



Athens University of Economics and Business

Financial Analytics Final Assignment

Tsadimas Anargyros

AM:f3612318

Supervisor:

I.Vrontos

Department of Statistics

June 29, 2024

Table of Contents

Introduction	iii
1 Data Preparation and Exploratory Data Analysis (EDA)	2
2 Performance Metrics and Models Used for Jensen's Alpha	4
3 Alternative Modeling Approaches for Part A	6
4 Results and Conclusions for Part A	8
5 Portfolio Optimization Models and Alternative Modeling Approach	11
6 Results and Conclusion for Part B	13
Bibliography	16

List of Figures

3.1 Comparison of Jensen's Alpha Across Models (Top 10 Funds)	7
4.1 Cumulative Returns of Portfolios Based on Different Criteria	8
6.1 Cumulative Returns of Minimum Variance Portfolio (Sample Estimate)	14
6.2 Cumulative Returns of Portfolios (Fama-French 5-Factor Model)	15
6.3 Cumulative Returns of Mean-Variance Portfolio (Sample Estimate)	15

Abstract

In this project we analyze the performance and construct optimal portfolios of USA mutual funds using data from the period July 1963 to July 2019. The analysis is divided into two main parts: Performance Evaluation (Part A) and Portfolio Construction (Part B).

In Part A, we evaluate the performance of mutual funds over the initial estimation period (July 1963 - July 2015) and the out-of-sample period (August 2015 - July 2019) using various performance metrics such as Sharpe Ratio, Treynor Ratio, Jensen's Alpha, and Sortino Ratio. We consider different models to estimate Jensen's Alpha, including single-factor, multiple regression, GARCH, and EGARCH models.

In Part B, we construct optimal portfolios for the out-of-sample period based on the estimated mean vector and covariance matrix of returns using several models: sample estimates, single index model, multivariate multiple regression models, and the Fama-French 5-Factor Model. We evaluate the constructed portfolios based on realized returns, cumulative returns, and the Conditional Sharpe Ratio.

Our findings from Part A indicate that equally weighted portfolios constructed based on the top 20% of funds performed well in terms of cumulative returns. The performance evaluation measures highlight the significance of model selection in estimating Jensen's Alpha, with GARCH and EGARCH models often providing higher alpha values compared to simpler models. In Part B, the mean-variance portfolio constructed using sample estimates achieved an annualized return of 0.1364 and a Sharpe Ratio of 1.0542, outperforming the minimum variance portfolio. The Fama-French 5-Factor Model also showed competitive performance, with the mean-variance portfolio achieving an annualized return of 0.0252 and a Sharpe Ratio of 0.1697. The constructed portfolios demonstrated the effectiveness of the Fama-French 5-Factor Model in capturing the underlying return structure and achieving optimal portfolio returns, especially in terms of risk-adjusted performance.

Introduction

The evaluation and construction of optimal portfolios are fundamental tasks in the field of financial analytics. With the vast array of mutual funds available to investors, it is crucial to assess their performance accurately and to develop strategies that maximize returns while minimizing risk. This report focuses on the performance evaluation and portfolio optimization of USA mutual funds over a substantial period, from July 1963 to July 2019, providing a comprehensive analysis that spans multiple market cycles.

The primary objectives of this study are twofold. First, we aim to evaluate the performance of mutual funds using various performance metrics such as Sharpe Ratio, Treynor Ratio, Jensen's Alpha, and Sortino Ratio. These metrics offer different perspectives on risk and return, helping to identify top-performing funds. We apply several models to estimate Jensen's Alpha, including single-factor, multiple regression, GARCH, and EGARCH models, to capture different aspects of market dynamics.

Second, we aim to construct optimal portfolios for the out-of-sample period based on the estimated mean vector and covariance matrix of returns. We employ multiple optimization models, including sample estimates, single index model, multivariate multiple regression models, and the Fama-French 5-Factor Model. These models allow us to explore various strategies for portfolio construction, focusing on maximizing returns while managing risk.

