# Multi-Factor ETF Return Prediction Based on Momentum Strategies

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**Executive Summary**

This paper explores the presence of lead-lag relationships among sector-based Exchange-Traded Funds (ETFs), established factor portfolios, and macroeconomic indicators. We focus on 11 SPDR Sector ETFs and integrate them with various factor sets derived from Fama-French models, as well as momentum, reversal, and macroeconomic signals such as Treasury yields and gold prices. By employing rigorous data preprocessing, we isolate market-neutral sector returns and engineer a range of lagged return features. These features are then tested for statistical significance using Fisher's $Z$-transformation, followed by clustering-based feature selection.

The selected lead-lag features are used in predictive models to forecast one-month-ahead residual ETF returns. We conduct extensive out-of-sample backtests with different weighting (e.g., equal, minimum variance) and rebalancing schemes, including dynamic rolling refits. The best performing portfolios achieve high Sharpe ratios and maintain low correlation with the broad market, indicating substantial diversification potential. For instance, certain equal-weighted strategies achieve test-period Sharpe ratios exceeding 3.0, and minimum-variance optimized portfolios can yield Sharpe ratios above 3.6 in the test phase.

Our approach extends the literature on factor timing and sector rotation by demonstrating that dynamic, data-driven feature selection can generate economically significant trading strategies. These findings suggest that temporal dependencies between sectors, factors, and macro signals are exploitable and robust, contributing to both academic research on factor momentum and practical portfolio management strategies.

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# Chapter 1

# Introduction

## 1.1 Background and Motivation

Factor investing and sector rotation strategies have gained widespread attention as tools to achieve excess returns and manage risk. Traditional factor models (e.g., Fama & French 1993, 2015) have expanded our understanding of risk premia beyond the market. However, these models typically assume static factor exposures. A growing body of research suggests that dynamic timing of factors and sectors can lead to improved portfolio performance. For instance, Arnott et al. (2018) show that factors themselves exhibit momentum-like behavior, termed "factor momentum," which can be even more pervasive than the well-documented industry momentum of Moskowitz & Grinblatt (1999).

Building on these insights, we examine whether sector-level ETFs, when combined with Fama-French and macroeconomic factors, display lead-lag relationships that can be systematically exploited. Past studies have highlighted various sources of cross-sectional predictability in returns (e.g., Jegadeesh & Titman 1993; Carhart 1997; Asness et al. 2013). Yet, few have integrated sector ETFs, factor returns, and macroeconomic indicators in a unified framework to extract robust predictive signals. Identifying and harnessing these signals can improve the risk-adjusted performance of portfolios, especially when factor selection is guided by data-driven techniques that filter for statistical significance.

## 1.2 Objectives and Contribution

This paper pursues several key objectives. First, it seeks to identify robust lead-lag patterns between 11 SPDR Sector ETFs and a broad set of factors and macroeconomic variables. Second, it employs rigorous statistical tests, notably Fisher's $Z$-transformation, alongside clustering methodologies, to isolate the most statistically significant and stable predictive features. Third, the study conducts comprehensive out-of-sample evaluations of portfolio strategies that leverage these identified relationships, considering different weighting methods and rebalancing intervals. Finally, it assesses performance relative to broad market benchmarks, focusing on metrics such as Sharpe ratios, Sortino ratios, and drawdowns.

We contribute to the literature by showing that a data-driven, dynamic approach to factor and sector selection can yield high risk-adjusted returns and maintain a low correlation with the overall market. These findings underscore the potential of sector-based strategies informed by factor timing and macroeconomic signals, offering an innovative extension to traditional, static factor exposures.

# Chapter 2

# Data and Methodology

## 2.1 Data Overview

We begin with daily return data for 11 SPDR Sector ETFs and a comprehensive set of factors and macroeconomic proxies. These include the Fama-French five factors (Market, SMB, HML, RMW, CMA), as well as supplemental factors such as momentum(Mom), short-term reversal (ST_Rev), and long-term reversal (LT_Rev), in addition to macroeconomic variables such as multiple Treasury maturities (3yr, 10yr, 30yr) and gold prices. Each series is aligned on a daily frequency.

From these raw returns, we form residual (market-neutral) ETF returns by removing the component explained by the broad market. Let $r_t^i$ denote the return of ETF $i$ on day $t$ and $r_t^m$ the market return (e.g., S&P 500) on day $t$. We first estimate a rolling beta $\beta_{t-2}^i$ over a two-year exponentially weighted window. The market-neutral residual return is given by:

$$\mathrm{resid}(r_t^i) = r_t^i - \beta_{t-2}^i r_t^m.$$

This residual return isolates sector-specific information by eliminating broad market influences.

## 2.2 Feature Engineering: Holding Period Returns and Lag Structures

### 2.2.1 Lagged Holding Period Returns

To capture lead-lag effects, we define a family of features that represent lagged holding period returns of both ETFs and factor portfolios. Consider a generic factor $j$ (which could represent another sector ETF, a Fama-French factor, or a macro indicator). We define a holding period $n$ as the length of the historical window used to compute the cumulative return, and a lag $m$ as the amount by which this cumulative return is shifted into the past relative to the forecasting date $t$.

Let $r_k^j$ be the daily return of factor $j$ on day $k$. Define the $n$-day holding period return ending on day $(t - m)$ as:

$$F_t^j(m, n) = \left( \prod_{k=t-m-n+1}^{t-m} (1 + r_k^j) \right) - 1.$$

Here:

- $n$ is the length of the holding period in days (e.g., one month corresponds to about 21 trading days).
- $m$ is the lag in days, i.e., how far back we look from day $t$.

This construction yields a rich set of candidate predictors by varying $m$ and $n$ over predefined grids. For example, if we consider $m$ and $n$ on a monthly scale (21 trading days), we can index $m$ and $n$ in units of months:

$$f_t^j(m, n) = \left( \prod_{k=t-(m\cdot\Delta)-n\cdot\Delta}^{t-(m\cdot\Delta)-1} (1 + r_k^j) \right) - 1,$$

where $\Delta$ is the number of trading days in a month (approximately 21). This allows us to explore various lag and holding period combinations, such as a 1-month holding period return lagged by 2 months, or a 3-month holding period return lagged by 1 month, and so forth.

### 2.2.2 Forecasting Variable: One-Month-Forward Returns

Our target variable $y_t$ for each ETF $i$ is the one-month-forward residual return. That is, starting from day $t$, we look forward over the next month (21 days) and compute:

$$y_t^{(i)} = \left( \prod_{k=t+1}^{t+21} (1 + \mathrm{resid}(r_k^i)) \right) - 1.$$

## 2.3 Statistical Significance Testing of Lead-Lag Features

### 2.3.1 Sample Correlations

For each ETF $i$, each candidate feature $f_t^j(m,n)$ derived from lagged holding returns of a factor $j$ (or another ETF), and each time $t$ within the training period, we can form pairs $(y_t^{(i)}, f_t^j(m,n))$. From these pairs, we estimate correlations over non-overlapping segments of the time series to reduce autocorrelation and avoid overlapping estimation windows.

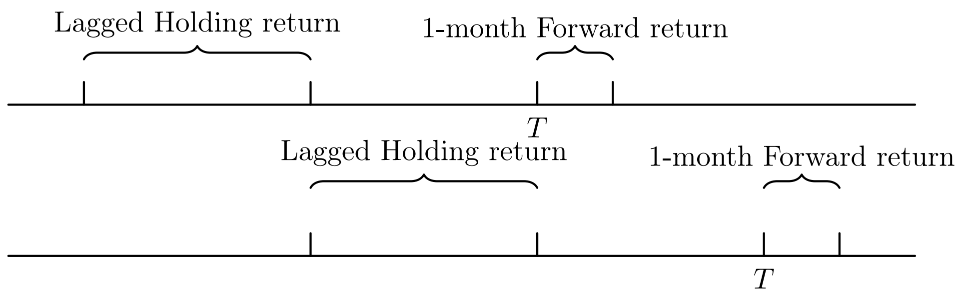


Figure 2.1: Illustration of non-overlapping sampling of return combinations

Specifically, consider a block size aligned with our holding period horizon (e.g., 42 days for 2 months). We sample multiple non-overlapping blocks of return combinations (e.g., 42 blocks for 42 days of holding period). For each block $b$ with sufficient data (at least 4 observations to compute correlation robustly), we compute the sample correlation:

$$r_b^{i,j} = \frac{\sum_t (y_{b,t}^{(i)} - \bar{y}_b^{(i)})(f_{b,t}^j(m,n) - \bar{f}_b^j(m,n))}{\sqrt{\sum_t (y_{b,t}^{(i)} - \bar{y}_b^{(i)})^2 \sum (f_{b,t}^j(m,n) - \bar{f}_b^j(m,n))^2}},$$

where $\bar{y}_b$ and $\bar{f}_b^f(m,n)$ are the sample means within block $b$. Notably, the values $y_{b,t}^{(i)}$ and $f_{b,t}^j(m,n)$ within a given block $b$ are computed using daily returns that are distinct from those used by other elements within the same block.

We thus obtain multiple estimates of $r_b^{i,j}$ from different sample blocks of non-overlapping returns. Each $r_b^{i,j}$ measures how the feature $f_t^j(m,n)$ correlates with the future returns $y_t^{(i)}$ within that block.

### 2.3.2 Fisher's $Z$-Transformation

A key step to aggregate these block-level correlations and assess their overall significance is to use the Fisher $Z$-transformation. The Fisher transform helps convert the correlation coefficient $r$ (which is bounded between -1 and 1) into a normally distributed variable $z$. The Fisher transformation is given by:

$$z_b = \tfrac{1}{2} \ln \left( \frac{1 + r_b}{1 - r_b} \right).$$

Under the null hypothesis that the true correlation is zero, the transformed variable $z_b$ is approximately normally distributed for sufficiently large $n_b$ (the number of observations in block $b$).

To combine multiple block-level estimates, consider that each block $b$ provides a correlation $r_b$ and a corresponding number of observations $n_b$. The variance of the Fisher-transformed correlation (under the null) is approximately $\frac{1}{n_b - 3}$. Thus, we can form a weighted average of these $z_b$ values, weighting by the degrees of freedom $w_b = n_b - 3$.

Define:

$$\bar{z} = \frac{\sum_b w_b z_b}{\sum_b w_b}, \quad \text{where } w_b = n_b - 3.$$

This yields a weighted mean of the Fisher-transformed correlations, putting more weight on larger blocks. The standard error of $\bar{z}$ under the null is:

$$se_{\bar{z}} = \frac{1}{\sqrt{\sum_b w_b}}.$$

### 2.3.3 Z-Score for Significance

We then compute a Z-score for the combined estimate:

$$Z = \frac{\bar{z}}{se_{\bar{z}}}.$$

Under the null hypothesis of no correlation, $Z$ is approximately standard normally distributed. From $Z$, we can compute a one-sided p-value and assess statistical significance. If $Z$ is large enough (e.g., exceeding the critical value for a 95% or 99% confidence level), we conclude that the aggregated positive correlation is statistically significant. Importantly, we focus solely on testing the significance of positive correlations, as our interest lies in the factor momentum lead-lag effect.

Finally, we invert the Fisher transformation to obtain an aggregated correlation estimate:

$$r_{\text{agg}} = \frac{e^{2\bar{z}} - 1}{e^{2\bar{z}} + 1}.$$

The result is a robust measure of the correlation between lagged features and future ETF returns, along with a significance test that accounts for multiple non-overlapping samples.

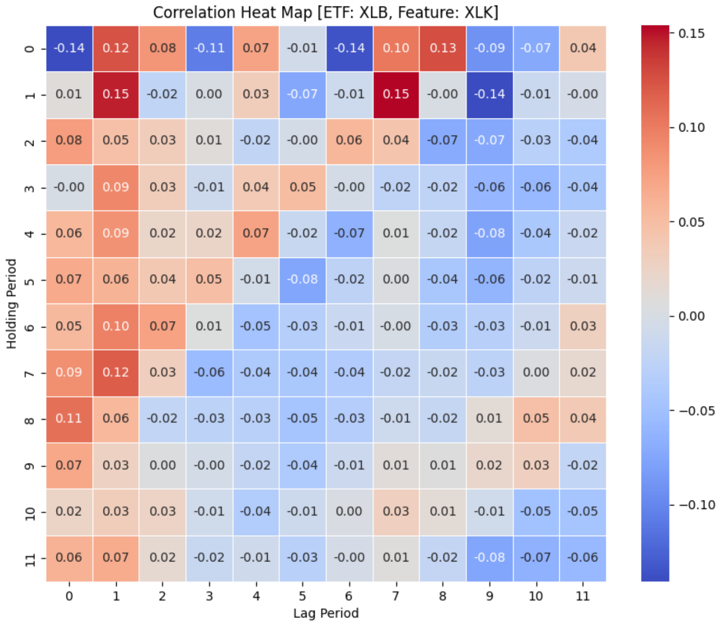


Figure 2.2: Correlation heatmap for the XLK ETF feature with respect to XLB ETF returns.

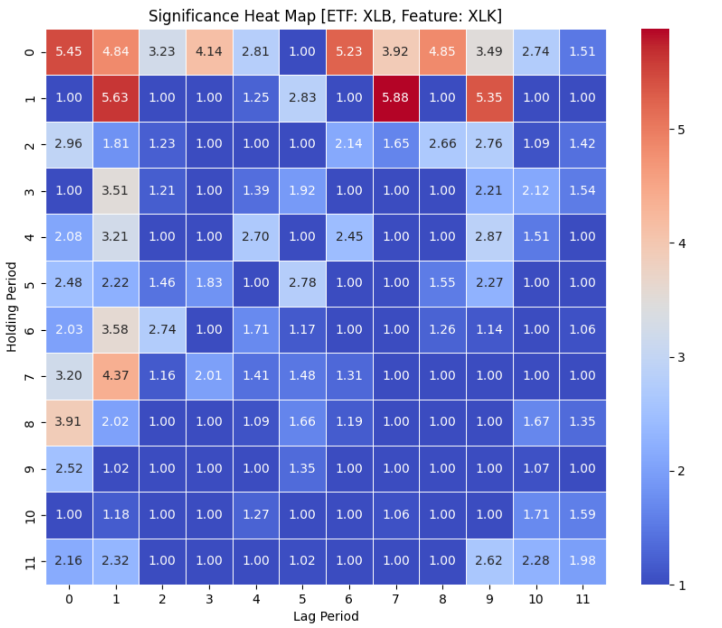


Figure 2.3: Significance heatmap for the XLK ETF feature with respect to the XLB ETF.

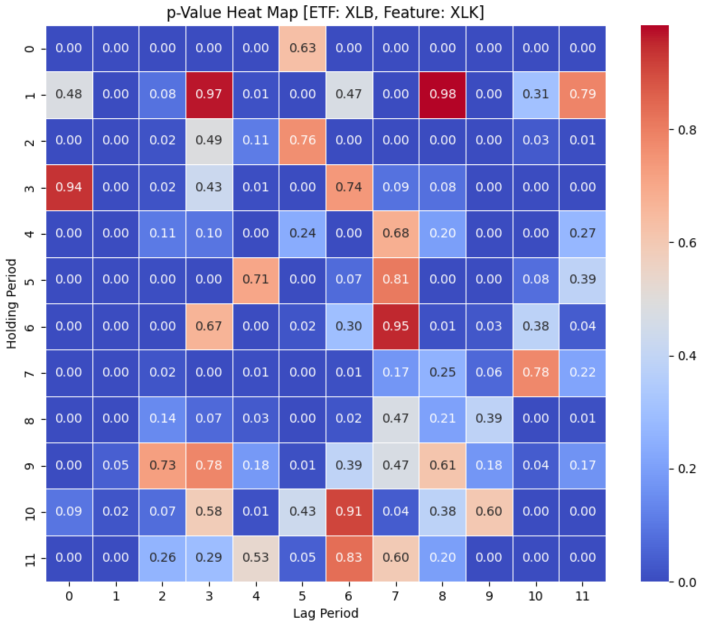


Figure 2.4: p-value heatmap for the XLK ETF feature with respect to XLB ETF returns.

## 2.4 Feature Selection and Clustering

### 2.4.1 Selecting Top Features

To further reduce dimensionality and mitigate multicollinearity, we apply k-means clustering to group similar (lag, holding) combinations. Within each cluster, we pick the combinations with the highest Z-scores. This ensures we retain only a small set of top-performing features from potentially thousands of candidates.

## 2.5 Factor Selection Methodology

After constructing a comprehensive set of candidate features, an important step is to identify the subset of factors that consistently enhances predictive performance. This selection process helps prevent overfitting, reduces complexity, and ensures that the chosen

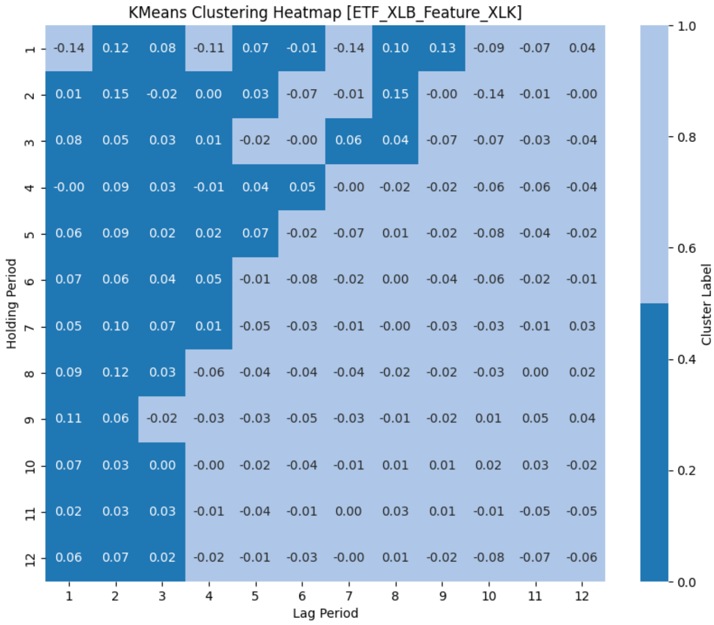


Figure 2.5: K-means Feature Clustering Heatmap for the XLB ETF returns with respect to XLK ETF returns.

factors provide meaningful economic and statistical value.

### 2.5.1 Procedure for Factor Set Determination

The factor selection process begins by establishing a baseline set of market-neutral ETF features. For each ETF $i$, we remove the broad market influence, defining the residual return as:

$$\mathrm{resid}(r_t^i) = r_t^i - \beta_{t-2}^i r_t^m.$$

This construction isolates sector-specific dynamics beyond general market movements. From this foundation, we then consider extending the baseline feature set with additional factors chosen to enhance predictive power. These may include risk-oriented measures (e.g., RMW, SMB), momentum-based factors (Mom, ST_Rev), and macroeconomic signals such as the 3-year Treasury yield (3yr_Treasury). To prevent overfitting, we restricted the maximum number of extra factors as 4.

With various candidate factor combinations in hand, we fit a predictive model over a designated training period. Let $F$ represent the chosen set of factors, and $X_{t,f}$ their corresponding lagged holding-period returns. We estimate:

$$y_t^{(i)} = \alpha + \sum_{f \in F} \beta_f X_{t,f} + \varepsilon_t.$$

We then leverage the model's predicted returns to construct portfolios over the training period. To objectively compare the factor sets, we compute the Sharpe ratio under multiple combinations of weighting schemes, rebalancing frequencies, and starting dates:

$$\text{Sharpe Ratio} = \frac{\text{Annualized Return}}{\text{Annualized Volatility}}.$$

By examining mean Sharpe ratios across these configurations, we identify the factor combinations that yield the most stable and robust performance.

After evaluating all candidate sets, we select the one achieving the highest mean Sharpe ratio across diverse scenarios. In this study, the optimal set consists of ETFs, RMW, ST_Rev, Mom, and 3yr_Treasury. Beyond the intrinsic sector-level signals from the market-neutral ETF returns, integrating profitability measures (RMW), short-term reversals (ST_Rev), momentum trends (Mom), and macro-driven interest-rate indicators (3yr_Treasury) further refines predictive accuracy. Thus, through systematic, empirically-driven factor selection, we arrive at a parsimonious and effective combination to underpin subsequent modeling and portfolio construction.

| **Factors** | **Mean Sharpe** |
|---|---|
| ETFs | 0.7628 |
| ETFs, RMW | 0.8279 |
| ETFs, Mom | 0.7155 |
| ETFs, HML | 0.8052 |
| ETFs, SMB | 0.9133 |
| ETFs, CMA | 0.8814 |
| ETFs, ST_Rev | 0.9036 |
| ETFs, LT_Rev | 0.8523 |
| ETFs, 3yr_Treasury | 0.7924 |
| ETFs, 10yr_Treasury | 0.8763 |
| ETFs, 30yr_Treasury | 0.8889 |
| ETFs, Mom, Gold | 0.9455 |
| ETFs, RMW, 3yr_Treasury | 0.8932 |
| ETFs, Mom, ST_Rev | 0.8681 |
| ETFs, RMW, Mom, 3yr_Treasury | 0.8304 |
| ETFs, RMW, Mom, Gold | 0.9138 |
| ETFs, Mom, ST_Rev, 3yr_Treasury | 0.9411 |
| ETFs, HML, LT_Rev, 10yr_Treasury | 0.9456 |
| ETFs, RMW, Mom, ST_Rev, 3yr_Treasury | 0.9746 |

Table 2.1: Mean Sharpe Ratios for Some Factor Combinations under Train Data

## 2.6 Predictive Modeling & Backtesting

### 2.6.1 Predictive Model

With the selected lead-lag features in hand, we specify a linear regression model:

$$y_t^{(i)} = \alpha + \sum_f \beta_f X_{t,f} + \varepsilon_t,$$

where $X_{t,f}$ are the chosen lagged holding period returns of selected factors and market-neutral ETF returns. We fit the model on a training data and then generate predictions out-of-sample. The out-of-sample predictions guide long-short portfolio construction: for each forecast, we take long positions in ETFs anticipated to produce positive returns and short positions in those expected to yield negative returns.

### 2.6.2 Backtesting Details

To ensure the robustness and reliability of our portfolio strategies, we employ a multi-faceted approach encompassing various weighting schemes, rebalancing frequencies, and sensitivity analyses. Specifically, the following methodologies are utilized:

- **Universe**: The backtesting analysis is conducted on an investment universe comprising 11 Exchange-Traded Funds (ETFs) in addition to SPY (SPDR S&P 500 ETF Trust), ensuring diversified exposure across various sectors and asset classes.
- **Train & Test Period**: The evaluation period is segmented into a training phase extending up to December 31, 2023, and a subsequent testing phase spanning from January 2024 to October 2024. This setting is applied to all weighting schemes except rolling equal weighting scheme.
- **Gross Exposure**: For portfolio construction, we adhere to a gross exposure constraint where the sum of the absolute weights of all positions equals one ($\sum |\text{Weights}| = 1$). This ensures that the portfolio remains fully invested without the use of leverage, promoting balanced exposure and effective risk management.
- **Weighting Schemes:** We implement multiple portfolio weighting schemes, including:
  - Equal Weighting: Assigning an identical weight to each of the selected market-neutral ETF factors. This passive approach ensures diversification and simplicity in portfolio construction.
  - Minimum Variance Optimization: Constructing portfolios by minimizing the overall portfolio variance. This optimization leverages a 6-month rolling covariance matrix derived from historical returns of the selected ETFs, ensuring that the covariance structure is updated regularly to reflect the most recent market dynamics. By focusing on risk reduction, this method seeks to achieve the lowest possible portfolio volatility.

- Rolling Equal Weighting: Enhancing the equal weighting scheme by incorporating a dynamic feature selection and training process. Specifically, this method employs a 3-year rolling training period, during which features are re-selected and the portfolio is re-trained on a monthly basis. This approach allows the portfolio to adapt to evolving market conditions and incorporate new insights, thereby maintaining relevance and effectiveness over time.

- **Rebalancing Frequencies:** To assess the impact of trading frequency on portfolio performance, we vary the rebalancing intervals as follows:
  - Monthly Rebalancing: Occurs every 21 trading days.
  - Bi-Weekly Rebalancing: Occurs every 10 trading days.
  - Weekly Rebalancing: Occurs every 5 trading days.
  - Daily Rebalancing: Occurs every trading day (1 day).
- **Sensitivity Analysis:** We evaluate the sensitivity of portfolio performance by systematically shifting the backtesting start date on a daily basis. This approach helps in assessing the consistency and stability of the strategies across different market conditions and time periods.
- **Transaction Costs:** To emulate realistic trading environments, we incorporate transaction costs into our backtesting framework. Specifically, we assume round-trip transaction costs, encompassing both the purchase and sale of ETF positions. The transaction costs are tested within a range of 0.01% to 0.03% per round trip, allowing us to analyze the strategies' performance under different cost scenarios.

The combination of these strategies and analytical approaches allows for a thorough assessment of portfolio robustness, risk management, and return optimization across different market environments and operational scenarios.

### 2.6.3 Backtest Results

We present representative backtest results under equal-weight, minimum variance, and 3-year rolling strategies. Figures 2.6, 2.8, and 2.10 display cumulative returns for selected shifts and rebalancing frequencies. Drawdown charts (Figures 2.7, 2.9) illustrate the strategies' resilience during market stress. Tables 2.2, 2.3, and 2.4 summarize performance metrics for the respective configurations.

As shown in Table 2.3, the minimum variance approach yields a Sharpe ratio exceeding 3.6 in the test period, demonstrating the effectiveness of combining factor timing signals with risk optimization. Additionally, the 3-year rolling strategy, which re-selects features and re-trains every month, achieves a portfolio correlation of 0.01 with the S&P 500, significantly below the 95% significance level of 0.08 (Table 2.4). This near-zero correlation indicates that the portfolio is effectively uncorrelated with market movements, successfully defending against losses during market downturns while maintaining robust performance. Table B.1 provides detailed backtesting results for various portfolio configurations.

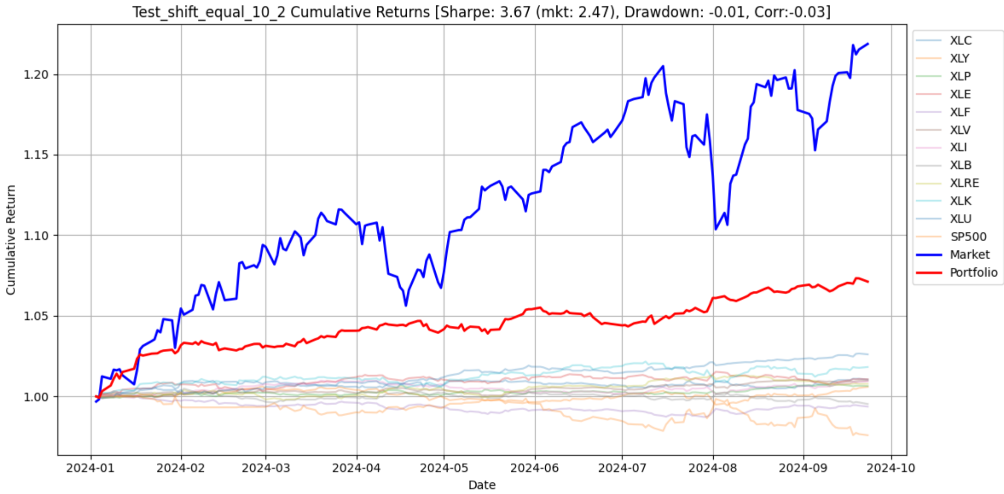


Figure 2.6: Cumulative returns [Equal Weight strategy, shift=2, 10-day rebalance, cost=0.018%].

