AI Trader - Automatic Asset Allocation Automatically Updated Factor-Risk Parity Model and Related Research System

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***Abstract*—This paper introduces automatically updated factor-based risk parity model that addresses the limitations of traditional approaches, which rely on static, one-time portfolio calculations and exclude key economic factors. By incorporating factors such as growth, interest rates, and inflation, the model enhances adaptability and robustness. A core feature is its automation, enabling monthly recalibration of portfolio weights to dynamically respond to market changes. Additionally, a custom research system supports flexible configuration of factors, assets, and recalibration intervals, allowing for dynamic portfolio construction and optimization. This study advances risk parity methodologies with an automated, factor-driven framework and provides a practical tool for continuous portfolio management, improving risk diversification and offering actionable insights for adaptive investment strategies.**

I. Introduction

Traditional risk parity models allocate portfolio weights based on the risk contributions of conventional asset classes. While widely used, these models are constrained by their reliance on static, one-time portfolio calculations, limiting their ability to adapt to dynamic and evolving market conditions. Furthermore, traditional models fail to incorporate underlying economic factors, such as growth, interest rates, and inflation, that play a crucial role in driving asset returns. These limitations hinder their effectiveness in providing robust and adaptive portfolio management strategies.

This paper addresses these challenges by introducing a novel **factor-based risk parity model** that integrates key economic factors into the risk allocation framework. This model enhances portfolio construction by capturing the fundamental drivers of asset performance, making it more responsive to changing market dynamics.

To complement this model, we developed a **custom research system designed to automate the portfolio management process**. A core feature of this system is its ability to periodically and automatically recalculate portfolio allocations, such as monthly updates to asset weights. Users can customize key aspects, including recalculation intervals and the selection of assets and factors, offering a highly flexible and adaptive approach to portfolio management. By combining automation with configurability, the system bridges the gap between theoretical innovation and practical application.

The **results of our research** demonstrate that the factor-based risk parity model provides a viable alternative to traditional approaches, particularly when paired with our research system. The system empowers users to experiment with various factor-asset combinations, enabling dynamic, customized portfolio construction and optimization.

In summary, this study tackles the limitations of traditional risk parity methods by offering a more dynamic, automated, and adaptable solution that aligns with real-world market conditions. These advancements have the potential to significantly improve risk diversification, enhance portfolio adaptability, and provide actionable insights for investment strategies.

II. Literature Review

A. Research on Traditional Asset Allocation Models

Traditional asset allocation models, based on the Mean-Variance Optimization (MVO) theory proposed by Markowitz (1952), optimize risk and return using historical data. However, Boudd (2013) identified their limitations in adapting to uncertainties, often leading to concentrated risk in a few asset classes. Similarly, Kelly (2014) noted the lack of dynamic adjustment capabilities, which exacerbates systemic risk during market disruptions. These shortcomings have led to the development of methods like risk parity and factor-based investment models, which emphasize better risk diversification and more stable returns.

B. Theoretical Foundations and Development of Risk Parity Models

Risk parity models extend the MVO framework by balancing risk contributions across assets. Sharpe (1964) introduced the Capital Asset Pricing Model (CAPM), laying the theoretical groundwork for risk parity models, while Fama and French (1992) expanded on this with their three-factor model. The practical application of risk parity was demonstrated by Bridgewater's "All Weather Strategy" (1996), which optimized long-term asset allocation by balancing risks across asset classes (Blyth, 2016).

Despite their strengths, risk parity models are not without limitations. Boudd (2013) and Bender (2019) highlighted failures in extreme conditions, such as breakdowns in ”stock-bond correlations.” Additionally, reliance on low-volatility assets like bonds restricts returns in low-interest-rate environments (Blyth, 2016), reducing the appeal of risk parity strategies in certain economic scenarios.

C. Progress in Factor-Based Investment Models

Factor-based models provide a granular approach to portfolio construction by decomposing asset returns into distinct factors. Sharpe (1964) pioneered single-factor analysis through CAPM, while Fama and French (1992) introduced a multi-factor framework by adding value and size factors. Ross (1976) further advanced this with the Arbitrage Pricing Theory (APT), which incorporates multiple factors into asset pricing.

