ORIE 5370 Optimization Modeling in Finance • Project Report

Tactical Asset Allocation Based on the Business Cycle

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https://github.com/HengliZhu/ORIE-5370-Project

Abstract

This report explores a tactical asset allocation (TAA) strategy based on the business cycle to enhance investment portfolio performance. Addressing the limitations of traditional Modern Portfolio Theory (MPT) and Strategic Asset Allocation (SAA), this study leverages a regime-based approach to dynamically adjust asset allocation in response to economic changes. Using a comprehensive dataset from the Chinese market over 13 years, the study categorizes business cycles into recovery, expansion, slowdown, and contraction stages, utilizing the Consumer Price Index (CPI) and Purchasing Manager Index (PMI) as indicators. Various portfolio optimization models, including equal weight, 60%/40% weight, Markowitz, and Black-Litterman, are compared. The Markowitz Stage Optimized and Black-Litterman models demonstrated superior performance in cumulative returns and Sharpe ratios, emphasizing the potential of regime-based TAA in optimizing asset allocation. These findings highlight the importance of a dynamic and adaptive approach to asset management, particularly in volatile market environments. Future research should consider expanding the dataset to multiple regions, incorporating additional macroeconomic indicators, and exploring advanced techniques and alternative strategies to further enhance portfolio resilience and performance.

1 Introduction

1.1 Background

In the realm of investment management, the decision on how to allocate assets and how to rebalance the portfolio across various market conditions are critical challenges that portfolio managers and individual investors encounter regularly. This challenge is particularly pronounced given the dynamic nature of markets, which are profoundly influenced by the cyclical fluctuations of the business cycle. These fluctuations often dictate the performance characteristics of asset classes through their associated risk premia—namely, the equity, credit, and term premia. Traditionally, modern portfolio theory (MPT) provides a portfolio optimization framework using the historical return and volatility and strategic asset allocation (SAA) provides a framework based on long-term return forecasts using historical data and forward-looking estimates [1]. However, the inherent limitations of MPT and SAA, primarily their historical focus view and static approach during volatile market conditions, necessitate a more adaptive strategy that can respond to economic changes in real time.

1.2 Motivation

The primary motivation for this study is to address the shortcomings of MPT and SAA by integrating tactical asset allocation (TAA) strategies that are sensitive to the stages of the business cycle. Unlike SAA, which maintains a consistent asset mix over an extended horizon, TAA adjusts the asset distribution based on short- to medium-term economic outlooks and risk assessments. This tactical approach allows for the exploitation of economic conditions that influence the performance of different asset classes. By applying a top-down approach, we could identify outperforming industries and asset classes to overweight in the portfolio [2]. Given the complex interplay of global economic activities and financial market responses, this approach is expected to help the sophisticated portfolio managers who are capable and confident to predict the business cycles to gain excess return.

1.3 Key Problem

The central problem explored in this research is the inefficacy of conventional asset allocation models to leverage the cyclical nature of performance across diverse macroeconomic regimes effectively. The study delves into how asset classes perform across the four stages of the business cycle: recovery, expansion, slowdown, and contraction. Each stage presents unique challenges and opportunities for asset allocation, dictated by varying economic growth rates and investor risk tolerance. The existing literature and practical applications often overlook the nuanced relationships between these stages and asset performance, leading to suboptimal investment outcomes. Our focus is on the Chinese market, where unique cultural, regulatory, and economic factors create a distinct environment. By analyzing market data and consumer insights, we aim to identify opportunities and challenges specific to this region, ensuring our approach is tailored to meet local demands and leverage growth potential.

This research proposes a regime-based TAA framework that utilizes a combination of Consumer Price Index (CPI) and Purchasing Manager Index (PMI) to categorize the business cycle into distinct regimes. By doing so, it aims to pinpoint when investors are most likely to be compensated for taking specific types of risks. This approach not only promises to refine the understanding of risk premia behavior across different economic conditions but also aims to offer investors a more granular toolset for adjusting their portfolios in alignment with both current and anticipated market dynamics.

The potential of this regime-based TAA to generate statistically significant excess returns is analyzed through empirical evidence, providing a compelling argument for its adoption over traditional methods. By bridging the gap between static long-term investment strategies and the requirements of a fluctuating economic environment, this framework seeks to equip investors with the capabilities to achieve superior risk-adjusted returns, thereby enhancing both the efficacy and resilience of investment portfolios in the face of economic uncertainties [3].

2 Data

2.1 Data Description

In our project, we have meticulously curated a comprehensive dataset from the WIND Database to analyze and optimize a portfolio based on business regime dynamics within the China market. This dataset encompasses close price data of 39 distinct assets, recorded over a span of 13 years, from January 1, 2011, to December 31, 2023, resulting in 2,490 records. These assets are strategically classified into three sectors, influenced by term, credit, and industry-specific factors, providing a holistic view for portfolio construction.

For the term-based classification, we utilize the China Government Bond Index, segmented by various maturity terms, including less than 3 months, 3 to 5 years, 7 to 10 years, less than 10 years, 10 years, and 30 years. This allows for a nuanced analysis of interest rate risks and maturity benefits. Regarding the credit aspect, we incorporate two pivotal corporate bond indexes. The first is the SSE Corporate Bond 30 Index, which comprises the 30 largest volume corporate bonds traded on the Shanghai Stock Exchange (SSE), known for their lower returns yet minimized credit risk. Conversely, the second, the China High Yield Corporate Bond Index, consists of bonds that offer higher returns at the expense of significantly greater credit risk, appealing to different risk tolerance levels among investors.

Additionally, the dataset includes industry indices representing 31 diverse sectors within the China stock market, ranging from agriculture to technology. This industry factor segmentation provides a comprehensive lens through which sector-specific trends and performances can be assessed, enabling targeted investment strategies that leverage the unique dynamics and opportunities within each sector. This rich dataset serves as the foundation for our analysis, supporting the strategic decision-making process in portfolio management by aligning investment choices with business cycle phases and market regime shifts.

2.2 Data Processing

The data processing involved several key steps: acquisition, cleaning, transformation, and validation. Initially, missing values were addressed through imputation or removal. The raw data was then normalized to ensure comparability across different assets and time periods, with daily log returns computed to stabilize variance. Key economic indicators, such as the Consumer Price Index (CPI) and Purchasing Manager Index (PMI), were calculated and normalized, with CPI compared to a 12-month moving average to determine inflation levels.

3 Business Cycle Identification

3.1 Identification Method

3.1.1 Growth Level

The Purchasing Managers' Index (PMI) is a leading indicator reflecting the confidence level of manufacturers regarding the next month's production levels. Since the manufacturing industry is a crucial catalyst for the entire economy, strong performance in this sector can signal positive economic growth.

The PMI index has a critical threshold of 50. A PMI value greater than 50 indicates economic expansion, while a value below 50 signals potential recession, drawing investor attention. Another important aspect is the relative trend of PMI changes. By comparing the current PMI to the previous period, we can assess performance: an increasing PMI suggests rising market confidence and positive sentiment, whereas a decreasing PMI indicates weaker confidence. Considering seasonal variations and anomalies in manufacturing, we can compare the current PMI to the same period last year for a more accurate measurement.

Empirical evidence shows that the stock market tends to have positive returns in the following month when the PMI is above 50. Returns are even higher when the

PMI, though below 50, is increasing, indicating rising optimism. Conversely, the market typically sees negative returns when the PMI is below 50 and declining.

In this project, we apply similar criteria: signaling positive economic growth when the PMI is above 50 or when the relative difference is positive, and signaling negative economic growth when the PMI is below 50 and decreasing.

