Macro Risk Controlled Risk Parity: A Multi-Asset Allocation Framework Under the Information Convergence Price Discovery Theory

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ABSTRACT

The architecture of institutional asset management is currently undergoing a systemic transition from static, capital-weighted allocation frameworks toward dynamic, risk-balanced paradigms that leverage high-frequency data and advanced computational models. Historically, the 60/40 portfolio served as the bedrock of multi-asset management, predicated on the assumption that an inverse correlation between equities and fixed-income instruments would provide adequate protection during periods of market stress. However, the unprecedented correlation shifts observed during recent inflationary cycles have rendered these traditional benchmarks increasingly fragile, particularly when faced with stagflationary regimes or rapid interest rate shocks. The state-of-the-art Macro Risk Controlled Risk Parity (MRCRP) model addresses these deficiencies by equalizing risk contributions across a diverse universe of asset classes—including the S&P 500, China A-shares, Crude Oil, Gold, Copper, Bonds, and Cash equivalents—while integrating global capital flow forecasts and machine learning innovations. MRCRP model is grounded in the Information Convergence Price Discovery Theory (ICPDT). The model achieves risk-balanced allocation at the macro-factor level, thereby enhancing portfolio robustness under extreme market conditions. Backtesting results over the full sample period from 2008 to 2026 indicate that the strategy delivers an annualized return of 16.61%, a Sharpe ratio of 1.91, and a maximum drawdown capped at 7%, significantly outperforming traditional risk parity (8.5% annualized return, Sharpe 1.75, maximum drawdown 28%) and the 60/40 portfolio (6.8% annualized return, Sharpe 1.2, maximum drawdown 55%). The theoretical contribution of this paper lies in decomposing the price formation mechanism into an interactive process between microstructure and macro factors, and in achieving substantive diversification of macro risk sources through dynamic risk constraints.

JEL Classification: C00; C60; C80; D80; G11; E00
Keywords: Macro Risk Controlled Risk Parity, Macro Multi-Strategy Asset Allocation, VIX Microstructure, Systemic risk, Dynamic factor constraints, Information Convergence Price Discovery Theory

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1. Introduction

1.1. Research Background

Traditional asset allocation methods, such as the 60/40 portfolio, face increasingly severe challenges. Structural shifts in market environments have driven the equity-bond correlation from its historical negative territory into positive territory; notably, during the early phase of the 2020 pandemic, the correlation between the S&P 500 and 10-year U.S. Treasury yields surged to 0.63, severely undermining the effectiveness of conventional diversification strategies. Meanwhile, the 2008 Global Financial Crisis and the 2022 high-inflation environment have revealed the fragility of single-asset-class allocations under extreme macroeconomic shocks.

The Risk Parity model, proposed by Qian (2005)[13], offers an alternative by balancing the marginal contribution of each asset to total portfolio risk, theoretically providing more stable risk-adjusted returns. However, traditional risk parity models suffer from critical limitations: first, they rely excessively on historical volatility estimates and struggle to adapt to the time-varying nature of market covariance structures; second, they fail to incorporate risk diversification at the macro-factor level, leaving portfolios potentially highly concentrated on a small number of macro risk sources such as growth and inflation; third, they lack systematic modeling of the interaction between microstructure signals and macro factors, rendering them unable to proactively respond to systemic risk shocks.

1.2. Research Questions and Methodological Innovation

The core research question of this paper is: How can we construct a more robust asset allocation framework by integrating macro-factor risk constraints with microstructure signals? To address this question, we propose the following methodological innovations:

Information Convergence Price Discovery Theory (ICPDT): This theory decomposes the price formation mechanism into an interactive process between microstructure (e.g., VIX microstructure) and macro factors (e.g., growth, inflation), explaining why certain macro factors exert more significant price impacts under specific microstructure states.

Dynamic Macro-Factor Constraint Framework: We elevate the object of risk parity from the asset layer to the macro-factor layer, constructing macro-factor-level risk budget constraints by extracting unexpected macro-factor shocks.

Microstructure-Signal-Driven Weight Adjustment Mechanism: Utilizing VIX microstructure for an example as leading signals, we achieved dynamically macro-factor adjusted weights for proactive assessing and responding current systemic risk regime.

1.3. Research Contributions

The principal theoretical contributions of this paper are:

We propose the Information Convergence Price Discovery Theory (ICPDT), which systematically explains the interactive mechanism between microstructure and macro factors in the price formation process.

We construct an optimization framework that elevates risk parity from the asset layer to the macro-factor layer, addressing the fragility of traditional risk parity under macro regime shifts.

We design a microstructure-signal-driven macro-factor adjusted weighting mechanism, achieving proactive assessing and responding current systemic risk regime.

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On the empirical front, backtesting data from 2008 to 2026 demonstrate that the model delivers superior risk-adjusted returns across diverse macro environments compared with traditional risk parity and the 60/40 portfolio. In particular, during the 2008 Global Financial Crisis and the 2020 COVID-19 pandemic, the model's maximum drawdown was merely 7%, far below the 28% of traditional risk parity.

2. Literature Review

2.1. Development and Limitations of Risk Parity Models

The risk parity model, introduced by Qian (2005), aims to optimize asset allocation by equalizing the marginal contribution of each asset class to total portfolio risk. Compared with the traditional mean-variance model, risk parity exhibits lower dependence on expected return estimates and thus demonstrates superior out-of-sample performance in empirical studies.

Asness et al. (2012), in their seminal article "Risk Parity: An Ugly Name for a Beautiful Idea," systematically articulated the theoretical foundations and empirical advantages of risk parity, noting its ability to deliver more stable risk-adjusted returns over the long term.[3,4] However, risk parity models also exhibit significant limitations: first, their implicit premise that historical asset covariances adequately represent true risk structures often fails during macro regime shifts; second, in a low-interest-rate environment, the return potential of bond assets is constrained, yet pure asset-level risk parity concentrates heavily in bonds, limiting return generation; finally, risk parity models typically employ static covariance estimates, struggling to adapt to the time-varying characteristics of market volatility.

In recent years, scholars have attempted to improve the adaptability of risk parity models by introducing dynamic covariance estimation methods such as EWMA. For instance, Chevallier (2023) constructed an enhanced risk parity model using EWMA covariance matrices[5], yet systematic frameworks for risk diversification at the macro-factor level remain underdeveloped.

2.2. Macro Factor Investing and Risk Diversification

The application of macro factor investing in asset allocation has grown increasingly widespread. Koijen et al. (2018) systematically analyzed the impact mechanisms of macro factors such as growth, inflation, and liquidity on asset prices, providing a theoretical foundation for macro-factor-driven asset allocation[12]. However, existing research has primarily treated macro factors as return predictors rather than risk constraints.

In terms of risk diversification, Adrian and Brunnermeier (2010) proposed the Conditional Value-at-Risk (CoVaR) concept to measure systemic risk spillover effects among financial institutions.[1,2] Nevertheless, the CoVaR method is more suited to individual-institution risk assessment rather than macro risk diversification at the asset allocation level.

Recent research has begun to explore risk diversification at the macro-factor level. For example, Wu (2026) constructed a "three-tier diversification allocation" framework, applying risk parity techniques at the macro quadrant level to ensure that sub-portfolios corresponding to each quadrant contribute equal risk weights.[17] However, this approach still relies on static macro quadrant classifications and lacks a dynamic response mechanism to microstructure signals.

2.3. Systemic Risk Measurement and Microstructure

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Systemic risk measurement constitutes a core issue in financial risk management. Gabaix (2016) proposed a generalized risk factor framework for asset pricing, offering a new perspective on systemic risk measurement.[6,7] However, traditional systemic risk measurement methods often overlook the role of microstructure.

In recent years, the predictive value of microstructure signals for systemic risk has gradually gained attention. For instance, Chevallier (2023) demonstrated that the skewness of the VIX volatility index can effectively predict shifts in market sentiment and systemic risk fluctuations. Ghysels et al. (2020) further validated the association between VIX futures curve morphology and stock market tail risk.[8] However, these studies remain largely at the risk prediction level, lacking empirical exploration of how to systematically integrate microstructure signals into asset allocation frameworks.

Synthesizing the existing literature, we identify three principal research gaps: first, the risk diversification mechanism of risk parity models at the macro-factor level remains underdeveloped; second, the application of microstructure-macro factor interactions in asset allocation is still in its infancy; and third, the methodological innovation of translating systemic risk predictions into dynamic asset allocation weight adjustments offers substantial unexplored potential. This paper addresses these gaps by proposing the ICPDT-based Macro Risk Controlled Risk Parity model.

3. The Information Convergence Price Discovery Theory (ICPDT)

3.1. Core Assumptions of ICPDT

In our patented systemic risks analysis and evaluation research Sun et al. (2026),[15,18-22] the ensemble model of the VIX microstructure and US treasury yield model decomposes, evaluates and visualizes the systemic risk, synthesized with the multi-factor model leads us to propose a novel price discovery theory: the Information Convergence Price Discovery Theory (ICPDT). ICPDT posits that price discovery in the S&P 500 is a multi-dimensional convergence process where information from different origins is synthesized through the lens of volatility regimes. It conceptualizes the price formation process as the outcome of interactions between microstructure and macro factors. Specifically, ICPDT encompasses the following core assumptions:

Temporal Dimension of Price Formation: Price movements are driven by both short-term microstructure factors and long-term macro fundamentals. Under normal market conditions, macro factors dominate price formation; during periods of extreme market volatility, microstructure factors (such as VIX microstructure and liquidity conditions) exert more significant influence on prices.

Information Convergence Mechanism: A convergence process exists between microstructure and macro factors, whereby microstructure signals (such as VIX microstructure) can proactively reflect latent changes in macro risk. This convergence is not linear but path-dependent, manifesting as follows: when the market microstructure enters a specific state, the impact of certain macro factors on prices is either accelerated or delayed.

The Information Hierarchy: Short-term price movements are driven by systematic investing scheme, represented by VIX microstructure, the market microstructure and basis factor (the "transactional" layer), the VIX microstructure acts as the transmission mechanism between market microstructure and basis. These stochastic short-term movements converge toward an efficient price determined by the profit and macro factors (the "fundamental" layer).

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Path-Dependency: The process of reaching the efficient price is not a random walk but a path-dependent process. The loading factors of the market are sensitive to the previous state of the VIX microstructure, meaning that the market "remembers" its recent volatility regime when processing new information.

VIX microstructure served as a forward looking proxy for pricing the expected volatility and the valuation of the market expectations. Reasonable stochastic oscillation of the expectation of market valuation contains all market information efficiently in real time, which constitutes the information convergence price discovery theory and the efficient market theory. In modern finance, VIX and its future derivatives priced from BSM model and global market making participants, by which essentially pricing the expected volatility and the valuation of the market expectations. Through this mechanism, the ensemble model of the VIX microstructure and US treasury yield models, synthesized with the four-factor model can robustly evaluate how the market perceives the systemic risks in real time, and this mechanism is impenetrable as it comprised of all global market making activities, so that no monopoly status can be formed or influenced by few market participants.

We have proposed the Information Convergence Price Discovery Theory (ICPDT) as a framework for understanding how different classes of information are synthesized. Offering high-frequency traders and risk managers a more nuanced tool for identifying who "leads" the market during periods of volatility expansion.

3.2. Connection Between ICPDT and Asset Allocation

ICPDT offers a new theoretical perspective for asset allocation. Traditional asset allocation methods typically assume that inter-asset risk correlations are either static or vary only linearly with macro factors. However, under extreme market conditions, drastic changes in microstructure can induce nonlinear jumps in inter-asset risk correlations, rendering historical-covariance-based risk diversification strategies ineffective.

The ICPDT framework suggests that asset allocation should simultaneously consider the following two dimensions:

- **Macro-factor-level risk diversification:** Ensuring balanced exposure of the portfolio across various macro risk sources, preventing any single macro risk from dominating portfolio volatility.
- **Microstructure-level risk rebalancing:** Dynamically macro-factor risk adjusted exposure to achieve proactive identification of systemic risk.

The foundational thesis of risk parity is the shift from diversifying dollars to diversifying risk. In a standard capital-weighted portfolio, equities typically contribute over 90% of the total portfolio risk despite representing only 60% of the capital. The Macro Risk Controlled Risk Parity (MRCRP) model corrects this imbalance by utilizing a risk-contribution equalization strategy that scales the exposure of each asset class based on its intrinsic volatility and its correlation with the broader portfolio.