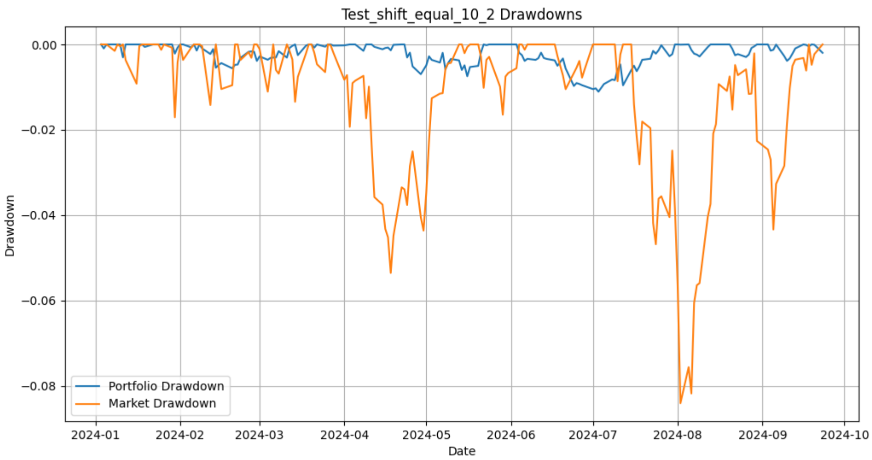


Figure 2.7: Drawdowns [Equal Weight strategy, shift=2, 10-day rebalance, cost=0.018%].

| | Train Evaluation | | Test Evaluation | |
|---|---|---|---|---|
| | Portfolio | Market | Portfolio | Market |
| Annual Return | 0.0253 | 0.0828 | 0.0999 | 0.3150 |
| Annual Volatility | 0.0292 | 0.1911 | 0.0272 | 0.1276 |
| Sharpe Ratio | 0.8675 | 0.4334 | 3.6678 | 2.4679 |
| Sortino Ratio | 1.2342 | 0.5383 | 5.5342 | 3.3361 |
| Maximum Drawdown | -0.0867 | -0.5647 | -0.0111 | -0.0841 |
| Turnover | 6.9526 | | 7.2284 | |

Table 2.2: Performance Metrics [Equal Weight strategy, shift=2, 10-day rebalance, cost=0.018%]

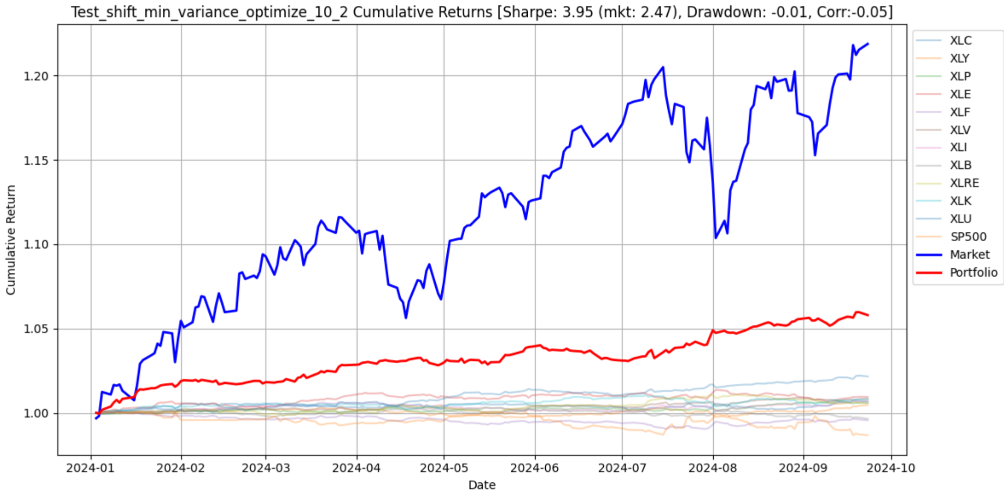


Figure 2.8: Cumulative returns [Min Variance strategy, shift=2, 10-day rebalance, cost=0.018%]

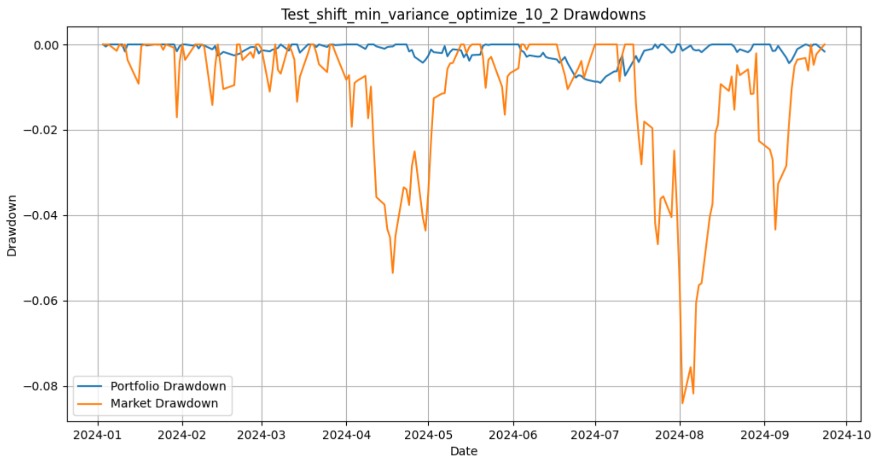


Figure 2.9: Drawdowns [Min Variance strategy, shift=2, 10-day rebalance, cost=0.018%]

| | Train Evaluation | | Test Evaluation | |
|---|---|---|---|---|
| | Portfolio | Market | Portfolio | Market |
| Annual Return | 0.0205 | 0.0816 | 0.0811 | 0.3150 |
| Annual Volatility | 0.0205 | 0.1895 | 0.0205 | 0.1276 |
| Sharpe Ratio | 1.0001 | 0.4309 | 3.9519 | 2.4679 |
| Sortino Ratio | 1.5152 | 0.5312 | 5.9305 | 3.3361 |
| Maximum Drawdown | -0.0515 | -0.5647 | -0.0090 | -0.0841 |
| Turnover | 4.9008 | | 5.2855 | |

Table 2.3: Performance Metrics [Min Variance strategy, shift=2, 10-day rebalance, cost=0.018%]

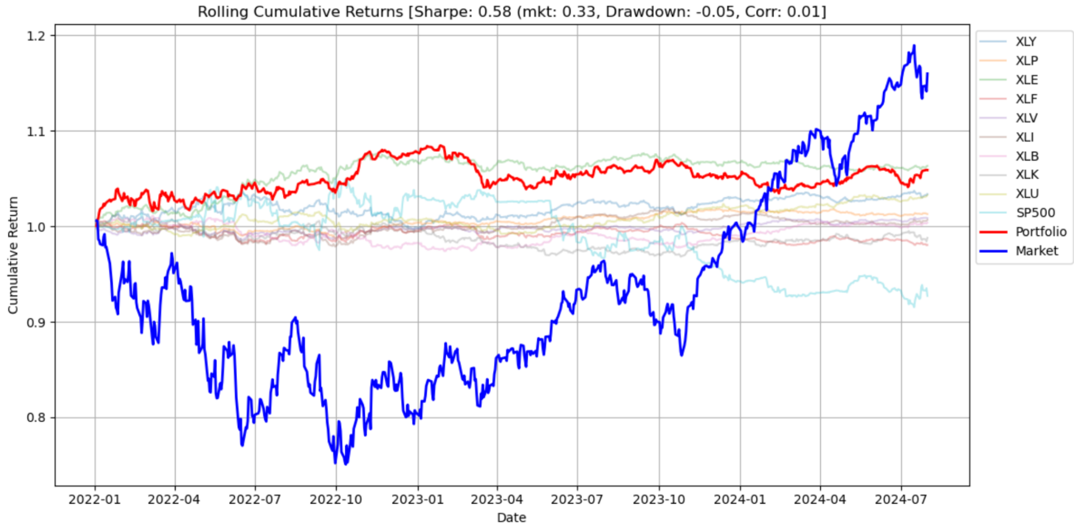


Figure 2.10: Cumulative returns [3-year Rolling strategy, Monthly rebalance, cost=0.018%]

| | Test Evaluation | |
|---|---|---|
| | Portfolio | Market |
| Annual Return | 0.0225 | 0.0594 |
| Annual Volatility | 0.0387 | 0.1804 |
| Sharpe Ratio | 0.5807 | 0.3292 |
| Sortino Ratio | 0.9439 | 0.4787 |
| Maximum Drawdown | -0.0462 | -0.2536 |

Table 2.4: Performance Metrics [Min Variance strategy, shift=2, 10-day rebalance, cost=0.018%]

## 2.7 Interpretation and Robustness

The consistent appearance of strong Sharpe ratios across various parameter choices suggests that lead-lag relationships are not spurious. While some shifts or weighting schemes deliver higher Sharpe ratios than others, the overall pattern indicates that the identified features provide genuine predictive value.

The zero or near-zero correlation with market returns in many configurations underscores the ability of these strategies to offer diversification benefits. This resilience persists even after accounting for trading costs and varying rebalancing frequencies.

# Chapter 3

# Discussion

## 3.1 Economic Rationale

The documented lead-lag relationships among sector ETFs, factors, and macroeconomic signals can be explained through multiple interrelated economic channels. At a high level, these patterns reflect how information—ranging from firm-level fundamentals to macroeconomic conditions—disseminates unevenly across the market. Sectors and factor portfolios often incorporate new data at different speeds, creating predictable time lags that attentive investors can exploit.

First, consider the baseline sector-level ETF features. Sector ETFs represent broad baskets of firms tied to common economic drivers, and new information affecting one industry often ripples out unevenly across related sectors. For instance, regulatory shifts benefiting healthcare providers might initially boost defensive sectors, which are typically more resilient in uncertain conditions, while growth-oriented sectors, such as technology or consumer discretionary, may take longer to adjust. Similarly, cyclical industries, which are more sensitive to economic cycles, might lag defensive industries during economic downturns but eventually catch up or outperform as recovery takes hold. This staggered adjustment process creates systematic lead-lag patterns that attentive investors can exploit. These dynamics align with the broader literature demonstrating that industries vary in their sensitivity to information and their position within economic rotations (e.g., Moskowitz & Grinblatt 1999), with certain sectors leading while others lag in predictable ways depending on the economic environment.

Second, integrating the RMW (robust-minus-weak profitability) factor introduces a fundamental lens. Profitability-based factors reflect slow-moving changes in firms' underlying economics. If highly profitable firms—captured by RMW—lead the market in adjusting to new conditions, then lagging sectors may later incorporate this profitability information. Over time, sectors more closely tied to fundamentally robust or weak firms will react to these signals, enabling persistent return predictability.

Third, the inclusion of the short-term reversal (ST_Rev) factor introduces a behavioral and liquidity-driven dimension to these lead-lag relationships. While the other factors highlighted primarily reflect slow-moving, fundamental attributes of firms, ST_Rev captures predictable, short-term corrections arising from temporary mispricings and investor overreactions. By leveraging the tendency of recent losers to outperform and recent winners to underperform over a one-month horizon, ST_Rev exploits transitory market inefficiencies. Consequently, sectors that have recently lagged, perhaps for reasons unrelated to longer-term fundamentals, may experience short-term rebounds. Over multi-month windows, these transient reversals can gradually transition into more persistent patterns as sectors incorporate fresh information and investor sentiments normalize. In this way, ST_Rev's behavioral underpinnings complement the fundamental and sector-level effects, collectively contributing to the observable lead-lag structures in returns.

Fourth, the momentum (Mom) factor provides another channel for lead-lag effects, reflecting the gradual incorporation of new information into asset prices (e.g., Jegadeesh & Titman 1993). When certain sectors or factor portfolios begin to outperform, often due to positive news or shifting investor sentiment, momentum can amplify these initial gains. As market participants gradually recognize the underlying signals, sectors slower to adjust also begin to rally, allowing the initial strength to diffuse through the cross section. This phenomenon, as documented by Arnott et al. (2019), highlights how momentum systematically propagates economic and informational shocks, ultimately creating persistent and exploitable lead-lag dynamics.

Finally, the inclusion of the lagged 3-year Treasury yield (3yr_Treasury) factor provides a macroeconomic cornerstone for understanding lead-lag dynamics within the context of the monetary policy cycle and investor expectations. Treasury yields encapsulate market views on monetary policy, growth, and inflation, with their lagged values offering insights into how investors anticipate future interest rate trends. A rising lagged 3-year yield may suggest that the market expects rates to peak and subsequently decline after specific months, with the timing and impact varying across industries. This expectation of falling future yields often translates into a favorable environment for interest-rate-sensitive sectors—such as utilities and REITs—and eventually cascades into more cyclical sectors as policy easing benefits broader economic activity. Ultimately, lagged yield shifts serve as a predictive signal for market-neutral returns, driving sector rotations and factor strategies as the market adjusts to anticipated monetary conditions.

In essence, the documented lead-lag relationships among sector ETFs, factors, and macroeconomic signals reflect a complex interplay of fundamental, behavioral, and macroeconomic dynamics. Sector ETFs reveal the uneven dissemination of information across industries, where defensive sectors may lead during uncertain conditions, and cyclical or growth-oriented sectors follow as economic environments shift. The RMW factor captures slow-moving profitability signals that ripple through sectors tied to fundamentally strong or weak firms, enabling predictability in return patterns. The ST_Rev factor exploits short-term behavioral corrections, as investor overreactions and mispricings drive temporary rebounds that cascade into longer-term adjustments. Momentum (Mom) reflects the gradual propagation of positive signals, amplifying sector and factor performance as information diffuses across the market. Finally, the lagged 3-year Treasury yield (3yr_Treasury) factor anchors these dynamics in a broader macroeconomic framework, providing predictive insights into how investors anticipate monetary policy shifts, with implications for sector rotations as interest-rate-sensitive industries lead and cyclical sectors eventually catch up.

Together, these factors represent a multidimensional view of market dynamics. Sector ETFs capture economic diversity, RMW conveys fundamental strength, ST_Rev identifies behavioral inefficiencies, Mom amplifies information flow, and 3yr_Treasury integrates the macroeconomic backdrop. These lead-lag relationships, driven by information frictions and investor behaviors, create persistent, exploitable patterns that align micro and macro market forces into actionable strategies for attentive investors.

# Chapter 4

# Conclusion

## 4.1 Summary of Findings

This paper demonstrates that significant lead-lag relationships exist between sector ETFs, factor returns, and macroeconomic indicators. By systematically identifying and testing these features, and by deploying linear predictive models, we construct strategies that achieve test-period Sharpe ratios exceeding 3.0 under certain conditions. The results are robust to various weighting schemes, rebalancing frequencies, and transaction costs.

## 4.2 Contributions

We extend the literature on factor momentum and sector rotation by showing that advanced feature selection and significance testing can uncover persistent lead-lag patterns. The strategies developed here can complement existing factor-based and macro-informed frameworks, offering new avenues for tactical asset allocation.

## 4.3 Future Directions

Potential avenues for further investigation include the application of nonlinear modeling techniques, such as random forests (Breiman, 2001) or gradient boosting methods (Chen & Guestrin, 2016), to better capture complex, nonlinear relationships. Additionally, incorporating alternative data sources and factor definitions—such as text-based signals (Hoberg & Phillips, 2018)—could provide richer informational content. Extending the analysis to longer sample periods and diverse market regimes would further validate out-of-sample stability.

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# Appendix A

# Appendix: Heatmaps for ETF-Factor Pairs

## A.1 Correlation Heatmaps

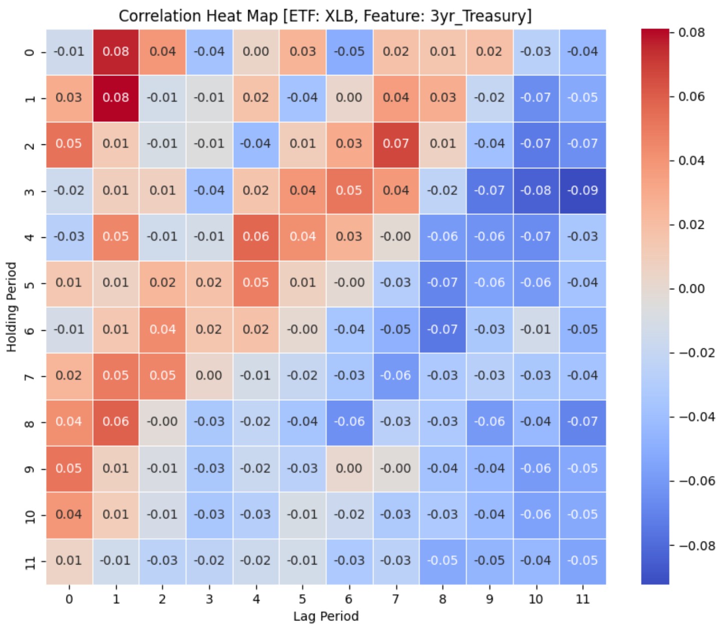


Figure A.1: Correlation heatmap for ETF XLB and factor 3yr Treasury Yield.

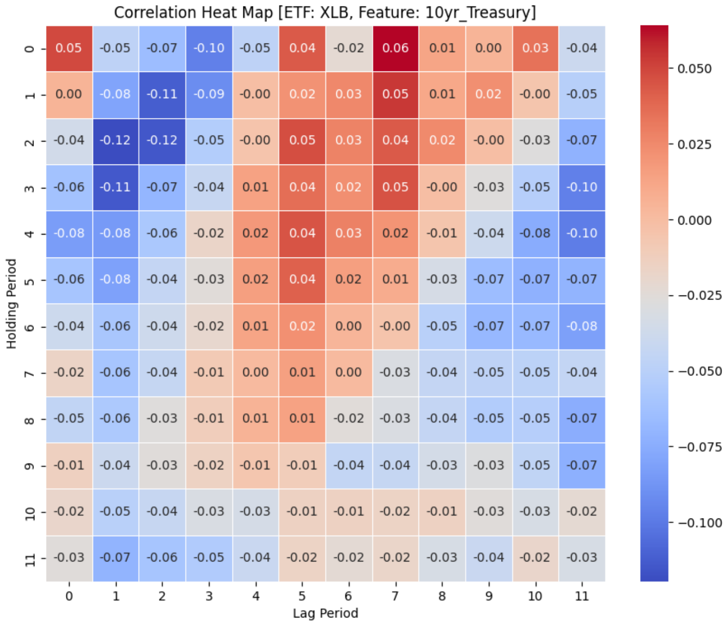

Figure A.2: Correlation heatmap for ETF XLB and factor 10yr Treasury Yield.

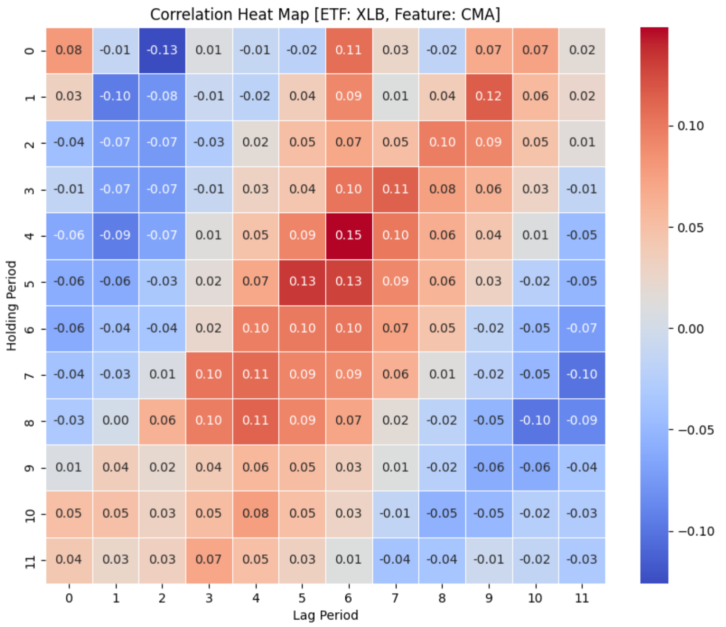

Figure A.3: Correlation heatmap for ETF XLB and factor CMA.

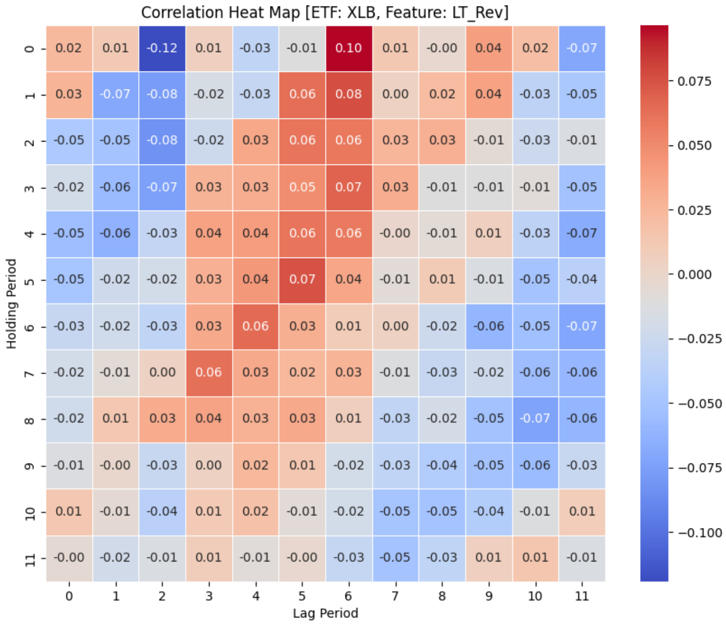


Figure A.4: Correlation heatmap for ETF XLB and factor LT_Rev.

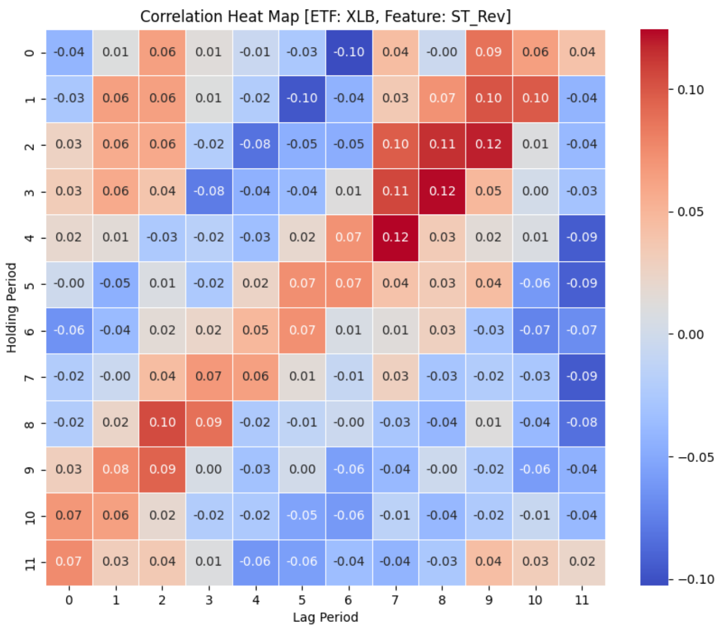


Figure A.5: Correlation heatmap for ETF XLB and factor ST_Rev.

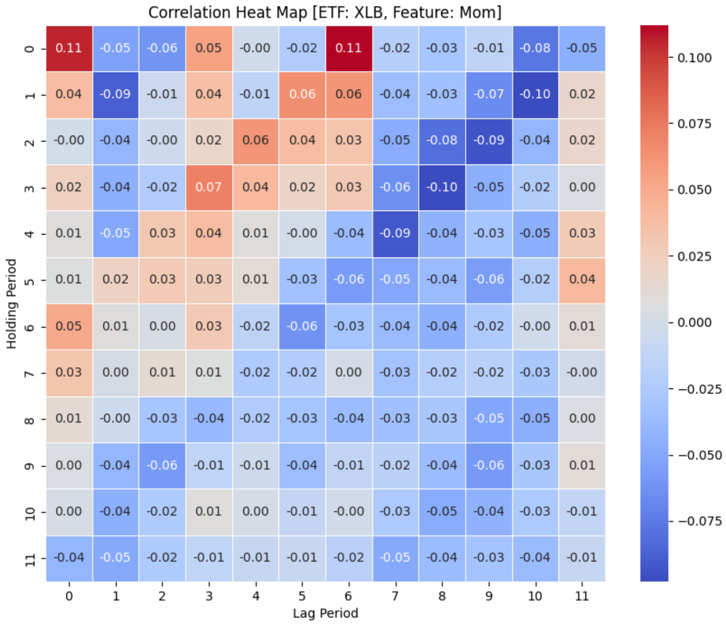


Figure A.6: Correlation heatmap for ETF XLB and factor Mom.

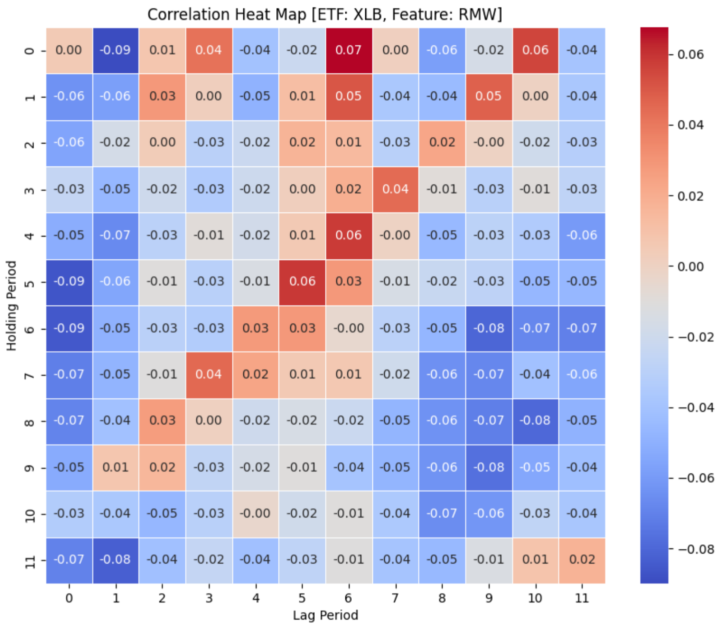


Figure A.7: Correlation heatmap for ETF XLB and factor RMW.

## A.2 Significance Heatmaps

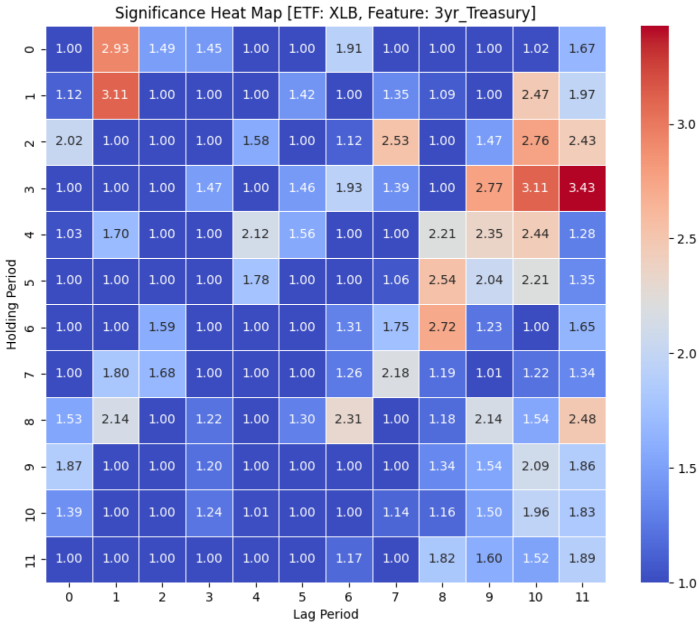


Figure A.8: Significance heatmap for ETF XLB and factor 3yr Treasury Yield.

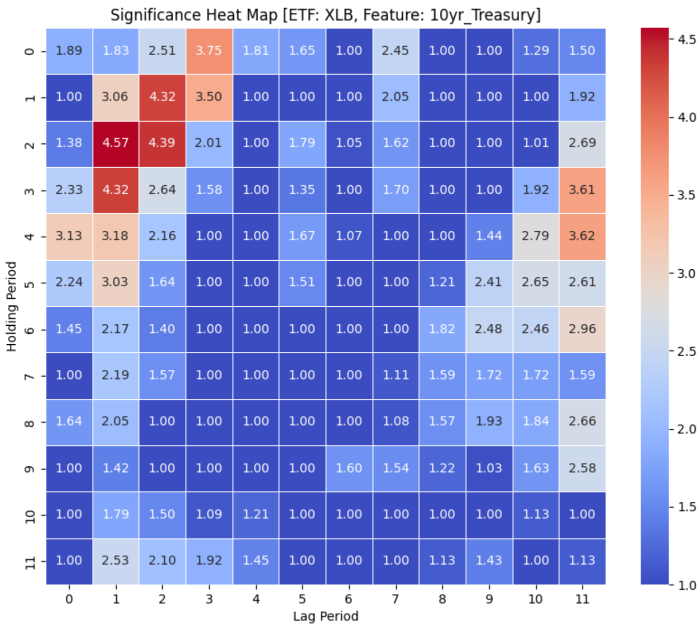


Figure A.9: Significance heatmap for ETF XLB and factor 10yr Treasury Yield.

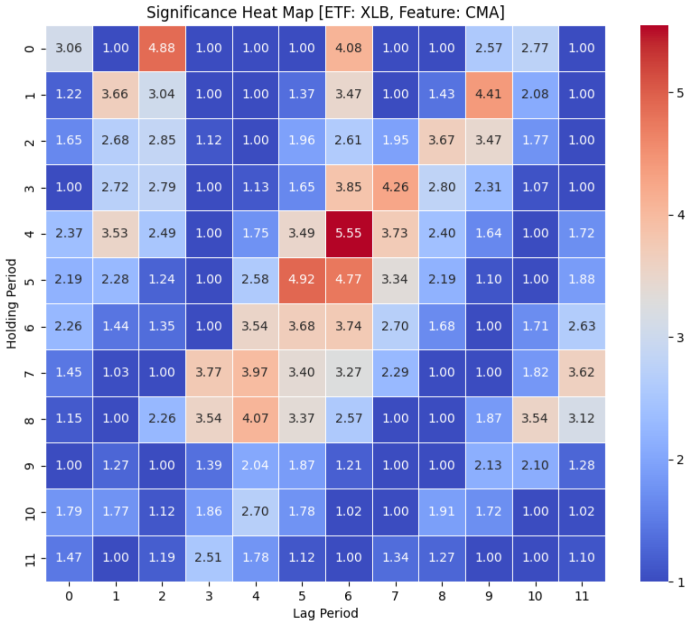


Figure A.10: Significance heatmap for ETF XLB and factor CMA.

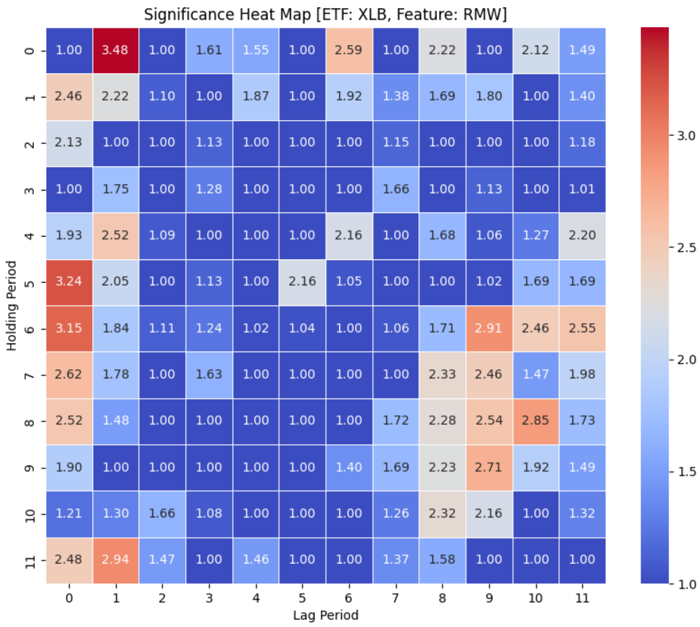


Figure A.11: Significance heatmap for ETF XLB and factor RMW.