3.1.2 Inflation Level

The Consumer Price Index (CPI) is a key indicator used to gauge the inflation level within an economy. The CPI is based on a fixed basket of goods and services, enabling consistent tracking of price changes over time and allowing for direct comparison to a base period. Released monthly and often earlier than the Personal Consumption Expenditures (PCE) Price Index, the CPI provides a timely measure of inflation.

For this report, we normalized the PCE index data relative to the base month. We calculated the percentage change in CPI each month and computed the 12-month moving average to filter out noise. After this data cleaning process, we compared the monthly change to the moving average. If the monthly change exceeds the 12-month moving average, we infer that inflation is increasing for that month. Conversely, if the monthly change is below the 12-month moving average, we infer a decreasing inflation level.

3.1.3 Business Stage

For simplicity, we consider growth to be positive only if the PMI value is greater than 50. We classified the business stages based on whether the PMI value is larger than 50 and whether the CPI percentage change is greater than its 12-month moving average.

	CPI pct > 12-month MA	CPI pct < 12-month MA
PMI > 50	Expansion	Recovery
PMI < 50	Slowdown	Contraction

Table 1 Principle of Business Regime Identification

By ignoring cases where the PMI value is below 50 but the relative trend is positive, we may miss some useful information, particularly during periods when equities are likely to have positive returns. However, this oversight does not significantly impact our results, as only three months within the research period meet this criterion.

3.2 Business Stage Result

Overall, there are 96 distinct business stages over the 20-year period, with approximately 70 business stages occurring during our focus period from 2011 to 2024. The results are as below:

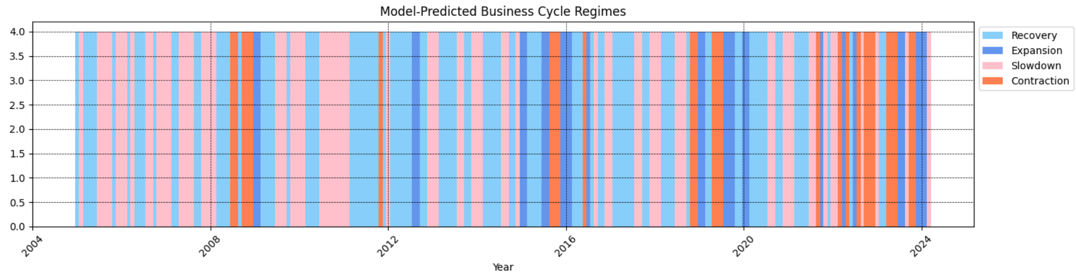

Figure 1 Model-Predicted Business Regimes

According to the charts, from 2004 to 2007, the business stage is predominantly characterized by alternating periods of recovery and expansion, with occasional slowdown phases indicating minor economic slowdowns. It reflects a generally robust pre-financial crisis economy with steady growth. From 2008 to 2009, the business regime is dominated by contraction, highlighting the severe economic downturn due to the global financial crisis. This period marks the sharpest economic decline on the chart, with minimal recovery or expansion phases. From 2010 to 2014, a notable shift towards recovery and expansion phases post-crisis appears, indicating the economic recovery and growth. Some intermittent slowdown phases suggest periods of slower growth but over all a positive trend. From 2015 to 2019, the business regime continues stability with frequent expansion phases, signifying sustained economic growth. Regular intervals of slowdown and occasional contraction phases indicate some economic challenges but overall resilience. From 2020 to 2024, significant presence of slowdown and contraction phases reflect the economic impact of the COVID-19 pandemic, with increased volatility with frequent changes between the different phases.

For asset allocation strategy, we hold the asset allocation within the single business cycle, and adjust our position and rebalance our portfolio whenever there is a transition between business stages.

4 Portfolio Optimization

4.1 Benchmark Model

4.1.1 Equal Weight Model

In this equal weight model, we assign equal weight to each of the 39 assets in the portfolio. Each asset is assigned a weight of approximately 2.564% and is held from

2011 to 2024. The resulting portfolio performance, as depicted in the PNL curve, exhibits significant volatility.

The chart below illustrates the Profit and Loss (PNL) curve for an equally weighted portfolio from 2011 to 2024, reflecting the cumulative returns of the portfolio. The analysis reveals several key periods of fluctuation and growth. From 2011 to 2014, the portfolio showed stable but modest growth. Between mid-2014 and early 2016, there was a significant spike in returns, peaking around mid-2015, followed by a decline due to market correction. From 2016 to 2018, the portfolio entered a recovery phase, showing resilience despite fluctuations, with an overall upward trend. During 2018 to early 2020, returns continued to grow amidst noticeable volatility. The period from 2020 to 2021 saw a decline in returns, likely due to the economic impact of the COVID-19 pandemic. From 2021 to 2023, the portfolio showed signs of recovery and growth in line with broader market trends, though it remained volatile. Towards the end of the period, from 2023 to 2024, there was a slight decline in returns, possibly indicating market instability.

Overall, despite significant volatility, the equally weighted portfolio demonstrated resilience, recovering from downturns and achieving long-term growth. This suggests that an equally weighted portfolio can be viable for long-term investment despite being sensitive to market-wide events.

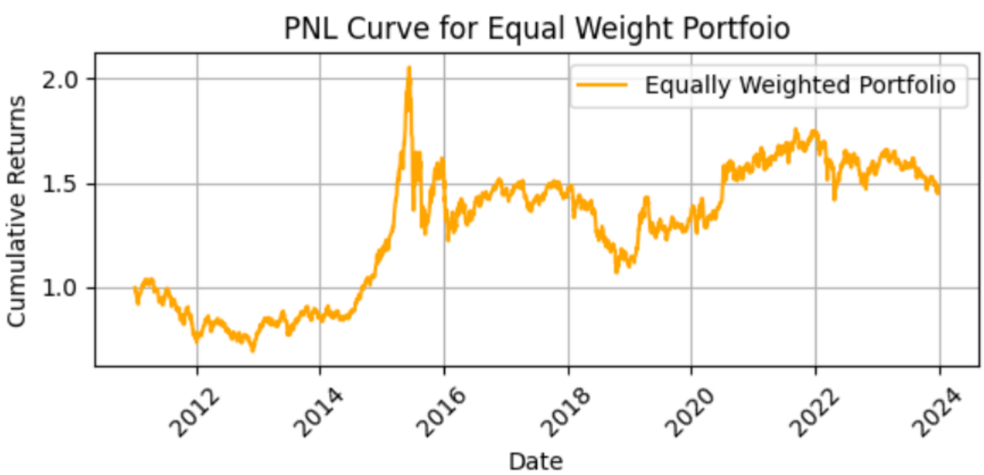

Figure 2 PNL Curve for Equal Weight Portfolio

4.1.2 60%/40% Weight Model

In the 60%/40% weight model, we assign 60% of the portfolio equally to 31 equity industry indexes and 40% equally to 8 bond indexes. Each equity gets 1.935% weight while each bond gets 5% weight.