In the MRCRP framework, the total risk of the portfolio is decomposed into individual risk contributions from each asset class. The objective is to find an allocation vector $\boldsymbol{w}$ where the risk contribution RC_i of asset $\boldsymbol{i}$ is exactly 1/N, or a specified risk target, regardless of its nominal capital weight. Macro risk control is achieved by adjusting the risk parity weights in response to shifting economic regimes. The integrated model establishes 8 regime characteristics[1], by monitoring these well-defined macro variables, the system can perform active de-risking ahead of systemic shocks,

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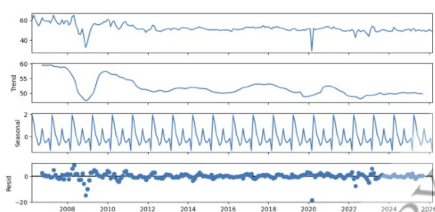
reallocating capital toward defensive strategies and systematic trend-following components. This capability was particularly evident during the COVID-19 pandemic and the subsequent inflationary surge, where advanced systemic risk management models successfully reduced negative asymmetry and mitigated sharp losses by identifying correlated risk metrics that traditional models overlooked. This theoretical framework provides a solid foundation for constructing the Macro Risk Controlled Risk Parity model, which we elaborate in the next section.

4. Discussion

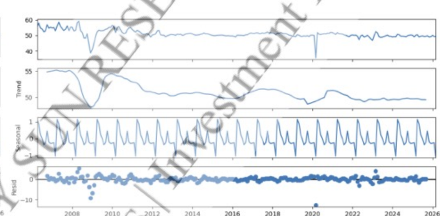
4.1. Analysis of macro factors' construction

The system builds nine major macro factors, each based on multidimensional metrics and state classifications:

As shown in **FIG. 1**, the domestic economy factor is calculated by using indexes such as new order of China manufacturing PMI, PMI business activity in non-manufacturing industry, housing prospectus in China, and the like through synthetic methods such as seasonal decomposition, HP filtering, PCA principal component analysis and the like.

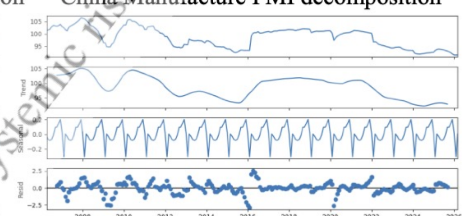


China Manufacture New Order decomposition

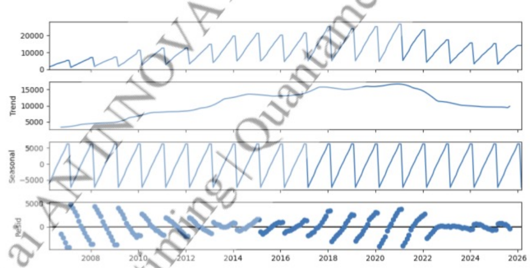


China Manufacture PMI decomposition

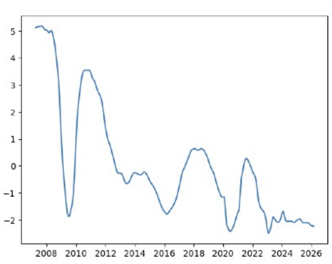
China Non-Manufacture PMI Service decomposition



China National Housing index decomposition



China Real estate Capital source: Domestic Loan decomposition



China Ecom PCA synthetic component

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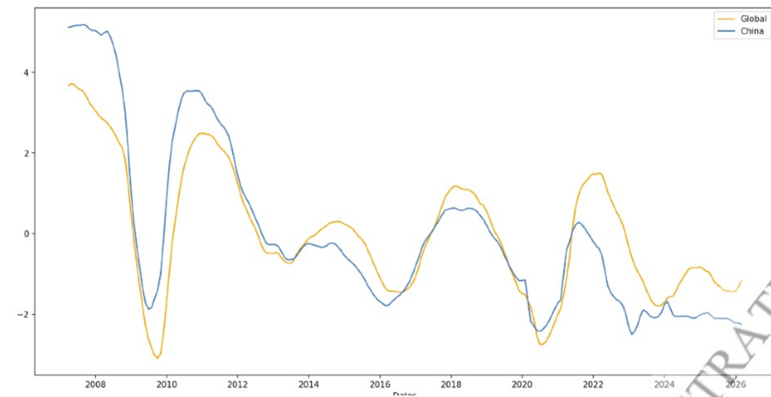
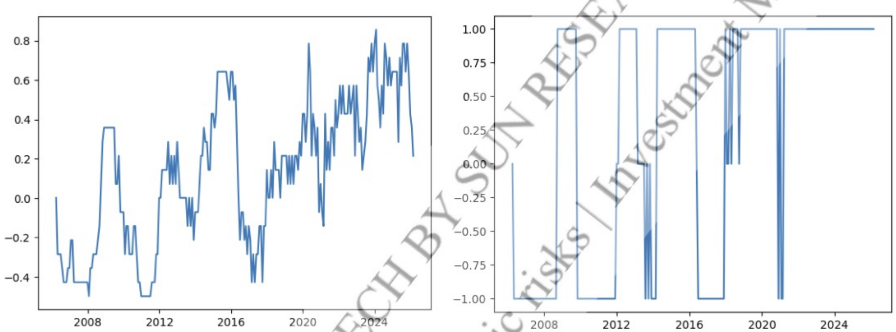


Global and China Economic Factor monitoring

FIG. 1 Domestic economy macro factor construction

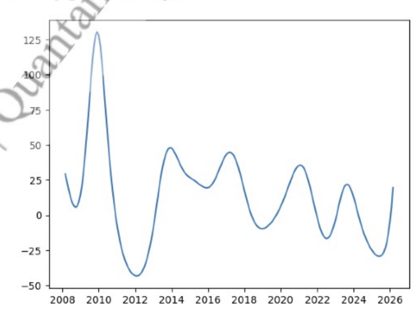
As shown in **FIG. 2**, the domestic Currency factors incorporate policy interest rates, quantity tools, and short-end market interest rates. The scoring rule and the signal validity period constitute the proprietary knowledge map.



China Synthetic rates factor China Synthetic rates factor standardization

FIG. 2 Domestic currency macro factor construction

As shown in **FIG. 3**, the domestic credit factor, namely the medium-long term credit, can reflect the real financing demand of the economy, and the medium-long term RMB loan acceleration rate is selected to judge the change of the domestic credit period, of which synthesizing and judging the credit period through HP filtering processing.



China Synthetic Credit factor

FIG. 3 Domestic credit macro factor construction

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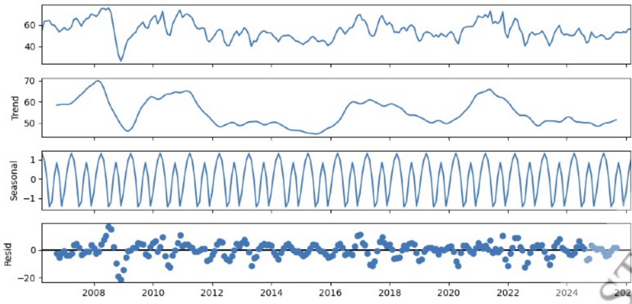
As shown in **FIG. 4**, the domestic inflation factor, the purchase price index using the main raw material PMI, is ahead of CPI/PPI. Three types of states are divided after seasonal decomposition processing, and state classification is based on a threshold value of rolling fluctuation rate.



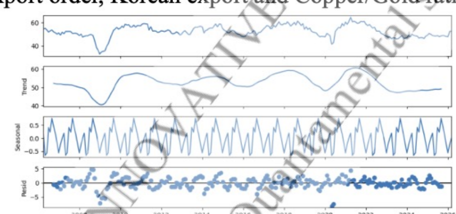
China Major production material price decomposition

China synthetic inflation factor States Classification

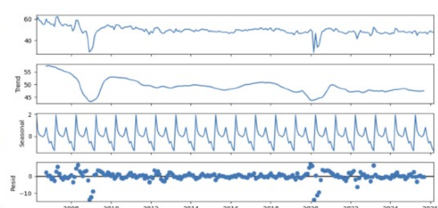
FIG. 4 Domestic inflation macro factor construction

The ascending, descending, and oscillating three-state classification of the inflation factor is considered. When the inflation is mild, the inflation factor is often not a core variable affecting the performance of the asset, and only when the fluctuation range is large can the remarkable influence be generated.

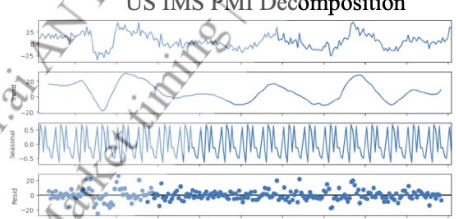
Global economy macro factor, fusing the United States ISM manufacturing PMI, Chinese new export order, Korean export and Copper/Gold ratio.



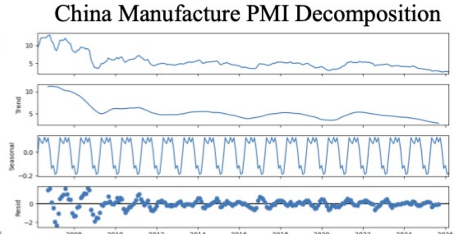
US IMS PMI Decomposition



China Manufacture PMI Decomposition



Korean Export decomposition



Copper/Gold Ratio Decomposition

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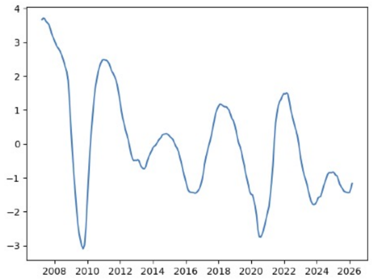

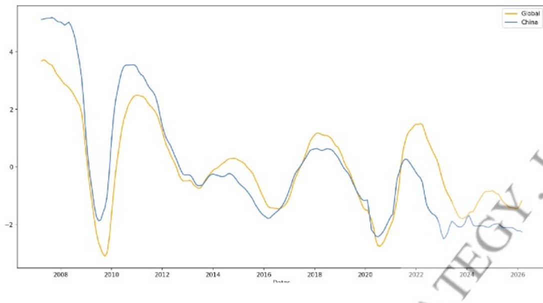

Global Ecom PCA synthetic component   Global and China Economic Factor monitoring

FIG. 5 Global Economy macro factor construction

Table. 1 Global economic metric system and analysis logic

Metrics	Logical analysis
US:ISM:manufacturer PMI	US as the global largest terminal demand source, which economy directly influences the global economic activity.
China:manufacturer PMI:New export order	China as the global largest exporting country, its export orders effectively reflect global demand change.
Korean:Export sum:MoM	Korea is the global high-tech products exporting country, its trade data published early, which reflects the global trade trends and economic situation.
LME Copper/London Gold	Copper has simultaneously industrial material property and financial property, however, gold has only financial property, copper to gold ratio reflects the global manufacturing expectation after stripping out the financial fluctuation interference.