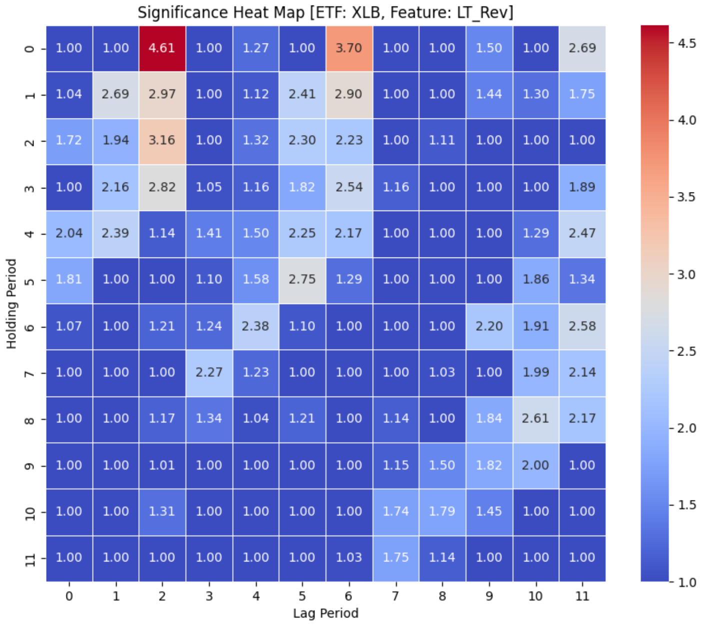


Figure A.12: Significance heatmap for ETF XLB and factor LT_Rev.

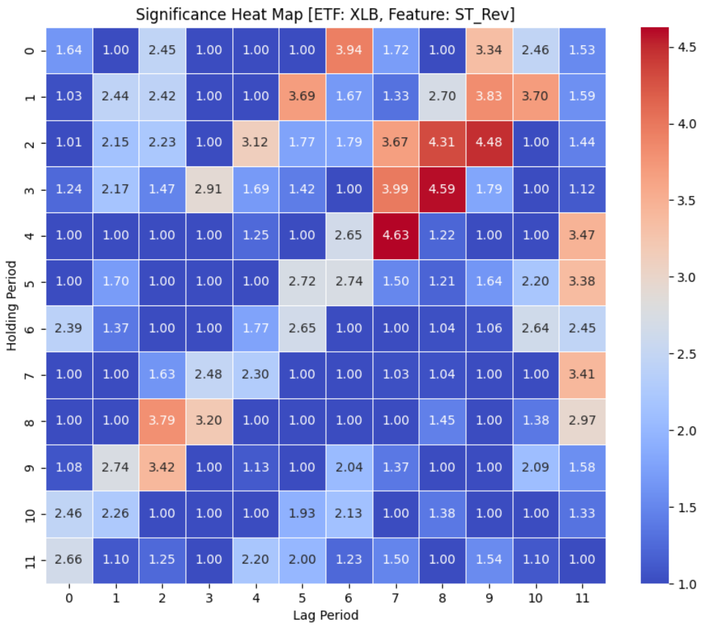


Figure A.13: Significance heatmap for ETF XLB and factor ST_Rev.

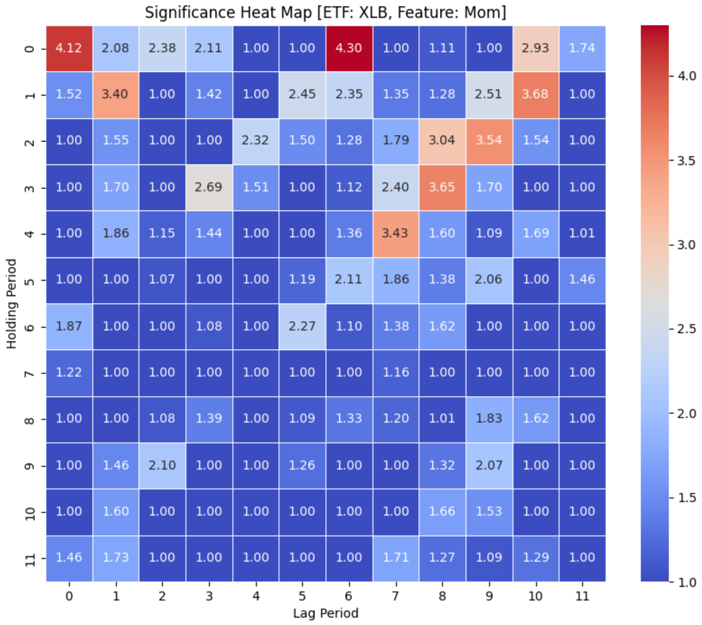

Figure A.14: Significance heatmap for ETF XLB and factor Mom.

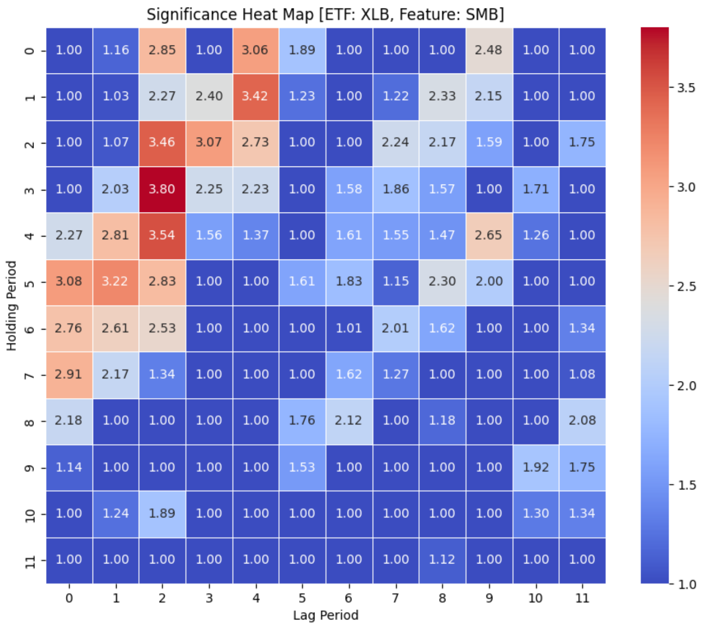

Figure A.15: Significance heatmap for ETF XLB and factor SMB.

## A.3 p values Heatmaps

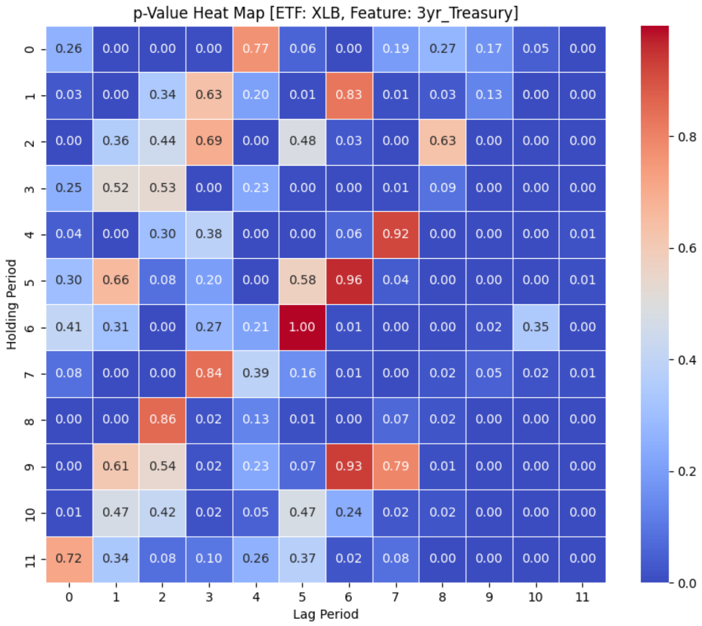


Figure A.16: p values heatmap for ETF XLB and factor 3yr Treasury Yield.

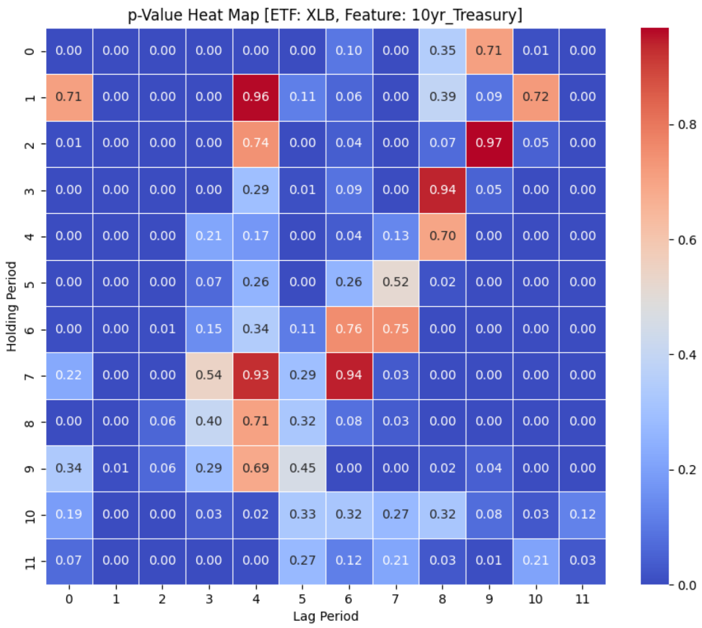


Figure A.17: p values heatmap for ETF XLB and factor 10yr Treasury Yield.

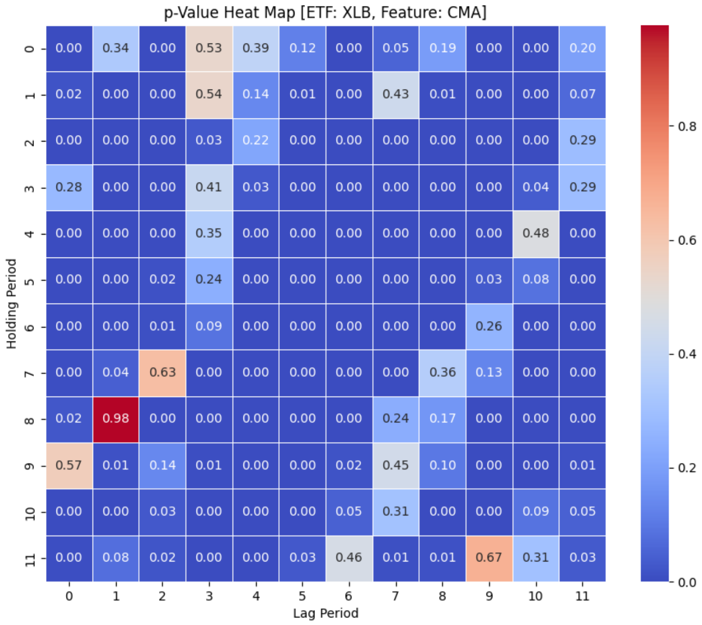


Figure A.18: p values heatmap for ETF XLB and factor CMA.

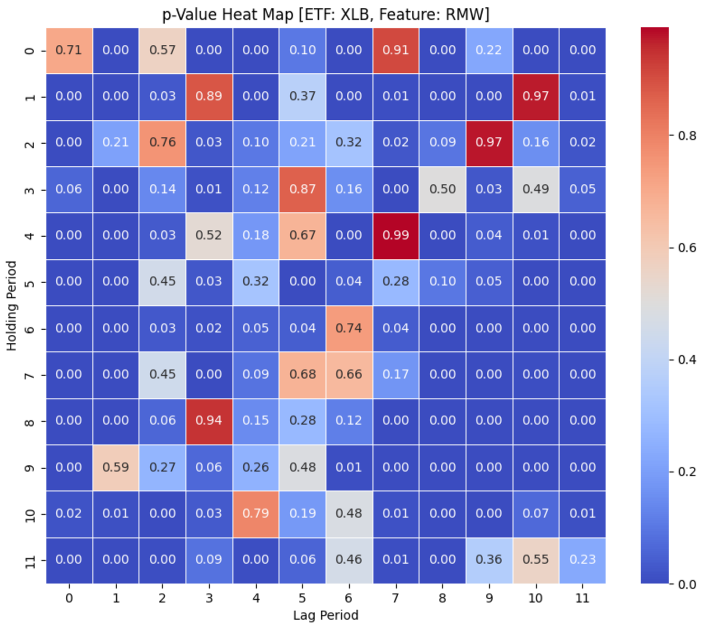


Figure A.19: p values heatmap for ETF XLB and factor RMW.

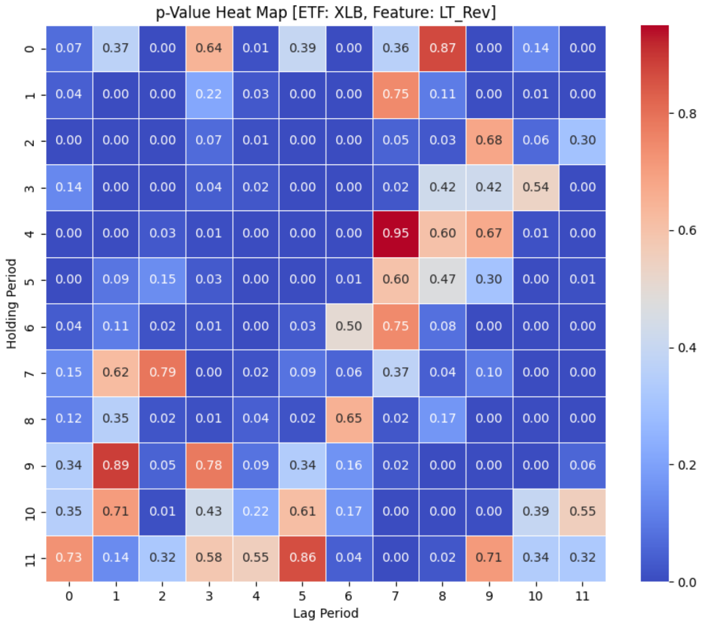


Figure A.20: p values heatmap for ETF XLB and factor LT_Rev.

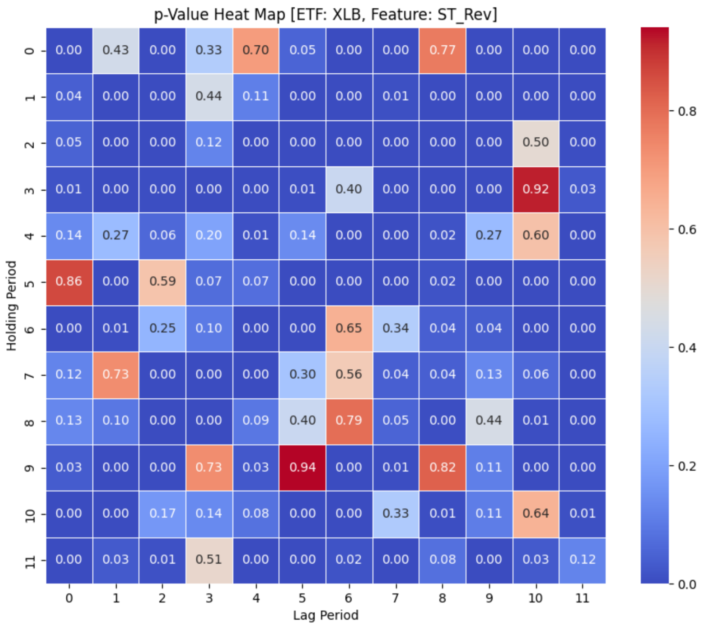


Figure A.21: p values heatmap for ETF XLB and factor ST_Rev.

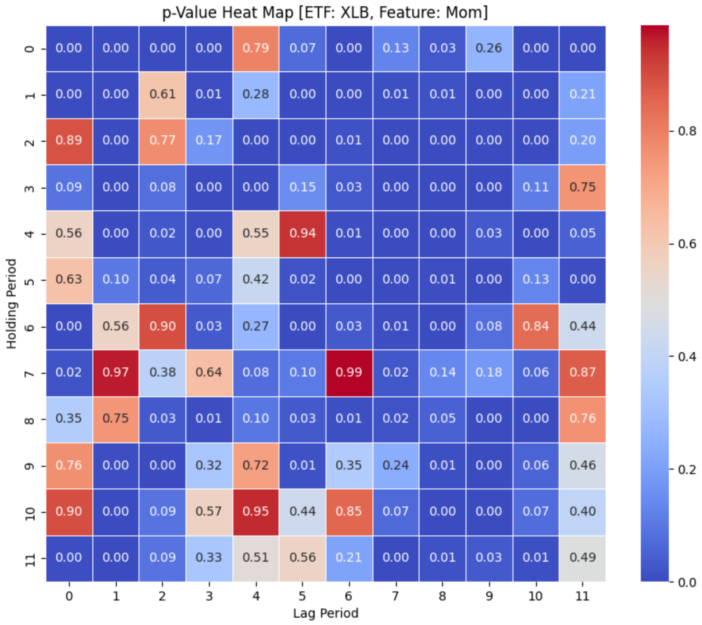


Figure A.22: p values heatmap for ETF XLB and factor Mom.

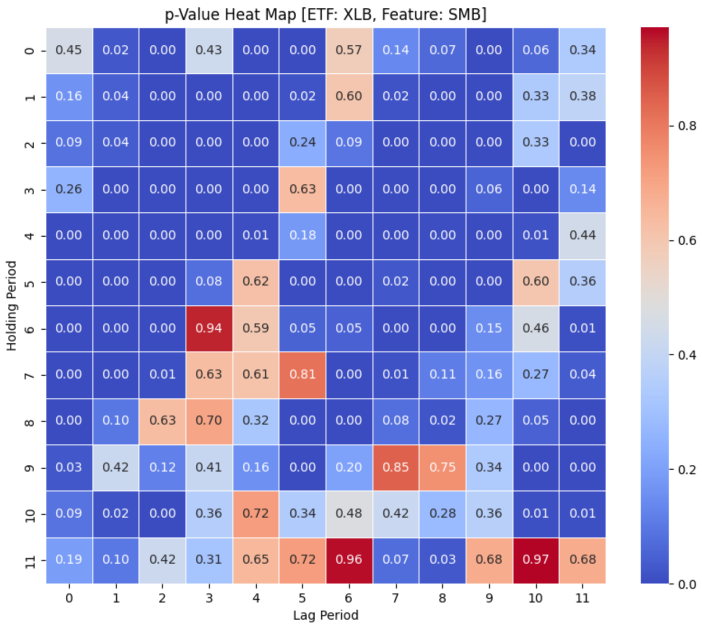


Figure A.23: p values heatmap for ETF XLB and factor SMB.

# A.4 Feature Clustering Heatmaps

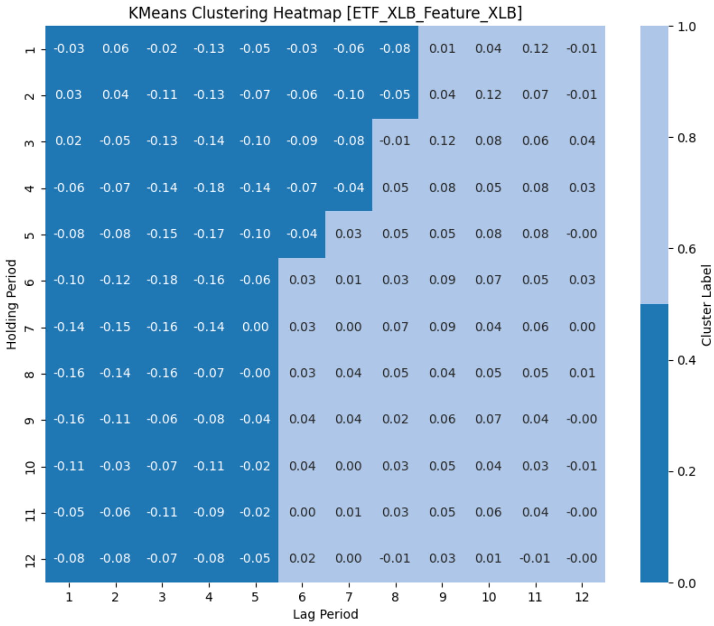


Figure A.24: Feature clustering heatmap for ETF XLB and factor XLB.

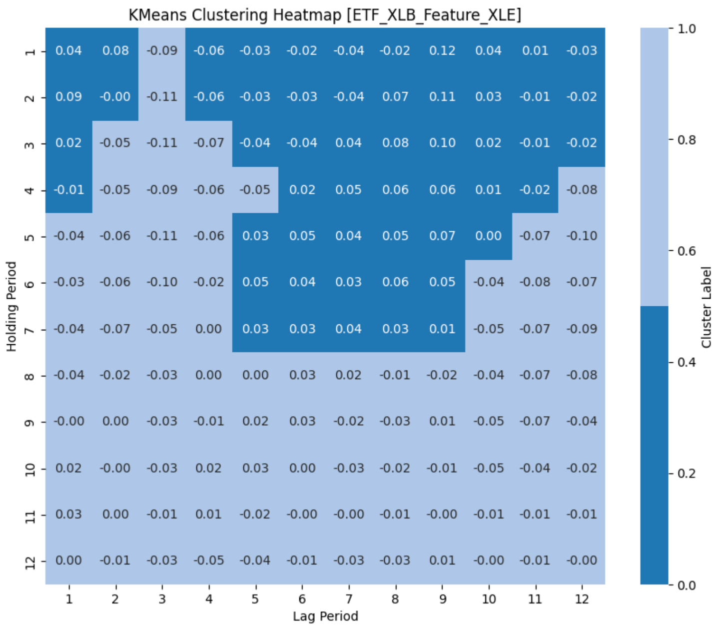


Figure A.25: Feature clustering heatmap for ETF XLB and factor XLE.

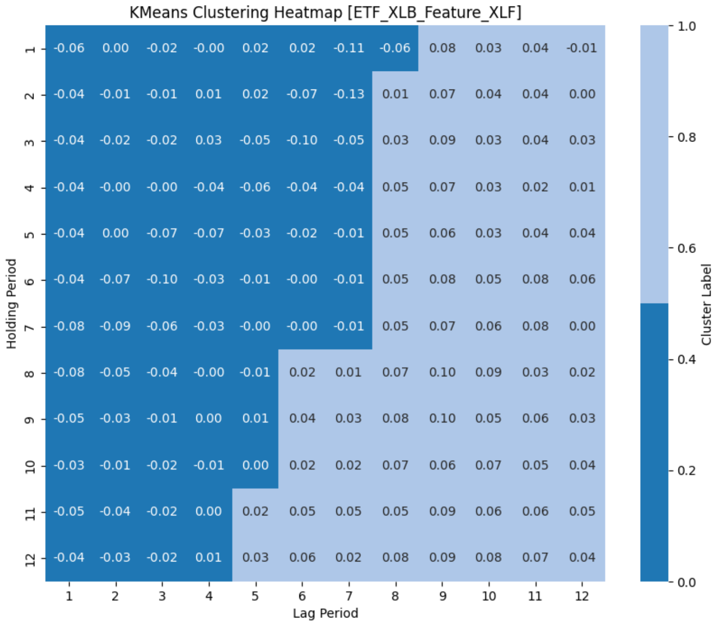

Figure A.26: Feature clustering heatmap for ETF XLB and factor XLF.

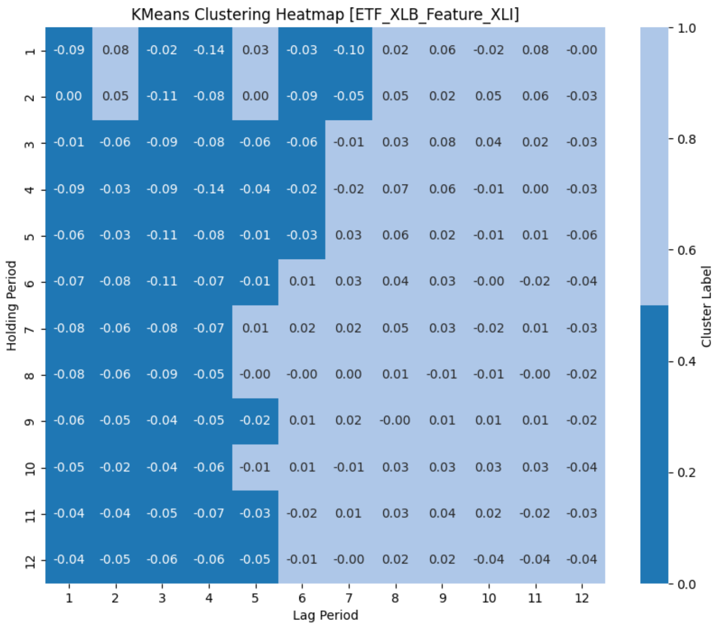

Figure A.27: Feature clustering heatmap for ETF XLB and factor XLI.

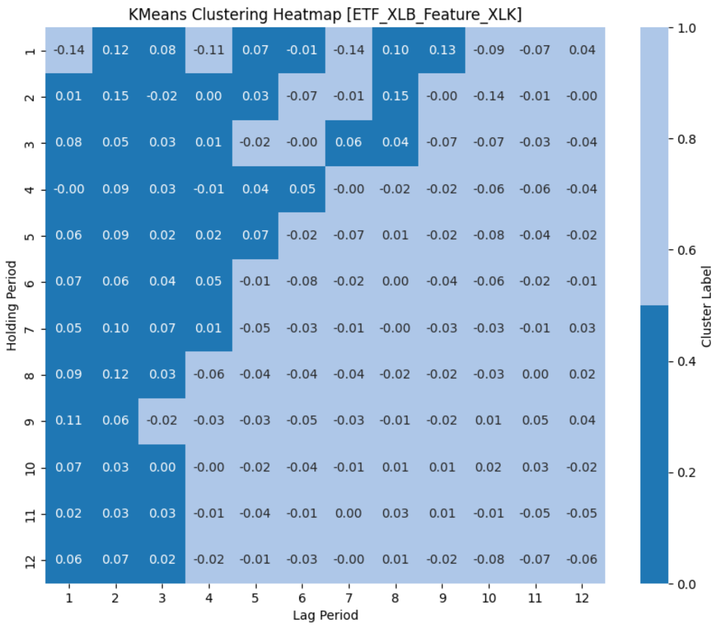


Figure A.28: Feature clustering heatmap for ETF XLB and factor XLK.

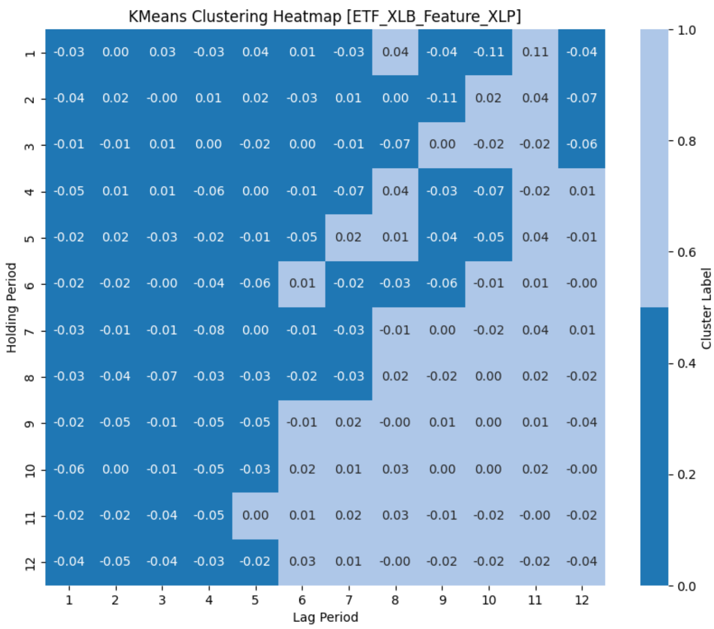


Figure A.29: Feature clustering heatmap for ETF XLB and factor XLP.

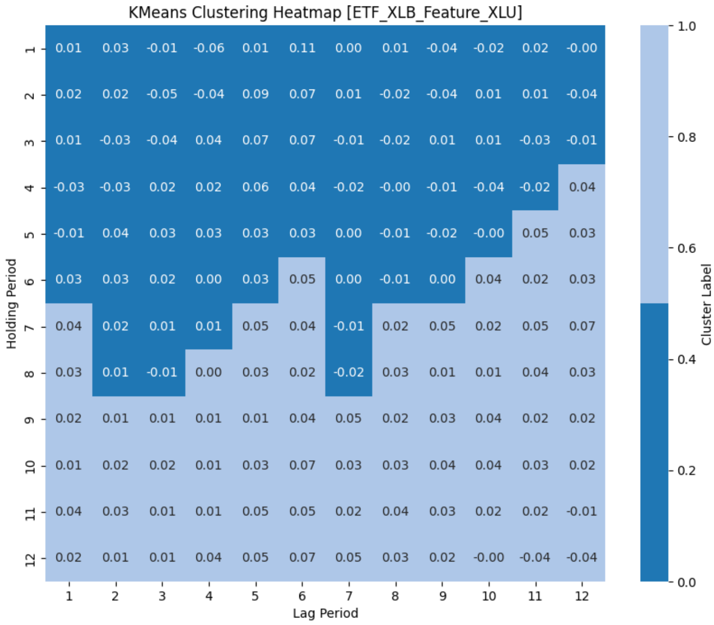


Figure A.30: Feature clustering heatmap for ETF XLB and factor XLU.