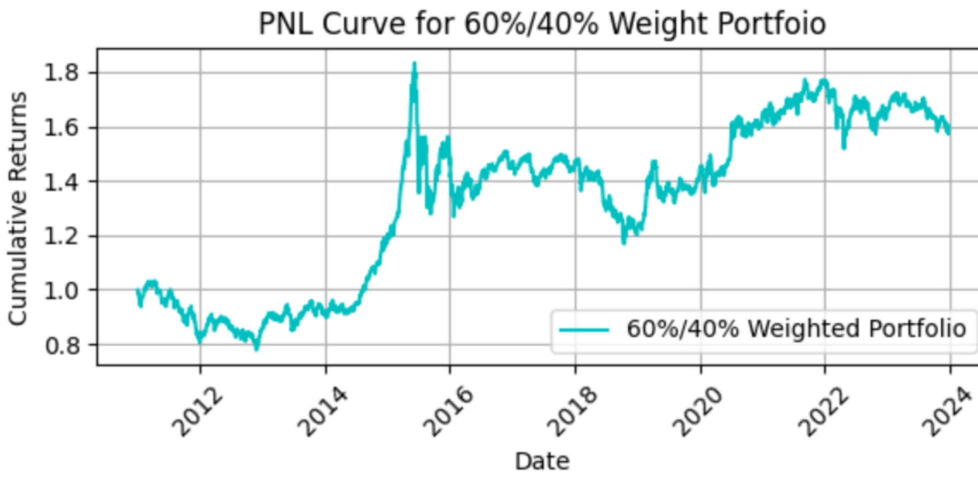

Figure 3 PNL Curve for 60%/40% Weight Portfolio

Above is the PNL curve for 60%/40% weight portfolio, the overall trend of growth and drawdown is the same with that of equal weight portfolio, but the cumulative return of 60%/40% weight portfolio is a little bit smaller than that of equal weight portfolio at all business regimes.

4.2 Markowitz Model

4.2.1 Theory

Investment in securities and other risky assets involves the crucial balance between expected returns and associated risks. To effectively manage a portfolio, understanding and quantifying both these elements are fundamental challenges that every market investor faces. The dual need to optimize returns while mitigating risks led to the development of groundbreaking approaches in the mid-20th century, particularly the Markowitz Portfolio Theory, or Modern Portfolio Theory (MPT), which emerged in the 1950s and early 1960s. Developed by Harry Markowitz, this theory revolutionized the field of investment portfolio management. The core idea of Markowitz Model is that portfolio diversification can reduce risk without necessarily compromising expected returns. According to MPT, the risk of any investment can be reduced and managed through diversification—specifically, by combining assets that do not move in tandem [4].

Markowitz introduced the concept of an 'efficient frontier', which represents a set of portfolios that offers the highest expected return for a given level of risk or the lowest risk for a given level of expected return. This framework involves constructing a covariance matrix of the returns of the assets, which helps in calculating the expected returns and the risks (measured as variance) of different portfolio combinations. Investors can use this efficient frontier as a guide to select a portfolio that aligns with their risk tolerance and investment goals. By plotting different portfolios on a graph—with risk on the x-axis and expected return on the y-axis—investors can visually identify the set of portfolios that are considered efficient. This method not only aids in the selection of optimal asset mixes but also helps in making strategic decisions about asset allocation based on quantitative measures rather than intuition alone.

The assumptions of Markowitz Model are shown below [5]:

1. Probability Distribution of Returns: Markowitz posited that investors consider all possible outcomes of their investment choices within the holding period, focusing on the entire probability distribution of returns. This comprehensive approach contrasts with merely considering potential average returns, thereby accounting for the variability and uncertainty inherent in investment returns.
2. Risk Evaluation Based on Expectations: According to Markowitz, the risk associated with any security portfolio is assessed based on the investors' expectations, which in practical terms often translates to the variance or standard deviation of portfolio returns. This measure captures the volatility of returns around their mean, providing a quantifiable measure of risk.
3. Dependency on Risk and Return: Investor decisions are assumed to be based purely on the risk-return profiles of securities. This assumption underlines the rational behavior of investors in seeking to maximize returns for a given level of risk, or equivalently, minimize risk for a given level of expected return.
4. Optimization at Given Risk Levels: At any specified level of risk, investors aim to achieve the maximum possible return. Conversely, for a given expected return, they strive to minimize risk. This trade-off is crucial in shaping investment choices and strategies.

Mathematically, we can utilize the formula below to express the objection and restriction of Markowitz Optimization Model:

$$Min\ \sigma^2 = var\left(\sum_i x_i r_i\right) = \sum_{i,j} x_i x_j cov(r_i, r_j)$$

$$s.t.\quad \sum_i x_i E(r_i) \geq \mu$$

$$\sum_i x_i \leq 1$$

$$x_i \geq 0$$

Here, $x_i$represents the proportion of funds invested in security i, and the total proportion of all investments $\sum_i x_i \leq 1$, which means it does not exceed the budget. The expected return r_i of the i-th stock is $E(r_i)$, and the covariance of the returns of the two stocks i and j is $cov(r_i, r_j)$. The expected return of the required investment portfolio is $\sum_i x_i E(r_i) \geq \mu$. In order to achieve the target expected return μ, the risk σ^2 can be minimized by adjusting the capital ratio x_i.

4.2.2 Markowitz Model - Benchmark

In this benchmark model, we applied Markowitz optimization to maximize the Sharpe ratio of the portfolio during the training period. We implemented constraints to ensure diversification, assigning a maximum weight of 50% to any individual asset and a minimum weight of 0.5% to maintain a well-diversified portfolio.