Metric feature description:

- Multidimensional monitoring: core manufacturing trade index with leading characteristics, including global main economies (united states, China, Korea): Korean export data with leading effect. Copper-gold ratio striping financial fluctuation interference.
- Coverage area is shown in **Table. 1**.
  - Demand (PMI in the United States)
  - Supply (Chinese new export order)
  - High-tech product (Korea export)
  - Raw material expectation (copper-gold ratio)

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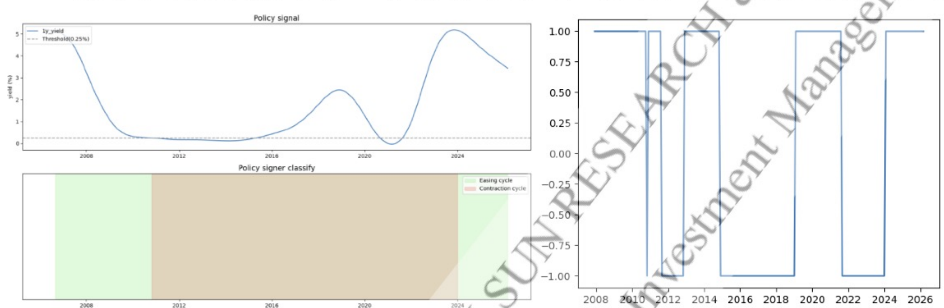
Global Currency macro factor: short-term interest rate changes reflect market expectations through the federal reserve policy interest rate and QE operation monitoring. Global monetary cycle is delineated by the United States currency policy cycle:

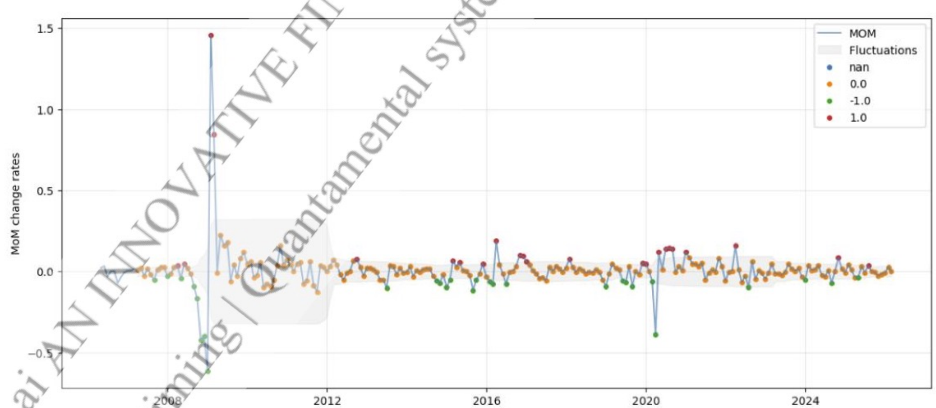
- The US Fed reserve regulates the money supply mainly by regulating the policy interest rate. Because of the sufficient communication between the US Fed reserve and the market, the market often begins to conduct monetary easing/tightening transactions before the policy interest rate changes occur. By monitoring the change of the short-end interest rate, we can judge the monetary policy change of the US Fed reserve traded in the current market.
- As shown in **FIG. 6**, after the financial crisis of 2008, the federal reserve quickly down-regulates the federal fund rate to approximately 0, which maintains a narrow fluctuation pattern for the short-end interest rates between 2009-2014. In this stage, to further stimulate economy, the US Fed reserve is mostly suppressing long-end interest rates through QE operations. The initiation and withdrawal of QE may represent US Fed Reserve's monetary policy standpoint.



US Synthetic policy rates factor US Synthetic policy rates factor standardization

FIG. 6 Global Currency macro factor construction

As shown in **FIG. 7**, global inflation macro factor is based on the break-even interest rates of 10 years US Bond, the state classification is the same as domestic inflation macro factor classification.



US inflation factor states

FIG. 7 Global inflation macro factor construction

As shown in **FIG. 8**, the US dollar macro factor, using the dollar index, the state classification

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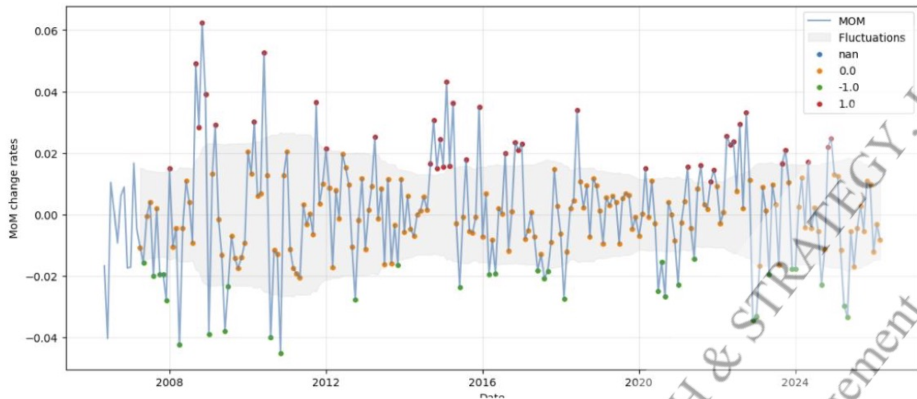
method is based on a particular volatility threshold, the same method as the inflation classification method.



US dollar factor states

FIG. 8 US dollar macro factor construction

As shown in **FIG. 9**, the global OFR macro factor, the state classification method is based on a specific volatility threshold using the OFR financial pressure index, the same method as the US dollar cycle classification method.

Global OFR states

FIG. 9 The global OFR macro factor construction

4.2. Multi-Asset Strategy Implementation

A sophisticated macro fund must operate across a spectrum of asset classes that respond differently to the global capital cycle. The MRCRP system integrates state-of-the-art strategies for seven distinct categories: the S&P 500, China A-shares, Crude Oil, Gold, Copper, Bonds, and Cash equivalents.

4.2.1. Asset allocation based on macro factor ratings:

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	China_equity	China_bond_yield	US_equity	Gold	Oil	Copper	Cash
2017-08-01	-1.0	0.0	1.10	1.0	1.0	1.0	1.0
2017-08-02	0.0	0.0	1.10	1.0	1.0	1.0	1.0
2017-08-03	0.0	0.0	0.80	1.0	1.0	1.0	1.0
2017-08-04	0.0	0.0	0.80	1.0	1.0	1.0	1.0
2017-08-07	0.0	0.0	0.80	1.0	1.0	1.0	1.0
...	...	...	...	...	...	...	...
2026-02-18	-1.0	0.0	0.55	1.0	1.0	1.0	1.0
2026-02-19	-1.0	0.0	0.55	1.0	1.0	1.0	1.0
2026-02-20	-1.0	0.0	0.67	1.0	1.0	1.0	1.0
2026-02-23	-1.0	0.0	0.55	1.0	1.0	1.0	1.0
2026-02-24	-1.0	0.0	0.55	1.0	1.0	1.0	1.0

Table 2. Calculated asset classes daily ratings with macro factors

The impact direction mapping constitutes the proprietary knowledge map, the impact direction (1, -1, 0) of the macro factor on the asset is determined by a logical deduction. For example, domestic economy factor is beneficial (1) for the China A800 and beneficial (1) for 10 year bond.

For the macro rating calculation, the macro rating for each asset is a weighted sum of the individual factor scores: asset rating = Σ (factor score x influence on direction coefficient), wherein the influencing direction coefficients are from our proprietary impact direction knowledge map. The rating results are classified into various discrete daily/monthly grades as shown in **Table 2**, and the buying, holding or selling decision is guided.

4.2.2. Macro asset allocation strategies

On the ground of global asset allocation, a risk budget model and a macro risk controlled model are built, and all-weather configuration is achieved.

4.2.2.1. Mathematical Formulation of Risk budget model

The model extends the risk parity concept, allowing subjective risk budget allocation.

Definition:

Portfolio weight vector $w=(w_1,w_2,\ldots,w_n)^T$, number of assets n.

Asset covariance matrix Σ.

Combined portfolio risk $\sigma_p = \sqrt{w^T \sum w}$

Risk Contribution (RC_i) of the *ith* asset: $RC_i = w_i \dfrac{\partial \sigma_p}{\partial w_i} = w_i \dfrac{\left(\sum w\right)_i}{\sqrt{w^T \sum w}}$

The risk budget vector $b=(b_1, b_2,., b_n)$, where b_i is the risk contribution of the i-th asset, satisfying $\Sigma b_i=1$.

Optimization problem: minimizing risk contribution bias, weight sum constraint is 1 and not negative:

† Core technical implementation protected by Chinese Patent Application No.CN202511140743.3A (Filed: 2025-08-14) and Patent Cooperation Treaty (PCT) international patent application No. PCT/CN2026/112498 (Filed: 2026-07-22). Full patent documentation is available via CNIPA/WIPO.

$$\min_{w} \sum_{i=1}^{N} \left(RCi - bi \cdot \sqrt{w^T \sum w}\right)^2$$

$$s.t. \begin{cases} w_1 + \cdots w_N = 1 \\ 0 \le w_i \le 1 \end{cases}$$

The solution uses a gradient descent algorithm, with the initial weights set based on historical volatility.

4.2.2.2. Mathematical Formulation of Macro Risk control model

➢ *Macro Factor Risk Contribution Matrix*

Definition: Macro risk number M, asset number N, we construct the macro factor risk contribution matrix K, whose element K_{ij} represents asset i's risk exposure to macro factor j:

$$K = \begin{bmatrix} d_{1,1} * k_{1,1} \cdots d_{1,N} * k_{1,N} \\ \vdots \\ d_{M,1} * k_{M,1} \cdots d_{M,N} * k_{M,N} \end{bmatrix}$$

To counter-impact macro risk, an exposure coefficient matrix and short-term bond/Cash equivalent (as a hedging tool) are introduced.

The exposure coefficient matrix K, element k_{ij}, represents the exposure intensity of the macro risk i to asset j (taking the last 5 months macro single-factor winning rate as a proxy). The impact direction matrix d_{ij} is from our proprietary direction impact knowledge map (1, -1, 0) and is the impact direction of the macro risk i on asset j. Since each macro dimension is less explanatory for short-term bond and cash equivalent, its exposure is fixed at 1.

The direction coefficient d_{ij} is based on our proprietary direction impact knowledge map:

When the macro factor is in a rising state, $d_{ij} = 1$, indicating positive exposure of the asset to the rising factor.

When the macro factor is in a falling state, $d_{ij} = -1$, indicating negative exposure of the asset to the falling factor.

When the macro factor is in an oscillating state, $d_{ij} = 0$, indicating no significant exposure of the asset to the oscillating factor.

1. *Macro-Factor Risk Constraints*

We introduce macro-factor risk constraints to equalize portfolio risk exposure at the macro-factor level:

$$\min_{w} \sum_{i=1}^{N} \left(RCi - bi \cdot \sqrt{w^T \sum w}\right)^2 + \|Kw\|_F^2$$

$$s.t. \begin{cases} w_1 + \cdots + w_N = 1 \\ 0 \le w_i \le 1 \end{cases}$$

where $\|Kw\|_F^2$ denotes the portfolio's risk exposure at the macro-factor level (F denotes the Frobenius norm), and the regularization parameter controlling the intensity of the macro-factor risk constraint.

† Core technical implementation protected by Chinese Patent Application No.CN202511140743.3A (Filed: 2025-08-14) and Patent Cooperation Treaty (PCT) international patent application No. PCT/CN2026/112498 (Filed: 2026-07-22). Full patent documentation is available via CNIPA/WIPO.

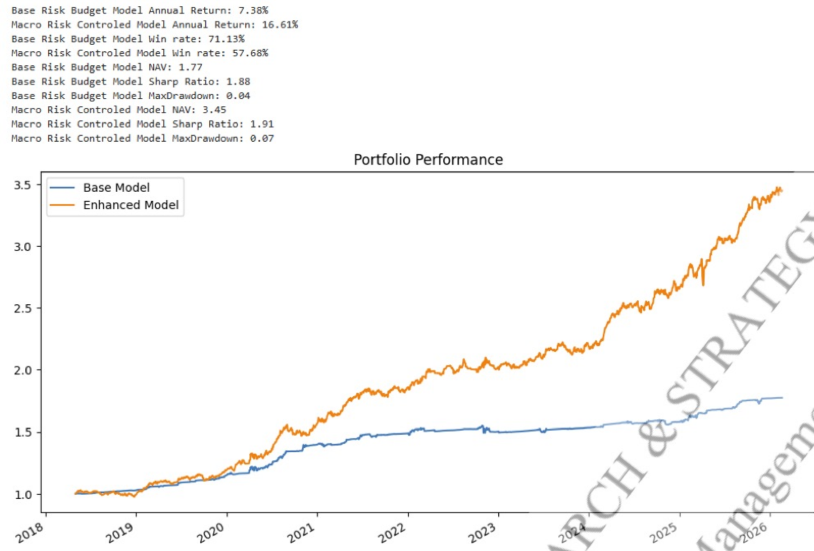
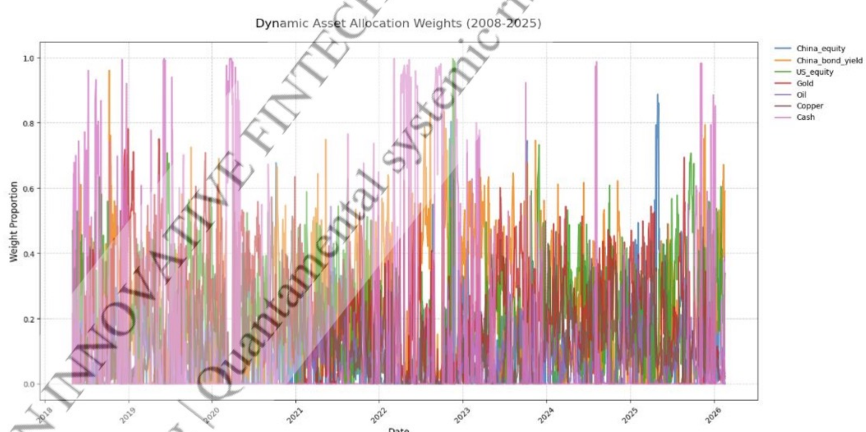


FIG. 10 The backtest result of the macro risk controlled model

As shown in **FIG. 10**, the backtest result of the macro risk controlled model generate an annual return of 16.61%, the Sharpe ratio is 1.91, and the maximum drawdown is 7%; the risk budget model annual return is 7.38%, the Sharpe ratio is 1.88, and the maximum drawdown is 4%, so that the model effectiveness is proved. As shown in **FIG. 11**, the macro risk controlled model backtest portfolio configuration changes over the period of 2008-2026.