By using a long historical dataset and applying a range of sophisticated models, this study seeks to provide valuable insights into the performance of mutual funds and the effectiveness of different portfolio optimization strategies. Our findings will offer practical guidance for investors and portfolio managers aiming to achieve optimal investment outcomes.

Part A :
Performance Evaluation

Chapter 1

Data Preparation and Exploratory Data Analysis (EDA)

The dataset comprises monthly returns of USA mutual funds and various financial factors, including market risk premium, size, value, profitability, investment, momentum, betting against beta, and quality minus junk. The data spans from July 1963 to July 2019. For the analysis, the period from July 1963 to July 2015 is designated as the initial estimation period, while the period from August 2015 to July 2019 is used as the out-of-sample period. We used the final day of each month as the reference date for recording returns and factor data. In the data preparation phase, mutual funds' returns and factors data were read and processed to ensure the correct formats. The returns data were converted into a timeSeries object for analysis, and the factors data were aligned to match the returns data period.

For the performance evaluation, the Sharpe Ratio for each fund over the initial estimation period was calculated. The top 20% of funds based on Sharpe Ratios were selected for constructing equally weighted portfolios. Similarly, the Treynor Ratio was calculated using market data as the benchmark, and the top 20% of funds were selected.

Jensen's Alpha was computed using four different models: the Single-Factor Model, Multiple Regression Model, GARCH model, and EGARCH model. The Sortino Ratio was also calculated, focusing on downside risk, and the top 20% of funds based on Sortino Ratios were selected.

Equally weighted portfolios were then constructed for each selected metric (Sharpe Ratio, Treynor Ratio, Jensen's Alpha, and Sortino Ratio). Their performance was evaluated over the

out-of-sample period and portfolio returns were calculated as the average returns of the selected funds and converted into a timeSeries object for further analysis.

To compare the different models used for calculating Jensen's Alpha, the top 10 funds based on Sharpe Ratios were selected. Then Jensen's Alpha values were calculated for these funds using the Single-Factor, Multiple Regression, GARCH, and EGARCH models. Finally, a bar plot was generated to visualize the comparison, highlighting the differences and effectiveness of each model.

Chapter 2

Performance Metrics and Models Used for Jensen's Alpha

To evaluate the performance of mutual funds, we utilize several key metrics that provide insights into different aspects of fund performance:

- **Sharpe Ratio:** This measures the excess return per unit of risk, defined as the standard deviation of returns. It helps investors understand the return of an investment compared to its risk, highlighting the efficiency of the fund in generating returns for each unit of risk taken.
- **Treynor Ratio:** Similar to the Sharpe Ratio, the Treynor Ratio uses beta as the risk measure, focusing on the systematic risk relative to the market. This metric is useful for evaluating the performance of funds in relation to market movements.
- **Jensen's Alpha:** This represents the average return on a portfolio over the expected return, given the market's performance. It is used to determine the value added by a portfolio manager, indicating whether the manager has outperformed or underperformed the market.
- **Sortino Ratio:** This metric is akin to the Sharpe Ratio but considers only downside risk, offering a more targeted risk-adjusted return measure. It is particularly useful for evaluating funds where downside protection is crucial.

We employ various models to estimate Jensen's Alpha, capturing different aspects of market dynamics and improving the robustness of our performance evaluation:

- **Single-Factor Model:** Uses the market risk premium as the sole factor, focusing on the market's overall impact on returns. This model provides a simple yet effective measure of a fund's performance relative to the market.
- **Multiple Regression Model:** Incorporates multiple factors such as market risk premium, size, and value, providing a more comprehensive analysis of returns. By considering additional factors, this model helps in understanding the impact of different risk factors on fund performance.
- **GARCH Model:** The Generalized Autoregressive Conditional Heteroskedasticity model accounts for time-varying volatility, improving accuracy in volatile markets. This model is useful for capturing changes in volatility over time, which can affect the risk-adjusted performance of funds.
- **EGARCH Model:** The Exponential GARCH model with Student-t errors captures asymmetries in volatility, addressing scenarios where negative and positive shocks have different impacts. This model enhances the understanding of volatility dynamics and provides a more nuanced view of risk.