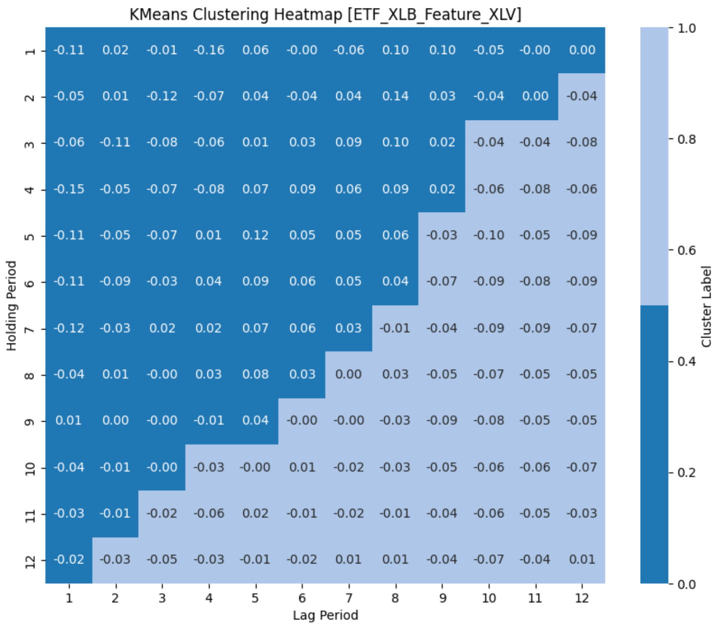


Figure A.31: Feature clustering heatmap for ETF XLB and factor XLV.

# Appendix B

# Appendix: Backtest Result

## B.1 Backtest Result Plots for Various Schemes

### B.1.1 Test Result Plots

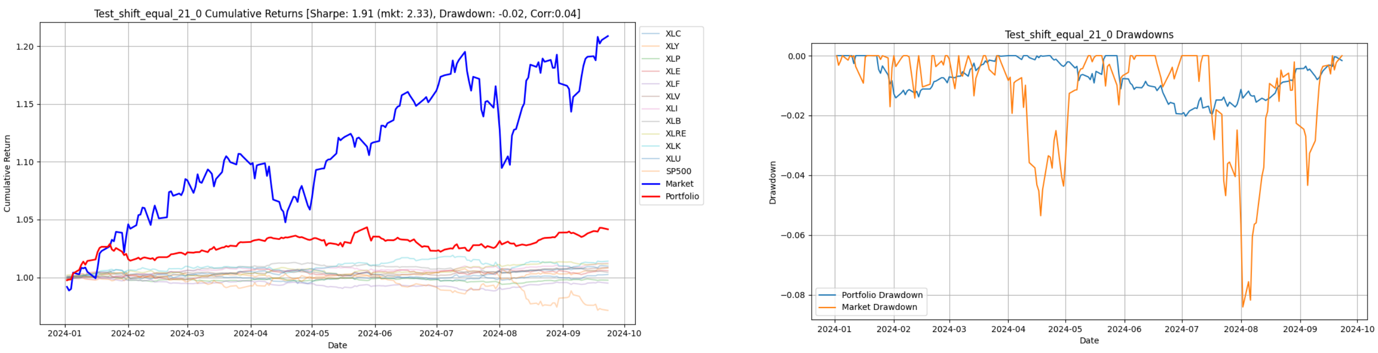


Figure B.1: Backtest Result [Equal-weight, Shift=0, 21-day Rebalance]

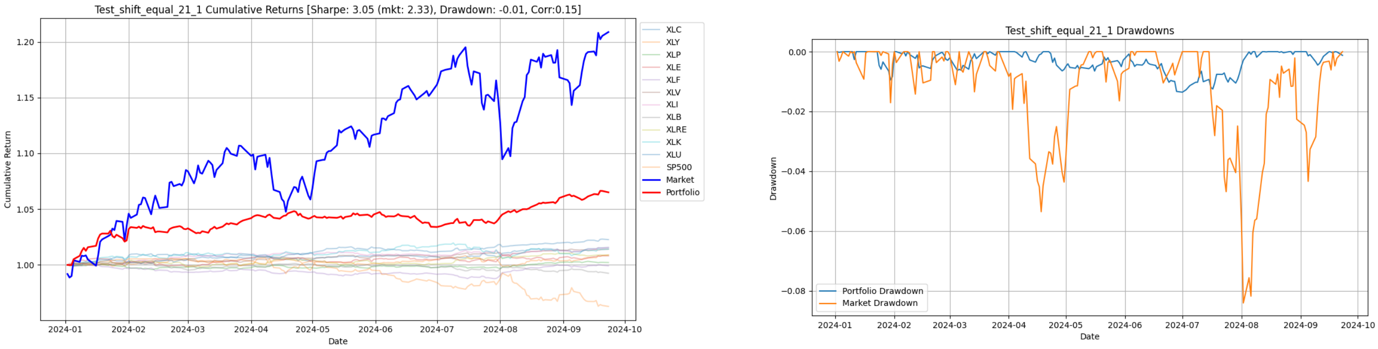


Figure B.2: Backtest Result [Equal-weight, Shift=1, 21-day Rebalance]

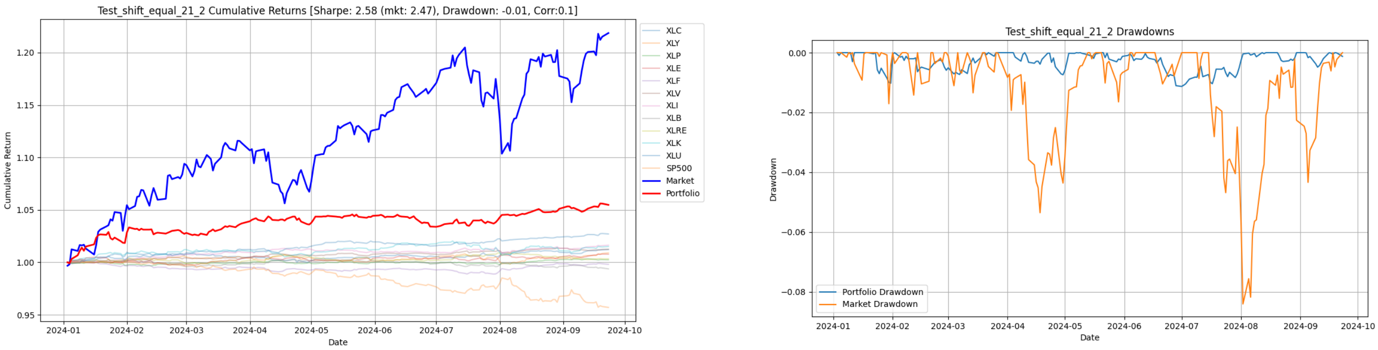


Figure B.3: Backtest Result [Equal-weight, Shift=2, 21-day Rebalance]

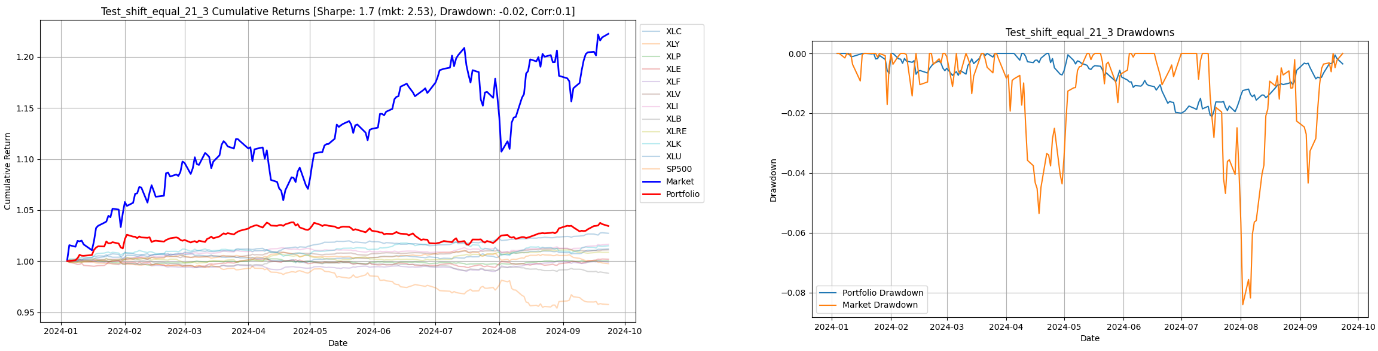


Figure B.4: Backtest Result [Equal-weight, Shift=3, 21-day Rebalance]

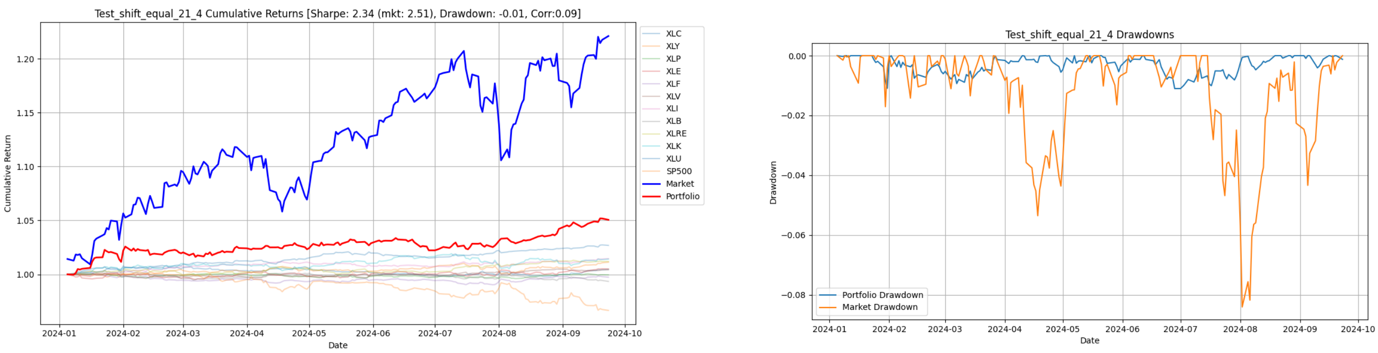


Figure B.5: Backtest Result [Equal-weight, Shift=4, 21-day Rebalance]

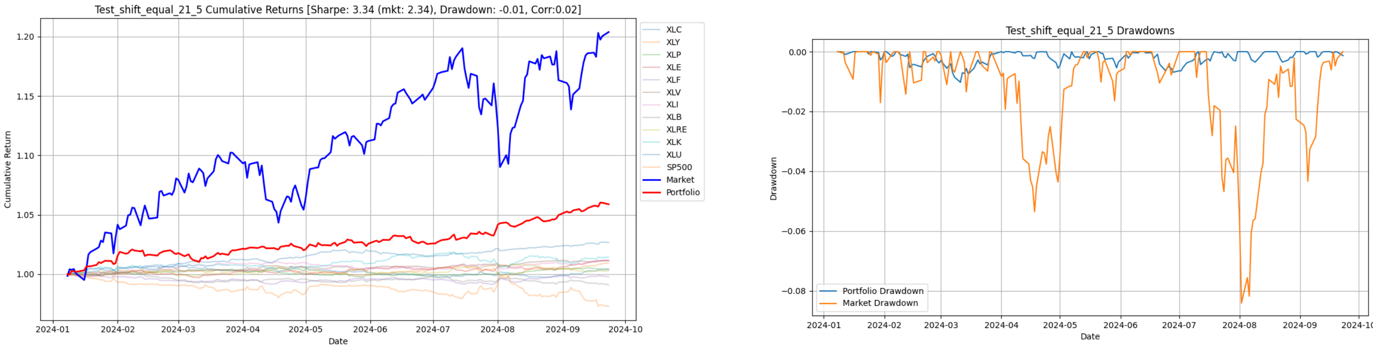


Figure B.6: Backtest Result [Equal-weight, Shift=5, 21-day Rebalance]

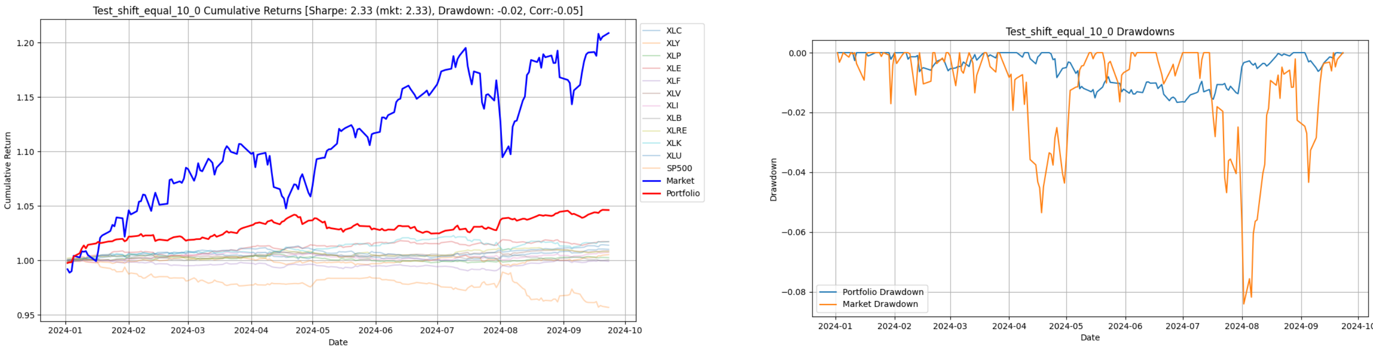


Figure B.7: Backtest Result [Equal-weight, Shift=0, 10-day Rebalance]

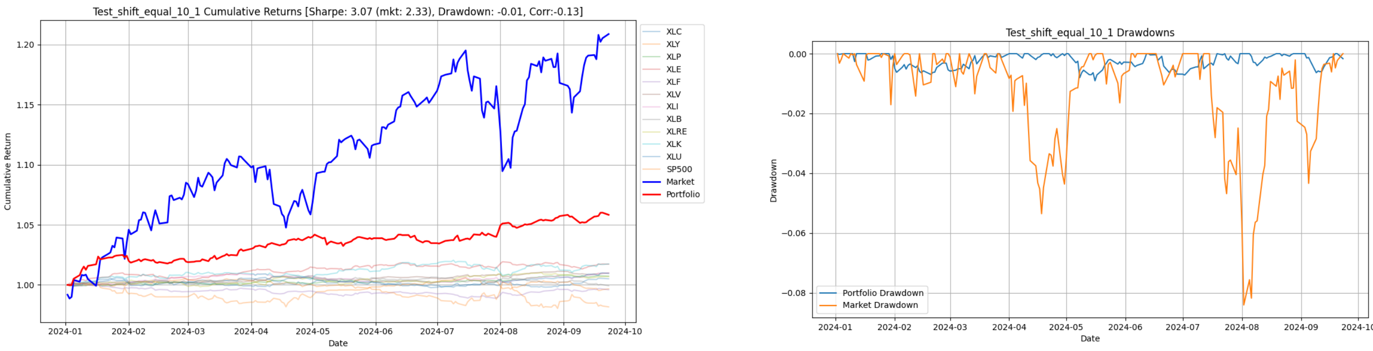


Figure B.8: Backtest Result [Equal-weight, Shift=1, 10-day Rebalance]

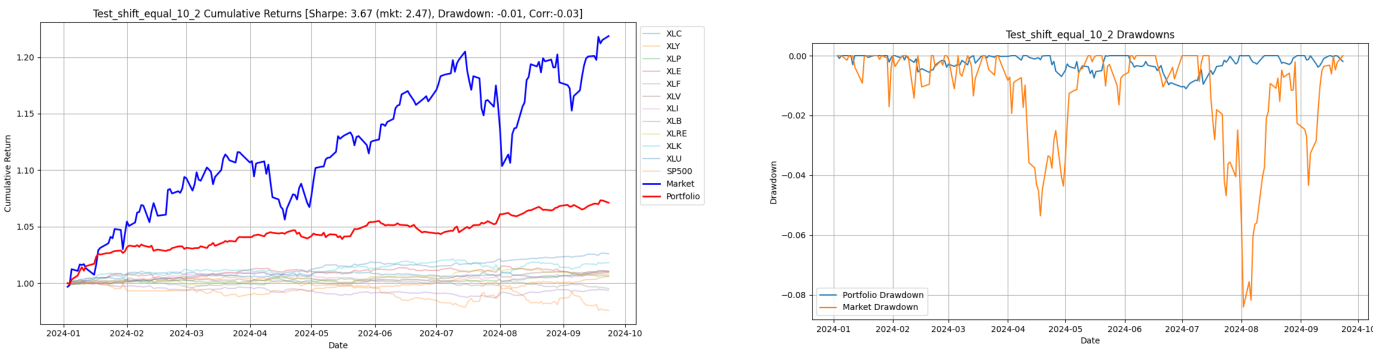


Figure B.9: Backtest Result [Equal-weight, Shift=2, 10-day Rebalance]

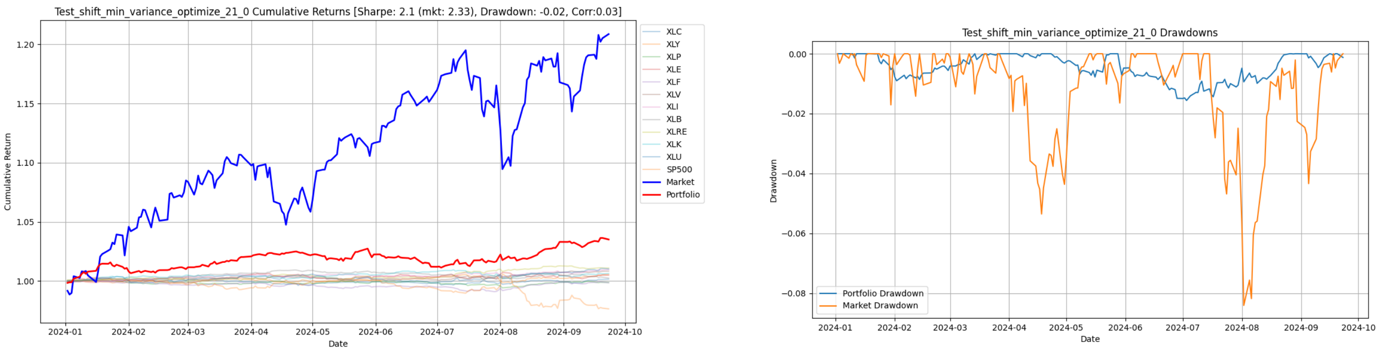


Figure B.10: Backtest Result [Min Variance, Shift=0, 21-day Rebalance]

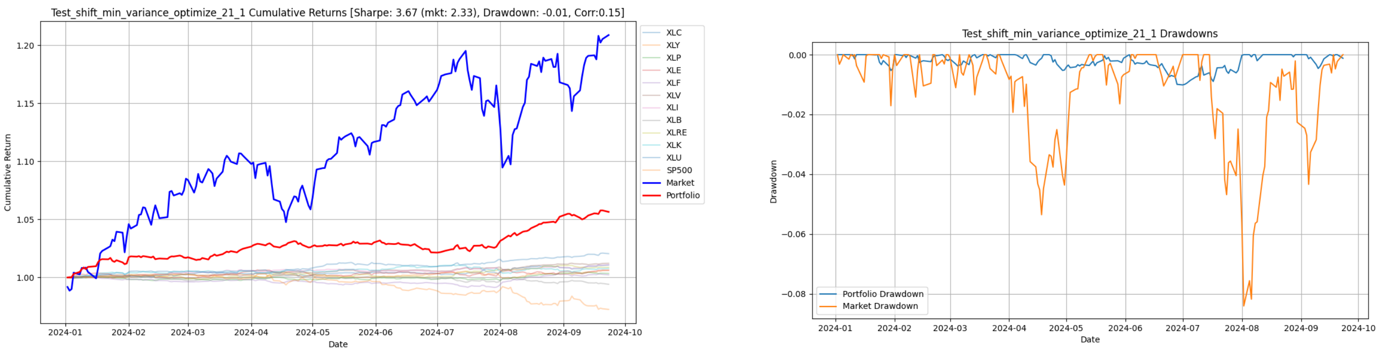


Figure B.11: Backtest Result [Min Variance, Shift=1, 21-day Rebalance]

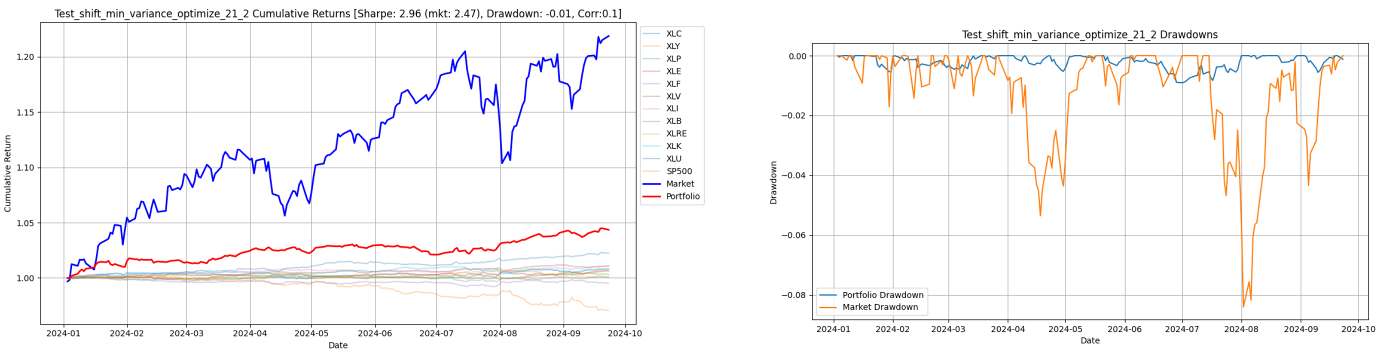


Figure B.12: Backtest Result [Min Variance, Shift=2, 21-day Rebalance]

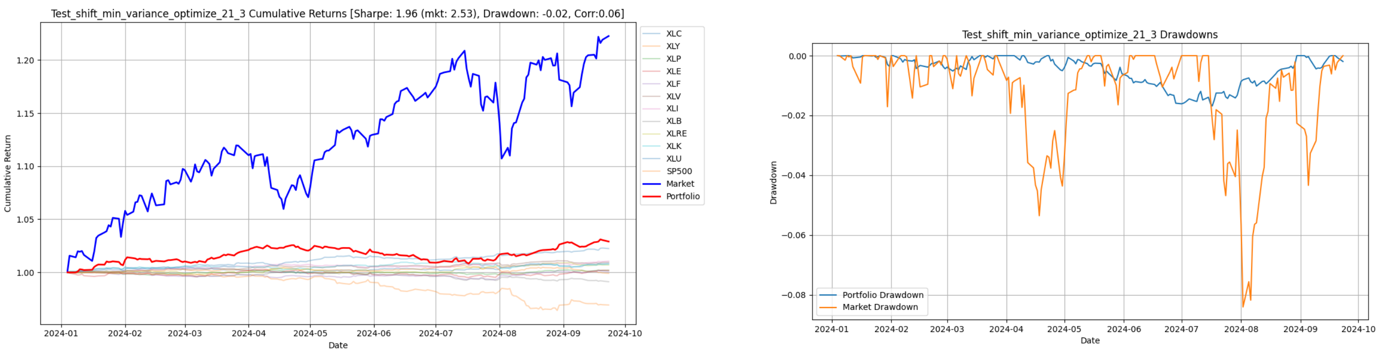


Figure B.13: Backtest Result [Min Variance, Shift=3, 21-day Rebalance]

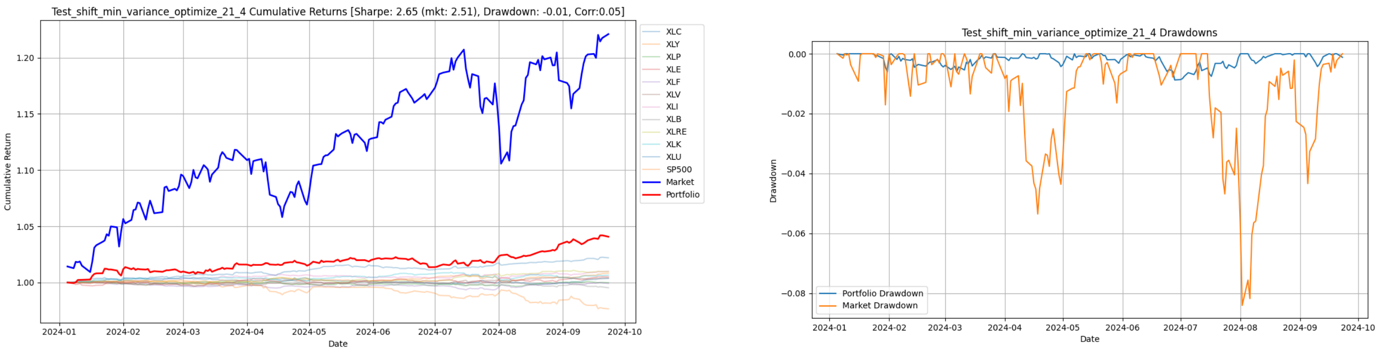


Figure B.14: Backtest Result [Min Variance, Shift=4, 21-day Rebalance]

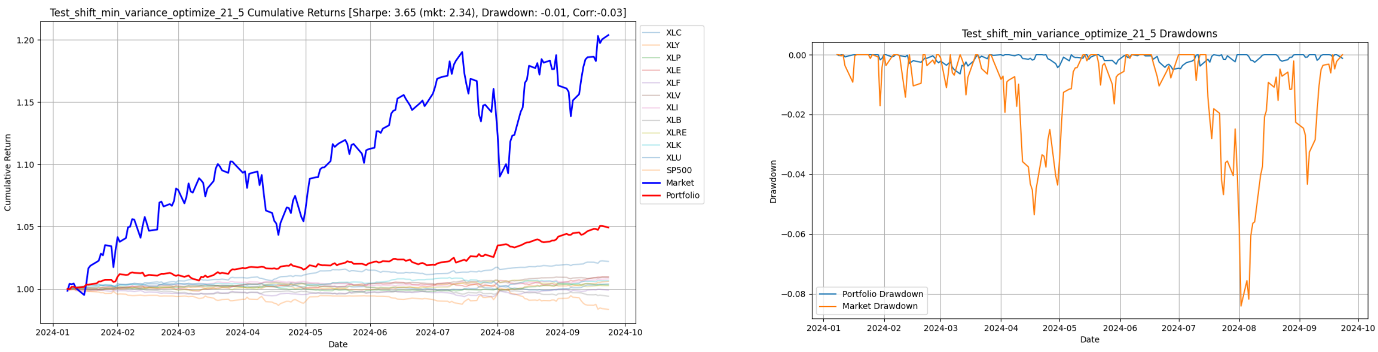


Figure B.15: Backtest Result [Min Variance, Shift=5, 21-day Rebalance]

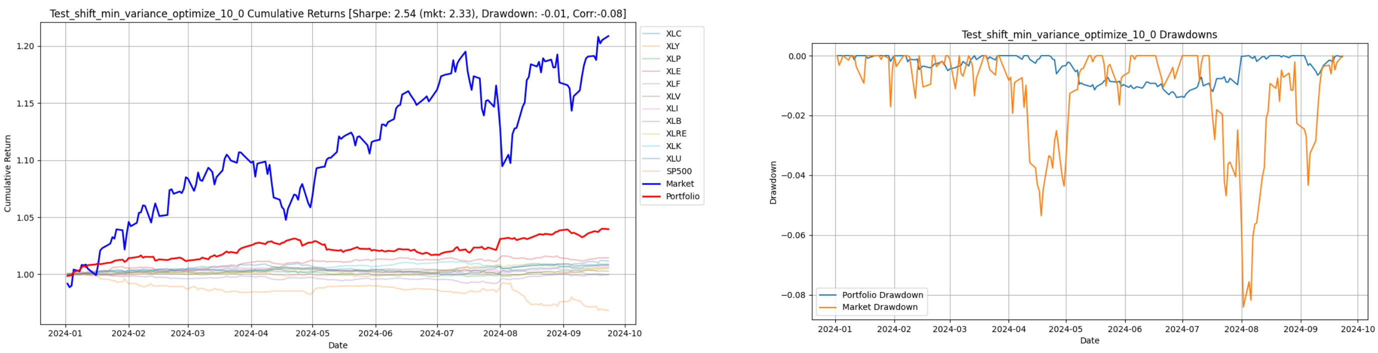


Figure B.16: Backtest Result [Min Variance, Shift=0, 10-day Rebalance]

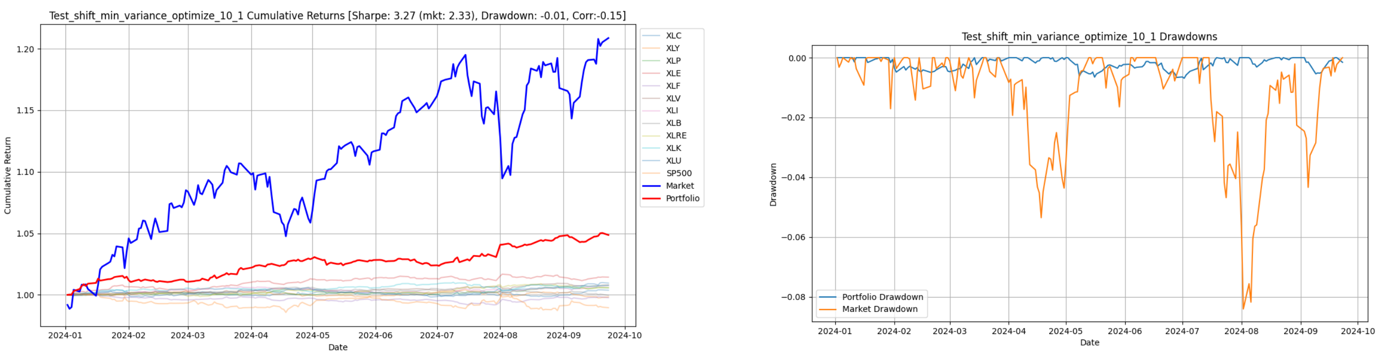


Figure B.17: Backtest Result [Min Variance, Shift=1, 10-day Rebalance]