† Core technical implementation protected by Chinese Patent Application No.CN202511140743.3A (Filed: 2025-08-14) and Patent Cooperation Treaty (PCT) international patent application No. PCT/CN2026/112498 (Filed: 2026-07-22). Full patent documentation is available via CNIPA/WIPO.

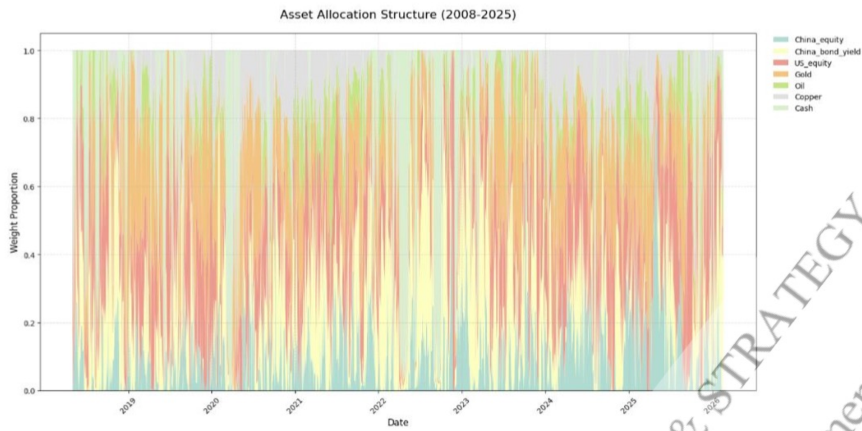


FIG. 11 The macro risk controlled model backtest portfolio configuration

As shown in **FIG. 12**, the backtest result of the investment phase macro risk controlled model generate an annual return of 12.14%, the Sharpe ratio is 2.05, and the maximum drawdown is 5%. The investment phase model is setup for the purpose of optimal Sharpe ratio with the best risk reward ratio for the initial investment phase.

```
Base Risk Budget Model Annual Return: 6.70%
Macro Risk Controled Model Annual Return: 12.14%
Base Risk Budget Model Win rate: 70.10%
Macro Risk Controled Model Win rate: 61.72%
Base Risk Budget Model NAV: 1.69
Base Risk Budget Model Sharp Ratio: 1.70
Base Risk Budget Model MaxDrawdown: 0.04
Macro Risk Controled Model NAV: 2.52
Macro Risk Controled Model Sharp Ratio: 2.05
Macro Risk Controled Model MaxDrawdown: 0.05
```

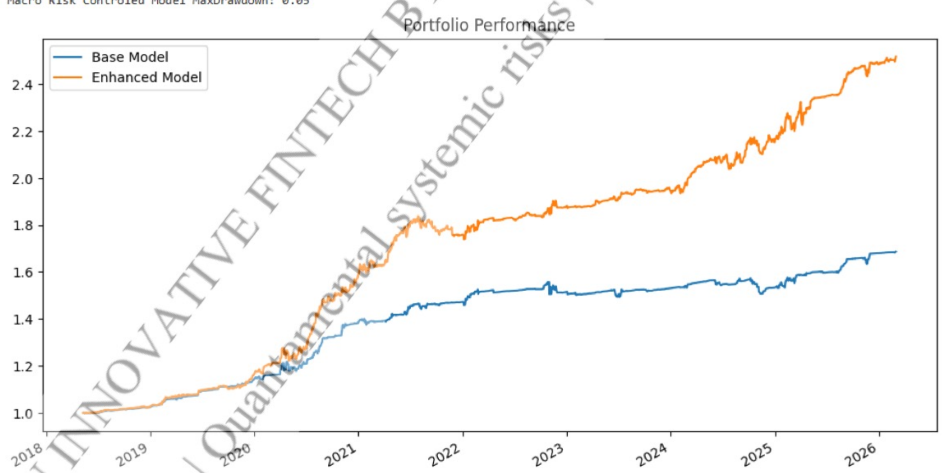


FIG. 12 The investment phase backtest result of the macro risk controlled model

As shown in **FIG. 13**, the investment phase macro risk controlled model backtest portfolio configuration changes over the period of 2008-2026.

† Core technical implementation protected by Chinese Patent Application No.CN202511140743.3A (Filed: 2025-08-14) and Patent Cooperation Treaty (PCT) international patent application No. PCT/CN2026/112498 (Filed: 2026-07-22). Full patent documentation is available via CNIPA/WIPO.

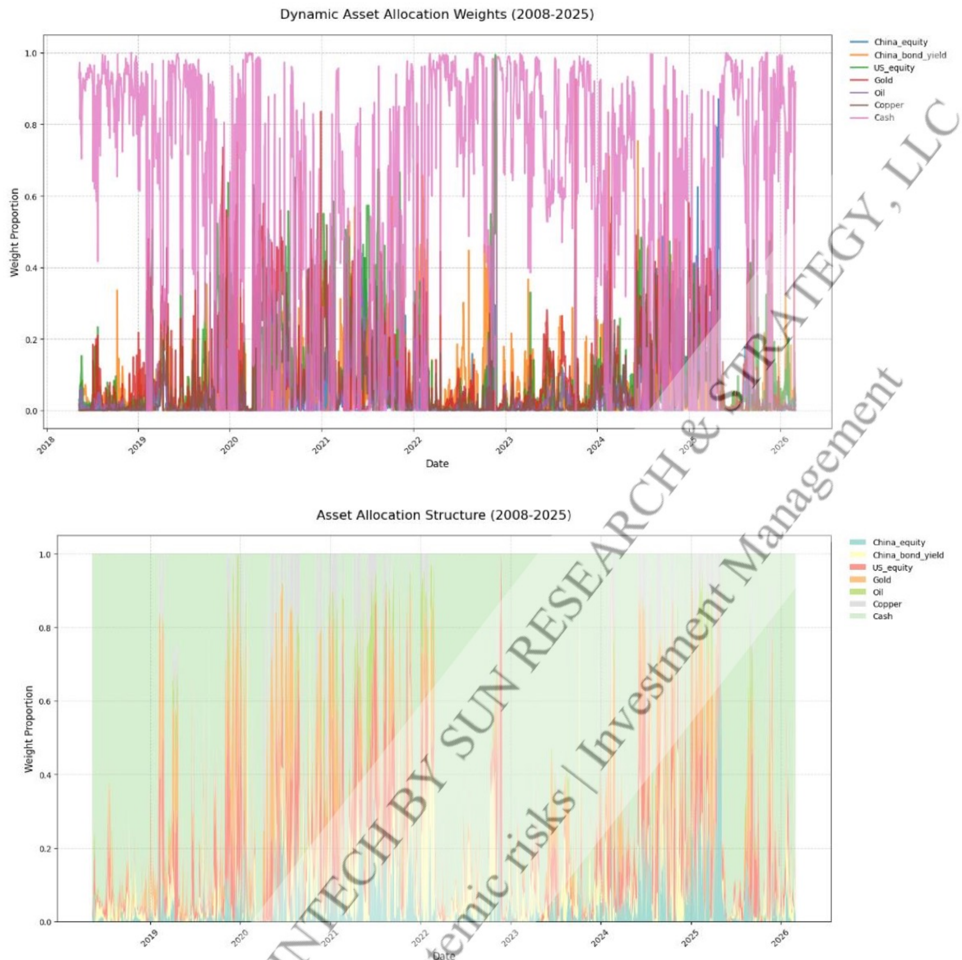


FIG. 13 The investment phase macro risk controlled model backtest portfolio configuration

As shown in **FIG. 14**, the backtest result of the long-short macro risk controlled model generate an annual return of 21.21%, the Sharpe ratio is 2.08, and the maximum drawdown is 9%; the long-short risk budget model annual return is 9.33%, the Sharpe ratio is 2.26, and the maximum drawdown is 4%. The long-short model is for more aggressive setup allowing taking the long and short positions of each asset.

† Core technical implementation protected by Chinese Patent Application No.CN202511140743.3A (Filed: 2025-08-14) and Patent Cooperation Treaty (PCT) international patent application No. PCT/CN2026/112498 (Filed: 2026-07-22). Full patent documentation is available via CNIPA/WIPO.

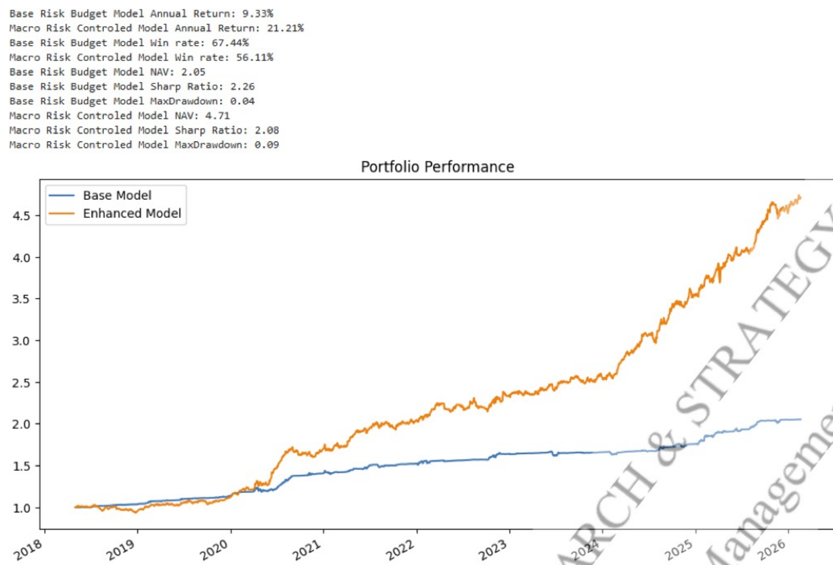


FIG. 14 The backtest result of the long-short macro risk controlled model

As shown in **FIG. 15**, the long-short macro risk controlled model backtest portfolio configuration changes over the period of 2008-2026.

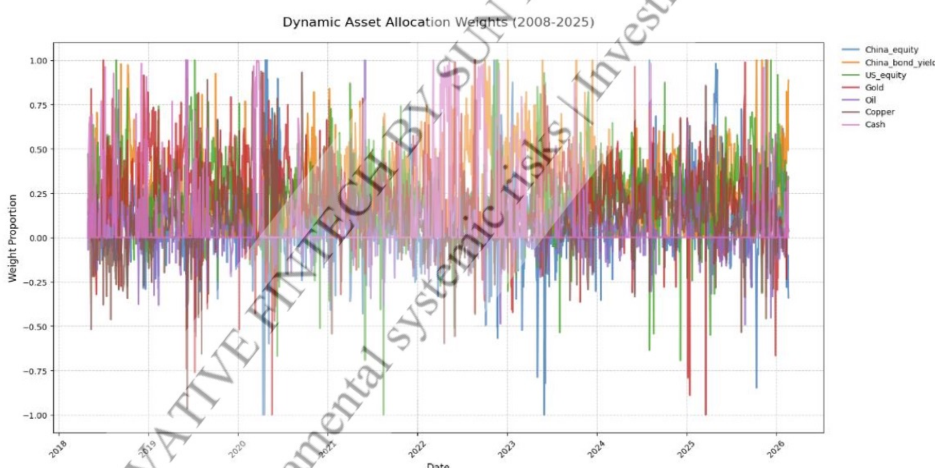


FIG. 15 The backtest result of the long-short macro risk controlled model

As shown in **FIG. 16**, the backtest result of the investment phase long-short macro risk controlled model generate an annual return of 16.14%, the Sharpe ratio is 2.12, and the maximum drawdown is 5%; the investment phase long-short risk budget model annual return is 10.49%, the Sharpe ratio is 2.23, and the maximum drawdown is 3%. The investment phase long-short model is setup for the purpose of optimal Sharpe ratio with the best risk reward ratio for the initial investment phase.