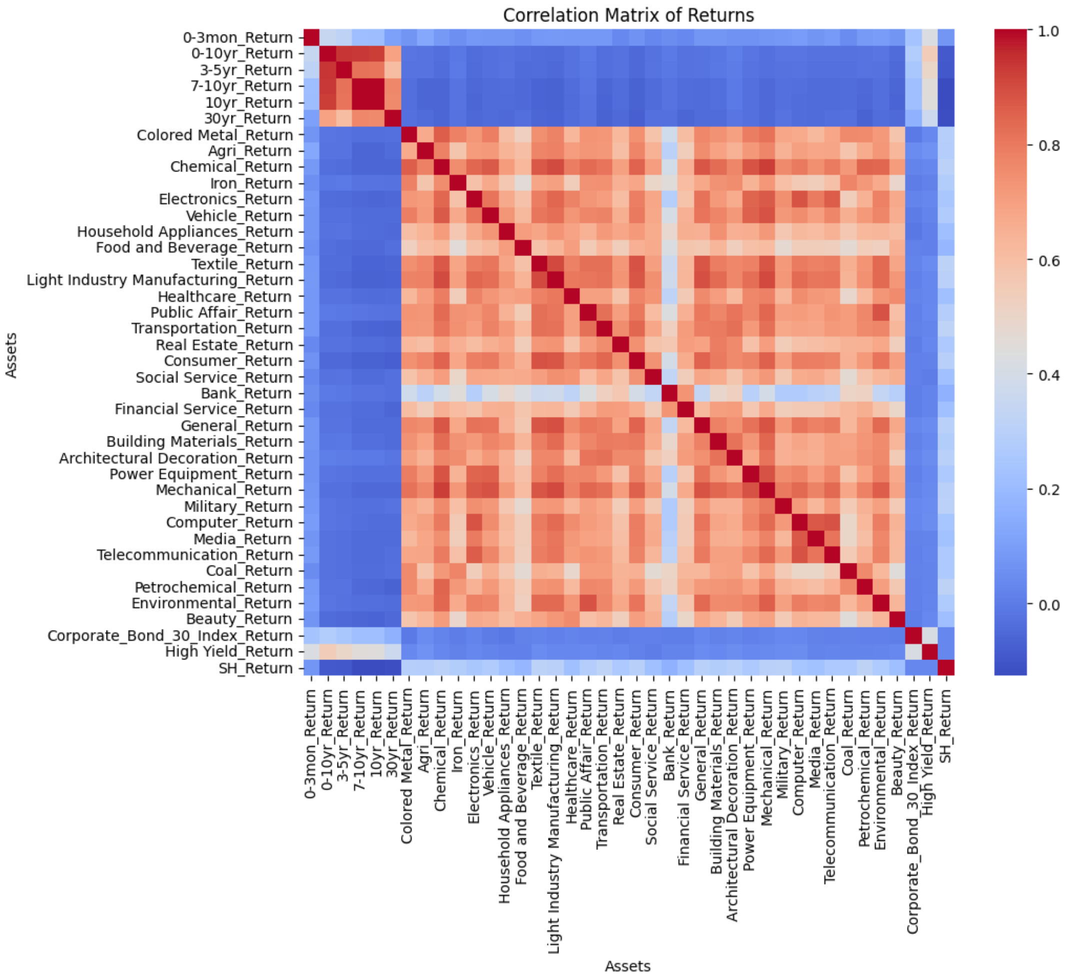

Figure 4 Correlation Matrix of Returns

The correlation matrix chart depicts the relationships between the returns of various assets, with darker red indicating strong positive correlations and darker blue signifying strong negative correlations. The chart reveals that assets within the same class or related industries, such as different bond maturities, tend to show high positive correlations, reflecting their similar market responses. Conversely, sectors like agriculture and electronics exhibit low or negative correlations with bonds and each other, indicating independent or opposite movements. Distinct clusters in the matrix highlight sector-specific behaviors, aiding in targeted investment strategies. The SSE Corporate Bond 30 Index and China High Yield Corporate Bond Index, show strong correlations, aligning with their category.

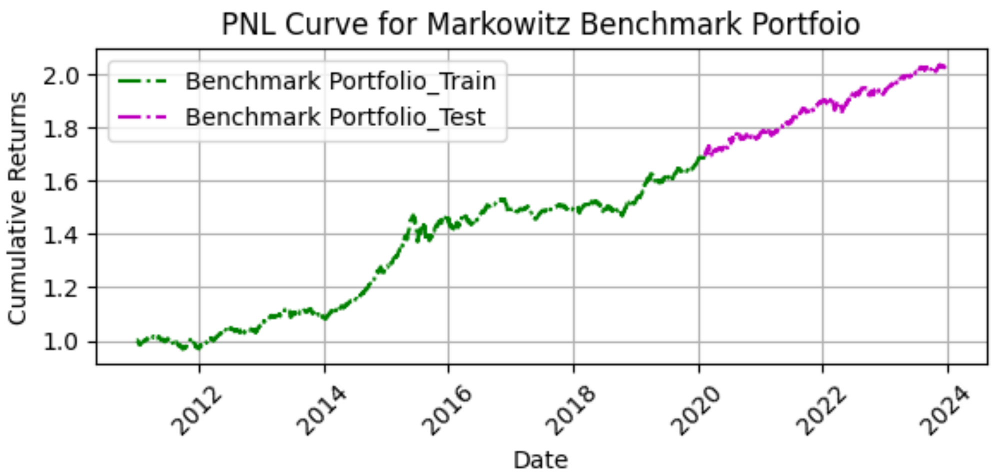

Figure 5 PNL Curve for Markowitz Benchmark Portfolio

The chart above illustrates the PNL curve for a Markowitz Benchmark Portfolio from 2011 to 2024, with cumulative returns split into training (2011-2019) and testing (2020-2024) phases. During the training period, represented by a green dashed line, the portfolio shows steady and consistent growth, with a gradual increase from 2011 to 2014, a notable spike in mid-2015 followed by a brief correction, and continued upward momentum until 2019. The testing period, shown in magenta, continues this positive trend despite the economic disruptions of the COVID-19 pandemic in 2020, demonstrating the portfolio's resilience and quick recovery. From 2021 onwards, the portfolio maintains steady growth, reaching approximately 2.0 in cumulative returns by 2024, effectively doubling the initial investment. This consistent performance underscores the effectiveness of Markowitz's optimization model, which balances risk and return through diversified asset allocation, proving to be a robust and adaptable long-term investment strategy.

4.2.3 Markowitz Model - Stage Optimized Result

In this stage-optimized Markowitz model, we aimed to find the optimal weight of each business stage separately. Every time the business stage transitioned from one to another, we switched our position to the pre-determined optimized weight for that specific stage. We maintained the same constraints of a 50% maximum weight and a 0.5% minimum weight for each individual asset to ensure diversification.

Business Stage	Top 3 Assets	Asset Weight
Contraction	30-year Government Bond	42.93%
	10-year Government Bond	38.57%
	Beauty Industry Stock	0.53%
Recovery	China High Field Corporate Bond Index	50.00%
	SSE Corporate Bond 30 Index	29.3%
	30-year Government Bond	2.69%
Slowdown	30-year Government Bond	41.99%
	China High Field Corporate Bond Index	31.50%
	Computer Science Industry	0.51%
Expansion	China High Field Corporate Bond Index	50.00%
	0-3 Month Government Bond Index	27.90%
	Bank Industry Stock	4.09%

Table 2 Asset Allocation of Different Business Regimes

The table above outlines the top three assets and their respective weights for each business stage—Contraction, Recovery, Slowdown, and Expansion—based on portfolio optimization. During economic contractions, the portfolio is heavily weighted towards long-term government bonds (42.93% in 30-year bonds and 38.57% in 10-year bonds) for stable returns, with minimal allocation to equity (0.53% in Beauty Industry stocks). In recovery phases, the focus shifts to higher-yield corporate bonds (50% in China High Yield Corporate Bond Index and 29.3% in SSE Corporate Bond 30 Index) for higher returns, with a smaller allocation to long-term government bonds (2.69%). During slowdowns, the portfolio maintains a significant allocation to long-term government bonds (41.99% in 30-year bonds), balancing this with high-yield corporate bonds (31.5%) and a small investment in the Computer Science Industry (0.51%). In expansion phases, the portfolio prioritizes high-yield corporate bonds (50%) to capitalize on growth opportunities, complemented by short-term government bonds (27.9%) and bank industry stocks (4.09%) for diversification and risk management [6].

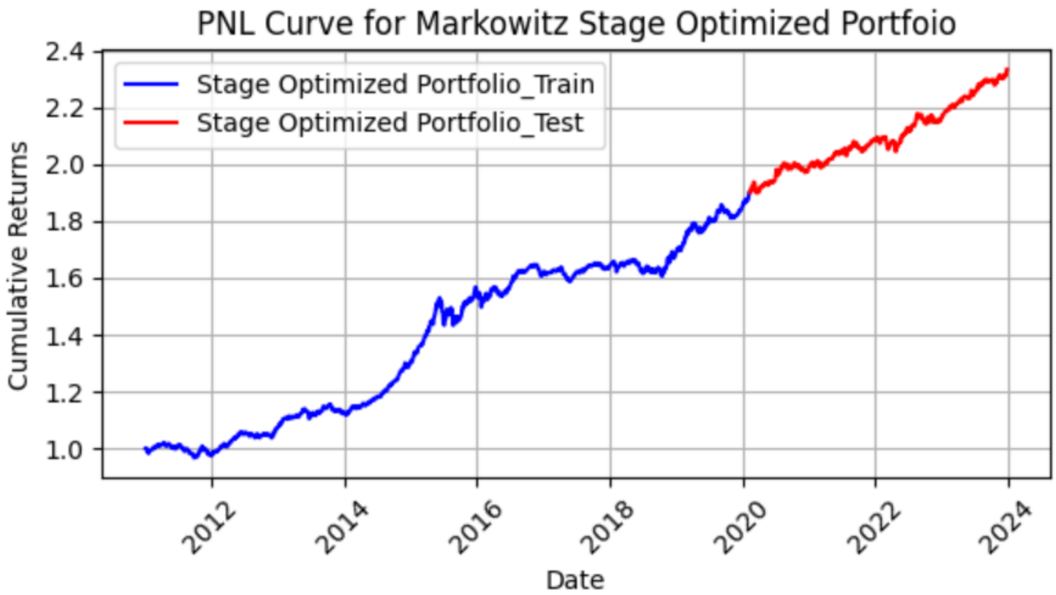

Figure 6 PNL Curve for Markowitz Stage Optimized Portfolio

Compared with Markowitz Benchmark, the Markowitz Stage Optimized Portfolio shows a more pronounced growth, particularly in the testing phase, achieving cumulative returns of about 2.4 by 2024. The Stage Optimized Portfolio exhibits a sharper increase in returns during the training period and a stronger recovery and growth during the testing phase, suggesting better performance and resilience compared to the Benchmark Portfolio. This comparison indicates that the stage-optimized approach, which adjusts asset allocation based on business cycles, leads to higher cumulative returns and better adaptation to market conditions, highlighting its effectiveness over the traditional Markowitz model in optimizing portfolio performance.