Recent developments have focused on practical applications of factor-based models. Kelly (2014) employed Principal Component Analysis (PCA) to identify key factors for portfolio optimization, while Bender (2019) categorized factors into macroeconomic (e.g., inflation) and style (e.g., momentum) groups, enhancing model robustness. Institutions such as BlackRock and Bridgewater have demonstrated the utility of these models in optimizing returns and managing risks.

Challenges remain for factor-based models. Kelly (2014) highlighted the reliance on high-quality data and the need for adaptability to changing market conditions. Blyth (2016) warned of underperformance during extreme market events, particularly when correlations between factors increase, reducing diversification benefits.

III. Data Sources

A. Data Overview

The data used in this project is divided into two main categories: asset data and factor data, each serving a distinct role in the construction and analysis of the factor-based risk parity model. All data is collected on a daily frequency, ensuring detailed temporal granularity for the analysis.

1) **Asset Data:**
   The asset data includes six key financial indices, covering stock, bond, and commodity markets in both the United States and China:
   - **SPX.GI:** S&P 500 Index (U.S. stock market).
   - **TY.CBT:** U.S. Treasury Bond Futures (U.S. bond market).
   - **CRB.RB:** CRB Index (U.S. commodity market).
   - **000001.SH:** Shanghai Composite Index (Chinese stock market).
   - **T.CFE:** Bond-related futures (Chinese bond market).
   - **NH0100.NHF:** Chinese Commodity Index (Chinese commodity market).
2) **Factor Data:**
   The factor data consists of five macroeconomic factors that reflect systematic risks:
   - **Growth Factor:** Risk associated with global economic growth.
   - **Inflation Factor:** Risk of exposure to changes in nominal prices.
   - **Credit Factor:** Risk of default or increase in credit spread associated with financial distress.
   - **Interest Factor:** Risk of bearing exposure to real interest rate changes.
   - **Exchange Rate Factor:** Risk associated with exchange rate fluctuations.

B. Data Sources

- **Asset Data:** Retrieved from ***Yahoo Finance***, which provides historical financial data for the selected indices.
- **Factor Data:** Collected from the ***Wind Database***, a comprehensive financial and economic data platform widely used in research and practice.

Note: Due to the cost of real-time data APIs, we opted for *Yahoo Finance* and the *Wind Database* for our experiments.

C. Data Preprocessing

To ensure data quality and usability, the following preprocessing steps were applied:

1) **Asset Data Preprocessing:**
   - The raw data collected for assets consisted of net value data, which required differentiation and normalization to ensure consistency across variables.
   - Missing or incomplete data points were cleaned and removed to maintain data integrity.
   - Since portfolio weights are recalculated monthly, monthly returns were computed based on the differentiated data to facilitate weight calculations.
2) **Factor Data Preprocessing:**
   - Traditional factor data typically has low-frequency observations, making it unsuitable for high-frequency portfolio analysis.
   - To address this, we refer to the academic literature and select high-frequency proxies to represent these low-frequency factors.(Table 1) For example:
     - Broad-market equity index returns were used to proxy economic growth.
     - Returns of long nominal bonds and short inflation-linked bonds were used to proxy inflation risks.

By applying these pre-processing techniques, we ensured that the asset and factor data were compatible with the experimental requirements and capable of supporting robust model calculations.

	Original Macroeconomic Factors	High-Frequency Factors
Growth Factors	PMI year-over-year difference, comparison of fixed asset investment completion, retail sales, export and import ratios	Growth indices, CRB commodity price indices, steel rebar, crude oil, and other high-frequency price indices
Inflation Factors	Weighted year-over-year fluctuations of CPI and PPI	Inflation expectations, core inflation indices
Interest Rate Factors	10-year government bond yield	Medium-term government bond yields (1–5 years)
Credit Factors	Weighted average yields of mid-to-long-term AA bonds over 3 years, yields of 3-year government bonds	Medium-term AA corporate bond yields (3–5 years), 3-year government bond yields
Exchange Rate Factors	U.S. Dollar Index	U.S. Dollar Index
Liquidity Factors	M2 growth rate compared to social financing	Growth rates of large and medium-sized financial institutions' loans and small and medium-sized enterprise loans