† Core technical implementation protected by Chinese Patent Application No.CN202511140743.3A (Filed: 2025-08-14) and Patent Cooperation Treaty (PCT) international patent application No. PCT/CN2026/112498 (Filed: 2026-07-22). Full patent documentation is available via CNIPA/WIPO.

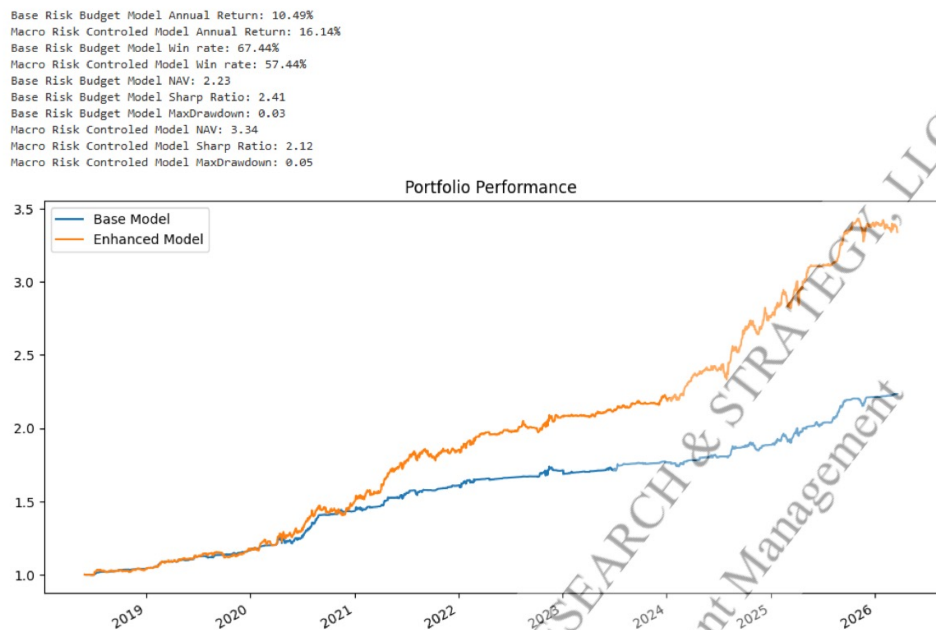


FIG. 16 The investment phase backtest result of the long-short macro risk controlled model

As shown in **FIG. 17**, the investment phase long-short macro risk controlled model backtest portfolio configuration changes over the period of 2008-2026.

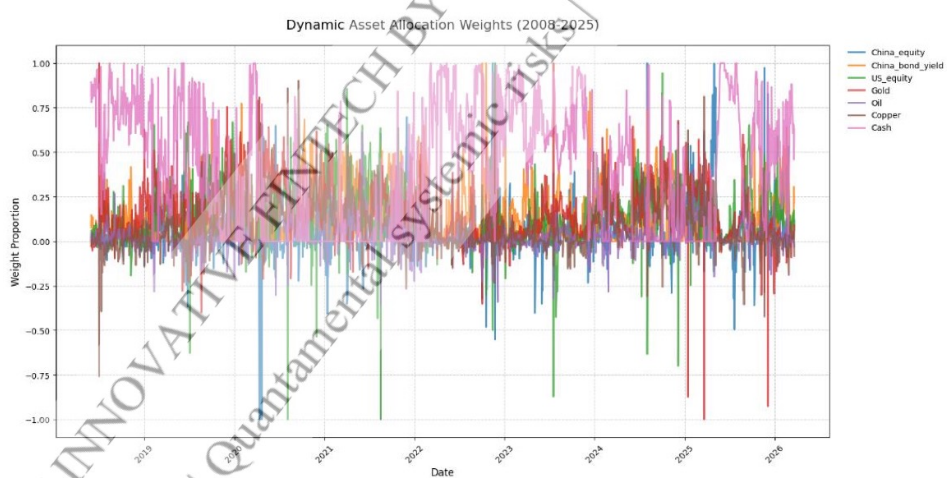


FIG. 17 The investment phase backtest result of the long-short macro risk controlled model

For some institutions seeking the best risk reward ratio of the portfolio, an arbitrary constraint on certain asset classes can be employed. With the optimization of the constraints' boundaries, the optimal risk reward ratio and the highest Sharpe ratio can be achieved for satisfying the risk appetite of the institutions. As shown in FIG. 9, the backtest result of the optimal constraint investment phase long-only macro risk controlled model generate an annual return of 12.08%, the Sharpe ratio is 2.55,

† Core technical implementation protected by Chinese Patent Application No.CN202511140743.3A (Filed: 2025-08-14) and Patent Cooperation Treaty (PCT) international patent application No. PCT/CN2026/112498 (Filed: 2026-07-22). Full patent documentation is available via CNIPA/WIPO.

and the maximum drawdown is 3%; the optimal constraint investment phase long-only risk budget model annual return is 6.48%, the Sharpe ratio is 2.79, and the maximum drawdown is 1%.

```
Base Risk Budget Model Annual Return: 6.48%
Macro Risk Controled Model Annual Return: 12.08%
Base Risk Budget Model Win rate: 70.79%
Macro Risk Controled Model Win rate: 60.64%
Base Risk Budget Model NAV: 1.66
Base Risk Budget Model Sharp Ratio: 2.79
Base Risk Budget Model MaxDrawdown: 0.01
Macro Risk Controled Model NAV: 2.51
Macro Risk Controled Model Sharp Ratio: 2.55
Macro Risk Controled Model MaxDrawdown: 0.03
```

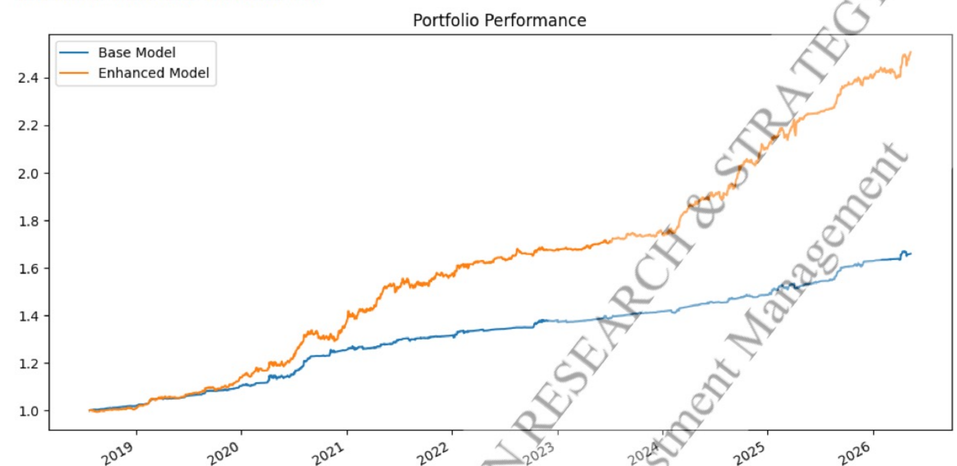
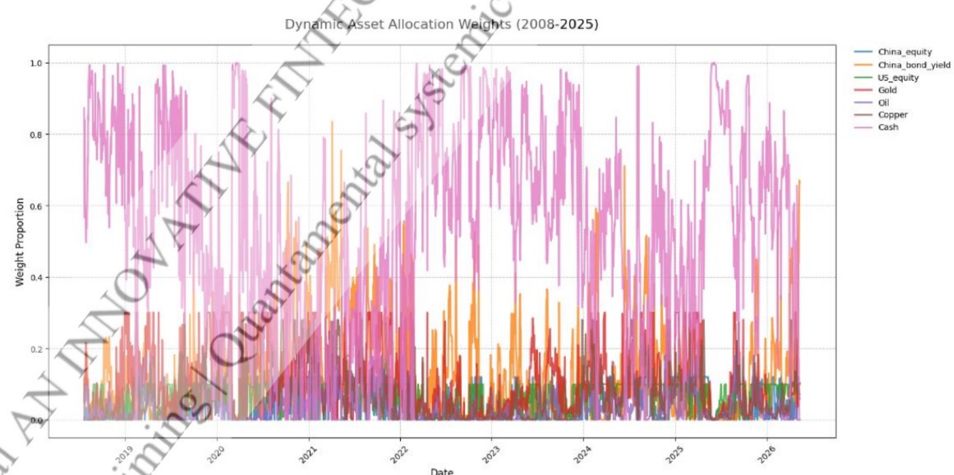


FIG. 18 The optimal constraint investment phase backtest result of the long only macro risk controlled model

As shown in **FIG. 19**, the optimal constraint investment phase long-only macro risk controlled model backtest portfolio configuration changes over the period of 2008-2026.



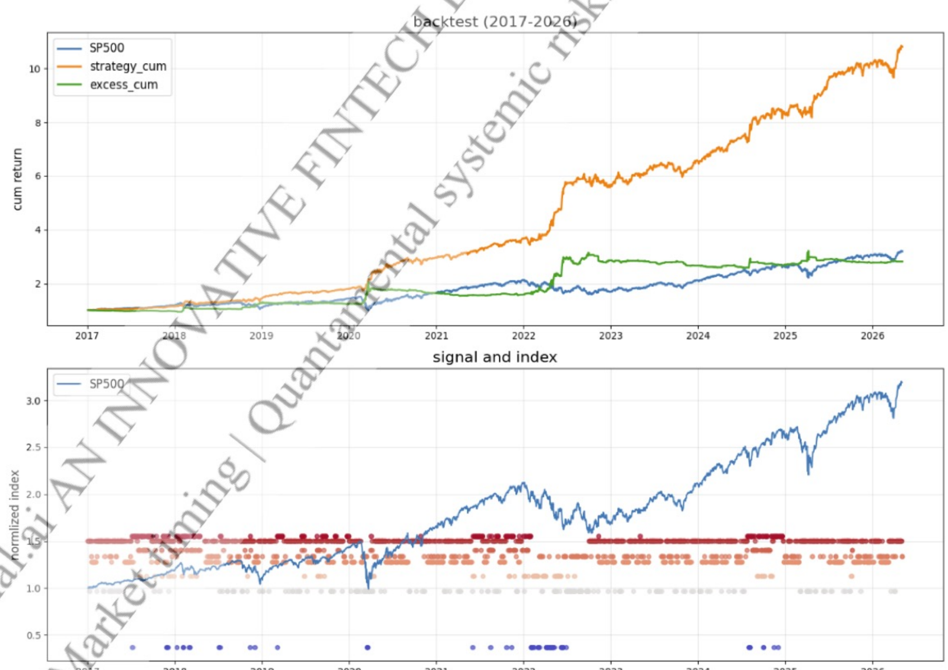
† Core technical implementation protected by Chinese Patent Application No.CN202511140743.3A (Filed: 2025-08-14) and Patent Cooperation Treaty (PCT) international patent application No. PCT/CN2026/112498 (Filed: 2026-07-22). Full patent documentation is available via CNIPA/WIPO.

FIG. 19 The optimal constraint investment phase backtest result of the long only macro risk controlled model

4.3. Analysis of multi-strategies of each asset classes:

4.3.1. Equity Markets: S&P 500 and China A Shares

The equity allocation is bifurcated to capture the divergent growth trajectories of the world's two largest economies. For the S&P 500, the system employs systemic risk management and dynamic Multi-Factor model, providing an annual return of 29.03% with a Sharpe ratio of 1.9 and a maximum drawdown of 8.54%.