4.3 Black-Litterman Model

4.3.1 Theory

The Black-Litterman model, developed by Fisher Black and Robert Litterman in 1992, represents a significant advancement in portfolio management, optimizing the earlier Markowitz model, which, despite its groundbreaking approach, faced practical challenges in real-world applications. These challenges included portfolios that were often hard to interpret, overly concentrated, overly sensitive to input changes, and prone to amplified estimation errors. Such issues made the Markowitz model less appealing to financial practitioners [7].

The Black-Litterman model addresses these concerns by integrating probabilistic statistical methods to meld the investors' subjective views with the objective market equilibrium returns. This integration creates a refined set of expected returns that account for both market data and individual investor insights. The model allows investors to express preferences over broad asset categories, adjusting the allocation based on these subjective views against market benchmarks. This approach results in portfolios that are intuitively understandable and whose allocations are easy to justify.

One of the key strengths of the Black-Litterman model is its use of a Bayesian framework to combine prior (subjective investor views) and likelihood (historical market data) information to arrive at a posterior distribution of expected returns. This method adjusts the weight given to subjective expectations based on the investor's confidence in their views. High confidence in subjective judgments leads to greater weight being placed on these views, pushing expected returns closer to subjective expectations. Conversely, when confidence in subjective assessments is low, the model leans more heavily on market equilibrium returns [8].

This intuitive and flexible framework makes the Black-Litterman model particularly appealing for institutional investors, who can base their subjective views on comprehensive top-down or bottom-up analyses. Meanwhile, individual investors might derive their views from more accessible sources such as media, internet, and financial analysts.

Since its introduction, the Black-Litterman model has gained widespread acceptance on Wall Street, becoming a mainstay in the asset allocation strategies of major firms, notably within the asset management division of Goldman Sachs. Its ability to provide clear, rational, and customizable investment strategies has solidified its position as a critical tool in modern financial portfolio management [9].

4.3.2 Stage Optimized Black-Litterman Model

In this Black-Litterman model, we first generated our view by only considering the historical performance. We compute the average return of each asset in each business stage within the training period. Then we return the top 5 and bottom 5 assets of each stage. We select the industries which are more reasonable to continue the outperforming/down-performing characters in the future testing period. For example, we believe Household Appliances industry is reasonable to outperform the market during the recovery period when customers are more comfortable with consumption, we would express the view of outperformance on it. We selected pairs of assets and express our view as a percentage difference in return. We took the positive return minus the negative return and use this difference as our view. We also set $\tau = 0.1$ to make our view more conservative. After experiment, setting τ to a larger value could improve the model performance but may resulting more overfitting issue in practice.

Stage	Asset 1	Asset 2	View (difference in return)
Contraction	Electronics	Iron	0.5
Contraction	Computer	Coal	0.4
Recovery	Household Appliances	High Yield	0.25
Slowdown	Financial Service	Transportation	0.2
Expansion	Social Service	Architectural Decoration	0.3

Table 3 Asset View of Different Business Regimes

The table above outlines asset views applied in Black-Litterman Model based on different business regimes. The view emphasizes expected return differentials for various asset pairs. During contractions, investments are directed towards sectors like Electronics and Iron, and Computer and Coal, with expected return differences of 0.5 and 0.4 respectively. In recovery phases, the allocation shifts to Household Appliances and high-yield bonds, with a moderate return differential of 0.25. During slowdown stage, the portfolio targets Financial Services and Transportation, with a lower return differential of 0.2. In expansion phases, investments focus on Social Services and Architectural Decoration, with a moderate return differential of 0.3.

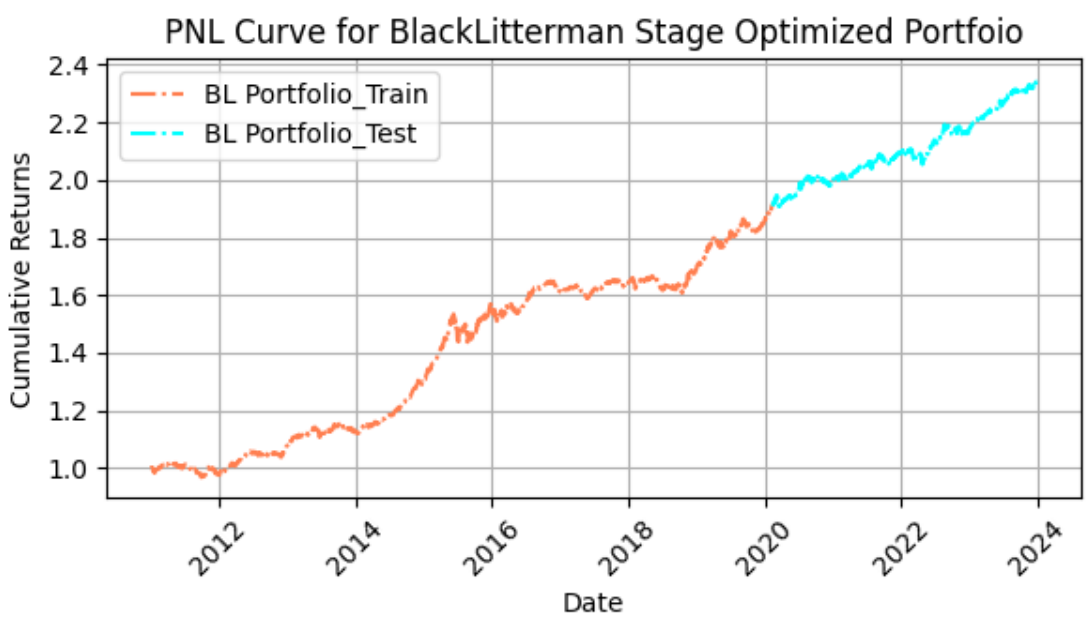

Figure 7 PNL Curve for Black-Litterman Stage Optimized Portfolio

The chart above displays the PNL curve for a Black-Litterman Stage Optimized Portfolio from 2011 to 2024, showing cumulative returns during the training (2011-

2019) and testing (2020-2024) periods. The red dashed line represents the training phase, indicating consistent growth with a notable rise around mid-2015 and an overall upward trend despite some fluctuations. The cyan dashed line represents the testing phase, where the portfolio maintains a strong positive trajectory, recovering quickly from the economic disruptions of the COVID-19 pandemic in 2020 and continuing to grow steadily. By 2024, the portfolio reaches approximately 2.4 in cumulative returns, more than doubling the initial investment over the 13-year period. This consistent growth and resilience during market volatility underscore the effectiveness of the Black-Litterman optimization approach, which integrates investor views with market equilibrium to optimize asset allocation. The portfolio's robust long-term performance and adaptability to changing market conditions make it a reliable strategy for investors seeking steady returns over extended periods.