TABLE I: High-frequency factor for Macroeconomics factor

IV. METHODOLOGY

A. Traditional Risk Parity Models

Based on the traditional risk parity formula, the portfolio risk under a given asset weight:

$$R(w) = \sqrt{w^T \Sigma w} = \sqrt{\sum_{i,j} \rho_{i,j} w_i w_j \sigma_i \sigma_j}$$

where:

- $R(w)$: Total portfolio risk
- w: Weight vector of assets
- Σ: Covariance matrix of assets
- $\rho_{i,j}$: Correlation coefficient between assets i and j
- σ_i: Standard deviation of asset i

The marginal risk contribution (MRC) for each asset is:

$$\text{MRC}_i = \frac{\partial R(w)}{\partial w_i} = \frac{1}{2} \cdot \frac{\partial (w^T \Sigma w)}{\partial w_i} = \frac{(\Sigma w)_i}{\sqrt{w^T \Sigma w}}$$

The total risk contribution (TRC) for asset i is:

$$\text{TRC}_i = w_i \cdot \text{MRC}_i = w_i \cdot \frac{(\Sigma w)_i}{\sqrt{w^T \Sigma w}}$$

In matrix form, the total risk contribution for the entire portfolio is:

$$\text{TRC} = \sum_{i=1}^{n} \text{TRC}_i = \sum_{i=1}^{n} w_i \cdot \frac{(\Sigma w)_i}{\sqrt{w^T \Sigma w}} = w^T \frac{\Sigma w}{\sqrt{w^T \Sigma w}} = R(w)$$

The optimization problem is then formulated as:

$$\min_{w} \sum_{i=1}^{n} \sum_{j=1}^{n} \left(\text{TRC}_i(w) - \text{TRC}_j(w) \right)^2$$

Subject to the following constraints:

$$\sum_{i=1}^{n} w_i = 1, \quad 0 \leq w_i \leq 1$$

B. Factor Exposure on Assets

Before implementing the factor-based risk parity model, it is essential to calculate the factor exposures (beta) of various assets to different factors. In this section, we employ **multiple linear regression** to estimate the beta values for each factor across assets, expressed as:

$$R_t = B_t F_t + e_t$$

where:

- R_t: The return of the asset at time t
- B_t: The beta (factor exposure) of the asset to the factors at time t
- F_t: The factors affecting the asset returns at time t
- e_t: The residual error term at time t

Using the Newton method and iterative training, we derive the regression coefficients for each asset. By applying multivariate linear regression, we estimate the exposure of asset classes to macro factors, represented by the coefficients B_t. Combining the coefficients from all assets, we construct the factor exposure matrix, which serves as the foundation for subsequent calculations.

C. Integrating Factor-Based Approaches

A key feature of the factor allocation framework is its ability to **automatically recalculate portfolio allocations monthly, dynamically updating asset weights to adapt to changing market conditions**. Using the asset factor exposure matrix, overall factor exposures can be calculated, and asset weights are determined by solving an optimization problem with constraints. This process improves upon traditional static allocation methods, enabling more adaptive portfolio management.

In a traditional risk parity portfolio, each asset's marginal risk contribution (MRC) equals its total risk contribution (TRC). The portfolio return's standard deviation is expressed as:

$$\sigma(w) = \sqrt{w^T \Sigma w}$$

For asset $i \, (i = 1, 2, \ldots, N)$, the *active risk contribution* (ARC) is defined as:

$$\text{ARC}_i = \frac{1}{\sigma(w)} \frac{\partial \sigma(w)}{\partial w_i} = \frac{w_i (\Sigma w)_i}{w^T \Sigma w}$$

The decomposition of asset returns is given as:

$$\begin{bmatrix} r_1 \\ r_2 \\ \vdots \\ r_N \end{bmatrix} = \begin{bmatrix} a_1 \\ a_2 \\ \vdots \\ a_N \end{bmatrix} + \begin{bmatrix} b_{11} & b_{12} & \cdots & b_{1K} \\ b_{21} & b_{22} & \cdots & b_{2K} \\ \vdots & \vdots & \ddots & \vdots \\ b_{N1} & b_{N2} & \cdots & b_{NK} \end{bmatrix} \begin{bmatrix} f_1 \\ f_2 \\ \vdots \\ f_K \end{bmatrix} + \begin{bmatrix} d_{11} & 0 & \cdots & 0 \\ 0 & d_{22} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & d_{NN} \end{bmatrix} \begin{bmatrix} e_1 \\ e_2 \\ \vdots \\ e_N \end{bmatrix}$$