† Core technical implementation protected by Chinese Patent Application No.CN202511140743.3A (Filed: 2025-08-14) and Patent Cooperation Treaty (PCT) international patent application No. PCT/CN2026/112498 (Filed: 2026-07-22). Full patent documentation is available via CNIPA/WIPO.

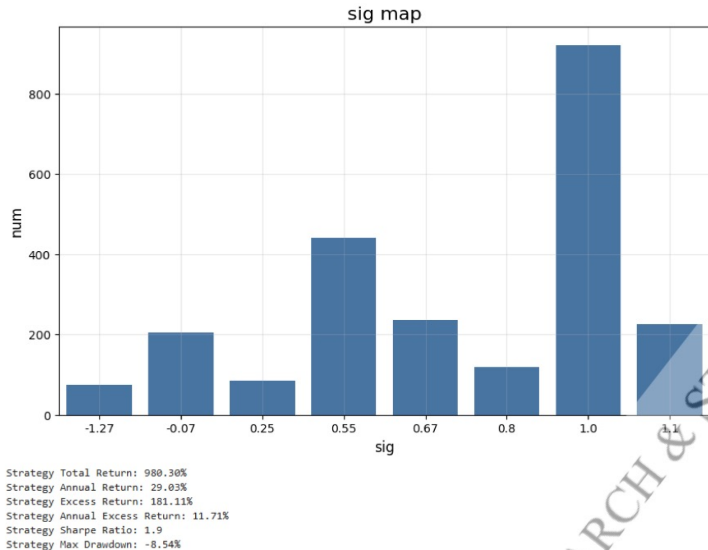
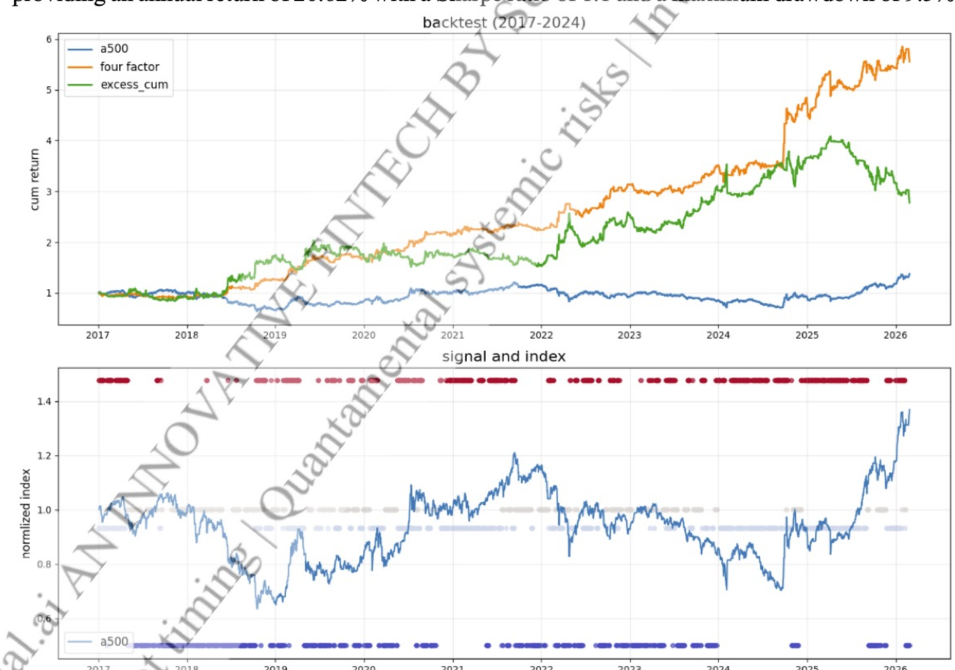


FIG.20 The empirical backtest result of the SP500 model

The strategy for China A-shares is specifically optimized to handle the high volatility and sentiment-driven nature of the Chinese market. The dynamic Multi-Factor model that extracts features from thousands of macroeconomic variables and alternative data for enhancing the predictive accuracy, providing an annual return of 20.62% with a Sharpe ratio of 1.1 and a maximum drawdown of 9.5%.



† Core technical implementation protected by Chinese Patent Application No.CN202511140743.3A (Filed: 2025-08-14) and Patent Cooperation Treaty (PCT) international patent application No. PCT/CN2026/112498 (Filed: 2026-07-22). Full patent documentation is available via CNIPA/WIPO.

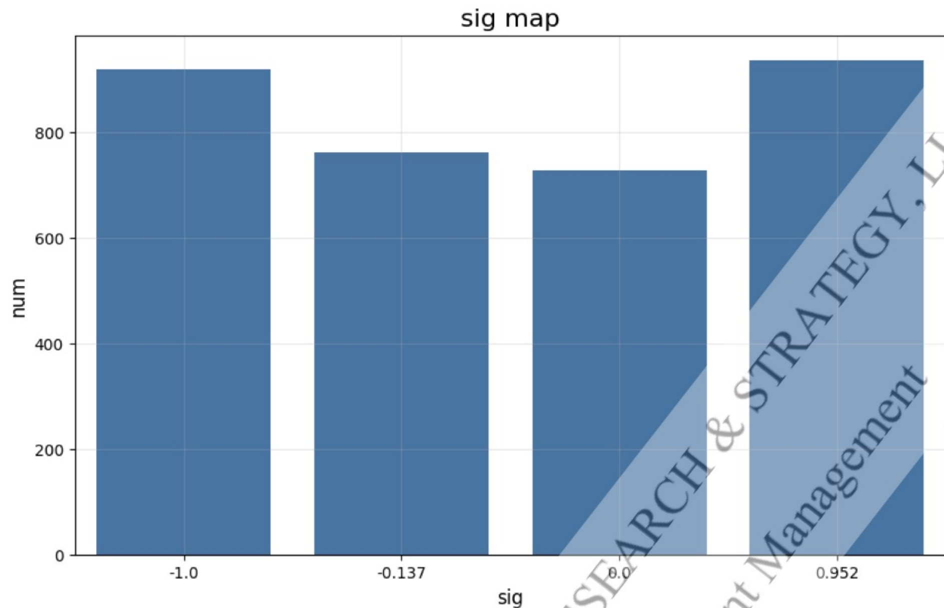


FIG.21 The empirical backtest result of the China A800 model

4.3.2. Hard Assets and Commodities: Gold, Oil, and Copper

Commodities function as the portfolio's primary defense against inflation and currency debasement. Gold is weighted as a hedge against systemic debt risks and "heart-attack" shocks in the global financial system. The Crude Oil strategy utilizes an multi-factor model with the embedment of geopolitical risks monitoring, by incorporating macro factors such as the U.S. dollar index, interest rates, and alternative factor such as global geopolitical index. Copper is monitored as a leading indicator of global manufacturing and rising growth, with its allocation adjusted based on another set of multi-factor model. The Gold multi-factor model provides an annual return of 13.9% with a Sharpe ratio of 1.1 and a maximum drawdown of 17.5%.

† Core technical implementation protected by Chinese Patent Application No.CN202511140743.3A (Filed: 2025-08-14) and Patent Cooperation Treaty (PCT) international patent application No. PCT/CN2026/112498 (Filed: 2026-07-22). Full patent documentation is available via CNIPA/WIPO.

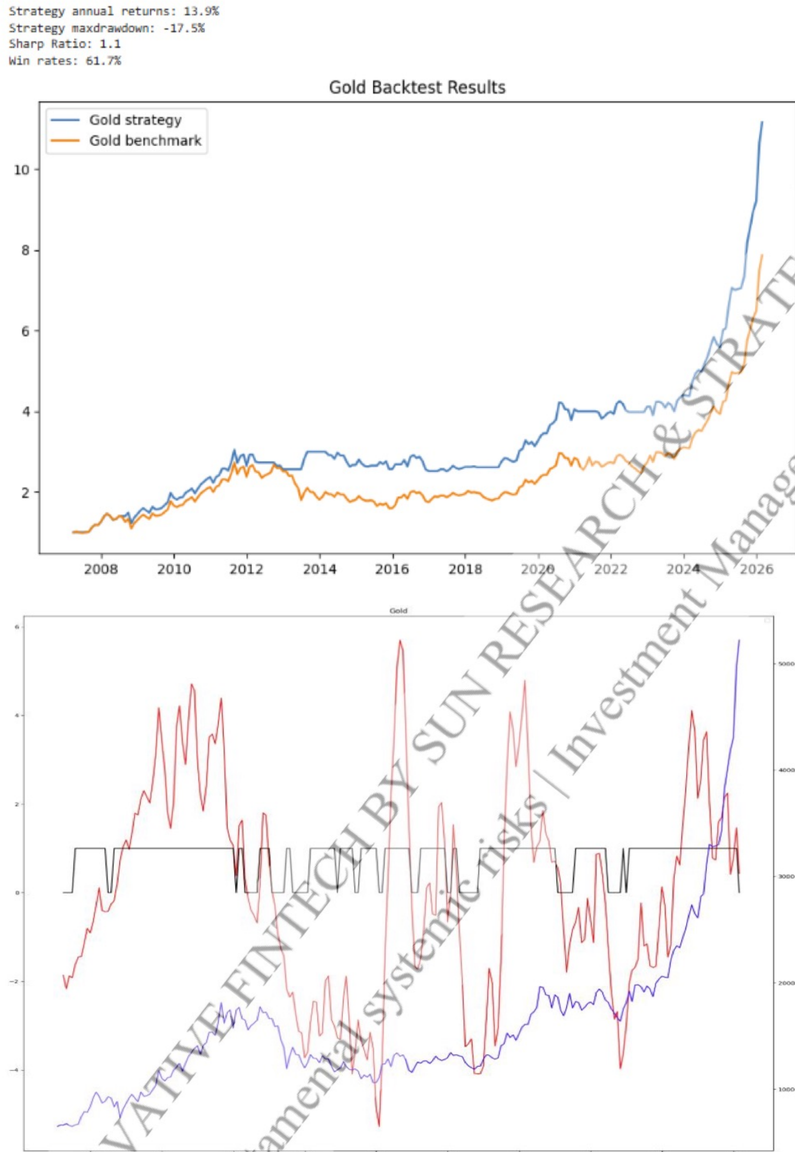
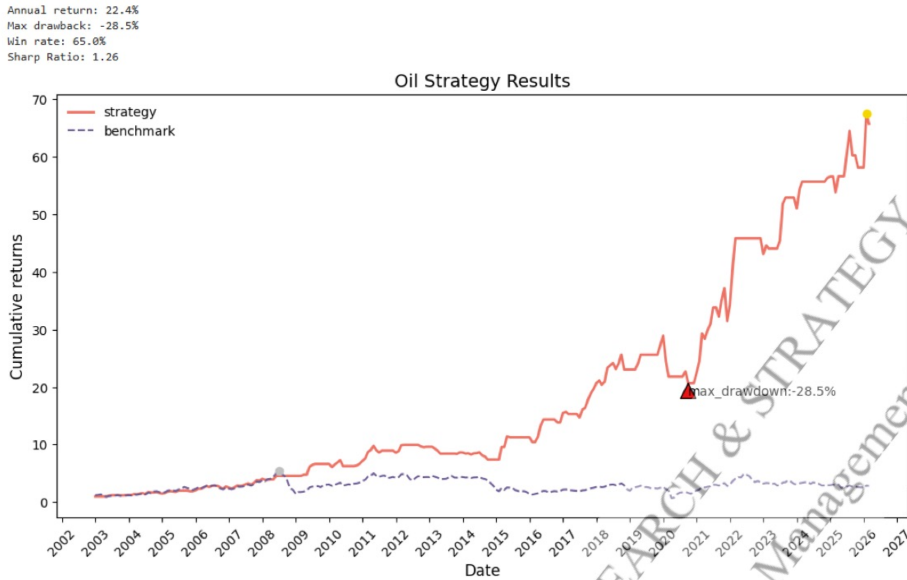


FIG. 22 The empirical backtest result of the Gold model

The Oil multi-factor model provides an annual return of 22.4% with a Sharpe ratio of 1.26 and a maximum drawdown of 28.5%.

† Core technical implementation protected by Chinese Patent Application No.CN202511140743.3A (Filed: 2025-08-14) and Patent Cooperation Treaty (PCT) international patent application No. PCT/CN2026/112498 (Filed: 2026-07-22). Full patent documentation is available via CNIPA/WIPO.