4.4 Model Performance Comparison

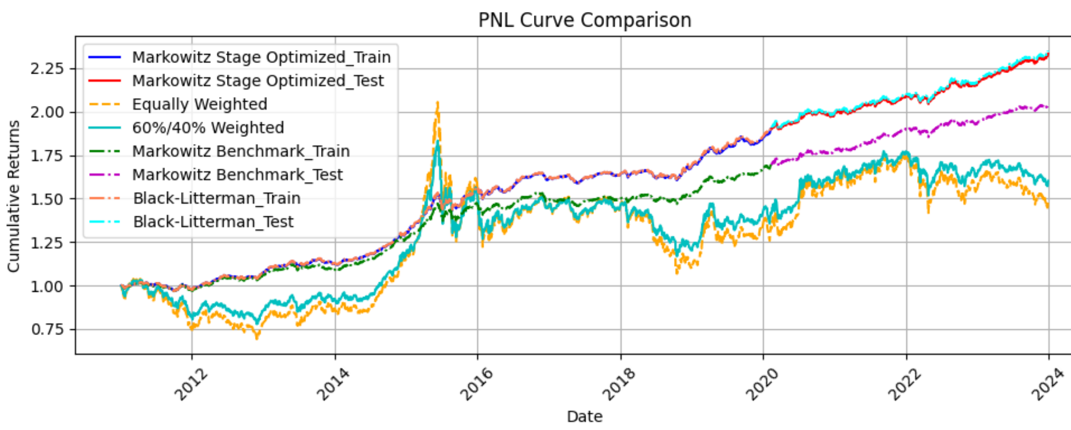

Figure 8 PNL Curve Comparison for 5 Portfolio

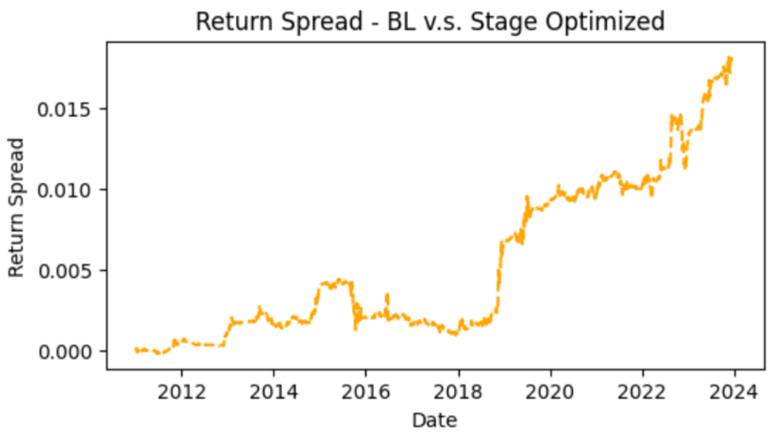

Figure 9 Return Spread of Black-Litterman Model and Markowitz Stage Optimized Model

Portfolio Type	Sharpe Ratio
Equal Weight Portfolio	0.2008

60%/40% Portfolio	0.3845
Benchmark Markowitz Model	1.7246
Stage Optimized Markowitz Portfolio	1.5068
Black-Litterman Model	1.51389

Table 4 Sharpe Ratio Comparison for 5 Models

The Equally Weighted model (orange line) exhibited significant volatility, particularly between 2015-2016 and 2020, which makes it have the smallest Sharpe ratio. While this model experienced sharp peaks and troughs, it ultimately showed minimal net gains, highlighting the higher risk associated with an equal distribution of weights among assets.

The 60%/40% Weighted model (green line) demonstrated more stability, with a smoother growth trajectory compared to the Equally Weighted model. Therefore, the Sharpe ratio of it is a little bit larger than that of Equally Weighted model. The notable rise around 2015-2016 and subsequent steadier performance underscores the benefits of a balanced allocation between equities and bonds, reducing volatility and providing more consistent returns.

The Markowitz Benchmark model (dotted green line for training and dotted magenta line for testing) showed a steady and consistent upward trend, especially during the testing period. The optimization of the Sharpe ratio during the training period contributed to stable growth, demonstrating the effectiveness of Markowitz optimization in balancing returns and risk.

The Markowitz Stage Optimized model (blue line for training and red line for testing) achieved a higher cumulative return compared with all the benchmark models, with minimal volatility. By dynamically adjusting portfolio weights based on market stages, this model effectively capitalized on market opportunities while maintaining stability. The Sharp ratio of this model is 1.5068. The sharp and consistent growth in both training and testing periods highlights the robustness and efficiency of stage-specific optimization.

The Black-Litterman model (dashed coral line for training and dashed cyan line for testing) presented a moderate growth trajectory with noticeable volatility. While it provided better returns than other benchmark models, it was outperformed by the Markowitz Stage Optimized model in Sharpe ratio, indicating that while the Black-Litterman approach offers a unique perspective on expected returns, it may not be as effective in managing risk-adjusted returns as the stage-optimized strategy. Black-Litterman model generate a PNL curve which is very similar to the Markowitz Stage Optimized model. The excess return of Black-Litterman model to Markowitz Stage Optimized model is just 1.75% over the entire 10+ years. This difference is negligible but it highlights the value of finding a better method to form and express our views in the Black-Litterman model.

5 Discussion

5.1 Conclusion

Focusing on the Chinese market, the study uses a comprehensive dataset spanning 13 years, categorizing the business cycle into recovery, expansion, slowdown, and contraction stages using the Consumer Price Index (CPI) and Purchasing Manager Index (PMI). Key findings include the significant trends from 2004 to 2024, where different business stages highlighted periods of recovery, expansion, slowdown, and contraction. The study compares various portfolio optimization models, such as the Equal Weight Model, which showed significant volatility with modest long-term growth, and the 60%/40% Weight Model, which demonstrated reduced volatility and more consistent returns. The traditional Markowitz Model, aimed at maximizing the Sharpe ratio, resulted in stable growth, while the Stage Optimized Markowitz Model, which adjusted asset allocation based on business cycle stages, achieved higher cumulative returns and better performance. The Black-Litterman Model, integrating investor views with market data, showed robust long-term performance and resilience to market changes. Performance comparisons revealed that the Markowitz Stage Optimized and Black-Litterman models outperformed others in cumulative returns and Sharpe ratio, with the Black-Litterman model providing slightly higher returns but with similar risk-adjusted performance. These findings highlight the potential of the regime-based TAA strategy in optimizing asset allocation by dynamically adjusting to business cycle stages, emphasizing the importance of a dynamic and adaptive approach to asset allocation in volatile market environments.

5.2 Limits

Despite the promising results, this study has several limitations that must be acknowledged. First, the reliance on historical data from the China market may limit the generalizability of the findings to other geographic regions or markets with different economic structures and dynamics. The unique characteristics of the Chinese economy, such as government policies and market regulations, could influence asset performance in ways that are not directly applicable elsewhere.

Second, the use of the Consumer Price Index (CPI) and Purchasing Managers' Index (PMI) as indicators for categorizing business cycle stages, while effective, may not fully capture the complexity of economic conditions. Other macroeconomic indicators, such as employment rates, industrial production, and consumer confidence, could provide additional insights into market dynamics and enhance the accuracy of business cycle identification.