Using this decomposition, portfolio returns can be expressed as:

$$r_p = w^T r = w^T a + w^T B f + w^T D e$$

For each factor $j \, (j = 1, 2, \ldots, K)$, the *factor risk contribution* (FRC) is defined as:

$$\text{FRC}_j = \frac{\gamma_j \cdot \frac{\partial \theta}{\partial \gamma_j}}{\gamma^T \cdot \frac{\partial \theta}{\partial \gamma}}$$

where:

$$\theta = \sqrt{\gamma^T S_{K \times K} \gamma}, \quad S_{K \times K} = \begin{bmatrix} s_{11} & \cdots & s_{1K} \\ \vdots & \ddots & \vdots \\ s_{K1} & \cdots & s_{KK} \end{bmatrix}$$

To balance the *active risk contributions* (ARCs), the optimization problem is:

$$\min \sum_{i=1}^{N} \left(\text{ARC}_i - \frac{1}{N} \right)^2$$

Subject to:

$$w^T 1 = 1, \quad w \geq 0$$

To balance the *factor risk contributions* (FRCs), the optimization problem is:

$$\min \sum_{j=1}^{K} \left(\text{FRC}_j - \frac{1}{K} \right)^2$$

Subject to:

$$w^T 1 = 1, \quad w \geq 0$$

By solving this optimization problem, we can derive the optimal weights for each asset in the portfolio. These weights are calculated based on the predefined objective of balancing either active risk contributions (ARCs) or factor risk contributions (FRCs). The optimization framework incorporates constraints to ensure that the portfolio weights sum to one and remain non-negative, aligning with practical portfolio construction principles.

A key feature of this approach is its automation. The system is designed to automatically solve the optimization problem at regular intervals, such as monthly, to dynamically recalculate portfolio weights. This automated recalibration ensures that the portfolio remains responsive to changing market conditions and aligns with the desired risk parity and factor exposure objectives. The periodic updates allow the portfolio to adapt to shifts in asset correlations, volatilities, and factor dynamics, enhancing its robustness and relevance in a volatile market environment.

Furthermore, the flexibility of this system allows users to customize the recalibration frequency and asset-factor selection. Users can experiment with different intervals (e.g., monthly or quarterly) and include various assets and factors that match their specific investment goals and market outlooks. This customization provides a tailored approach to portfolio management while maintaining the benefits of automation.

In summary, the ability to automatically solve the optimization problem and adjust portfolio weights at regular intervals represents a significant advancement over traditional static allocation methods. This dynamic and automated approach not only improves the adaptability of the portfolio but also empowers users to construct strategies that are aligned with their unique requirements and changing market landscapes.

V. System Overview

A. System Architecture

The system implements factor-based risk parity analysis using a Python back-end for computations and a lightweight front-end for visualizations. It also includes a flexible data storage approach to support future upgrades. The key components are:

1) **Backend (Python):**
    - Processes and normalizes raw CSV data using Pandas and Numpy.
    - Extracts volatilizes and correlations using linear regression (Scikit-learn).
    - Computes portfolio weights using SciPy optimization.
    - Outputs processed results as CSV files for visualization.
2) **Frontend (JavaScript, HTML, CSS):**
    - Displays factor analysis results through interactive visualizations.
    - Shows risk contributions and portfolio back testing metrics.
3) **Data Storage:**
    - Uses CSV files for simplicity and back-end compatibility.
    - Planned transition to API-based real-time data retrieval.

The system is optimized for efficiency while adapting to future enhancements.

