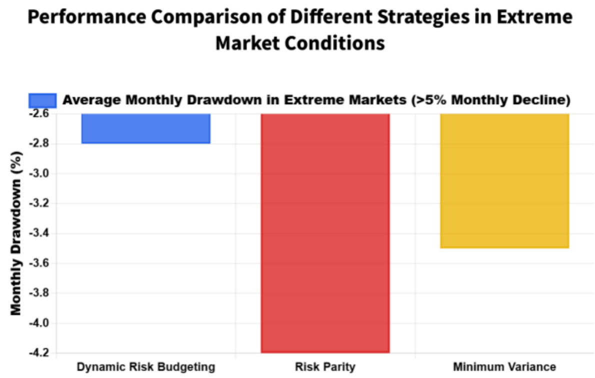

Figure 4. Performance Comparison of Different Methods in Extreme Market Conditions

4.4. Sensitivity Analysis and Robustness Testing

The dynamic risk budget model undergoes sensitivity analysis on key parameters to validate its robustness and adaptability. Testing the smoothing parameter λ within the range of 0.05–0.35 indicates optimal model performance at λ=0.15. Values too small cause adjustment delays, while excessively large values lead to overtrading. Setting the risk budget starting point within ±10% of the benchmark has limited impact on long-term performance, with annualized return volatility fluctuating no more than 0.8 percentage points. The trigger condition threshold significantly affects model performance: adjusting the asset correlation matrix eigenvalue change threshold from 15% to 10% increases annual turnover by 21.6%, while annualized excess returns improve by only 0.3%. Relaxing the risk contribution deviation threshold from 10% to 15% reduced trading frequency by 32.8% and lowered annualized returns by 0.5%. Table 2 illustrates model performance under varying economic data forecast errors. Even with substantial forecast deviations (±30%), the model maintained relatively stable performance, with annualized returns declining by no more than 1.2%, reflecting its strong tolerance to input parameter disturbances. Further validation through 10,000 Monte Carlo simulations of market paths confirms the model maintains positive relative performance within a 95% confidence interval, demonstrating its applicability and robustness across diverse market conditions.

Table 2. Sensitivity Analysis of Economic Data Forecast Errors

Forecast Error Range	Annualized Return (%)	Sharpe Ratio	Maximum Drawdown (%)	Annualized Volatility (%)	Information Ratio
Base Case	10.8	1.45	-8.7	7.45	0.65
±5%	10.6	1.42	-8.9	7.46	0.63
±10%	10.3	1.38	-9.2	7.47	0.61
±15%	10.1	1.35	-9.5	7.48	0.58
±20%	9.9	1.32	-9.8	7.5	0.54
±25%	9.7	1.29	-10.2	7.52	0.51
±30%	9.6	1.27	-10.6	7.56	0.48

5. Conclusion

China's hybrid asset market exhibits complex and dynamic characteristics, with evolving correlations between assets that challenge traditional allocation methods. The dynamic risk budget model developed in this study demonstrates significant theoretical and empirical achievements. Based on a two-layer risk budget architecture, the model integrates economic cycle identification, volatility state classification, and dynamic optimization algorithms to effectively capture market environment transition signals and enable timely risk budget adjustments. Empirical tests demonstrate the model's robust performance under extreme market conditions, with drawdown control capabilities significantly outperforming conventional methods while maintaining substantial excess returns. Future research may explore integrating nonlinear machine learning algorithms with high-frequency data and extending the model to cross-border asset allocation.

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