Third, the study's approach to expressing views in the Black-Litterman model, based solely on historical performance and conservative adjustments, may lead to suboptimal outcomes. The subjective nature of these views and the chosen level of conservatism (τ) can significantly impact the model's performance. Additionally, the simplification of the business cycle into only four stages might overlook more nuanced economic shifts that could be leveraged for more precise asset allocation adjustments.

5.3 Future Improvements

Future research could address these limitations by expanding the dataset to include multiple geographic regions and markets, allowing for a more comprehensive analysis of the regime-based TAA framework's applicability and effectiveness. This would also enable a comparative analysis of how different economic environments influence the performance of the proposed strategies.

Enhancing the business cycle identification process by incorporating a broader range of macroeconomic indicators could improve the robustness of the regime classification. Advanced machine learning techniques could be employed to analyze these indicators, providing a more nuanced understanding of economic conditions and enabling more accurate predictions of market phases.

Additionally, refining the approach to forming and expressing views in the Black-Litterman model could lead to improved outcomes. Incorporating real-time data analysis, sentiment analysis from news and social media, and expert forecasts could provide more informed and dynamic views, enhancing the model's adaptability to changing market conditions.

Finally, exploring the integration of alternative investment strategies, such as factor-based investing or risk parity approaches, with the regime-based TAA framework could offer further diversification benefits and enhance the resilience of investment portfolios. By continuously adapting to new economic insights and technological advancements, future research can build on the findings of this study to develop more sophisticated and effective investment strategies.

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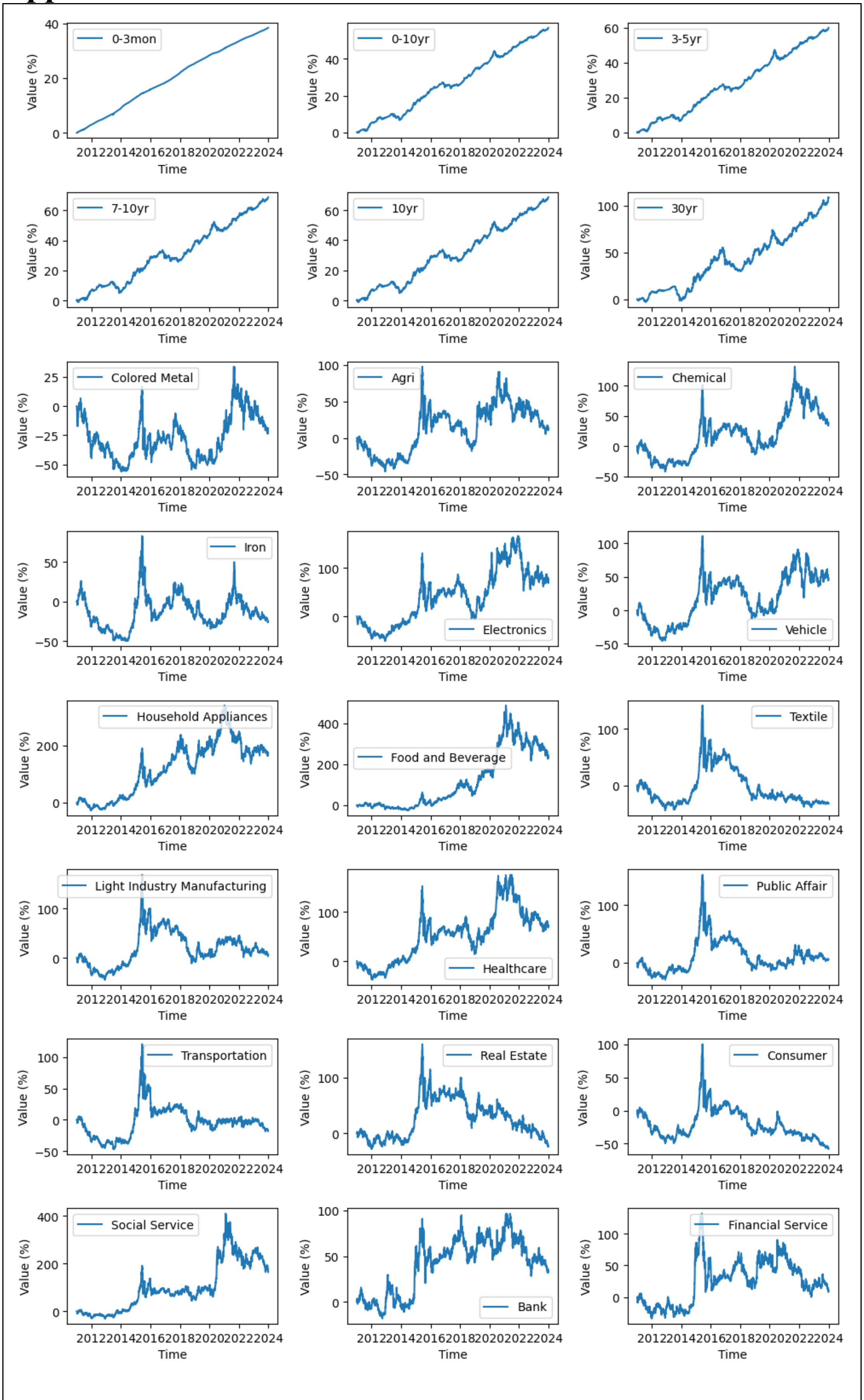
Appendix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0-10yr
3-5yr
7-10yr
10yr
30yr
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Agri
Chemical
Iron
Electronics
Vehicle
Household Appliances
Food and Beverage
Textile
Light Industry Manufacturing
Healthcare
Public Affair
Transportation
Real Estate
Consumer
Social Service
Bank
Financial Service
Value (%)
Time
2012201420162018202020222024