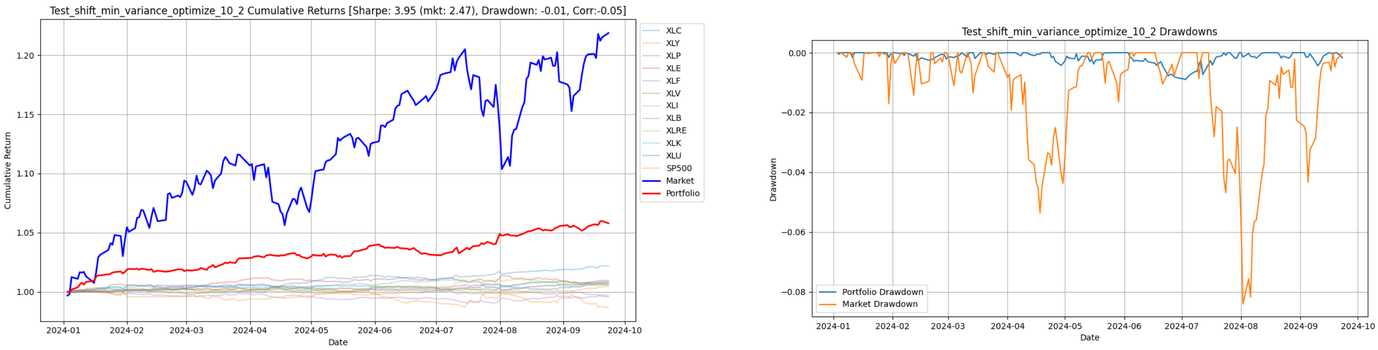


Figure B.18: Backtest Result [Min Variance, Shift=2, 10-day Rebalance]

### B.1.2 Train Result Plots

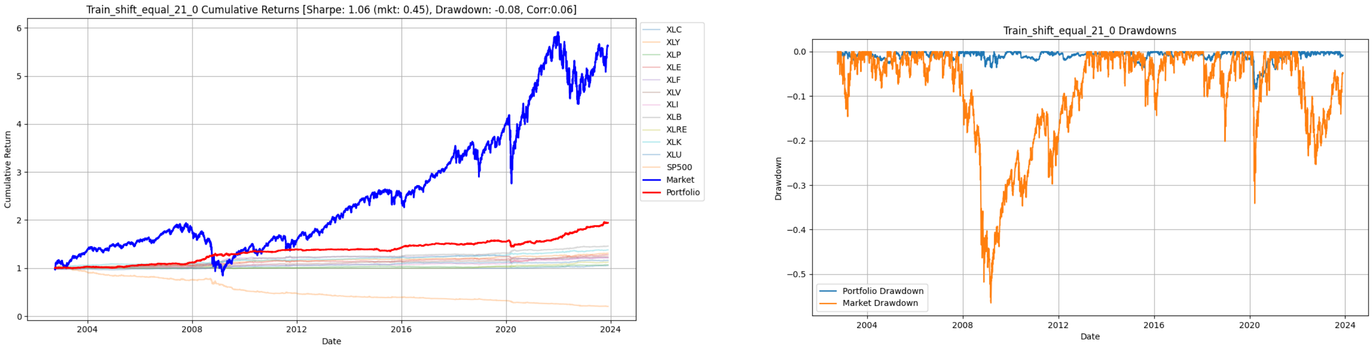


Figure B.19: Backtest Result [Equal-weight, Shift=0, 21-day Rebalance]

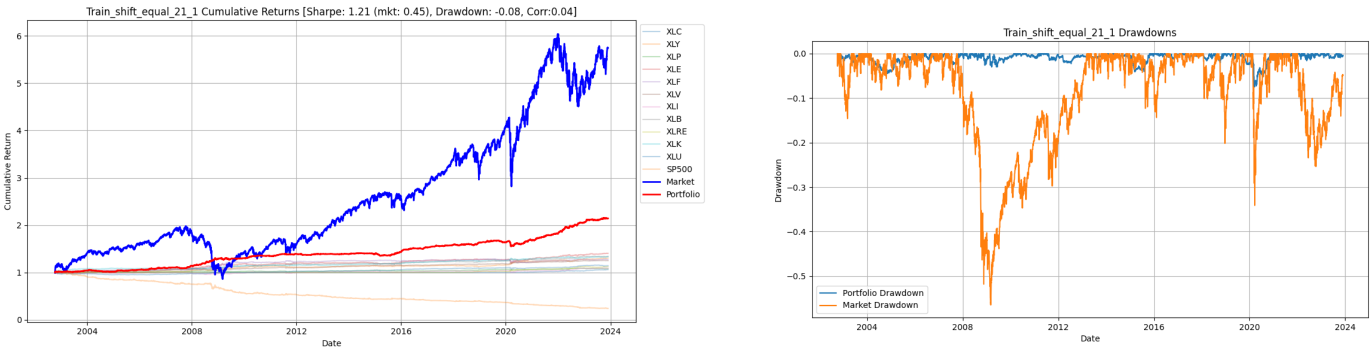


Figure B.20: Backtest Result [Equal-weight, Shift=1, 21-day Rebalance]

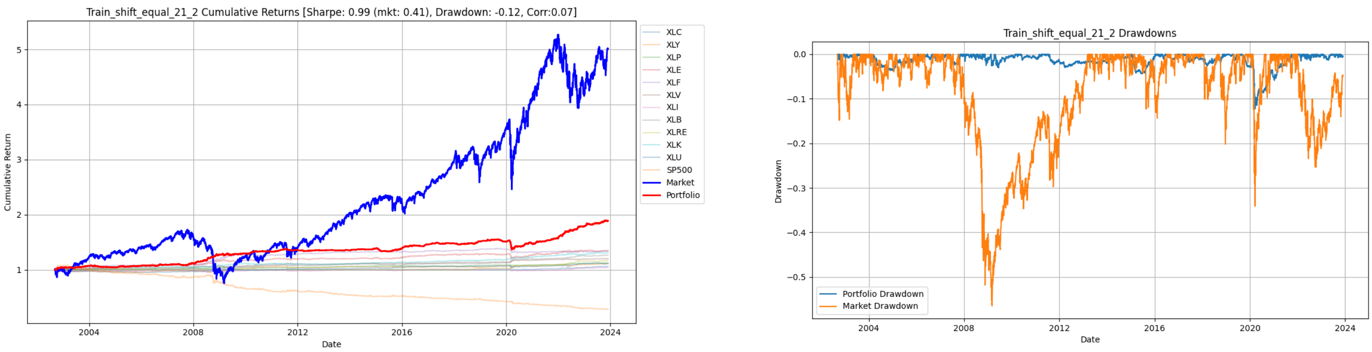


Figure B.21: Backtest Result [Equal-weight, Shift=2, 21-day Rebalance]

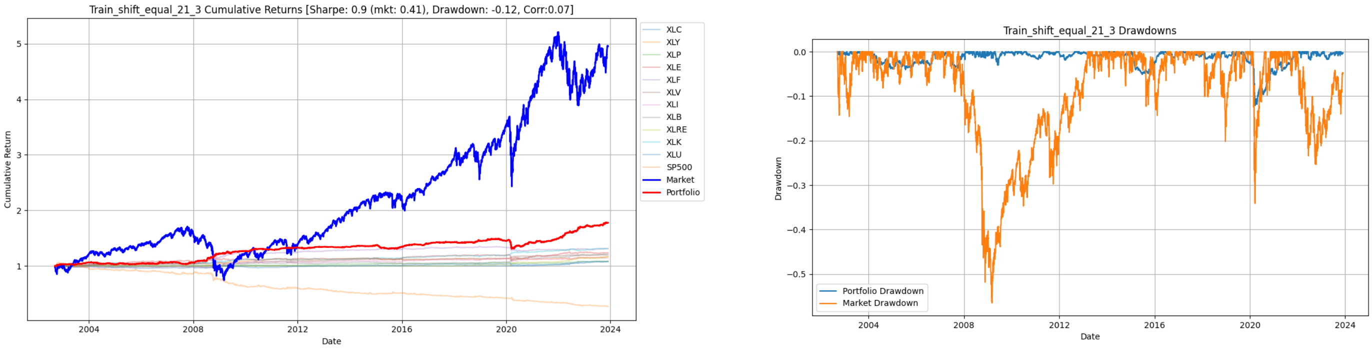


Figure B.22: Backtest Result [Equal-weight, Shift=3, 21-day Rebalance]

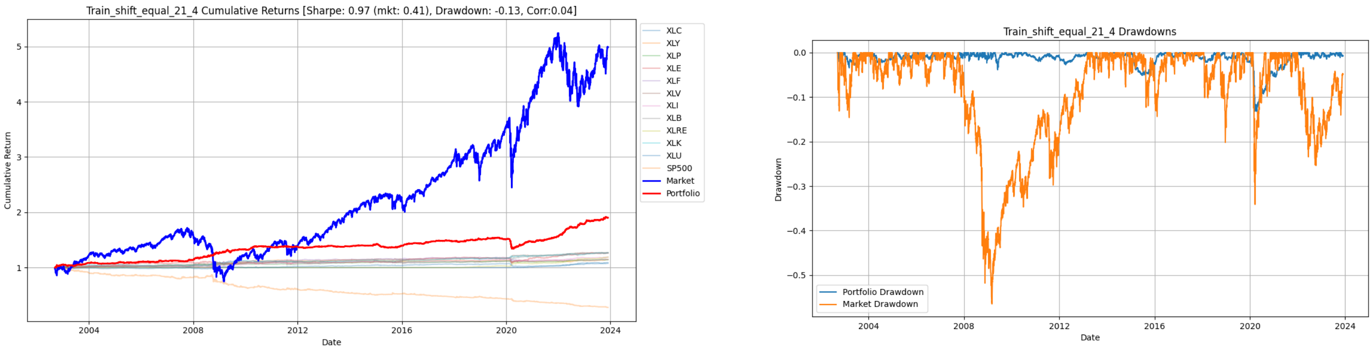


Figure B.23: Backtest Result [Equal-weight, Shift=4, 21-day Rebalance]

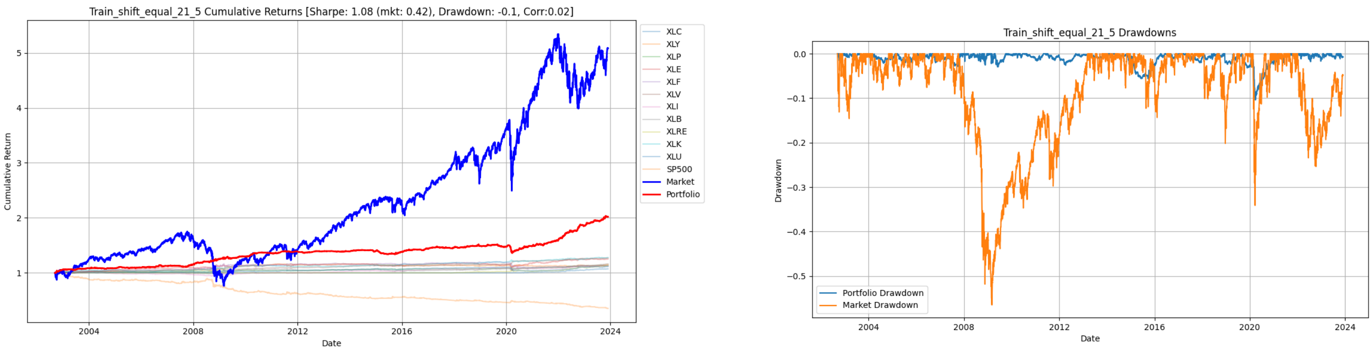


Figure B.24: Backtest Result [Equal-weight, Shift=5, 21-day Rebalance]

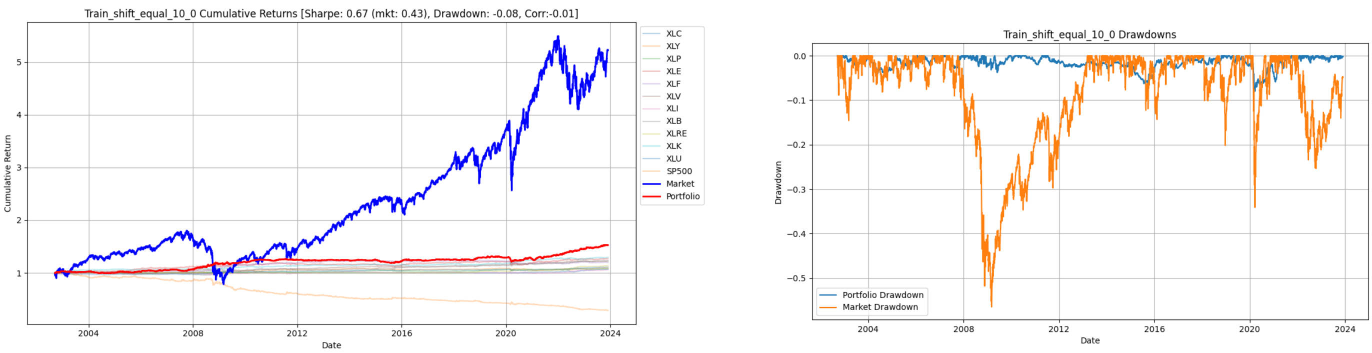


Figure B.25: Backtest Result [Equal-weight, Shift=0, 10-day Rebalance]

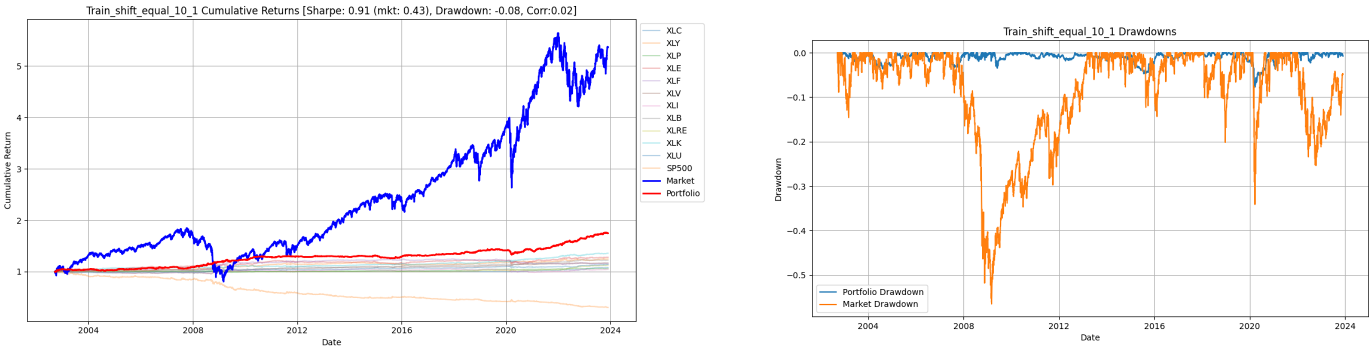


Figure B.26: Backtest Result [Equal-weight, Shift=1, 10-day Rebalance]

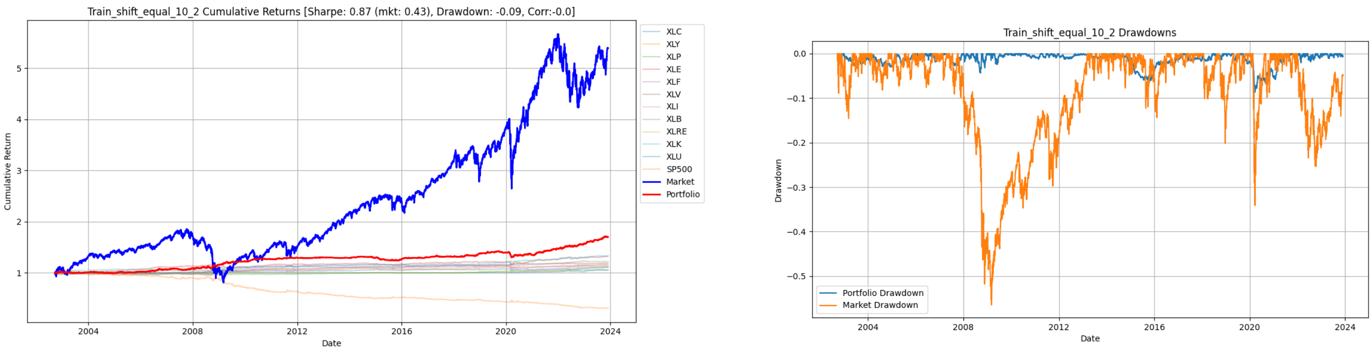


Figure B.27: Backtest Result [Equal-weight, Shift=2, 10-day Rebalance]

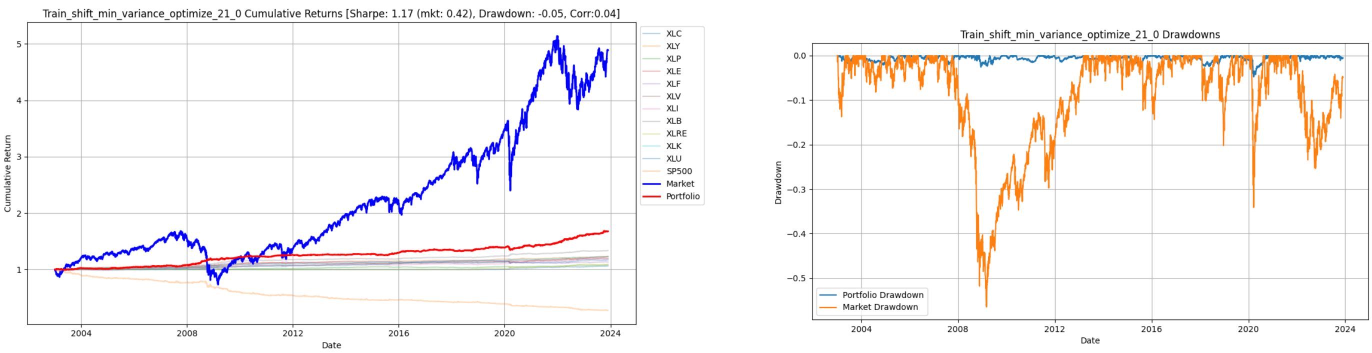


Figure B.28: Backtest Result [Min Variance, Shift=0, 21-day Rebalance]

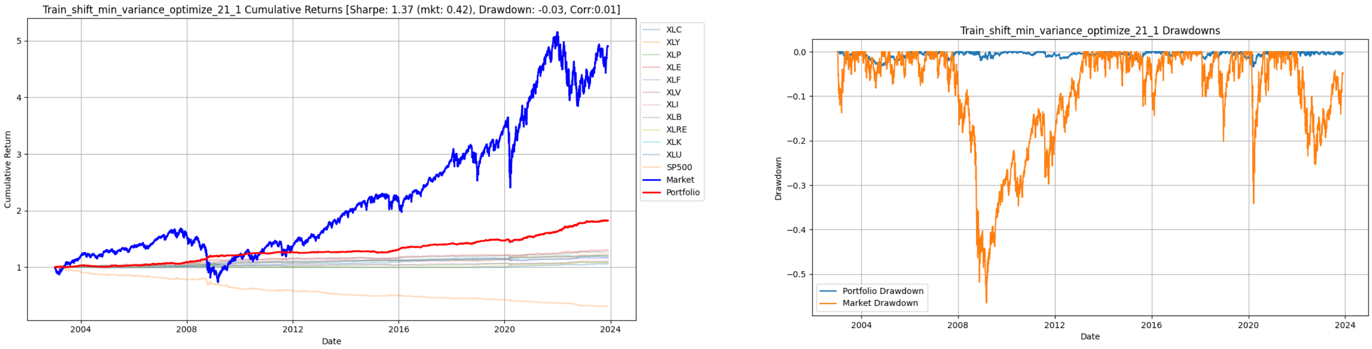


Figure B.29: Backtest Result [Min Variance, Shift=1, 21-day Rebalance]

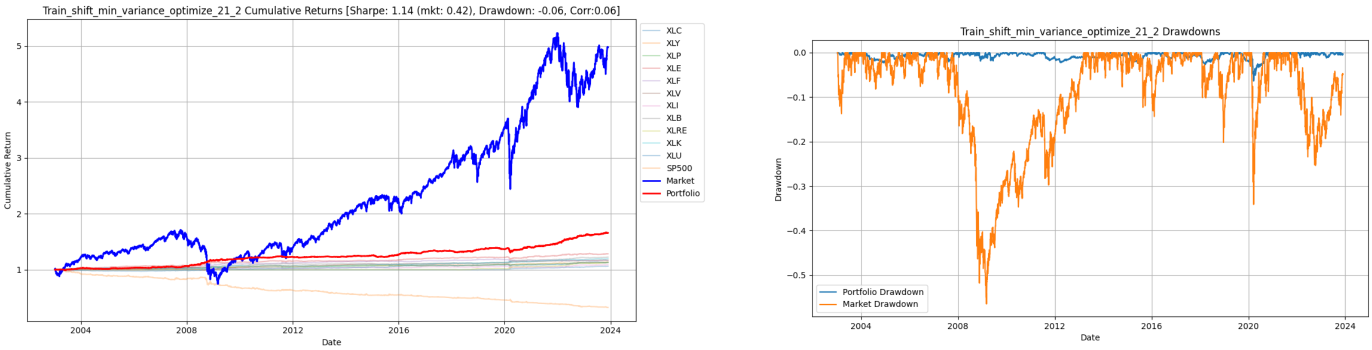


Figure B.30: Backtest Result [Min Variance, Shift=2, 21-day Rebalance]

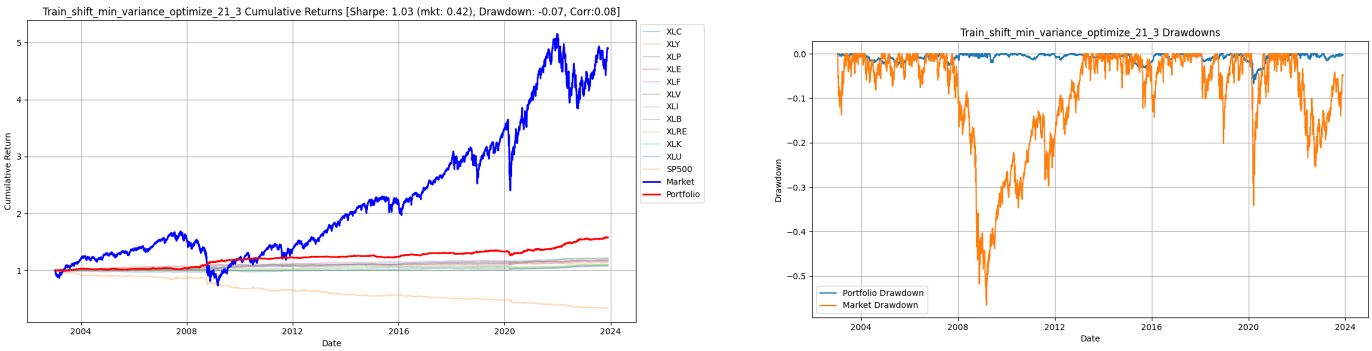


Figure B.31: Backtest Result [Min Variance, Shift=3, 21-day Rebalance]

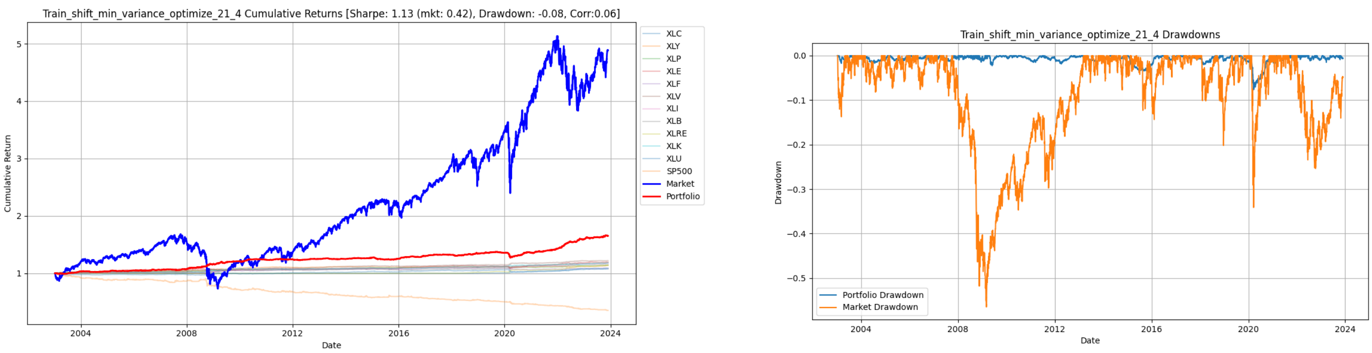


Figure B.32: Backtest Result [Min Variance, Shift=4, 21-day Rebalance]

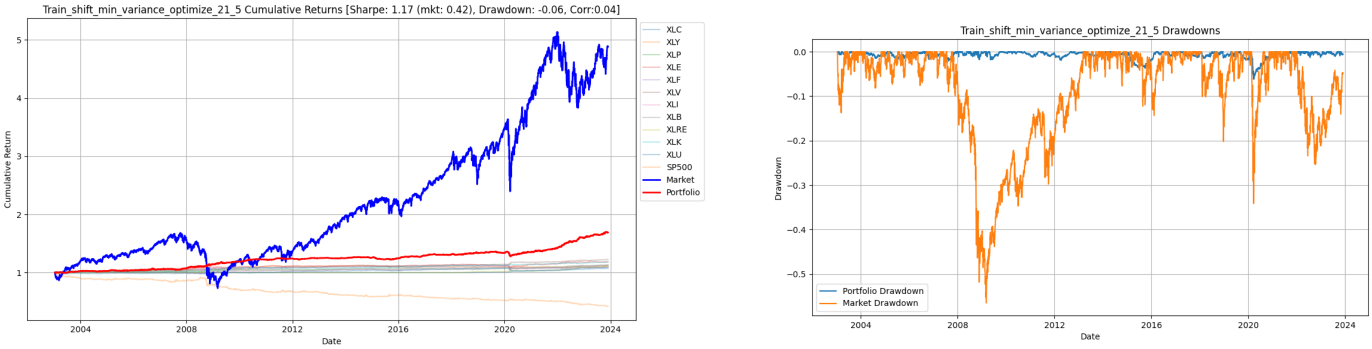


Figure B.33: Backtest Result [Min Variance, Shift=5, 21-day Rebalance]

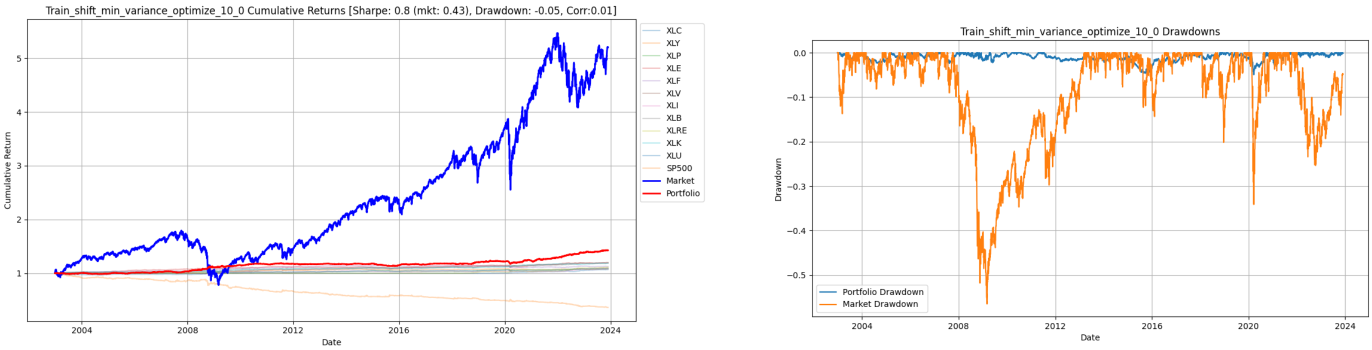


Figure B.34: Backtest Result [Min Variance, Shift=0, 10-day Rebalance]

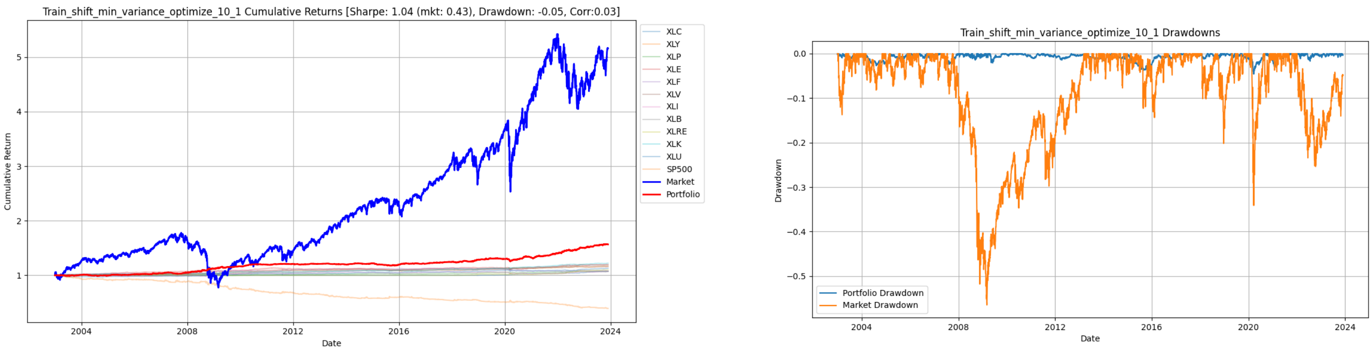


Figure B.35: Backtest Result [Min Variance, Shift=1, 10-day Rebalance]