B. Functional Modules

The system workflow consists of three integrated modules:

1) **Data Input Module:**
    - Imports and pre-processed CSV files, supporting various financial data formats (e.g., asset returns).
2) **Model Computation Module:**
    - Applies machine learning models for factor extraction and evaluates risk metrics.
    - Runs the risk parity algorithm to compute optimal weights and exports results to CSV.
3) **Visualization Module:**
    - Visualize results using interactive charts and tables, including:
        - Factor contributions and correlations.
        - Portfolio weights and risk breakdowns.
        - Performance performance metrics backtest.

While the current design focuses on static data workflows, the system is ready for future API integration to enhance scalability and efficiency.

C. Web Dashboard Overview

The system includes a dynamic web dashboard that showcases the results of the factor-based risk parity model. The dashboard provides the following features(Figure 1):

- **Interactive Charts:**
    - *"Yield Over Time"* chart visualizes the performance of assets and model portfolios over the specified period.
    - *"Allocation Over Time"* chart displays the evolving weights of different assets in the portfolio, highlighting automatic monthly recalibration.
- **Exposure Metrics:**
    - A detailed *"Exposure Matrix"* showing the factor exposure coefficients for each asset.
- **Correlation Matrices:**
    - *"Asset Correlation Matrix"* provides insights into the relationships between selected assets.

– *"Factor Correlation Matrix"* highlights the interdependence among economic factors.

This interactive dashboard allows users to intuitively explore model outputs, monitor portfolio adjustments, and analyze factor contributions, offering practical insights for real-time portfolio management.

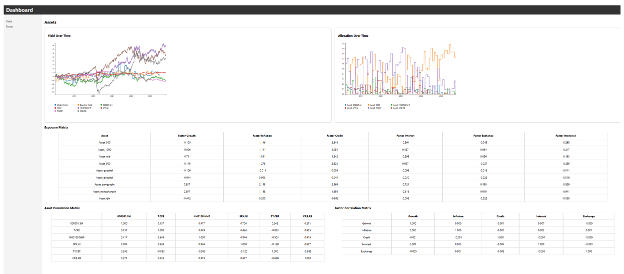

Fig. 1: Web sample interface.

D. Application Workflow

The system provides a streamlined process for implementing the factor-based risk parity model, combining Python-based computation with an interactive web interface for visualization. Below, we outline the steps required to use the application:

1) Data Preparation: To begin, users need to manually download the required asset and factor data from platforms like Yahoo Finance or Wind. These data files should be saved in the designated `Risk_Factor_Model_Data` folder. This manual data collection step reflects current budgetary constraints but ensures compatibility with public and private data sources.

2) Code Execution: The computational backbone of the system resides in the `Risk_Factor_Model_Code` folder. Users must:

- Update the file paths in the code to reference the downloaded data in the `Risk_Factor_Model_Data` folder.
- Customize the key function, `factor_risk_parity_model`, to define specific configurations.
- **Function Usage:**

```
factor_risk_parity_model(
    dataframes["Asset"],
    dataframes["Factor"],
    "Factor_Risk_Parity",
    1
)
```

The final parameter in the function (e.g., `1` in this case) specifies the recalibration interval in months for portfolio weight adjustments. Users can modify this parameter to adapt the frequency of recalculations to their requirements.

Data Flexibility: The system supports the integration of additional asset and factor data, provided they conform to the example dataset format. This flexibility allows users to expand their experiments with various combinations of assets and factors for robust analysis.

Upon completing these steps, users run the Python scripts to generate essential outputs such as factor exposure matrices and optimized portfolio weights. The outputs are saved as CSV files for subsequent visualization.

3) Web-Based Visualization: The results generated from the Python scripts can be visualized interactively through the web-based dashboard. To launch the visualization module:

- Transfer the processed CSV files to the `Risk_Factor_Web_Demo` folder.
- Use a terminal to navigate to the folder containing the `index.html` file and start a local server with the following command:

```
python -m http.server 8000
```

- Open a web browser and access the dashboard at `http://localhost:8000`.

The dashboard provides intuitive charts and tables to explore results, such as yield trends, portfolio allocations over time, factor exposures, and correlation matrices.

4) Notes and Future Directions:

- **Data Handling:** Currently, the system utilizes CSV files for simplicity. Future upgrades may integrate API-based real-time data retrieval to automate data collection.
- **Dependencies:** Users must ensure that essential libraries (`Pandas`, `Numpy`, `Scikit-learn`, etc.) are installed before executing the scripts.
- **Scalability:** The modular design supports scaling and customization, making the system adaptable to a wide range of portfolio management research needs.