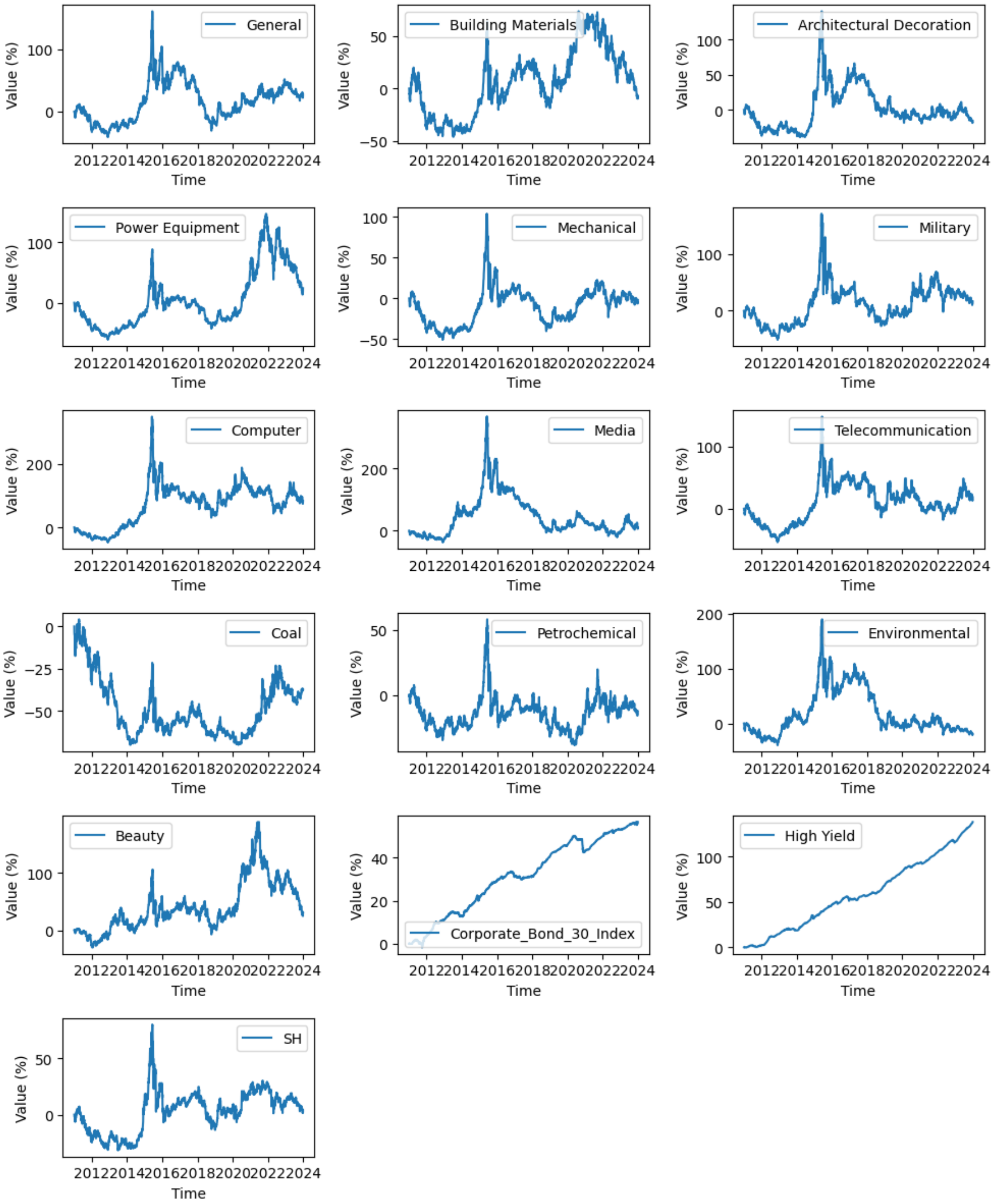

Figure 1 Value of All Assets over Time

```
Optimal weights for stage 1: [0. 005       0. 005       0. 005       0. 005       0. 38569038  0. 42930967
 0. 005       0. 005       0. 005       0. 005       0. 005       0. 005
 0. 005       0. 005       0. 005       0. 005       0. 005       0. 005
 0. 005       0. 005       0. 005       0. 005       0. 005       0. 005
 0. 005       0. 005       0. 005       0. 005       0. 005       0. 005
 0. 005       0. 005       0. 005       0. 005       0. 005       0. 005
 0. 00500003  0. 005       0. 005       ]
Optimal weights for stage 2: [0. 005       0. 005       0. 005       0. 005       0. 005       0. 02690422
 0. 005       0. 005       0. 005       0. 005       0. 005       0. 005
 0. 005       0. 005       0. 005       0. 005       0. 005       0. 005
 0. 005       0. 005       0. 005       0. 005       0. 005       0. 005
 0. 005       0. 005       0. 005       0. 005       0. 005       0. 005
 0. 005       0. 005       0. 005       0. 005       0. 005       0. 005
 0. 005       0. 29309578  0. 5        ]
```

```
Optimal weights for stage 3: [0.005      0.005      0.005      0.005      0.005      0.49999995
 0.005      0.005      0.005      0.005      0.00500002 0.005
 0.005      0.005      0.005      0.005      0.00500001 0.005
 0.005      0.005      0.005      0.005      0.005      0.005
 0.005      0.005      0.005      0.005      0.005      0.005
 0.00500003 0.005      0.005      0.005      0.005      0.005
 0.005      0.005      0.31500068]
Optimal weights for stage 4: [0.27900614 0.005      0.005      0.005      0.005      0.005
 0.005      0.005      0.005      0.005      0.005      0.005
 0.005      0.005      0.005      0.005      0.005      0.005
 0.005      0.005      0.005      0.005      0.04099386 0.005
 0.005      0.005      0.005      0.005      0.005      0.005
 0.005      0.005      0.005      0.005      0.005      0.005
 0.005      0.005      0.5       ]
```

Figure 2 Asset Allocation Weight for Markowitz Stage Optimized Model

```
Index(['Date', '0-3mon_Return', '0-10yr_Return', '3-5yr_Return',
       '7-10yr_Return', '10yr_Return', '30yr_Return', 'Colored Metal_Return',
       'Agri_Return', 'Chemical_Return', 'Iron_Return', 'Electronics_Return',
       'Vehicle_Return', 'Household Appliances_Return',
       'Food and Beverage_Return', 'Textile_Return',
       'Light Industry Manufacturing_Return', 'Healthcare_Return',
       'Public Affair_Return', 'Transportation_Return', 'Real Estate_Return',
       'Consumer_Return', 'Social Service_Return', 'Bank_Return',
       'Financial Service_Return', 'General_Return',
       'Building Materials_Return', 'Architectural Decoration_Return',
       'Power Equipment_Return', 'Mechanical_Return', 'Military_Return',
       'Computer_Return', 'Media_Return', 'Telecommunication_Return',
       'Coal_Return', 'Petrochemical_Return', 'Environmental_Return',
       'Beauty_Return', 'Corporate_Bond_30_Index_Return', 'High Yield_Return',
       'Stage'],
      dtype='object')
```

Figure 3 Column Name (excluding 'Date' and 'Stage')

```
[0.005      0.005      0.005      0.005      0.005      0.12035698
 0.005      0.005      0.005      0.005      0.005      0.005
 0.005      0.005      0.005      0.005      0.005      0.005
 0.005      0.005      0.005      0.005      0.005      0.005
 0.005      0.005      0.005      0.005      0.005      0.005
 0.005      0.005      0.005      0.005      0.005      0.005
 0.005      0.19964302 0.5       ]
```

Figure 4 Asset Allocation Weight for Markowitz Benchmark Model

```
Optimized Weights for stage 1: [0.005 0.005 0.005 0.005 0.315 0.5   0.005 0.005 0.005 0.005 0.005 0.005
 0.005 0.005 0.005 0.005 0.005 0.005 0.005 0.005 0.005 0.005 0.005 0.005
 0.005 0.005 0.005 0.005 0.005 0.005 0.005 0.005 0.005 0.005 0.005 0.005
 0.005 0.005 0.005]

Optimized Weights for stage 2: [0.005   0.005   0.005   0.005   0.005   0.03407 0.005   0.005   0.005
 0.005   0.005   0.005   0.005   0.005   0.005   0.005   0.005   0.005
 0.005   0.005   0.005   0.005   0.005   0.005   0.005   0.005   0.005
 0.005   0.005   0.005   0.005   0.005   0.005   0.005   0.005   0.005
 0.005   0.28593 0.5    ]

Optimized Weights for stage 3: [0.005 0.005 0.005 0.005 0.005 0.5   0.005 0.005 0.005 0.005 0.005 0.005
 0.005 0.005 0.005 0.005 0.005 0.005 0.005 0.005 0.005 0.005 0.005 0.005
 0.005 0.005 0.005 0.005 0.005 0.005 0.005 0.005 0.005 0.005 0.005 0.005
 0.005 0.005 0.315]

Optimized Weights for stage 4: [0.27514 0.005   0.005   0.005   0.005   0.005   0.005   0.005   0.005
 0.005   0.005   0.005   0.005   0.005   0.005   0.005   0.005   0.005
 0.005   0.005   0.005   0.005   0.04486 0.005   0.005   0.005   0.005
 0.005   0.005   0.005   0.005   0.005   0.005   0.005   0.005   0.005
 0.005   0.005   0.5    ]
```

Figure 5 Asset Allocation Weight for Black-Litterman Model