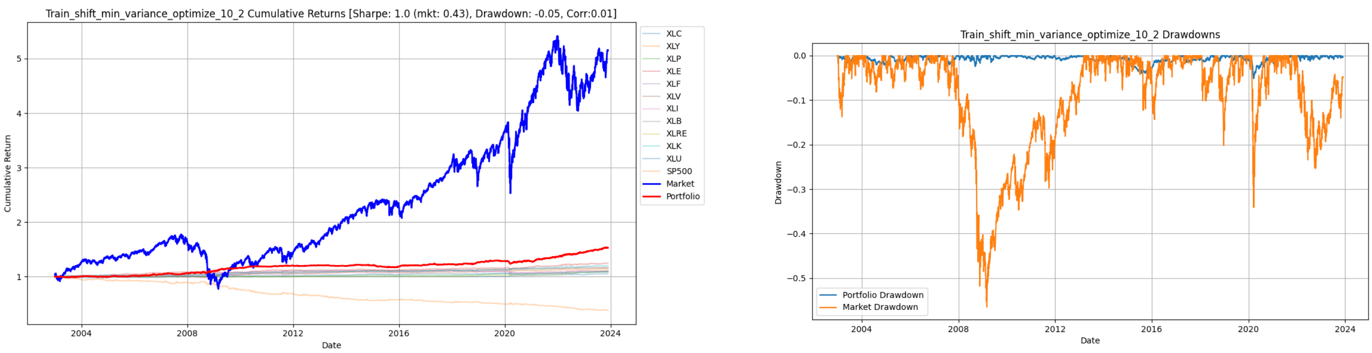


Figure B.36: Backtest Result [Min Variance, Shift=2, 10-day Rebalance]

## B.2 Backtesting Results Table

Table B.1: Comprehensive Backtesting Results

| | | | | Train | | | | | | Test | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Weight | Rebalance | Shift | Cost | AnnRet | AnnVol | Sharpe | Sortino | MaxDD | Turnover | AnnRet | AnnVol | Sharpe | Sortino | MaxDD | Turnover |
| equal | 21 | 0 | 0.001 | 0.0358 | 0.0300 | 1.1942 | 1.5941 | -0.0836 | 4.6512 | 0.0614 | 0.0302 | 2.0363 | 2.8509 | -0.0196 | 4.3810 |
| equal | 21 | 1 | 0.001 | 0.0406 | 0.0302 | 1.3456 | 1.8612 | -0.0735 | 4.6340 | 0.0952 | 0.0297 | 3.2112 | 5.4911 | -0.0128 | 5.2353 |
| equal | 21 | 2 | 0.001 | 0.0341 | 0.0306 | 1.1163 | 1.4369 | -0.1202 | 4.5117 | 0.0808 | 0.0296 | 2.7249 | 4.4139 | -0.0112 | 4.7538 |
| equal | 21 | 3 | 0.001 | 0.0311 | 0.0306 | 1.0170 | 1.3292 | -0.1191 | 4.3181 | 0.0527 | 0.0282 | 1.8702 | 3.1539 | -0.0203 | 5.3013 |
| equal | 21 | 4 | 0.001 | 0.0346 | 0.0315 | 1.0959 | 1.4068 | -0.1299 | 4.5363 | 0.0760 | 0.0305 | 2.4962 | 4.3289 | -0.0110 | 5.2235 |
| equal | 21 | 5 | 0.001 | 0.0376 | 0.0310 | 1.2113 | 1.6410 | -0.1022 | 4.6132 | 0.0877 | 0.0250 | 3.5073 | 5.8241 | -0.0099 | 4.4780 |
| equal | 21 | 6 | 0.001 | 0.0359 | 0.0308 | 1.1675 | 1.5749 | -0.1046 | 4.6531 | 0.0826 | 0.0253 | 3.2680 | 5.1065 | -0.0110 | 4.7279 |
| equal | 21 | 7 | 0.001 | 0.0365 | 0.0307 | 1.1899 | 1.5825 | -0.1013 | 4.7908 | 0.0593 | 0.0289 | 2.0539 | 3.3327 | -0.0132 | 4.6696 |
| equal | 21 | 8 | 0.001 | 0.0354 | 0.0313 | 1.1294 | 1.5630 | -0.0904 | 4.7237 | 0.0614 | 0.0290 | 2.1193 | 3.2833 | -0.0117 | 5.5345 |
| equal | 21 | 9 | 0.001 | 0.0406 | 0.0314 | 1.2933 | 1.7858 | -0.0568 | 4.5300 | 0.0412 | 0.0304 | 1.3571 | 2.2405 | -0.0190 | 5.3159 |
| equal | 21 | 10 | 0.001 | 0.0366 | 0.0302 | 1.2110 | 1.6911 | -0.0561 | 4.7107 | 0.0240 | 0.0230 | 1.0404 | 1.6601 | -0.0127 | 5.3987 |
| equal | 21 | 11 | 0.001 | 0.0315 | 0.0301 | 1.0450 | 1.4255 | -0.0777 | 4.7408 | 0.0131 | 0.0237 | 0.5540 | 0.8096 | -0.0151 | 5.2669 |
| equal | 21 | 12 | 0.001 | 0.0328 | 0.0305 | 1.0759 | 1.4871 | -0.0695 | 4.6548 | 0.0494 | 0.0262 | 1.8842 | 2.9191 | -0.0124 | 5.7488 |
| equal | 21 | 13 | 0.001 | 0.0325 | 0.0304 | 1.0677 | 1.4858 | -0.0549 | 4.6679 | 0.0504 | 0.0259 | 1.9438 | 2.9024 | -0.0138 | 5.7792 |
| equal | 21 | 14 | 0.001 | 0.0406 | 0.0320 | 1.2718 | 1.8013 | -0.0770 | 4.6247 | 0.0290 | 0.0239 | 1.2156 | 1.8488 | -0.0111 | 4.9788 |
| equal | 21 | 15 | 0.001 | 0.0383 | 0.0297 | 1.2910 | 1.8772 | -0.0578 | 4.4768 | 0.0300 | 0.0247 | 1.2145 | 1.7848 | -0.0143 | 3.9256 |
| equal | 21 | 16 | 0.001 | 0.0333 | 0.0299 | 1.1123 | 1.5053 | -0.0991 | 4.7032 | 0.0660 | 0.0252 | 2.6195 | 3.8994 | -0.0081 | 4.6379 |
| equal | 21 | 17 | 0.001 | 0.0385 | 0.0296 | 1.3006 | 1.8040 | -0.0843 | 4.5328 | 0.0477 | 0.0281 | 1.6985 | 2.5112 | -0.0133 | 5.0115 |
| equal | 21 | 18 | 0.001 | 0.0304 | 0.0299 | 1.0141 | 1.3984 | -0.0863 | 4.5706 | 0.0754 | 0.0297 | 2.5368 | 4.3665 | -0.0112 | 5.3832 |
| equal | 21 | 19 | 0.001 | 0.0286 | 0.0306 | 0.9353 | 1.2321 | -0.1043 | 4.5809 | 0.0598 | 0.0286 | 2.0944 | 3.4251 | -0.0186 | 5.0297 |

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| | | | | Train | | | | | | Test | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Weight | Rebalance | Shift | Cost | AnnRet | AnnVol | Sharpe | Sortino | MaxDD | Turnover | AnnRet | AnnVol | Sharpe | Sortino | MaxDD | Turnover |
| equal | 21 | 20 | 0.001 | 0.0338 | 0.0310 | 1.0894 | 1.4602 | -0.0928 | 4.7223 | 0.0320 | 0.0273 | 1.1729 | 1.5506 | -0.0257 | 4.8524 |
| equal | 10 | 0 | 0.001 | 0.0262 | 0.0301 | 0.8720 | 1.2222 | -0.0757 | 7.3390 | 0.0700 | 0.0272 | 2.5713 | 3.3144 | -0.0152 | 6.8864 |
| equal | 10 | 1 | 0.001 | 0.0326 | 0.0291 | 1.1225 | 1.5961 | -0.0747 | 7.2314 | 0.0879 | 0.0262 | 3.3497 | 4.9278 | -0.0087 | 7.7747 |
| equal | 10 | 2 | 0.001 | 0.0311 | 0.0291 | 1.0677 | 1.5193 | -0.0844 | 6.9526 | 0.1063 | 0.0271 | 3.9150 | 5.8872 | -0.0109 | 7.2284 |
| equal | 10 | 3 | 0.001 | 0.0322 | 0.0292 | 1.1030 | 1.5628 | -0.0947 | 6.9750 | 0.0626 | 0.0243 | 2.5753 | 3.8999 | -0.0143 | 7.2159 |
| equal | 10 | 4 | 0.001 | 0.0328 | 0.0294 | 1.1172 | 1.5404 | -0.0831 | 6.8385 | 0.0516 | 0.0283 | 1.8225 | 2.8956 | -0.0206 | 8.5491 |
| equal | 10 | 5 | 0.001 | 0.0322 | 0.0291 | 1.1070 | 1.5535 | -0.0741 | 7.0858 | 0.0567 | 0.0260 | 2.1799 | 3.6784 | -0.0137 | 7.6021 |
| equal | 10 | 6 | 0.001 | 0.0326 | 0.0300 | 1.0876 | 1.4706 | -0.0890 | 7.3325 | 0.0525 | 0.0233 | 2.2546 | 3.6961 | -0.0140 | 6.5615 |
| equal | 10 | 7 | 0.001 | 0.0367 | 0.0307 | 1.1946 | 1.6788 | -0.0741 | 7.0640 | 0.0328 | 0.0248 | 1.3220 | 2.0048 | -0.0192 | 7.4664 |
| equal | 10 | 8 | 0.001 | 0.0322 | 0.0298 | 1.0823 | 1.5538 | -0.0723 | 6.9727 | 0.0670 | 0.0265 | 2.5293 | 3.7237 | -0.0168 | 7.2570 |
| equal | 10 | 9 | 0.001 | 0.0294 | 0.0303 | 0.9721 | 1.4044 | -0.0866 | 7.1931 | 0.0591 | 0.0252 | 2.3483 | 3.4002 | -0.0115 | 7.8366 |
| equal | 5 | 0 | 0.001 | 0.0218 | 0.0290 | 0.7524 | 1.0754 | -0.0704 | 10.7404 | 0.0656 | 0.0271 | 2.4259 | 3.7236 | -0.0113 | 10.2120 |
| equal | 5 | 1 | 0.001 | 0.0269 | 0.0292 | 0.9225 | 1.2821 | -0.0805 | 11.3205 | 0.0542 | 0.0251 | 2.1614 | 3.4280 | -0.0108 | 10.5682 |
| equal | 5 | 2 | 0.001 | 0.0251 | 0.0290 | 0.8655 | 1.2462 | -0.0806 | 10.9304 | 0.0851 | 0.0256 | 3.3297 | 5.1741 | -0.0136 | 11.2526 |
| equal | 5 | 3 | 0.001 | 0.0261 | 0.0290 | 0.8984 | 1.2770 | -0.0716 | 10.9620 | 0.0753 | 0.0245 | 3.0730 | 4.7388 | -0.0133 | 9.8940 |
| equal | 5 | 4 | 0.001 | 0.0253 | 0.0295 | 0.8579 | 1.2055 | -0.0791 | 10.5620 | 0.0562 | 0.0265 | 2.1221 | 3.3843 | -0.0178 | 11.9637 |
| equal | 1 | 0 | 0.001 | 0.0000 | 0.0291 | 0.0008 | 0.0012 | -0.1765 | 28.2487 | 0.0302 | 0.0266 | 1.1332 | 1.6893 | -0.0094 | 25.9143 |
| min_var | 21 | 0 | 0.001 | 0.0279 | 0.0214 | 1.3047 | 1.8809 | -0.0470 | 3.4225 | 0.0517 | 0.0231 | 2.2377 | 3.2132 | -0.0151 | 3.5585 |
| min_var | 21 | 1 | 0.001 | 0.0321 | 0.0213 | 1.5029 | 2.2476 | -0.0338 | 3.3918 | 0.0819 | 0.0214 | 3.8280 | 6.6419 | -0.0099 | 3.8169 |
| min_var | 21 | 2 | 0.001 | 0.0273 | 0.0215 | 1.2677 | 1.8065 | -0.0622 | 3.3410 | 0.0638 | 0.0205 | 3.1181 | 5.0393 | -0.0090 | 3.5333 |
| min_var | 21 | 3 | 0.001 | 0.0248 | 0.0215 | 1.1555 | 1.6592 | -0.0659 | 3.1971 | 0.0440 | 0.0206 | 2.1301 | 3.5546 | -0.0161 | 3.9498 |
| min_var | 21 | 4 | 0.001 | 0.0271 | 0.0216 | 1.2548 | 1.7869 | -0.0750 | 3.3181 | 0.0607 | 0.0216 | 2.8031 | 4.9052 | -0.0087 | 3.7469 |
| min_var | 21 | 5 | 0.001 | 0.0283 | 0.0217 | 1.3015 | 1.8518 | -0.0606 | 3.3419 | 0.0728 | 0.0191 | 3.8089 | 6.8363 | -0.0062 | 3.1966 |
| min_var | 21 | 6 | 0.001 | 0.0268 | 0.0217 | 1.2331 | 1.7515 | -0.0697 | 3.3760 | 0.0697 | 0.0196 | 3.5631 | 5.9409 | -0.0069 | 3.2540 |

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| | | | | Train | | | | | | Test | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Weight | Rebalance | Shift | Cost | AnnRet | AnnVol | Sharpe | Sortino | MaxDD | Turnover | AnnRet | AnnVol | Sharpe | Sortino | MaxDD | Turnover |
| min_var | 21 | 7 | 0.001 | 0.0274 | 0.0213 | 1.2877 | 1.8639 | -0.0524 | 3.4240 | 0.0473 | 0.0204 | 2.3216 | 3.8587 | -0.0097 | 3.1820 |
| min_var | 21 | 8 | 0.001 | 0.0263 | 0.0212 | 1.2417 | 1.8244 | -0.0494 | 3.4024 | 0.0492 | 0.0217 | 2.2707 | 3.8409 | -0.0077 | 4.1181 |
| min_var | 21 | 9 | 0.001 | 0.0290 | 0.0213 | 1.3634 | 1.9912 | -0.0387 | 3.2690 | 0.0318 | 0.0236 | 1.3488 | 2.1031 | -0.0121 | 3.7844 |
| min_var | 21 | 10 | 0.001 | 0.0294 | 0.0215 | 1.3690 | 1.9796 | -0.0363 | 3.3466 | 0.0270 | 0.0187 | 1.4438 | 2.4929 | -0.0095 | 3.8947 |
| min_var | 21 | 11 | 0.001 | 0.0241 | 0.0216 | 1.1159 | 1.5648 | -0.0469 | 3.3770 | 0.0205 | 0.0188 | 1.0882 | 1.8197 | -0.0120 | 3.8418 |
| min_var | 21 | 12 | 0.001 | 0.0257 | 0.0218 | 1.1771 | 1.6602 | -0.0385 | 3.3332 | 0.0444 | 0.0209 | 2.1257 | 3.2674 | -0.0105 | 3.9326 |
| min_var | 21 | 13 | 0.001 | 0.0254 | 0.0217 | 1.1682 | 1.6354 | -0.0397 | 3.3507 | 0.0475 | 0.0211 | 2.2483 | 3.3844 | -0.0117 | 4.0634 |
| min_var | 21 | 14 | 0.001 | 0.0308 | 0.0218 | 1.4124 | 2.0717 | -0.0528 | 3.2944 | 0.0346 | 0.0213 | 1.6201 | 2.4569 | -0.0104 | 3.9621 |
| min_var | 21 | 15 | 0.001 | 0.0288 | 0.0211 | 1.3614 | 2.0099 | -0.0361 | 3.2299 | 0.0366 | 0.0214 | 1.7111 | 2.6593 | -0.0112 | 3.3089 |
| min_var | 21 | 16 | 0.001 | 0.0261 | 0.0216 | 1.2061 | 1.6941 | -0.0598 | 3.4168 | 0.0661 | 0.0220 | 2.9965 | 4.5513 | -0.0076 | 3.6854 |
| min_var | 21 | 17 | 0.001 | 0.0295 | 0.0213 | 1.3889 | 2.0147 | -0.0445 | 3.3146 | 0.0495 | 0.0236 | 2.0985 | 3.2928 | -0.0110 | 4.0519 |
| min_var | 21 | 18 | 0.001 | 0.0241 | 0.0211 | 1.1410 | 1.6619 | -0.0425 | 3.3199 | 0.0678 | 0.0238 | 2.8474 | 5.1551 | -0.0091 | 4.1276 |
| min_var | 21 | 19 | 0.001 | 0.0232 | 0.0219 | 1.0572 | 1.5094 | -0.0506 | 3.3743 | 0.0520 | 0.0230 | 2.2621 | 3.9372 | -0.0137 | 3.8066 |
| min_var | 21 | 20 | 0.001 | 0.0246 | 0.0216 | 1.1413 | 1.6506 | -0.0466 | 3.4071 | 0.0349 | 0.0233 | 1.4959 | 2.0145 | -0.0209 | 3.9968 |
| min_var | 10 | 0 | 0.001 | 0.0214 | 0.0214 | 1.0021 | 1.4865 | -0.0465 | 5.2109 | 0.0592 | 0.0214 | 2.7645 | 3.8429 | -0.0130 | 5.1180 |
| min_var | 10 | 1 | 0.001 | 0.0259 | 0.0207 | 1.2502 | 1.8945 | -0.0438 | 5.1381 | 0.0723 | 0.0206 | 3.5139 | 5.5330 | -0.0064 | 5.5541 |
| min_var | 10 | 2 | 0.001 | 0.0245 | 0.0204 | 1.2002 | 1.8205 | -0.0499 | 4.9008 | 0.0857 | 0.0204 | 4.1954 | 6.3226 | -0.0088 | 5.2856 |
| min_var | 10 | 3 | 0.001 | 0.0239 | 0.0207 | 1.1555 | 1.6936 | -0.0604 | 5.0002 | 0.0560 | 0.0197 | 2.8369 | 4.7479 | -0.0121 | 5.1718 |
| min_var | 10 | 4 | 0.001 | 0.0255 | 0.0211 | 1.2084 | 1.7331 | -0.0481 | 4.8956 | 0.0436 | 0.0213 | 2.0508 | 3.2885 | -0.0180 | 5.8185 |
| min_var | 10 | 5 | 0.001 | 0.0252 | 0.0208 | 1.2088 | 1.7657 | -0.0433 | 5.0673 | 0.0510 | 0.0203 | 2.5112 | 4.2569 | -0.0106 | 5.3544 |
| min_var | 10 | 6 | 0.001 | 0.0252 | 0.0211 | 1.1975 | 1.6973 | -0.0515 | 5.1878 | 0.0497 | 0.0194 | 2.5609 | 4.3059 | -0.0113 | 4.9836 |
| min_var | 10 | 7 | 0.001 | 0.0275 | 0.0215 | 1.2802 | 1.8932 | -0.0445 | 5.0441 | 0.0333 | 0.0221 | 1.5076 | 2.1942 | -0.0166 | 5.9630 |
| min_var | 10 | 8 | 0.001 | 0.0255 | 0.0211 | 1.2065 | 1.8408 | -0.0371 | 4.9726 | 0.0635 | 0.0219 | 2.9046 | 4.4617 | -0.0142 | 5.1106 |
| min_var | 10 | 9 | 0.001 | 0.0235 | 0.0215 | 1.0935 | 1.6566 | -0.0476 | 5.0990 | 0.0556 | 0.0213 | 2.6081 | 3.8648 | -0.0116 | 5.7175 |

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| | | | | Train | | | | | | Test | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Weight | Rebalance | Shift | Cost | AnnRet | AnnVol | Sharpe | Sortino | MaxDD | Turnover | AnnRet | AnnVol | Sharpe | Sortino | MaxDD | Turnover |
| min_var | 5 | 0 | 0.001 | 0.0174 | 0.0207 | 0.8375 | 1.2520 | -0.0448 | 7.4837 | 0.0540 | 0.0209 | 2.5863 | 3.9893 | -0.0085 | 7.2742 |
| min_var | 5 | 1 | 0.001 | 0.0218 | 0.0206 | 1.0593 | 1.5705 | -0.0448 | 7.7836 | 0.0478 | 0.0201 | 2.3739 | 4.0541 | -0.0093 | 7.6603 |
| min_var | 5 | 2 | 0.001 | 0.0195 | 0.0206 | 0.9481 | 1.4330 | -0.0475 | 7.5427 | 0.0676 | 0.0216 | 3.1340 | 4.4735 | -0.0112 | 8.4799 |
| min_var | 5 | 3 | 0.001 | 0.0204 | 0.0209 | 0.9774 | 1.4438 | -0.0445 | 7.6100 | 0.0649 | 0.0207 | 3.1316 | 5.1710 | -0.0111 | 7.1283 |
| min_var | 5 | 4 | 0.001 | 0.0200 | 0.0212 | 0.9431 | 1.3647 | -0.0475 | 7.3265 | 0.0503 | 0.0210 | 2.3957 | 4.0757 | -0.0134 | 8.3081 |
| min_var | 1 | 0 | 0.001 | 0.0037 | 0.0209 | 0.1757 | 0.2588 | -0.0833 | 18.2822 | 0.0308 | 0.0218 | 1.4091 | 2.0689 | -0.0069 | 17.8670 |
| equal | 21 | 0 | 0.002 | 0.0310 | 0.0301 | 1.0299 | 1.3757 | -0.0848 | 4.6512 | 0.0568 | 0.0303 | 1.8724 | 2.6117 | -0.0204 | 4.3810 |
| equal | 21 | 1 | 0.002 | 0.0358 | 0.0303 | 1.1820 | 1.6330 | -0.0756 | 4.6340 | 0.0895 | 0.0297 | 3.0146 | 5.1831 | -0.0138 | 5.2353 |
| equal | 21 | 2 | 0.002 | 0.0295 | 0.0307 | 0.9603 | 1.2362 | -0.1229 | 4.5117 | 0.0757 | 0.0298 | 2.5401 | 4.1717 | -0.0113 | 4.7538 |
| equal | 21 | 3 | 0.002 | 0.0266 | 0.0307 | 0.8679 | 1.1340 | -0.1219 | 4.3181 | 0.0471 | 0.0284 | 1.6605 | 2.8259 | -0.0215 | 5.3013 |
| equal | 21 | 4 | 0.002 | 0.0299 | 0.0316 | 0.9442 | 1.2128 | -0.1327 | 4.5363 | 0.0704 | 0.0306 | 2.3028 | 3.9632 | -0.0110 | 5.2235 |
| equal | 21 | 5 | 0.002 | 0.0328 | 0.0311 | 1.0528 | 1.4256 | -0.1047 | 4.6132 | 0.0828 | 0.0251 | 3.3006 | 5.5090 | -0.0103 | 4.4780 |
| equal | 21 | 6 | 0.002 | 0.0311 | 0.0309 | 1.0081 | 1.3602 | -0.1067 | 4.6531 | 0.0775 | 0.0253 | 3.0649 | 4.7921 | -0.0114 | 4.7279 |
| equal | 21 | 7 | 0.002 | 0.0315 | 0.0308 | 1.0231 | 1.3610 | -0.1054 | 4.7908 | 0.0544 | 0.0290 | 1.8721 | 3.0389 | -0.0144 | 4.6696 |
| equal | 21 | 8 | 0.002 | 0.0305 | 0.0314 | 0.9703 | 1.3411 | -0.0968 | 4.7237 | 0.0555 | 0.0292 | 1.9045 | 2.9745 | -0.0125 | 5.5345 |
| equal | 21 | 9 | 0.002 | 0.0359 | 0.0314 | 1.1401 | 1.5713 | -0.0570 | 4.5300 | 0.0357 | 0.0306 | 1.1674 | 1.9073 | -0.0205 | 5.3159 |
| equal | 21 | 10 | 0.002 | 0.0317 | 0.0303 | 1.0454 | 1.4586 | -0.0589 | 4.7107 | 0.0184 | 0.0232 | 0.7964 | 1.2733 | -0.0139 | 5.3987 |
| equal | 21 | 11 | 0.002 | 0.0266 | 0.0303 | 0.8795 | 1.1993 | -0.0826 | 4.7408 | 0.0078 | 0.0240 | 0.3246 | 0.4666 | -0.0167 | 5.2669 |
| equal | 21 | 12 | 0.002 | 0.0280 | 0.0306 | 0.9146 | 1.2629 | -0.0755 | 4.6548 | 0.0434 | 0.0263 | 1.6489 | 2.5904 | -0.0132 | 5.7488 |
| equal | 21 | 13 | 0.002 | 0.0277 | 0.0306 | 0.9052 | 1.2564 | -0.0558 | 4.6679 | 0.0443 | 0.0260 | 1.7062 | 2.5551 | -0.0145 | 5.7792 |
| equal | 21 | 14 | 0.002 | 0.0358 | 0.0320 | 1.1182 | 1.5882 | -0.0817 | 4.6247 | 0.0239 | 0.0242 | 0.9901 | 1.5007 | -0.0126 | 4.9788 |
| equal | 21 | 15 | 0.002 | 0.0337 | 0.0298 | 1.1296 | 1.6365 | -0.0590 | 4.4768 | 0.0260 | 0.0247 | 1.0497 | 1.5570 | -0.0143 | 3.9256 |
| equal | 21 | 16 | 0.002 | 0.0285 | 0.0301 | 0.9464 | 1.2824 | -0.1032 | 4.7032 | 0.0611 | 0.0252 | 2.4185 | 3.6102 | -0.0089 | 4.6379 |
| equal | 21 | 17 | 0.002 | 0.0338 | 0.0297 | 1.1384 | 1.5793 | -0.0871 | 4.5328 | 0.0424 | 0.0284 | 1.4938 | 2.1774 | -0.0139 | 5.0115 |

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| | | | | Train | | | | | | Test | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Weight | Rebalance | Shift | Cost | AnnRet | AnnVol | Sharpe | Sortino | MaxDD | Turnover | AnnRet | AnnVol | Sharpe | Sortino | MaxDD | Turnover |
| equal | 21 | 18 | 0.002 | 0.0257 | 0.0301 | 0.8534 | 1.1772 | -0.0887 | 4.5706 | 0.0696 | 0.0297 | 2.3479 | 4.0509 | -0.0117 | 5.3832 |
| equal | 21 | 19 | 0.002 | 0.0239 | 0.0307 | 0.7789 | 1.0276 | -0.1085 | 4.5809 | 0.0545 | 0.0285 | 1.9108 | 3.1551 | -0.0195 | 5.0297 |
| equal | 21 | 20 | 0.002 | 0.0289 | 0.0311 | 0.9285 | 1.2468 | -0.0951 | 4.7223 | 0.0270 | 0.0273 | 0.9878 | 1.3225 | -0.0266 | 4.8524 |
| equal | 10 | 0 | 0.002 | 0.0187 | 0.0302 | 0.6180 | 0.8645 | -0.0811 | 7.3390 | 0.0626 | 0.0277 | 2.2648 | 2.8788 | -0.0170 | 6.8864 |
| equal | 10 | 1 | 0.002 | 0.0252 | 0.0292 | 0.8612 | 1.2227 | -0.0782 | 7.2314 | 0.0795 | 0.0265 | 3.0020 | 4.4236 | -0.0092 | 7.7747 |
| equal | 10 | 2 | 0.002 | 0.0239 | 0.0292 | 0.8176 | 1.1629 | -0.0872 | 6.9526 | 0.0983 | 0.0273 | 3.6052 | 5.4401 | -0.0111 | 7.2284 |
| equal | 10 | 3 | 0.002 | 0.0250 | 0.0293 | 0.8532 | 1.2078 | -0.1011 | 6.9750 | 0.0550 | 0.0245 | 2.2481 | 3.4491 | -0.0163 | 7.2159 |
| equal | 10 | 4 | 0.002 | 0.0258 | 0.0295 | 0.8740 | 1.2036 | -0.0887 | 6.8385 | 0.0426 | 0.0286 | 1.4920 | 2.3796 | -0.0226 | 8.5491 |
| equal | 10 | 5 | 0.002 | 0.0249 | 0.0292 | 0.8518 | 1.1942 | -0.0787 | 7.0858 | 0.0487 | 0.0260 | 1.8704 | 3.1795 | -0.0144 | 7.6021 |
| equal | 10 | 6 | 0.002 | 0.0251 | 0.0301 | 0.8315 | 1.1229 | -0.0958 | 7.3325 | 0.0456 | 0.0233 | 1.9595 | 3.1917 | -0.0144 | 6.5615 |
| equal | 10 | 7 | 0.002 | 0.0294 | 0.0308 | 0.9536 | 1.3422 | -0.0783 | 7.0640 | 0.0252 | 0.0250 | 1.0051 | 1.5244 | -0.0205 | 7.4664 |
| equal | 10 | 8 | 0.002 | 0.0250 | 0.0299 | 0.8371 | 1.1979 | -0.0791 | 6.9727 | 0.0593 | 0.0266 | 2.2314 | 3.2976 | -0.0176 | 7.2570 |
| equal | 10 | 9 | 0.002 | 0.0220 | 0.0304 | 0.7250 | 1.0468 | -0.0925 | 7.1931 | 0.0509 | 0.0254 | 2.0055 | 2.9463 | -0.0125 | 7.8366 |
| equal | 5 | 0 | 0.002 | 0.0109 | 0.0292 | 0.3734 | 0.5320 | -0.1227 | 10.7404 | 0.0548 | 0.0274 | 2.0036 | 3.0452 | -0.0131 | 10.2120 |
| equal | 5 | 1 | 0.002 | 0.0153 | 0.0294 | 0.5224 | 0.7236 | -0.0908 | 11.3205 | 0.0432 | 0.0252 | 1.7110 | 2.7005 | -0.0120 | 10.5682 |
| equal | 5 | 2 | 0.002 | 0.0139 | 0.0292 | 0.4782 | 0.6889 | -0.1441 | 10.9304 | 0.0730 | 0.0259 | 2.8234 | 4.3787 | -0.0157 | 11.2526 |
| equal | 5 | 3 | 0.002 | 0.0149 | 0.0292 | 0.5100 | 0.7218 | -0.1043 | 10.9620 | 0.0647 | 0.0247 | 2.6177 | 4.0374 | -0.0143 | 9.8940 |
| equal | 5 | 4 | 0.002 | 0.0146 | 0.0297 | 0.4903 | 0.6878 | -0.1100 | 10.5620 | 0.0436 | 0.0267 | 1.6335 | 2.6108 | -0.0206 | 11.9637 |
| equal | 1 | 0 | 0.002 | -0.0278 | 0.0293 | -0.9487 | -1.3373 | -0.5033 | 28.2487 | 0.0038 | 0.0269 | 0.1405 | 0.2074 | -0.0149 | 25.9143 |
| min_var | 21 | 0 | 0.002 | 0.0244 | 0.0214 | 1.1357 | 1.6363 | -0.0478 | 3.4225 | 0.0480 | 0.0233 | 2.0597 | 2.9005 | -0.0157 | 3.5585 |
| min_var | 21 | 1 | 0.002 | 0.0286 | 0.0214 | 1.3346 | 1.9931 | -0.0344 | 3.3918 | 0.0777 | 0.0214 | 3.6339 | 6.2863 | -0.0102 | 3.8169 |
| min_var | 21 | 2 | 0.002 | 0.0239 | 0.0216 | 1.1038 | 1.5705 | -0.0642 | 3.3410 | 0.0600 | 0.0205 | 2.9246 | 4.8050 | -0.0091 | 3.5333 |
| min_var | 21 | 3 | 0.002 | 0.0215 | 0.0216 | 0.9983 | 1.4306 | -0.0677 | 3.1971 | 0.0398 | 0.0208 | 1.9159 | 3.2492 | -0.0170 | 3.9498 |
| min_var | 21 | 4 | 0.002 | 0.0237 | 0.0217 | 1.0937 | 1.5542 | -0.0770 | 3.3181 | 0.0567 | 0.0217 | 2.6108 | 4.5437 | -0.0087 | 3.7469 |