This application workflow underscores the system's dual strengths: flexibility in experimenting with asset and factor combinations and automated monthly portfolio recalibration for dynamic portfolio management. These features make it a practical tool for advancing research and refining investment strategies.

VI. Experiment

To evaluate the performance of the factor-based risk parity model, we conducted a series of experiments comparing it to the traditional risk parity model. These experiments analyzed factor exposures, portfolio weight optimization, and overall performance metrics across both approaches. The experiments covered the period from April 2018 to September 2023.

A. Construction of the Factor-Based Risk Parity Model

1) Factor Exposure Calculation: The factor exposure matrix was computed using multiple linear regression to quantify the relationship between each asset and target factors. These calculations are automated and updated monthly to ensure the portfolio dynamically reflects changing market conditions. The regression coefficients serve as the basis for optimization (Figure 2).

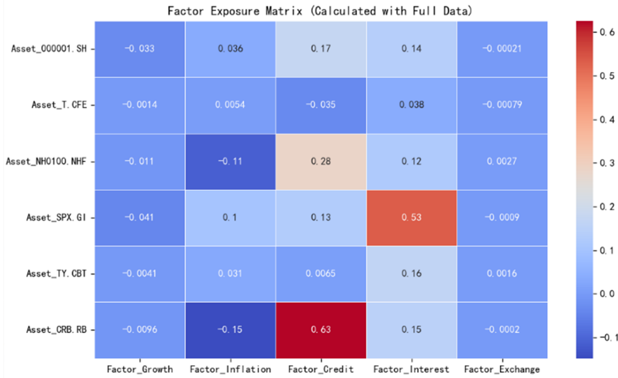

Fig. 2: The factor exposure matrix of the factor-based risk parity model.

2) Asset Allocation by using Factor-Based Risk Parity Model over time: From the figure, we observe that the factor-based risk parity model predominantly allocates to government bonds from both countries in most months. This behavior likely stems from the model's preference for assets with lower risk exposures, as government bonds typically exhibit minimal volatility and risk compared to other asset classes. The automated allocation process reflects the model's inherent tendency to prioritize stability by favoring low-risk assets.

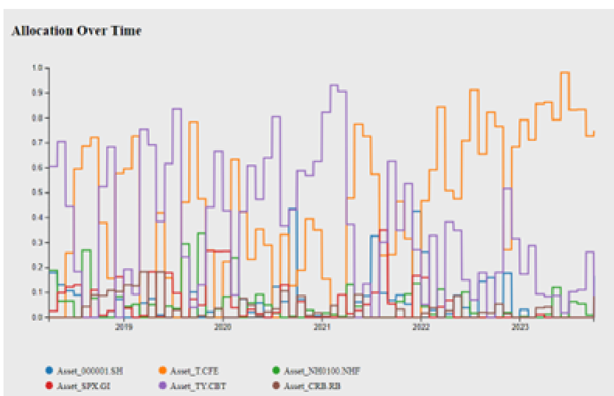

Fig. 3: Assets allocation over time for our model (monthly update).

B. Portfolio Performance Analysis

1) Portfolio Net Value Comparison: The net asset value (NAV) comparison shows that the factor-based portfolio closely follows bond-related futures, highlighting its risk-averse nature (Figure 4). The monthly recalculation of portfolio weights ensures that the factor-based model consistently adapts to market changes while maintaining alignment with target factor exposures.

2) Return Rate Analysis: Daily return rates revealed that the factor-based model underperformed after December 2018, struggling with critical adjustments during volatile periods. Despite this, the overall trends of both models remain similar (Figure 5).

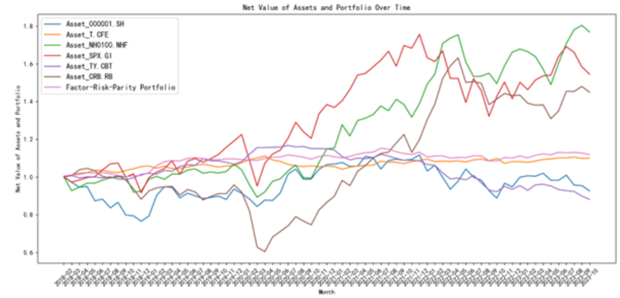

Fig. 4: Net asset value over time for our model portfolio and individual assets in the portfolio.