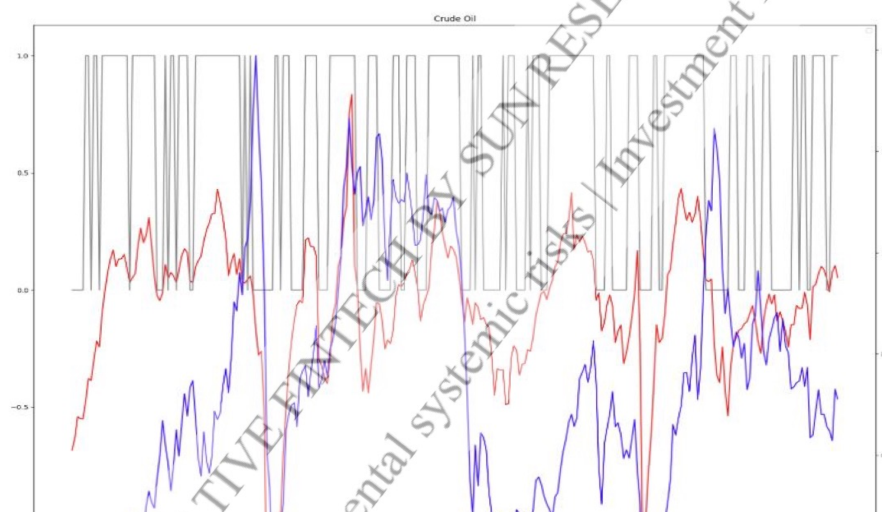


FIG.23 The empirical backtest result of the Crude Oil model

The Copper multi-factor model provides an annual return of 10.68% with a Sharpe ratio of 0.98 and a maximum drawdown of 28.41%.

† Core technical implementation protected by Chinese Patent Application No.CN202511140743.3A (Filed: 2025-08-14) and Patent Cooperation Treaty (PCT) international patent application No. PCT/CN2026/112498 (Filed: 2026-07-22). Full patent documentation is available via CNIPA/WIPO.

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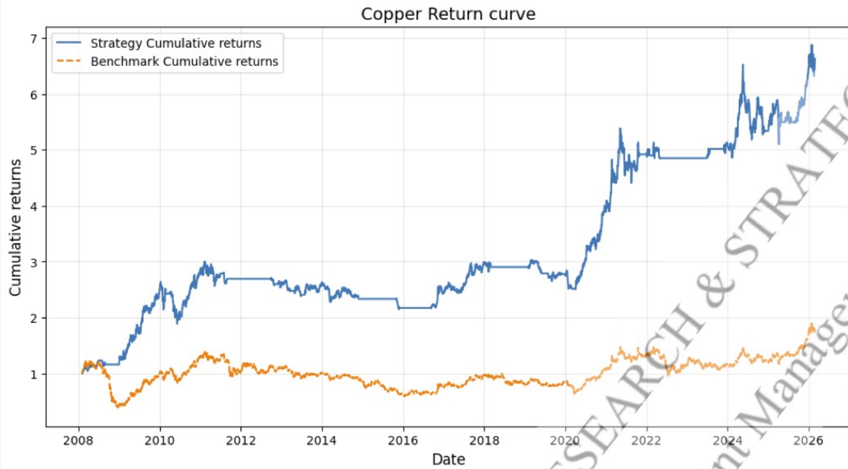
============================= COPPER Backtest start ============================

==========================================================
【COPPER Performance report】
Indicator          Strategy      Benchmark
Total returns       562.71%        80.55%
Annual yields        10.68%         3.22%
Max drawdown        -28.41%       -69.17%
Sharp ratio           0.98          0.25
==========================================================
```



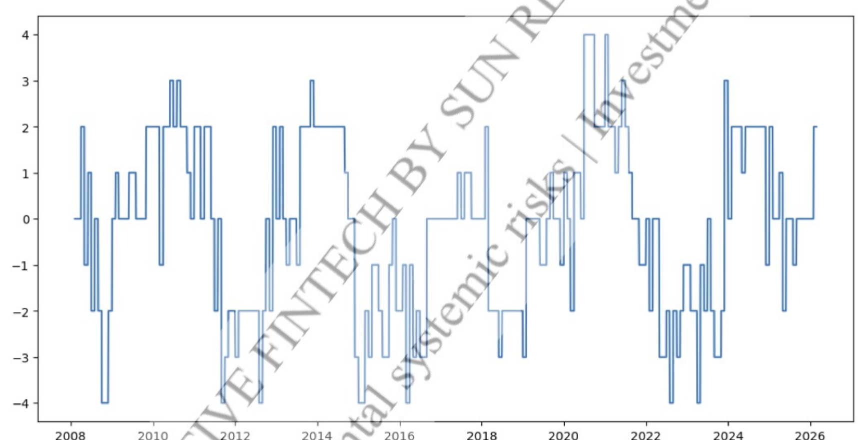


FIG.24 The empirical backtest result of the Copper model

4.3.3. Fixed Income and Liquidity Management

Bonds are the cornerstone of the risk parity framework, providing a low-volatility anchor. We utilize China 10 Year Treasury bond for building the multi-factor model, as the data is more accessible. The multi-factor model provides an annual return of 6.28% with a Sharpe ratio of 2.36 and a maximum drawdown of 13.9%.

† Core technical implementation protected by Chinese Patent Application No.CN202511140743.3A (Filed: 2025-08-14) and Patent Cooperation Treaty (PCT) international patent application No. PCT/CN2026/112498 (Filed: 2026-07-22). Full patent documentation is available via CNIPA/WIPO.

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============================== CHINA 10Y BOND YIELD Backtest start ==============================

============================================================
【CHINA 10Y BOND YIELD Performance report】
Indicator            Strategy      Benchmark
Total returns         211.20%         73.17%
Annual yields           6.28%          2.99%
Max drawdown          -13.90%        -43.39%
Sharp ratio              2.36           0.30
============================================================
```

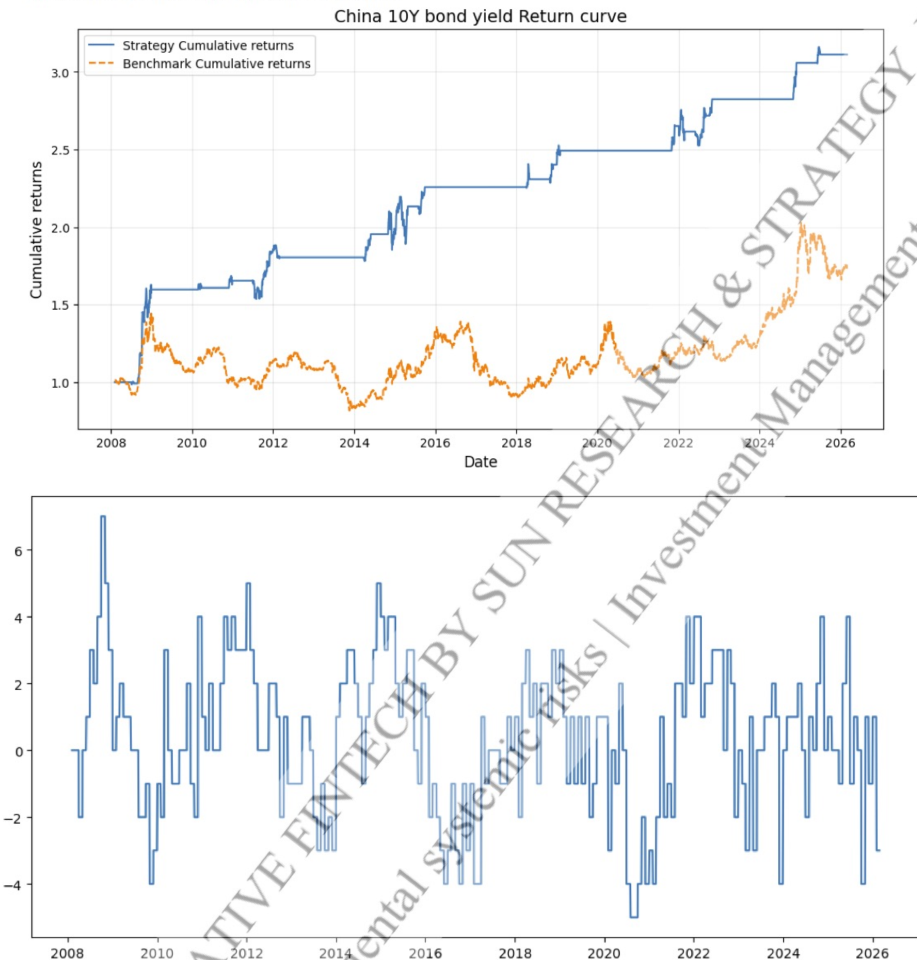

FIG.25 The empirical backtest result of the China 10Y Bond model

Cash equivalents and dry powder are parked in ultra-short-term vehicles and monetary fund to maintain liquidity while providing a modest risk-free return. We utilize China short term instrument index for building the multi-factor model for cash equivalent, as the data is more accessible. We built the multi-factor model for cash equivalent for the main goal of increasing the Sharpe ratio. The multi-factor model provides an annual return of 1.79% with a Sharpe ratio of 11.41 and a maximum drawdown of 0.2%.

† Core technical implementation protected by Chinese Patent Application No.CN202511140743.3A (Filed: 2025-08-14) and Patent Cooperation Treaty (PCT) international patent application No. PCT/CN2026/112498 (Filed: 2026-07-22). Full patent documentation is available via CNIPA/WIPO.

【CASH Performance report】

Indicator	Strategy	Benchmark
Total returns	39.30%	91.76%
Annual yields	1.79%	3.55%
Max drawdown	-0.20%	-0.50%
Sharp ratio	11.41	9.25

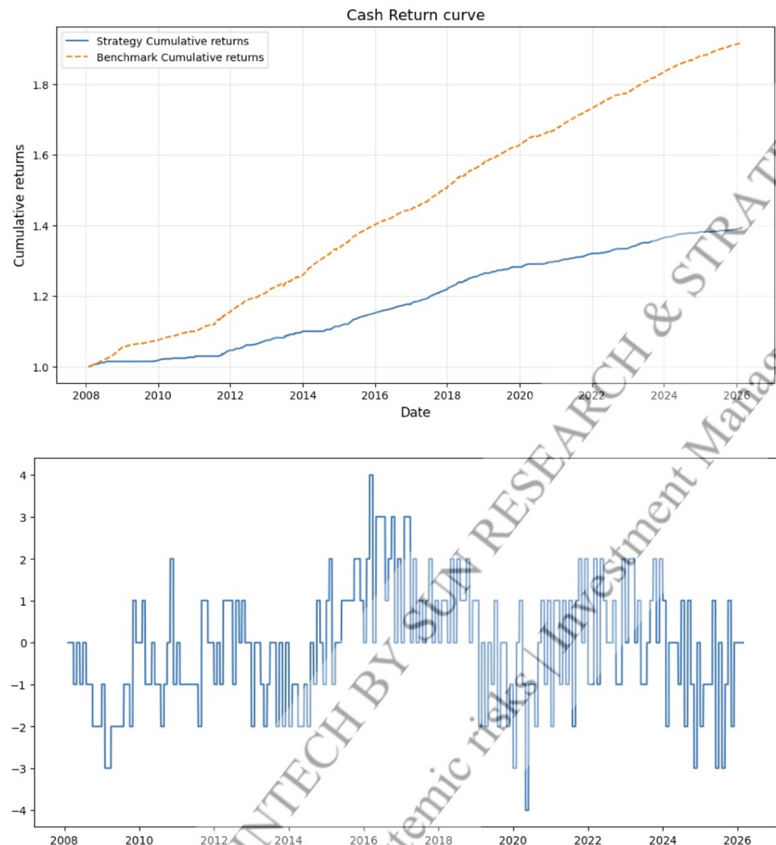

FIG. 26 The empirical backtest result of the China Cash equivalent model

5. Model Advantages and Innovation

5.1. Macro Risk Diversification Mechanism

Compared with traditional risk parity models, the core advantage of the MRCRP model lies in achieving substantive diversification at the macro risk level. While traditional risk parity achieves risk balance at the asset level, portfolios often remain highly concentrated on a small number of macro risk sources such as growth and inflation. For example, approximately 93% of the 60/40 portfolio's risk contribution derives from the economic growth factor. The MRCRP model ensures balanced portfolio exposure across various macro risk sources through macro-factor-level risk constraints, thereby enhancing macro adaptability.