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| | | | | Train | | | | | | Test | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Weight | Rebalance | Shift | Cost | AnnRet | AnnVol | Sharpe | Sortino | MaxDD | Turnover | AnnRet | AnnVol | Sharpe | Sortino | MaxDD | Turnover |
| min_var | 21 | 5 | 0.002 | 0.0248 | 0.0218 | 1.1389 | 1.6188 | -0.0620 | 3.3419 | 0.0694 | 0.0192 | 3.6107 | 6.5273 | -0.0065 | 3.1966 |
| min_var | 21 | 6 | 0.002 | 0.0233 | 0.0218 | 1.0704 | 1.5203 | -0.0711 | 3.3760 | 0.0662 | 0.0196 | 3.3826 | 5.6164 | -0.0071 | 3.2540 |
| min_var | 21 | 7 | 0.002 | 0.0239 | 0.0214 | 1.1172 | 1.6149 | -0.0549 | 3.4240 | 0.0440 | 0.0204 | 2.1505 | 3.5814 | -0.0111 | 3.1820 |
| min_var | 21 | 8 | 0.002 | 0.0228 | 0.0213 | 1.0733 | 1.5741 | -0.0543 | 3.4024 | 0.0449 | 0.0218 | 2.0572 | 3.4838 | -0.0083 | 4.1181 |
| min_var | 21 | 9 | 0.002 | 0.0257 | 0.0214 | 1.2021 | 1.7525 | -0.0389 | 3.2690 | 0.0279 | 0.0237 | 1.1764 | 1.8180 | -0.0131 | 3.7844 |
| min_var | 21 | 10 | 0.002 | 0.0260 | 0.0216 | 1.2047 | 1.7394 | -0.0369 | 3.3466 | 0.0230 | 0.0188 | 1.2265 | 2.1314 | -0.0106 | 3.8947 |
| min_var | 21 | 11 | 0.002 | 0.0207 | 0.0217 | 0.9523 | 1.3367 | -0.0505 | 3.3770 | 0.0166 | 0.0190 | 0.8709 | 1.4123 | -0.0130 | 3.8418 |
| min_var | 21 | 12 | 0.002 | 0.0223 | 0.0219 | 1.0165 | 1.4331 | -0.0423 | 3.3332 | 0.0403 | 0.0209 | 1.9272 | 3.0083 | -0.0110 | 3.9326 |
| min_var | 21 | 13 | 0.002 | 0.0219 | 0.0218 | 1.0055 | 1.4031 | -0.0404 | 3.3507 | 0.0433 | 0.0212 | 2.0424 | 3.0859 | -0.0122 | 4.0634 |
| min_var | 21 | 14 | 0.002 | 0.0275 | 0.0219 | 1.2532 | 1.8400 | -0.0564 | 3.2944 | 0.0305 | 0.0216 | 1.4132 | 2.1317 | -0.0116 | 3.9621 |
| min_var | 21 | 15 | 0.002 | 0.0254 | 0.0212 | 1.1992 | 1.7646 | -0.0370 | 3.2299 | 0.0332 | 0.0214 | 1.5479 | 2.4296 | -0.0112 | 3.3089 |
| min_var | 21 | 16 | 0.002 | 0.0226 | 0.0217 | 1.0399 | 1.4591 | -0.0624 | 3.4168 | 0.0622 | 0.0221 | 2.8180 | 4.2988 | -0.0076 | 3.6854 |
| min_var | 21 | 17 | 0.002 | 0.0261 | 0.0213 | 1.2242 | 1.7742 | -0.0467 | 3.3146 | 0.0452 | 0.0238 | 1.8988 | 2.9444 | -0.0114 | 4.0519 |
| min_var | 21 | 18 | 0.002 | 0.0207 | 0.0212 | 0.9757 | 1.4173 | -0.0468 | 3.3199 | 0.0634 | 0.0238 | 2.6699 | 4.7913 | -0.0094 | 4.1276 |
| min_var | 21 | 19 | 0.002 | 0.0197 | 0.0220 | 0.8970 | 1.2811 | -0.0527 | 3.3743 | 0.0480 | 0.0230 | 2.0895 | 3.6279 | -0.0144 | 3.8066 |
| min_var | 21 | 20 | 0.002 | 0.0212 | 0.0217 | 0.9757 | 1.4119 | -0.0470 | 3.4071 | 0.0307 | 0.0233 | 1.3172 | 1.7926 | -0.0217 | 3.9968 |
| min_var | 10 | 0 | 0.002 | 0.0161 | 0.0215 | 0.7489 | 1.1075 | -0.0504 | 5.2109 | 0.0538 | 0.0217 | 2.4815 | 3.3890 | -0.0142 | 5.1180 |
| min_var | 10 | 1 | 0.002 | 0.0206 | 0.0208 | 0.9912 | 1.4985 | -0.0464 | 5.1381 | 0.0664 | 0.0207 | 3.2034 | 4.9891 | -0.0070 | 5.5541 |
| min_var | 10 | 2 | 0.002 | 0.0195 | 0.0206 | 0.9502 | 1.4388 | -0.0519 | 4.9008 | 0.0800 | 0.0206 | 3.8904 | 5.8330 | -0.0091 | 5.2856 |
| min_var | 10 | 3 | 0.002 | 0.0188 | 0.0208 | 0.9043 | 1.3233 | -0.0652 | 5.0002 | 0.0506 | 0.0198 | 2.5509 | 4.2914 | -0.0135 | 5.1718 |
| min_var | 10 | 4 | 0.002 | 0.0205 | 0.0212 | 0.9672 | 1.3843 | -0.0493 | 4.8956 | 0.0375 | 0.0214 | 1.7544 | 2.8463 | -0.0193 | 5.8185 |
| min_var | 10 | 5 | 0.002 | 0.0200 | 0.0209 | 0.9552 | 1.3945 | -0.0483 | 5.0673 | 0.0454 | 0.0203 | 2.2318 | 3.8339 | -0.0112 | 5.3544 |
| min_var | 10 | 6 | 0.002 | 0.0199 | 0.0212 | 0.9404 | 1.3317 | -0.0535 | 5.1878 | 0.0445 | 0.0194 | 2.2945 | 3.8192 | -0.0117 | 4.9836 |
| min_var | 10 | 7 | 0.002 | 0.0223 | 0.0215 | 1.0355 | 1.5330 | -0.0450 | 5.0441 | 0.0271 | 0.0223 | 1.2196 | 1.7754 | -0.0177 | 5.9630 |

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| | | | | Train | | | | | | Test | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Weight | Rebalance | Shift | Cost | AnnRet | AnnVol | Sharpe | Sortino | MaxDD | Turnover | AnnRet | AnnVol | Sharpe | Sortino | MaxDD | Turnover |
| min_var | 10 | 8 | 0.002 | 0.0204 | 0.0213 | 0.9612 | 1.4626 | -0.0403 | 4.9726 | 0.0580 | 0.0219 | 2.6524 | 4.1042 | -0.0149 | 5.1106 |
| min_var | 10 | 9 | 0.002 | 0.0183 | 0.0216 | 0.8483 | 1.2830 | -0.0518 | 5.0990 | 0.0496 | 0.0214 | 2.3110 | 3.4513 | -0.0124 | 5.7175 |
| min_var | 5 | 0 | 0.002 | 0.0098 | 0.0209 | 0.4683 | 0.6988 | -0.0697 | 7.4837 | 0.0463 | 0.0211 | 2.1988 | 3.3951 | -0.0093 | 7.2742 |
| min_var | 5 | 1 | 0.002 | 0.0139 | 0.0207 | 0.6706 | 0.9910 | -0.0566 | 7.7836 | 0.0398 | 0.0202 | 1.9726 | 3.3065 | -0.0102 | 7.6603 |
| min_var | 5 | 2 | 0.002 | 0.0119 | 0.0207 | 0.5732 | 0.8661 | -0.0867 | 7.5427 | 0.0586 | 0.0219 | 2.6806 | 3.7853 | -0.0127 | 8.4799 |
| min_var | 5 | 3 | 0.002 | 0.0127 | 0.0210 | 0.6029 | 0.8880 | -0.0690 | 7.6100 | 0.0574 | 0.0208 | 2.7536 | 4.5753 | -0.0124 | 7.1283 |
| min_var | 5 | 4 | 0.002 | 0.0125 | 0.0213 | 0.5890 | 0.8506 | -0.0750 | 7.3265 | 0.0416 | 0.0211 | 1.9691 | 3.3509 | -0.0153 | 8.3081 |
| min_var | 1 | 0 | 0.002 | -0.0145 | 0.0210 | -0.6916 | -1.0137 | -0.3007 | 18.2822 | 0.0125 | 0.0220 | 0.5674 | 0.8229 | -0.0093 | 17.8670 |
| equal | 21 | 0 | 0.003 | 0.0262 | 0.0303 | 0.8653 | 1.1534 | -0.0878 | 4.6512 | 0.0521 | 0.0305 | 1.7073 | 2.3788 | -0.0213 | 4.3810 |
| equal | 21 | 1 | 0.003 | 0.0310 | 0.0305 | 1.0177 | 1.4010 | -0.0777 | 4.6340 | 0.0838 | 0.0298 | 2.8115 | 4.8410 | -0.0148 | 5.2353 |
| equal | 21 | 2 | 0.003 | 0.0248 | 0.0309 | 0.8042 | 1.0332 | -0.1256 | 4.5117 | 0.0706 | 0.0300 | 2.3522 | 3.9071 | -0.0115 | 4.7538 |
| equal | 21 | 3 | 0.003 | 0.0222 | 0.0309 | 0.7190 | 0.9366 | -0.1250 | 4.3181 | 0.0416 | 0.0287 | 1.4506 | 2.4753 | -0.0226 | 5.3013 |
| equal | 21 | 4 | 0.003 | 0.0252 | 0.0318 | 0.7923 | 1.0160 | -0.1356 | 4.5363 | 0.0648 | 0.0308 | 2.1067 | 3.5878 | -0.0110 | 5.2235 |
| equal | 21 | 5 | 0.003 | 0.0280 | 0.0313 | 0.8942 | 1.2072 | -0.1100 | 4.6132 | 0.0780 | 0.0253 | 3.0869 | 5.1892 | -0.0108 | 4.4780 |
| equal | 21 | 6 | 0.003 | 0.0263 | 0.0310 | 0.8484 | 1.1426 | -0.1088 | 4.6531 | 0.0724 | 0.0254 | 2.8544 | 4.4349 | -0.0117 | 4.7279 |
| equal | 21 | 7 | 0.003 | 0.0266 | 0.0311 | 0.8565 | 1.1368 | -0.1095 | 4.7908 | 0.0495 | 0.0293 | 1.6896 | 2.7238 | -0.0157 | 4.6696 |
| equal | 21 | 8 | 0.003 | 0.0256 | 0.0316 | 0.8111 | 1.1164 | -0.1038 | 4.7237 | 0.0497 | 0.0294 | 1.6884 | 2.6535 | -0.0133 | 5.5345 |
| equal | 21 | 9 | 0.003 | 0.0312 | 0.0316 | 0.9863 | 1.3537 | -0.0576 | 4.5300 | 0.0302 | 0.0309 | 0.9787 | 1.5994 | -0.0219 | 5.3159 |
| equal | 21 | 10 | 0.003 | 0.0268 | 0.0305 | 0.8797 | 1.2239 | -0.0639 | 4.7107 | 0.0129 | 0.0234 | 0.5535 | 0.8737 | -0.0151 | 5.3987 |
| equal | 21 | 11 | 0.003 | 0.0218 | 0.0305 | 0.7141 | 0.9712 | -0.0875 | 4.7408 | 0.0025 | 0.0244 | 0.1016 | 0.1434 | -0.0185 | 5.2669 |
| equal | 21 | 12 | 0.003 | 0.0232 | 0.0308 | 0.7535 | 1.0362 | -0.0819 | 4.6548 | 0.0374 | 0.0265 | 1.4111 | 2.2273 | -0.0139 | 5.7488 |
| equal | 21 | 13 | 0.003 | 0.0229 | 0.0308 | 0.7430 | 1.0261 | -0.0567 | 4.6679 | 0.0383 | 0.0262 | 1.4651 | 2.2094 | -0.0153 | 5.7792 |
| equal | 21 | 14 | 0.003 | 0.0310 | 0.0322 | 0.9640 | 1.3692 | -0.0864 | 4.6247 | 0.0188 | 0.0245 | 0.7674 | 1.1478 | -0.0141 | 4.9788 |
| equal | 21 | 15 | 0.003 | 0.0291 | 0.0300 | 0.9681 | 1.3935 | -0.0610 | 4.4768 | 0.0219 | 0.0248 | 0.8836 | 1.3193 | -0.0143 | 3.9256 |

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| | | | | Train | | | | | | Test | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Weight | Rebalance | Shift | Cost | AnnRet | AnnVol | Sharpe | Sortino | MaxDD | Turnover | AnnRet | AnnVol | Sharpe | Sortino | MaxDD | Turnover |
| equal | 21 | 16 | 0.003 | 0.0236 | 0.0303 | 0.7806 | 1.0562 | -0.1072 | 4.7032 | 0.0561 | 0.0254 | 2.2118 | 3.3103 | -0.0099 | 4.6379 |
| equal | 21 | 17 | 0.003 | 0.0292 | 0.0299 | 0.9754 | 1.3506 | -0.0899 | 4.5328 | 0.0372 | 0.0288 | 1.2912 | 1.8458 | -0.0145 | 5.0115 |
| equal | 21 | 18 | 0.003 | 0.0210 | 0.0303 | 0.6930 | 0.9524 | -0.0911 | 4.5706 | 0.0639 | 0.0297 | 2.1524 | 3.7135 | -0.0122 | 5.3832 |
| equal | 21 | 19 | 0.003 | 0.0192 | 0.0308 | 0.6226 | 0.8207 | -0.1129 | 4.5809 | 0.0492 | 0.0286 | 1.7228 | 2.8430 | -0.0204 | 5.0297 |
| equal | 21 | 20 | 0.003 | 0.0240 | 0.0313 | 0.7677 | 1.0298 | -0.0974 | 4.7223 | 0.0220 | 0.0275 | 0.8017 | 1.0882 | -0.0275 | 4.8524 |
| equal | 10 | 0 | 0.003 | 0.0112 | 0.0305 | 0.3679 | 0.5120 | -0.1048 | 7.3390 | 0.0553 | 0.0282 | 1.9638 | 2.4465 | -0.0188 | 6.8864 |
| equal | 10 | 1 | 0.003 | 0.0178 | 0.0295 | 0.6027 | 0.8508 | -0.0822 | 7.2314 | 0.0711 | 0.0268 | 2.6516 | 3.9204 | -0.0096 | 7.7747 |
| equal | 10 | 2 | 0.003 | 0.0168 | 0.0295 | 0.5701 | 0.8070 | -0.0900 | 6.9526 | 0.0904 | 0.0275 | 3.2889 | 4.9420 | -0.0114 | 7.2284 |
| equal | 10 | 3 | 0.003 | 0.0178 | 0.0295 | 0.6053 | 0.8538 | -0.1074 | 6.9750 | 0.0474 | 0.0247 | 1.9190 | 2.9849 | -0.0183 | 7.2159 |
| equal | 10 | 4 | 0.003 | 0.0188 | 0.0297 | 0.6325 | 0.8681 | -0.0954 | 6.8385 | 0.0337 | 0.0289 | 1.1654 | 1.8598 | -0.0246 | 8.5491 |
| equal | 10 | 5 | 0.003 | 0.0176 | 0.0295 | 0.5991 | 0.8369 | -0.0935 | 7.0858 | 0.0407 | 0.0261 | 1.5577 | 2.6611 | -0.0151 | 7.6021 |
| equal | 10 | 6 | 0.003 | 0.0176 | 0.0304 | 0.5779 | 0.7775 | -0.1032 | 7.3325 | 0.0388 | 0.0234 | 1.6596 | 2.7009 | -0.0148 | 6.5615 |
| equal | 10 | 7 | 0.003 | 0.0222 | 0.0310 | 0.7138 | 1.0044 | -0.0860 | 7.0640 | 0.0175 | 0.0253 | 0.6920 | 1.0453 | -0.0218 | 7.4664 |
| equal | 10 | 8 | 0.003 | 0.0179 | 0.0301 | 0.5941 | 0.8461 | -0.0981 | 6.9727 | 0.0516 | 0.0267 | 1.9309 | 2.8580 | -0.0185 | 7.2570 |
| equal | 10 | 9 | 0.003 | 0.0147 | 0.0306 | 0.4803 | 0.6916 | -0.1058 | 7.1931 | 0.0427 | 0.0256 | 1.6630 | 2.4713 | -0.0136 | 7.8366 |
| equal | 5 | 0 | 0.003 | 0.0001 | 0.0295 | 0.0035 | 0.0050 | -0.2115 | 10.7404 | 0.0441 | 0.0277 | 1.5885 | 2.3804 | -0.0157 | 10.2120 |
| equal | 5 | 1 | 0.003 | 0.0039 | 0.0297 | 0.1316 | 0.1811 | -0.1770 | 11.3205 | 0.0322 | 0.0255 | 1.2634 | 1.9935 | -0.0138 | 10.5682 |
| equal | 5 | 2 | 0.003 | 0.0029 | 0.0294 | 0.0988 | 0.1420 | -0.2211 | 10.9304 | 0.0610 | 0.0263 | 2.3212 | 3.5631 | -0.0178 | 11.2526 |
| equal | 5 | 3 | 0.003 | 0.0038 | 0.0295 | 0.1299 | 0.1826 | -0.1798 | 10.9620 | 0.0542 | 0.0251 | 2.1655 | 3.3362 | -0.0161 | 9.8940 |
| equal | 5 | 4 | 0.003 | 0.0039 | 0.0300 | 0.1298 | 0.1813 | -0.1745 | 10.5620 | 0.0312 | 0.0270 | 1.1530 | 1.8448 | -0.0234 | 11.9637 |
| equal | 1 | 0 | 0.003 | -0.0549 | 0.0297 | -1.8483 | -2.5826 | -0.7109 | 28.2487 | -0.0219 | 0.0274 | -0.8002 | -1.1598 | -0.0249 | 25.9143 |
| min_var | 21 | 0 | 0.003 | 0.0209 | 0.0216 | 0.9661 | 1.3871 | -0.0487 | 3.4225 | 0.0443 | 0.0235 | 1.8811 | 2.6394 | -0.0164 | 3.5585 |
| min_var | 21 | 1 | 0.003 | 0.0251 | 0.0215 | 1.1650 | 1.7328 | -0.0362 | 3.3918 | 0.0736 | 0.0215 | 3.4312 | 5.9724 | -0.0105 | 3.8169 |
| min_var | 21 | 2 | 0.003 | 0.0205 | 0.0218 | 0.9394 | 1.3313 | -0.0661 | 3.3410 | 0.0563 | 0.0206 | 2.7259 | 4.5388 | -0.0093 | 3.5333 |

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| | | | | Train | | | | | | Test | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Weight | Rebalance | Shift | Cost | AnnRet | AnnVol | Sharpe | Sortino | MaxDD | Turnover | AnnRet | AnnVol | Sharpe | Sortino | MaxDD | Turnover |
| min_var | 21 | 3 | 0.003 | 0.0183 | 0.0217 | 0.8411 | 1.1983 | -0.0696 | 3.1971 | 0.0357 | 0.0210 | 1.7008 | 2.9155 | -0.0180 | 3.9498 |
| min_var | 21 | 4 | 0.003 | 0.0203 | 0.0218 | 0.9319 | 1.3184 | -0.0790 | 3.3181 | 0.0527 | 0.0218 | 2.4146 | 4.1505 | -0.0087 | 3.7469 |
| min_var | 21 | 5 | 0.003 | 0.0214 | 0.0219 | 0.9757 | 1.3815 | -0.0636 | 3.3419 | 0.0660 | 0.0194 | 3.4067 | 6.1573 | -0.0068 | 3.1966 |
| min_var | 21 | 6 | 0.003 | 0.0199 | 0.0219 | 0.9069 | 1.2847 | -0.0726 | 3.3760 | 0.0627 | 0.0196 | 3.1957 | 5.2541 | -0.0073 | 3.2540 |
| min_var | 21 | 7 | 0.003 | 0.0204 | 0.0216 | 0.9466 | 1.3621 | -0.0580 | 3.4240 | 0.0406 | 0.0206 | 1.9774 | 3.2797 | -0.0124 | 3.1820 |
| min_var | 21 | 8 | 0.003 | 0.0193 | 0.0214 | 0.9043 | 1.3193 | -0.0591 | 3.4024 | 0.0406 | 0.0220 | 1.8421 | 3.0985 | -0.0088 | 4.1181 |
| min_var | 21 | 9 | 0.003 | 0.0223 | 0.0215 | 1.0398 | 1.5103 | -0.0392 | 3.2690 | 0.0240 | 0.0239 | 1.0046 | 1.5583 | -0.0141 | 3.7844 |
| min_var | 21 | 10 | 0.003 | 0.0226 | 0.0217 | 1.0396 | 1.4969 | -0.0397 | 3.3466 | 0.0190 | 0.0189 | 1.0074 | 1.7392 | -0.0117 | 3.8947 |
| min_var | 21 | 11 | 0.003 | 0.0172 | 0.0219 | 0.7886 | 1.1055 | -0.0540 | 3.3770 | 0.0126 | 0.0193 | 0.6566 | 1.0505 | -0.0139 | 3.8418 |
| min_var | 21 | 12 | 0.003 | 0.0189 | 0.0220 | 0.8558 | 1.2028 | -0.0460 | 3.3332 | 0.0362 | 0.0210 | 1.7251 | 2.7143 | -0.0115 | 3.9326 |
| min_var | 21 | 13 | 0.003 | 0.0185 | 0.0220 | 0.8427 | 1.1696 | -0.0411 | 3.3507 | 0.0390 | 0.0213 | 1.8328 | 2.8224 | -0.0127 | 4.0634 |
| min_var | 21 | 14 | 0.003 | 0.0241 | 0.0220 | 1.0930 | 1.6034 | -0.0600 | 3.2944 | 0.0264 | 0.0219 | 1.2074 | 1.8005 | -0.0129 | 3.9621 |
| min_var | 21 | 15 | 0.003 | 0.0221 | 0.0214 | 1.0364 | 1.5173 | -0.0390 | 3.2299 | 0.0298 | 0.0215 | 1.3826 | 2.1836 | -0.0112 | 3.3089 |
| min_var | 21 | 16 | 0.003 | 0.0191 | 0.0219 | 0.8733 | 1.2218 | -0.0652 | 3.4168 | 0.0582 | 0.0221 | 2.6332 | 4.0228 | -0.0083 | 3.6854 |
| min_var | 21 | 17 | 0.003 | 0.0227 | 0.0215 | 1.0585 | 1.5280 | -0.0515 | 3.3146 | 0.0410 | 0.0241 | 1.6996 | 2.5860 | -0.0119 | 4.0519 |
| min_var | 21 | 18 | 0.003 | 0.0173 | 0.0214 | 0.8102 | 1.1697 | -0.0514 | 3.3199 | 0.0591 | 0.0238 | 2.4854 | 4.4958 | -0.0096 | 4.1276 |
| min_var | 21 | 19 | 0.003 | 0.0163 | 0.0221 | 0.7365 | 1.0490 | -0.0559 | 3.3743 | 0.0441 | 0.0230 | 1.9127 | 3.3223 | -0.0152 | 3.8066 |
| min_var | 21 | 20 | 0.003 | 0.0177 | 0.0218 | 0.8099 | 1.1688 | -0.0477 | 3.4071 | 0.0266 | 0.0234 | 1.1364 | 1.5621 | -0.0225 | 3.9968 |
| min_var | 10 | 0 | 0.003 | 0.0108 | 0.0217 | 0.4988 | 0.7330 | -0.0670 | 5.2109 | 0.0484 | 0.0220 | 2.2011 | 2.9550 | -0.0155 | 5.1180 |
| min_var | 10 | 1 | 0.003 | 0.0154 | 0.0210 | 0.7338 | 1.1021 | -0.0501 | 5.1381 | 0.0605 | 0.0209 | 2.8894 | 4.5069 | -0.0077 | 5.5541 |
| min_var | 10 | 2 | 0.003 | 0.0145 | 0.0207 | 0.7020 | 1.0569 | -0.0539 | 4.9008 | 0.0743 | 0.0207 | 3.5805 | 5.3181 | -0.0093 | 5.2856 |
| min_var | 10 | 3 | 0.003 | 0.0137 | 0.0210 | 0.6548 | 0.9545 | -0.0700 | 5.0002 | 0.0452 | 0.0200 | 2.2621 | 3.8696 | -0.0149 | 5.1718 |
| min_var | 10 | 4 | 0.003 | 0.0155 | 0.0213 | 0.7270 | 1.0371 | -0.0584 | 4.8956 | 0.0315 | 0.0216 | 1.4589 | 2.3795 | -0.0206 | 5.8185 |
| min_var | 10 | 5 | 0.003 | 0.0148 | 0.0211 | 0.7031 | 1.0242 | -0.0629 | 5.0673 | 0.0398 | 0.0204 | 1.9489 | 3.3525 | -0.0118 | 5.3544 |

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| Weight | Rebalance | Shift | Cost | Train AnnRet | Train AnnVol | Train Sharpe | Train Sortino | Train MaxDD | Train Turnover | Test AnnRet | Test AnnVol | Test Sharpe | Test Sortino | Test MaxDD | Test Turnover |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| min_var | 10 | 6 | 0.003 | 0.0146 | 0.0214 | 0.6854 | 0.9673 | -0.0574 | 5.1878 | 0.0393 | 0.0194 | 2.0230 | 3.3523 | -0.0122 | 4.9836 |
| min_var | 10 | 7 | 0.003 | 0.0172 | 0.0217 | 0.7916 | 1.1696 | -0.0456 | 5.0441 | 0.0210 | 0.0225 | 0.9344 | 1.3552 | -0.0188 | 5.9630 |
| min_var | 10 | 8 | 0.003 | 0.0154 | 0.0214 | 0.7174 | 1.0860 | -0.0560 | 4.9726 | 0.0527 | 0.0220 | 2.3969 | 3.6976 | -0.0155 | 5.1106 |
| min_var | 10 | 9 | 0.003 | 0.0132 | 0.0218 | 0.6044 | 0.9117 | -0.0722 | 5.0990 | 0.0436 | 0.0216 | 2.0133 | 3.0244 | -0.0132 | 5.7175 |
| min_var | 5 | 0 | 0.003 | 0.0022 | 0.0211 | 0.1062 | 0.1578 | -0.1198 | 7.4837 | 0.0387 | 0.0213 | 1.8161 | 2.7864 | -0.0111 | 7.2742 |
| min_var | 5 | 1 | 0.003 | 0.0060 | 0.0210 | 0.2887 | 0.4240 | -0.0958 | 7.7836 | 0.0319 | 0.0203 | 1.5703 | 2.6230 | -0.0111 | 7.6603 |
| min_var | 5 | 2 | 0.003 | 0.0043 | 0.0209 | 0.2043 | 0.3076 | -0.1456 | 7.5427 | 0.0497 | 0.0222 | 2.2341 | 3.1193 | -0.0143 | 8.4799 |
| min_var | 5 | 3 | 0.003 | 0.0050 | 0.0212 | 0.2349 | 0.3443 | -0.1083 | 7.6100 | 0.0499 | 0.0210 | 2.3753 | 3.9994 | -0.0136 | 7.1283 |
| min_var | 5 | 4 | 0.003 | 0.0052 | 0.0215 | 0.2400 | 0.3454 | -0.1063 | 7.3265 | 0.0330 | 0.0213 | 1.5461 | 2.6771 | -0.0172 | 8.3081 |
| min_var | 1 | 0 | 0.003 | -0.0324 | 0.0212 | -1.5272 | -2.2258 | -0.5033 | 18.2822 | -0.0054 | 0.0223 | -0.2444 | -0.3503 | -0.0141 | 17.8670 |