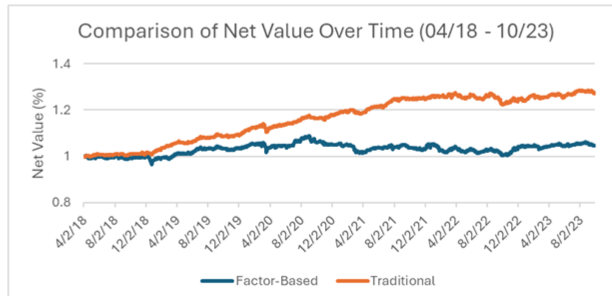

Fig. 5: Daily return rate over time comparison for the factor-based and traditional risk parity model.

C. Performance Metrics

Table 2 summarizes the cumulative return rates, annualized returns, volatility, and Sharpe ratios for both models, calculated using a 3% risk-free rate. The results indicate that the factor-based model significantly underperformed the traditional risk parity model in terms of returns and risk-adjusted performance. However, the factor-based model demonstrated comparable volatility levels, suggesting some consistency in risk control.

Metric	Factor-Based	Traditional
Total Return	4.69%	27.38%
Annualized Return	0.87%	4.66%
Volatility	3.63%	2.72%

TABLE II: The cumulative return rates, annualized return rates, and volatility rates of the two models.

D. Discussion of Results

The factor-based model's underperformance may stem from:

1) Factor Selection: Suboptimal factors limited its ability to capture market dynamics.
2) Market Conditions: Poor economic performance during the analyzed period favored the conservative bond-heavy traditional model.

However, the automated monthly recalculation of asset weights in the factor-based model ensures it remains responsive to changing conditions, demonstrating its potential for further optimization with better factor selection.

E. Future Directions

To improve the effectiveness of the factor-based risk parity model, future experiments could focus on:

- Enhanced Factor Selection: Incorporating more representative or better-performing factors to refine the model's predictions.
- Alternative Market Periods: Testing the model during different economic cycles to evaluate its performance under varying market conditions.

This experiment highlights the limitations and potential of the factor-based risk parity model while emphasizing the critical importance of factor selection and market context in portfolio optimization. The findings offer a foundation for further refinement and development of the model.

VII. Conclusion

This study introduced a factor-based risk parity model alongside a comprehensive research package to facilitate flexible experimentation and model exploration. The proposed model addresses limitations of traditional risk parity approaches by incorporating economic factors into the risk allocation framework and allowing for dynamic portfolio adjustments. Although the factor-based model underperformed the traditional approach under certain conditions—particularly during economic downturns where bond-heavy allocations provide greater stability—our research highlights the potential of factor-driven methodologies and the practical utility of the developed system.

Key findings include:

1) **Model Insights:** The performance of the factor-based risk parity model is highly dependent on the selection of factors. Suboptimal factors may hinder its ability to capture market dynamics, particularly during volatile or recessionary periods. By contrast, the traditional risk parity model, with its conservative allocation strategy favoring low-risk assets like bonds, demonstrated superior performance in maintaining stability during downturns.
2) **Package Utility:** The developed research package is a significant contribution, enabling users to construct, analyze, and backtest portfolios with various factor-asset combinations. It supports automatic recalibration of asset weights at adjustable time intervals, such as monthly updates, and offers users the freedom to experiment with different factors and assets. The system provides detailed insights into portfolio allocations, factor exposures, and backtesting results, making it an invaluable tool for advancing research and refining portfolio management strategies.

In conclusion, while the factor-based risk parity model has certain limitations, the research package represents a powerful platform for innovation in factor-driven allocation strategies. Future work should focus on improving factor selection methods, testing the model across diverse economic environments, and scaling the system to support real-time data integration and global market applications. By continuing to enhance both the methodology and the supporting tools, this research lays the groundwork for more adaptive and robust portfolio management strategies.

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