5.2. Innovative algorithm group

The system's core algorithm groups comprises:

➢ The three-dimensional data fusion engine integrates macro data (nine factors), alternative data

† Core technical implementation protected by Chinese Patent Application No.CN202511140743.3A (Filed: 2025-08-14) and Patent Cooperation Treaty (PCT) international patent application No. PCT/CN2026/112498 (Filed: 2026-07-22). Full patent documentation is available via CNIPA/WIPO.

(e.g., VIX microstructure, traffic volume, satellite data) and real-time market data. Feature engineering uses dynamic weight algorithms.

- The TIC funds flow prediction module integrates XGBoost (short term mode), lightGBM (long term trend), GBR (robust) stacking models. Residual correction adopts PCA (principal component analysis) dimensionality reduction and elastic network regression.
- Knowledge graph based on nine macro factors mapping structure, automated processing of macro factors and asset correlations.

The invention has the advantages that multidimensional data fusion resolves the traditional limitation.

5.3. *Data breadth*

- The method integrates nine macro factors (domestic economy/currency/credit/inflation, global economy/currency/inflation, US dollar cycle, Global OFR) and alternative data (VIX microstructure, copper-gold ratio, Korean export, non-commercial holdings, etc.) to solve the problem of dislocation of the traditional model depending on a single index.
- A high-frequency real-time data source (such as CBOE VIX derivative data) is introduced, so that the TIC capital flow prediction lag is shortened from 75 days to near real time, improving the prediction power of the equity strategies.

5.4. *Scientific nature of factor construction*

- The leading indicators (such as the synthetic method of the leading CPI/PPI with respect to PMI raw material, copper-gold ratio stripping financial fluctuation, etc.) are adopted to construct factors, so that the prediction power is enhanced.
- Performing three-state classification (uptrend/downtrend/oscillation) on factors such as inflation, OFR, etc., and accurately identifying a macro inflection point.

5.5. *Dynamic algorithm group for realizing intelligent decision*

Risk control innovation: Macro risk controlled risk parity model, by managing the combined macro risk exposure, a more robust asset allocation model is achieved. Based on a macro factor system constructed by our scientific approach, the combined macro risk control is realized. Each factor represents a relatively important class of macro risk, and the direction of impact varies for different classes of assets. In the portfolio optimization process, macro risk controlled conditions are added so that the exposure of the portfolio to each macro risk is as close to 0 as possible. For domestic currency, domestic inflation, global currency and global inflation, these 4 types of macro risks have no reverse exposing assets available for risk hedging, and a cash equivalent instrument is introduced as a hedging asset.

Macro risk controlled risk parity asset allocation model core concept:

- Not predicting macro environment, acknowledging uncertainty in future economic status
- Risk balanced allocation: average allocation of portfolio risk budget to major macro states
- Robust return objective to ensure relatively stable returns are obtained in any economic environment

Risk exposure optimization function:

† Core technical implementation protected by Chinese Patent Application No.CN202511140743.3A (Filed: 2025-08-14) and Patent Cooperation Treaty (PCT) international patent application No. PCT/CN2026/112498 (Filed: 2026-07-22). Full patent documentation is available via CNIPA/WIPO.

$$\min_{w} \sum_{i=1}^{N} \left(RCi - bi \cdot \sqrt{w^T \sum w} \right)^2 + \|Kw\|_F^2$$

$$s.t. \begin{cases} w_1 + \cdots + w_N = 1 \\ 0 \leq w_i \leq 1 \end{cases}$$

The macro risk is restrained to be close to zero through matrix constraints, and the annual return of the all-weather asset allocation strategy for the macro risk controlled model reaches 16.61%.

5.6. *Innovation in international capital flow forecasting*

A significant innovation in the MRCRP model is its integration of real-time global capital flow forecasts. Traditional models often rely on residency-based capital flow data, which fails to capture the complexity of modern financial holdings. The state-of-the-art approach "redraws the map" by real time forecasting international capital flows, accurately reflecting the financial behavior of international capital market.

5.7. *Technical barriers and engineering value*

Algorithm barriers:

- Cross-modal fusion of VIX microstructure data, macro factors, and alternative data.
- Systematic implementation capability.
- Automatic knowledge graph mapping with macro factors and the asset impact directions (such as OFR and gold positive correlation).
- The localized data security mechanism meets financial institution compliance requirements.

5.8. *Initial Investment Phase: Adaptability and Real-World Scaling*

A critical innovation for the successful deployment of the MRCRP fund is the "Initial Investment Phase" strategy. This phase is designed to increase the adaptability of the quantitative model to real-world market conditions, where liquidity and slippage can undermine theoretical performance.

5.9. *Adaptive Learning from AI driven alternative information analysis*

Traditional automated trading depended on fixed rules, which often failed during regime shifts. The state-of-the-art MRCRP model utilizes adaptive AI driven alternative information analysis to efficiently ingest economic and political information, sentiment, and major economic/social events information. This shift from rigid to adaptive approach improves adaptability in real world implementation and allows the system to evolve its liquidity strategies as regime shift driven by international market participants become more influential in creating volatility clusters. To mitigate "black-box" risks, the system incorporates formal governance and oversight by panels of experts, moving from "proof of concept" to "proof of value" through enterprise scaling.

The performance metrics of the MRCRP model are a result of its multi-layered approach to risk and return. The core allocation targets a risk appetite profile that aligns with each multi-asset fund, delivering consistency through regimes where traditional strategies faltered.

5.10. *Drawdown Mitigation and Robustness*

The maximum drawdown is strictly controlled at 7-9% through several mechanisms:

† Core technical implementation protected by Chinese Patent Application No.CN202511140743.3A (Filed: 2025-08-14) and Patent Cooperation Treaty (PCT) international patent application No. PCT/CN2026/112498 (Filed: 2026-07-22). Full patent documentation is available via CNIPA/WIPO.

Tail Risk to Tailwind: The systemic risk evaluation model's focus on leading information proxies and tail risk theory allows it to "de-risk" before shocks, as seen in the reduction of negative asymmetry during the COVID-19 and 2022 rate-hike cycles.
Asset Class Caps: Risk is managed through optimized asset constraints (e.g., maximum 35% per Gold, 10% per SP500) to prevent concentration risk, for the purpose of satisfying institution's risk appetite and compliance requirement.
Real time international capital flow forecasts: By anticipating shifts in the international capital flow cycle, the model can rotate asset class allocation ahead of capital flight surges.
Internal daily value-versus-growth style rotations: By constructing a multi-factor value-versus-growth style rotations model, we can adjust portfolio style concentration with agility, which providing a higher degree of allocation accuracy, as shown in **FIG. 27** the empirical backtest result of the China value-versus-growth style rotation model.

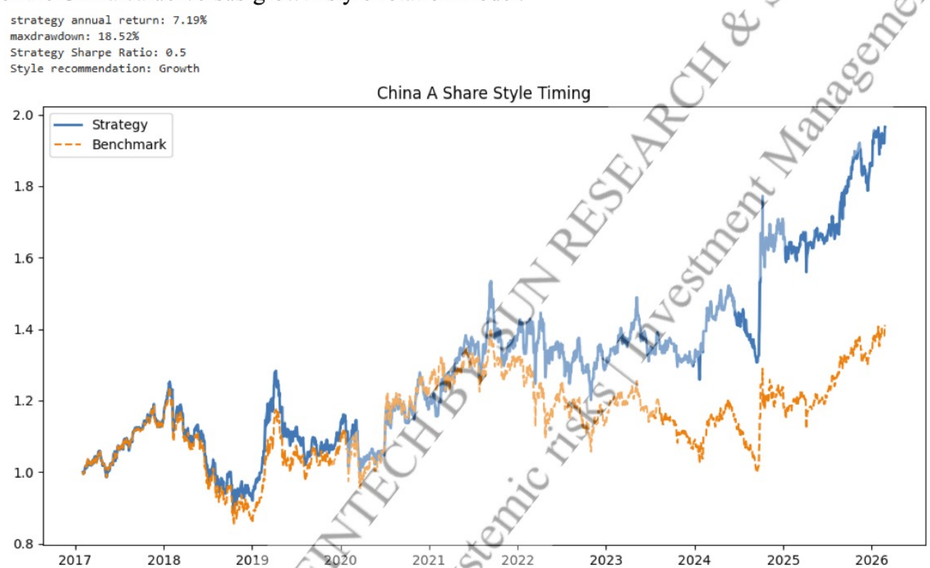

FIG.27 The empirical backtest of the China value-versus-growth style rotation model

6. Comparison with Existing Literature

Compared with existing literature, the innovations of this paper are manifested in three dimensions:
Theoretical framework innovation: We propose the Information Convergence Price Discovery Theory (ICPDT), which explains the interactive mechanism between microstructure and macro factors in the price formation process—a theoretical framework that has not been adequately developed in existing literature.
Methodological innovation: We elevate risk parity from the asset level to the macro-factor level, offering a new perspective for asset allocation research.
Empirical analysis: Through thorough backtesting from 2017 to 2026 and in-depth analysis of key crisis periods, we demonstrate the robustness of the MRCRP model across diverse macro environments, particularly its exceptional performance in maximum drawdown control.

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7. Future Outlook and Scalability

The evolution of the Macro RCRP model lies in the convergence of AI and multi-modal data fusion. Current state-of-the-art research is exploring AI agents that leverage real time alternative data fusion methods that integrate heterogeneous data sources like satellite imagery and high-frequency data. The fund's architecture is positioned to lead in a "2026 world" characterized by high debt levels, global fragmentation, and expensive equity valuations. By combining technological sophistication with transparent governance and human oversight, the system moves from mere algorithmic trading to comprehensive investment management. This "bulletproof" strategy offers a pathway for institutional investors to weather volatile macro regimes while delivering the risk-adjusted returns required for long-term capital preservation and growth.

8. Conclusion

This paper proposes a Macro Risk Controlled Risk Parity (MRCRP) model based on the Information Convergence Price Discovery Theory (ICPDT), which constructs a more robust asset allocation framework by integrating macro-factor risk constraints with microstructure systemic risk management. The core contribution of ICPDT lies in explaining the interactive mechanism between microstructure and macro factors in the price formation process, providing a new theoretical perspective for asset allocation.
The development of a state-of-the-art Macro Risk Controlled Risk Parity model represents a definitive advancement in multi-strategy investment management. By integrating seven diverse asset classes with innovations in capital flow forecasting and tail-risk management, the system achieves an exceptional performance profile. The core strategy's 16.61% annual return and 1.91 Sharpe ratio, supported by a 7% maximum drawdown, demonstrates the efficacy of equalizing risk contributions rather than capital. Furthermore, the long-short variant's 21.21% return and 2.08 Sharpe ratio highlight the value of harvesting volatility and factor-driven alpha. Empirical results indicate that over the period from 2017 to 2026, the MRCRP model significantly outperforming traditional risk parity and the 60/40 portfolio. Particularly during the 2020 COVID-19 pandemic, the model's maximum drawdown was merely 7%, far below the traditional risk parity.
From the perspective of asset allocation practice, the MRCRP model offers important implications for institutional investors: in an increasingly complex macro environment, asset allocation should not focus solely on risk diversification at the asset level but should emphasize substantive diversification of macro risk sources. Critical to this success is the "bulletproof" architecture, which provides resilience across all kinds of environments, such as growth and inflation seasons, and the "Initial Investment Phase" strategy, which utilizes customizing adaptability in real-world systemic investing, to ensure a robust and consistent performance under all kinds of situation in real-time and real-world application. As global capital flows become increasingly complex and geopolitical and economic pressures intensify, the ability to "redraw the map" on a nationality basis and extract geopolitical and economic signals via multi expert panel AI agents will remain a primary competitive advantage. This holistic approach ensures that the fund remains not only robust but "bulletproof" against the systemic uncertainties of the modern financial landscape.

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In summary, the Macro Risk Controlled Risk Parity model proposed in this paper provides a new theoretical and methodological framework for asset allocation research, possessing significant academic value and practical relevance.

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