# Appendix C

# Appendix: Fitting Results

## C.1 OLS Fitting Results for Each ETFs

Table C.1: OLS Regression Results for Dependent Variable XLC
*Training $R^2$ = 0.234, Adjusted $R^2$ = 0.220, Test $R^2$ = −0.662, F-statistic = 16.73 (p<0.001), No. of Observations = 1287*

| **Variable** | **Coefficient** | **Std. Error** | **t-value** | **P>\|t\|** | **[0.025, 0.975]** |
|---|---|---|---|---|---|
| const | 0.0093 | 0.004 | 2.557 | 0.011 | [0.002, 0.016] |
| XLC(2,2) | 0.2978 | 0.036 | 8.224 | 0.000 | [0.227, 0.369] |
| XLY(5,3) | 0.1507 | 0.024 | 6.383 | 0.000 | [0.104, 0.197] |
| XLY(12,6) | -0.0505 | 0.018 | -2.778 | 0.006 | [-0.086, -0.015] |
| XLP(8,7) | -0.0008 | 0.033 | -0.024 | 0.981 | [-0.066, 0.065] |
| XLP(2,9) | -0.2943 | 0.051 | -5.806 | 0.000 | [-0.394, -0.195] |
| XLE(2,2) | -0.0112 | 0.016 | -0.690 | 0.490 | [-0.043, 0.021] |
| XLE(10,6) | -0.0459 | 0.009 | -4.869 | 0.000 | [-0.064, -0.027] |
| XLF(7,1) | -0.1121 | 0.030 | -3.784 | 0.000 | [-0.170, -0.054] |
| XLF(2,2) | -0.2680 | 0.040 | -6.706 | 0.000 | [-0.346, -0.190] |
| XLV(9,1) | 0.0039 | 0.043 | 0.092 | 0.927 | [-0.081, 0.088] |
| XLV(9,6) | 0.0495 | 0.036 | 1.383 | 0.167 | [-0.021, 0.120] |
| XLI(1,6) | -0.0303 | 0.024 | -1.268 | 0.205 | [-0.077, 0.017] |
| XLB(1,4) | 0.0562 | 0.022 | 2.538 | 0.011 | [0.013, 0.100] |
| XLRE(12,7) | -0.0237 | 0.022 | -1.098 | 0.272 | [-0.066, 0.019] |
| XLK(10,7) | -0.0424 | 0.017 | -2.436 | 0.015 | [-0.077, -0.008] |
| XLU(9,5) | 0.0266 | 0.029 | 0.922 | 0.357 | [-0.030, 0.083] |
| XLU(2,9) | 0.2211 | 0.036 | 6.106 | 0.000 | [0.150, 0.292] |
| RMW(12,5) | 0.0215 | 0.050 | 0.432 | 0.666 | [-0.076, 0.119] |
| Mom(10,3) | 0.0392 | 0.024 | 1.626 | 0.104 | [-0.008, 0.086] |
| Mom(4,7) | -0.0692 | 0.026 | -2.644 | 0.008 | [-0.121, -0.018] |
| ST_Rev(8,2) | 0.1188 | 0.039 | 3.073 | 0.002 | [0.043, 0.195] |
| 3yr_Treasury(10,4) | 0.0010 | 0.001 | 1.288 | 0.198 | [-0.000, 0.002] |
| 3yr_Treasury(5,7) | 0.0016 | 0.000 | 6.692 | 0.000 | [0.001, 0.002] |

Table C.2: OLS Regression Results for Dependent Variable XLY
*Training* $R^2$ = 0.071, *Adjusted* $R^2$ = 0.067, *Test* $R^2 = -0.103$, *F-statistic = 18.23 (p<0.001), No. of Observations = 5491*

| **Variable** | **Coefficient** | **Std. Error** | **t-value** | **P>\|t\|** | **[0.025, 0.975]** |
|---|---|---|---|---|---|
| const | 0.0089 | 0.001 | 7.410 | 0.000 | [0.007, 0.011] |
| XLY(9,1) | 0.0520 | 0.017 | 3.031 | 0.002 | [0.018, 0.086] |
| XLY(3,8) | 0.0126 | 0.007 | 1.797 | 0.072 | [-0.001, 0.026] |
| XLP(11,2) | 0.0427 | 0.018 | 2.327 | 0.020 | [0.007, 0.079] |
| XLP(4,3) | -0.0311 | 0.018 | -1.725 | 0.085 | [-0.066, 0.004] |
| XLE(7,1) | 0.0105 | 0.010 | 1.020 | 0.308 | [-0.010, 0.031] |
| XLF(5,2) | 0.0689 | 0.011 | 5.993 | 0.000 | [0.046, 0.091] |
| XLV(8,2) | -0.0297 | 0.018 | -1.638 | 0.101 | [-0.065, 0.006] |
| XLI(2,1) | -0.2859 | 0.030 | -9.469 | 0.000 | [-0.345, -0.227] |
| XLI(5,1) | -0.1438 | 0.024 | -5.907 | 0.000 | [-0.192, -0.096] |
| XLB(2,1) | 0.2074 | 0.027 | 7.610 | 0.000 | [0.154, 0.261] |
| XLB(9,3) | -0.0005 | 0.010 | -0.054 | 0.957 | [-0.019, 0.018] |
| XLK(5,1) | 0.0016 | 0.021 | 0.075 | 0.940 | [-0.040, 0.043] |
| XLK(8,2) | 0.0066 | 0.015 | 0.455 | 0.649 | [-0.022, 0.035] |
| XLU(2,1) | 0.0996 | 0.019 | 5.201 | 0.000 | [0.062, 0.137] |
| XLU(7,10) | -0.0143 | 0.008 | -1.908 | 0.056 | [-0.029, 0.000] |
| RMW(1,1) | -0.0950 | 0.036 | -2.672 | 0.008 | [-0.165, -0.025] |
| RMW(12,2) | 0.0740 | 0.024 | 3.040 | 0.002 | [0.026, 0.122] |
| Mom(1,4) | -0.0886 | 0.011 | -7.852 | 0.000 | [-0.111, -0.066] |
| Mom(1,1) | 0.1372 | 0.019 | 7.058 | 0.000 | [0.099, 0.175] |
| ST_Rev(9,3) | 0.0660 | 0.016 | 4.173 | 0.000 | [0.035, 0.097] |
| ST_Rev(10,12) | -0.0265 | 0.006 | -4.159 | 0.000 | [-0.039, -0.014] |
| 3yr_Treasury(1,2) | 0.0007 | 0.000 | 3.885 | 0.000 | [0.000, 0.001] |
| 3yr_Treasury(11,4) | 0.0008 | 0.000 | 4.968 | 0.000 | [0.000, 0.001] |

Table C.3: OLS Regression Results for Dependent Variable XLE
*Training $R^2$ = 0.052, Adjusted $R^2$ = 0.048, Test $R^2$ = 0.002, F-statistic = 16.24 (p<0.001), No. of Observations = 5386*

| **Variable** | **Coefficient** | **Std. Error** | **t-value** | **P>\|t\|** | **[0.025, 0.975]** |
|---|---|---|---|---|---|
| const | -0.0028 | 0.002 | -1.734 | 0.083 | [-0.006, 0.000] |
| XLY(8,2) | -0.0122 | 0.026 | -0.471 | 0.637 | [-0.063, 0.039] |
| XLP(3,3) | 0.0460 | 0.022 | 2.080 | 0.038 | [0.003, 0.089] |
| XLE(6,5) | 0.0240 | 0.007 | 3.245 | 0.001 | [0.010, 0.039] |
| XLE(10,3) | -0.0160 | 0.010 | -1.639 | 0.101 | [-0.035, 0.003] |
| XLF(1,1) | -0.0500 | 0.016 | -3.170 | 0.002 | [-0.081, -0.019] |
| XLF(11,7) | 0.0424 | 0.009 | 4.847 | 0.000 | [0.025, 0.060] |
| XLV(8,2) | 0.0442 | 0.026 | 1.697 | 0.090 | [-0.007, 0.095] |
| XLI(8,2) | 0.0033 | 0.027 | 0.121 | 0.904 | [-0.050, 0.057] |
| XLI(12,4) | -0.0169 | 0.014 | -1.237 | 0.216 | [-0.044, 0.010] |
| XLB(9,3) | -0.0779 | 0.013 | -5.936 | 0.000 | [-0.104, -0.052] |
| XLB(11,11) | 0.0102 | 0.008 | 1.258 | 0.209 | [-0.006, 0.026] |
| XLK(2,2) | 0.0398 | 0.013 | 2.951 | 0.003 | [0.013, 0.066] |
| XLU(4,3) | 0.0817 | 0.016 | 4.964 | 0.000 | [0.049, 0.114] |
| RMW(5,1) | 0.2843 | 0.047 | 5.994 | 0.000 | [0.191, 0.377] |
| Mom(7,1) | 0.0139 | 0.022 | 0.620 | 0.535 | [-0.030, 0.058] |
| ST_Rev(9,1) | -0.0458 | 0.028 | -1.632 | 0.103 | [-0.101, 0.009] |
| ST_Rev(12,11) | 0.0645 | 0.009 | 7.475 | 0.000 | [0.048, 0.081] |
| 3yr_Treasury(1,8) | 0.0005 | 0.000 | 4.493 | 0.000 | [0.000, 0.001] |

Table C.4: OLS Regression Results for Dependent Variable XLF
*Training* $R^2 = 0.090$*, Adjusted* $R^2 = 0.087$*, Test* $R^2 = -1.620$*, F-statistic = 28.94 (p<0.001), No. of Observations = 5575*

| **Variable** | **Coefficient** | **Std. Error** | **t-value** | **P>\|t\|** | **[0.025, 0.975]** |
|---|---|---|---|---|---|
| const | -0.0017 | 0.001 | -1.358 | 0.175 | [-0.004, 0.001] |
| XLY(12,1) | -0.0939 | 0.017 | -5.383 | 0.000 | [-0.128, -0.060] |
| XLP(5,1) | -0.2397 | 0.034 | -6.984 | 0.000 | [-0.307, -0.172] |
| XLE(2,1) | 0.0609 | 0.015 | 3.956 | 0.000 | [0.031, 0.091] |
| XLE(12,11) | 0.0069 | 0.005 | 1.521 | 0.128 | [-0.002, 0.016] |
| XLF(4,1) | 0.0145 | 0.014 | 1.043 | 0.297 | [-0.013, 0.042] |
| XLV(9,1) | -0.0817 | 0.025 | -3.314 | 0.001 | [-0.130, -0.033] |
| XLV(7,3) | 0.2040 | 0.018 | 11.128 | 0.000 | [0.168, 0.240] |
| XLI(2,1) | -0.0322 | 0.023 | -1.400 | 0.162 | [-0.077, 0.013] |
| XLI(12,12) | -0.0264 | 0.006 | -4.368 | 0.000 | [-0.038, -0.015] |
| XLB(5,1) | -0.0307 | 0.020 | -1.561 | 0.119 | [-0.069, 0.008] |
| XLK(8,2) | -0.0865 | 0.013 | -6.514 | 0.000 | [-0.113, -0.060] |
| XLK(9,7) | 0.0239 | 0.006 | 3.943 | 0.000 | [0.012, 0.036] |
| XLU(3,3) | 0.1298 | 0.014 | 9.308 | 0.000 | [0.102, 0.157] |
| RMW(5,2) | 0.0953 | 0.027 | 3.562 | 0.000 | [0.043, 0.148] |
| Mom(2,2) | -0.1457 | 0.022 | -6.745 | 0.000 | [-0.188, -0.103] |
| Mom(3,1) | 0.0308 | 0.027 | 1.130 | 0.258 | [-0.023, 0.084] |
| ST_Rev(4,3) | 0.1472 | 0.017 | 8.462 | 0.000 | [0.113, 0.181] |
| ST_Rev(12,1) | 0.0392 | 0.023 | 1.677 | 0.094 | [-0.007, 0.085] |
| 3yr_Treasury(8,5) | 0.0010 | 0.000 | 7.027 | 0.000 | [0.001, 0.001] |

Table C.5: OLS Regression Results for Dependent Variable XLV
*Training* $R^2$ = 0.069, *Adjusted* $R^2$ = 0.066, *Test* $R^2$ = 0.113, *F-statistic = 18.10 (p<0.001), No. of Observations = 5365*

| **Variable** | **Coefficient** | **Std. Error** | **t-value** | **P>\|t\|** | **[0.025, 0.975]** |
|---|---|---|---|---|---|
| const | 0.0033 | 0.001 | 3.403 | 0.001 | [0.001, 0.005] |
| XLY(9,1) | -0.0184 | 0.019 | -0.962 | 0.336 | [-0.056, 0.019] |
| XLY(8,4) | 0.0224 | 0.007 | 3.016 | 0.003 | [0.008, 0.037] |
| XLP(4,2) | -0.0795 | 0.015 | -5.255 | 0.000 | [-0.109, -0.050] |
| XLP(11,7) | 0.0654 | 0.009 | 6.971 | 0.000 | [0.047, 0.084] |
| XLE(1,1) | 0.0423 | 0.007 | 6.023 | 0.000 | [0.029, 0.056] |
| XLF(8,2) | -0.0149 | 0.012 | -1.225 | 0.220 | [-0.039, 0.009] |
| XLF(12,3) | 0.0206 | 0.006 | 3.472 | 0.001 | [0.009, 0.032] |
| XLV(9,1) | -0.0441 | 0.018 | -2.446 | 0.014 | [-0.079, -0.009] |
| XLI(4,3) | 0.0324 | 0.008 | 3.888 | 0.000 | [0.016, 0.049] |
| XLI(8,2) | 0.0007 | 0.015 | 0.043 | 0.965 | [-0.029, 0.031] |
| XLB(5,1) | -0.0031 | 0.011 | -0.288 | 0.774 | [-0.025, 0.018] |
| XLK(9,1) | 0.0112 | 0.019 | 0.599 | 0.549 | [-0.025, 0.048] |
| XLK(9,9) | -0.0077 | 0.005 | -1.457 | 0.145 | [-0.018, 0.003] |
| XLU(6,2) | 0.0967 | 0.011 | 8.527 | 0.000 | [0.074, 0.119] |
| XLU(6,7) | -0.0457 | 0.007 | -6.188 | 0.000 | [-0.060, -0.031] |
| RMW(10,3) | 0.0527 | 0.018 | 2.931 | 0.003 | [0.017, 0.088] |
| RMW(5,8) | -0.0329 | 0.012 | -2.737 | 0.006 | [-0.056, -0.009] |
| Mom(6,2) | -0.0621 | 0.011 | -5.821 | 0.000 | [-0.083, -0.041] |
| Mom(5,8) | 0.0134 | 0.006 | 2.124 | 0.034 | [0.001, 0.026] |
| ST_Rev(9,3) | 0.0255 | 0.013 | 1.920 | 0.055 | [-0.001, 0.052] |
| ST_Rev(9,6) | 0.0332 | 0.011 | 3.145 | 0.002 | [0.013, 0.054] |
| 3yr_Treasury(1,8) | 0.0002 | 5.85e-05 | 3.140 | 0.002 | [6.9e-05, 0.000] |

Table C.6: OLS Regression Results for Dependent Variable XLI
*Training* $R^2 = 0.072$*, Adjusted* $R^2 = 0.069$*, Test* $R^2 = -0.285$*, F-statistic = 21.14 (p<0.001), No. of Observations = 5449*

| **Variable** | **Coefficient** | **Std. Error** | **t-value** | **P>\|t\|** | **[0.025, 0.975]** |
|---|---|---|---|---|---|
| const | 0.0050 | 0.001 | 4.287 | 0.000 | [0.003, 0.007] |
| XLY(3,1) | 0.1160 | 0.014 | 8.213 | 0.000 | [0.088, 0.144] |
| XLY(6,10) | 0.0250 | 0.006 | 4.182 | 0.000 | [0.013, 0.037] |
| XLP(5,1) | -0.1555 | 0.025 | -6.255 | 0.000 | [-0.204, -0.107] |
| XLP(11,1) | 0.0444 | 0.030 | 1.496 | 0.135 | [-0.014, 0.103] |
| XLE(9,1) | 0.0625 | 0.013 | 4.775 | 0.000 | [0.037, 0.088] |
| XLF(5,2) | 0.0001 | 0.009 | 0.014 | 0.989 | [-0.018, 0.018] |
| XLF(10,12) | -0.0136 | 0.004 | -3.811 | 0.000 | [-0.021, -0.007] |
| XLV(6,4) | 0.0333 | 0.014 | 2.369 | 0.018 | [0.006, 0.061] |
| XLV(11,2) | -0.0100 | 0.016 | -0.645 | 0.519 | [-0.041, 0.021] |
| XLI(9,1) | -0.1111 | 0.021 | -5.215 | 0.000 | [-0.153, -0.069] |
| XLB(11,1) | -0.0168 | 0.017 | -0.991 | 0.322 | [-0.050, 0.016] |
| XLK(8,2) | 0.0073 | 0.012 | 0.626 | 0.531 | [-0.016, 0.030] |
| XLK(9,2) | -0.0106 | 0.012 | -0.908 | 0.364 | [-0.033, 0.012] |
| XLU(6,1) | 0.0520 | 0.017 | 3.076 | 0.002 | [0.019, 0.085] |
| RMW(11,1) | -0.0240 | 0.034 | -0.705 | 0.481 | [-0.091, 0.043] |
| Mom(1,1) | 0.0444 | 0.016 | 2.791 | 0.005 | [0.013, 0.076] |
| ST_Rev(3,1) | 0.1185 | 0.021 | 5.675 | 0.000 | [0.078, 0.159] |
| ST_Rev(10,12) | -0.0161 | 0.006 | -2.763 | 0.006 | [-0.028, -0.005] |
| 3yr_Treasury(2,9) | 0.0000 | 0.000 | 0.386 | 0.699 | [-0.000, 0.000] |
| 3yr_Treasury(9,9) | 0.0003 | 0.000 | 3.750 | 0.000 | [0.000, 0.000] |

Table C.7: OLS Regression Results for Dependent Variable XLB
*Training* $R^2 = 0.080$*, Adjusted* $R^2 = 0.076$*, Test* $R^2 = -0.474$*, F-statistic = 22.36 (p<0.001), No. of Observations = 5449*

| **Variable** | **Coefficient** | **Std. Error** | **t-value** | **P>\|t\|** | **[0.025, 0.975]** |
|---|---|---|---|---|---|
| const | 0.0038 | 0.001 | 2.746 | 0.006 | [0.001, 0.007] |
| XLY(2,2) | 0.0669 | 0.013 | 5.287 | 0.000 | [0.042, 0.092] |
| XLP(5,1) | -0.2259 | 0.025 | -9.083 | 0.000 | [-0.275, -0.177] |
| XLP(11,1) | 0.1105 | 0.026 | 4.312 | 0.000 | [0.060, 0.161] |
| XLE(9,1) | 0.0590 | 0.012 | 4.880 | 0.000 | [0.035, 0.083] |
| XLE(6,8) | -0.0312 | 0.005 | -6.780 | 0.000 | [-0.040, -0.022] |
| XLF(4,3) | 0.0192 | 0.008 | 2.453 | 0.014 | [0.004, 0.035] |
| XLF(9,8) | 0.0344 | 0.006 | 5.589 | 0.000 | [0.022, 0.047] |
| XLV(8,2) | -0.0594 | 0.018 | -3.271 | 0.001 | [-0.095, -0.024] |
| XLI(2,1) | -0.1845 | 0.032 | -5.854 | 0.000 | [-0.246, -0.123] |
| XLB(2,1) | 0.1507 | 0.028 | 5.325 | 0.000 | [0.095, 0.206] |
| XLB(9,3) | -0.0148 | 0.010 | -1.426 | 0.154 | [-0.035, 0.006] |
| XLK(8,2) | 0.0033 | 0.013 | 0.252 | 0.801 | [-0.023, 0.029] |
| XLK(11,9) | -0.0046 | 0.006 | -0.805 | 0.421 | [-0.016, 0.007] |
| XLU(6,1) | 0.0604 | 0.019 | 3.253 | 0.001 | [0.024, 0.097] |
| XLU(6,10) | 0.0225 | 0.009 | 2.651 | 0.008 | [0.006, 0.039] |
| RMW(7,1) | 0.0358 | 0.037 | 0.982 | 0.326 | [-0.036, 0.107] |
| Mom(7,1) | -0.0747 | 0.017 | -4.389 | 0.000 | [-0.108, -0.041] |
| Mom(12,6) | 0.0410 | 0.009 | 4.433 | 0.000 | [0.023, 0.059] |
| ST_Rev(8,5) | 0.0625 | 0.014 | 4.404 | 0.000 | [0.035, 0.090] |
| ST_Rev(10,12) | -0.0097 | 0.008 | -1.255 | 0.210 | [-0.025, 0.005] |
| 3yr_Treasury(2,2) | 0.0014 | 0.000 | 7.358 | 0.000 | [0.001, 0.002] |

Table C.8: OLS Regression Results for Dependent Variable XLRE
*Training* $R^2 = 0.161$, *Adjusted* $R^2 = 0.153$, *Test* $R^2 = -0.197$, *F-statistic = 19.48 (p<0.001), No. of Observations = 1944*

| **Variable** | **Coefficient** | **Std. Error** | **t-value** | **P>\|t\|** | **[0.025, 0.975]** |
|---|---|---|---|---|---|
| const | -0.0102 | 0.002 | -5.485 | 0.000 | [-0.014, -0.007] |
| XLY(8,1) | 0.0459 | 0.022 | 2.107 | 0.035 | [0.003, 0.089] |
| XLY(4,1) | 0.1097 | 0.022 | 4.913 | 0.000 | [0.066, 0.154] |
| XLP(6,2) | 0.1765 | 0.030 | 5.838 | 0.000 | [0.117, 0.236] |
| XLE(1,2) | 0.0045 | 0.010 | 0.425 | 0.671 | [-0.016, 0.025] |
| XLF(1,5) | 0.0036 | 0.012 | 0.295 | 0.768 | [-0.020, 0.027] |
| XLF(9,2) | -0.0136 | 0.019 | -0.722 | 0.470 | [-0.051, 0.023] |
| XLV(10,7) | 0.1229 | 0.020 | 6.061 | 0.000 | [0.083, 0.163] |
| XLV(1,3) | -0.0378 | 0.024 | -1.552 | 0.121 | [-0.085, 0.010] |
| XLI(7,1) | -0.0204 | 0.048 | -0.428 | 0.669 | [-0.114, 0.073] |
| XLB(7,1) | 0.0116 | 0.047 | 0.248 | 0.804 | [-0.080, 0.103] |
| XLB(6,10) | -0.0054 | 0.011 | -0.512 | 0.609 | [-0.026, 0.015] |
| XLRE(2,3) | 0.0182 | 0.018 | 1.003 | 0.316 | [-0.017, 0.054] |
| XLK(10,9) | -0.0035 | 0.011 | -0.331 | 0.741 | [-0.024, 0.017] |
| XLU(7,1) | 0.0256 | 0.030 | 0.849 | 0.396 | [-0.034, 0.085] |
| RMW(11,1) | 0.4438 | 0.053 | 8.344 | 0.000 | [0.339, 0.548] |
| Mom(12,3) | 0.0857 | 0.019 | 4.600 | 0.000 | [0.049, 0.122] |
| ST_Rev(9,2) | 0.0316 | 0.036 | 0.873 | 0.383 | [-0.039, 0.103] |
| ST_Rev(6,5) | 0.1490 | 0.028 | 5.396 | 0.000 | [0.095, 0.203] |
| 3yr_Treasury(9,1) | -0.0005 | 0.001 | -0.927 | 0.354 | [-0.002, 0.001] |

Table C.9: OLS Regression Results for Dependent Variable XLK
*Training $R^2$ = 0.085, Adjusted $R^2$ = 0.082, Test $R^2$ = 0.056, F-statistic = 22.87 (p<0.001), No. of Observations = 5407*

| **Variable** | **Coefficient** | **Std. Error** | **t-value** | **P>\|t\|** | **[0.025, 0.975]** |
|---|---|---|---|---|---|
| const | 0.0177 | 0.001 | 11.966 | 0.000 | [0.015, 0.021] |
| XLY(8,3) | 0.0033 | 0.015 | 0.224 | 0.823 | [-0.026, 0.032] |
| XLP(4,2) | -0.2356 | 0.024 | -9.968 | 0.000 | [-0.282, -0.189] |
| XLP(10,3) | -0.1101 | 0.019 | -5.690 | 0.000 | [-0.148, -0.072] |
| XLE(11,7) | -0.0122 | 0.005 | -2.585 | 0.010 | [-0.021, -0.003] |
| XLF(8,3) | -0.0687 | 0.012 | -5.844 | 0.000 | [-0.092, -0.046] |
| XLV(5,6) | 0.0764 | 0.012 | 6.348 | 0.000 | [0.053, 0.100] |
| XLV(8,12) | -0.0128 | 0.008 | -1.646 | 0.100 | [-0.028, 0.002] |
| XLI(4,2) | 0.0755 | 0.014 | 5.217 | 0.000 | [0.047, 0.104] |
| XLI(9,3) | 0.1967 | 0.020 | 9.889 | 0.000 | [0.158, 0.236] |
| XLB(9,3) | -0.1131 | 0.018 | -6.219 | 0.000 | [-0.149, -0.077] |
| XLK(9,1) | 0.0642 | 0.016 | 3.912 | 0.000 | [0.032, 0.096] |
| XLK(1,9) | -0.0427 | 0.007 | -6.297 | 0.000 | [-0.056, -0.029] |
| XLU(5,3) | 0.0020 | 0.012 | 0.170 | 0.865 | [-0.021, 0.025] |
| XLU(11,2) | -0.0031 | 0.015 | -0.209 | 0.834 | [-0.033, 0.026] |
| RMW(10,2) | -0.0335 | 0.023 | -1.434 | 0.152 | [-0.079, 0.012] |
| RMW(12,12) | 0.0175 | 0.010 | 1.805 | 0.071 | [-0.002, 0.037] |
| Mom(2,7) | -0.0704 | 0.009 | -8.271 | 0.000 | [-0.087, -0.054] |
| Mom(7,1) | -0.0262 | 0.018 | -1.488 | 0.137 | [-0.061, 0.008] |
| ST_Rev(2,1) | 0.0583 | 0.020 | 2.954 | 0.383 | [0.020, 0.097] |
| ST_Rev(10,12) | -0.0352 | 0.007 | -4.809 | 0.000 | [-0.050, -0.021] |
| 3yr_Treasury(1,1) | -0.0012 | 0.000 | -3.001 | 0.003 | [-0.002, -0.000] |
| 3yr_Treasury(11,10) | 0.0002 | 0.000 | 2.650 | 0.008 | [0.000, 0.000] |

Table C.10: OLS Regression Results for Dependent Variable XLU
*Training* $R^2 = 0.056$, *Adjusted* $R^2 = 0.052$, *Test* $R^2 = -0.194$, *F-statistic = 15.27 (p<0.001), No. of Observations = 5449*

| **Variable** | **Coefficient** | **Std. Error** | **t-value** | **P>\|t\|** | **[0.025, 0.975]** |
|---|---|---|---|---|---|
| const | 0.0010 | 0.001 | 0.974 | 0.330 | [-0.001, 0.003] |
| XLY(1,3) | -0.0162 | 0.012 | -1.329 | 0.184 | [-0.040, 0.008] |
| XLY(8,11) | 0.0154 | 0.005 | 2.900 | 0.004 | [0.005, 0.026] |
| XLP(2,2) | 0.0304 | 0.019 | 1.574 | 0.115 | [-0.007, 0.068] |
| XLE(1,6) | -0.0079 | 0.005 | -1.716 | 0.086 | [-0.017, 0.001] |
| XLE(10,1) | 0.0383 | 0.009 | 4.361 | 0.000 | [0.021, 0.056] |
| XLF(1,3) | 0.0312 | 0.011 | 2.894 | 0.004 | [0.010, 0.052] |
| XLF(1,9) | 0.0046 | 0.005 | 0.973 | 0.330 | [-0.005, 0.014] |
| XLV(2,1) | -0.0562 | 0.019 | -2.921 | 0.001 | [-0.094, -0.018] |
| XLV(11,2) | 0.1163 | 0.014 | 8.272 | 0.000 | [0.089, 0.144] |
| XLI(9,1) | 0.0129 | 0.025 | 0.515 | 0.606 | [-0.036, 0.062] |
| XLI(2,3) | 0.0270 | 0.010 | 2.632 | 0.009 | [0.007, 0.047] |
| XLB(9,1) | -0.0262 | 0.023 | -1.122 | 0.262 | [-0.072, 0.020] |
| XLK(12,1) | 0.0403 | 0.014 | 2.821 | 0.005 | [0.012, 0.068] |
| XLK(11,9) | 0.0021 | 0.005 | 0.398 | 0.690 | [-0.008, 0.012] |
| XLU(6,3) | 0.0374 | 0.010 | 3.673 | 0.000 | [0.017, 0.057] |
| XLU(12,1) | -0.0752 | 0.016 | -4.713 | 0.000 | [-0.106, -0.044] |
| RMW(11,1) | 0.2125 | 0.029 | 7.228 | 0.000 | [0.155, 0.270] |
| Mom(5,2) | 0.0012 | 0.011 | 0.115 | 0.909 | [-0.019, 0.022] |
| ST_Rev(2,1) | 0.0807 | 0.019 | 4.300 | 0.000 | [0.044, 0.118] |
| ST_Rev(12,12) | -0.0197 | 0.005 | -3.753 | 0.000 | [-0.030, -0.009] |
| 3yr_Treasury(1,5) | 0.0003 | 0.000 | 2.313 | 0.021 | [0.000, 0.000] |