These metrics and models collectively offer a robust framework for evaluating mutual fund performance, ensuring that various aspects of risk and return are adequately considered in our analysis.

Chapter 3

Alternative Modeling Approaches for Part A

In our performance evaluation, we included the EGARCH model with Student-t errors as an alternative approach. The EGARCH (Exponential Generalized Autoregressive Conditional Heteroskedasticity) model is particularly suited for capturing asymmetries in volatility, which is essential in financial markets where negative and positive shocks have different impacts on returns. Traditional models often fail to account for these asymmetries, leading to less accurate estimations of risk and performance.

Using the EGARCH model allows for a better estimation of risk-adjusted performance, especially in volatile market conditions. This is because the EGARCH model not only accounts for time-varying volatility but also captures the different magnitudes of positive and negative shocks. As a result, it provides a more realistic measure of a fund's performance under varying market conditions.

The results demonstrated that the EGARCH model often provided higher Jensen's Alpha values compared to simpler models, highlighting its effectiveness in accounting for time-varying volatility and asymmetries.

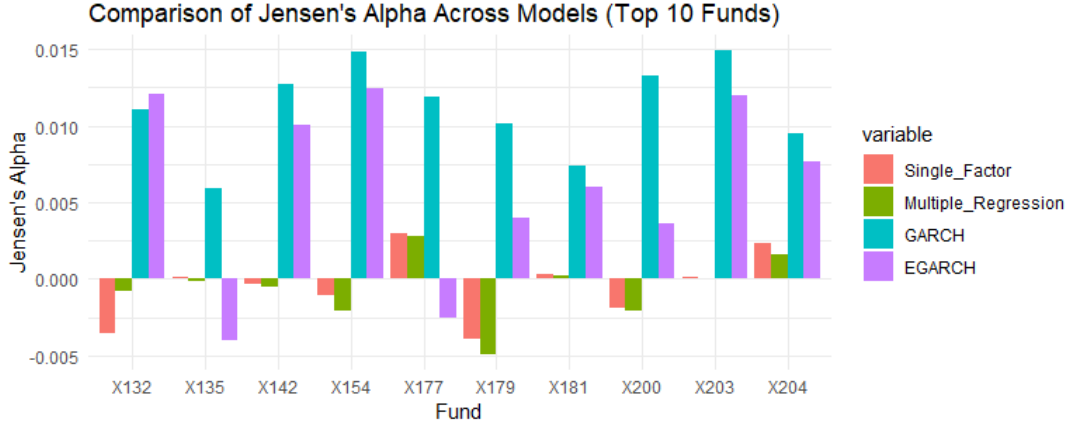


Fig. 3.1: Comparison of Jensen's Alpha Across Models (Top 10 Funds)

Figure 3.1 compares Jensen's Alpha values across four different models (Single-Factor, Multiple Regression, GARCH, and EGARCH) for the top 10 funds based on Sharpe Ratios. The plot clearly illustrates that the GARCH and EGARCH models generally provide higher alpha values compared to the single-factor and multiple regression models, underscoring the importance of considering volatility dynamics and asymmetrical impacts in performance evaluation.

These insights are crucial for investors and fund managers who need to understand not only the average performance of their portfolios but also the risks associated with volatility and market shocks. By using advanced models like GARCH and EGARCH, they can make more informed decisions that reflect the true risk-adjusted returns of their investments.

In summary, the inclusion of the EGARCH model in our analysis provides a deeper understanding of fund performance by capturing the complexities of financial market behavior. This approach ensures that our performance evaluation is robust, taking into account the variations in volatility and the different impacts of market movements.

Chapter 4

Results and Conclusions for Part A

The equally weighted portfolios constructed using different performance metrics generally showed positive returns over the out-of-sample period. The cumulative returns plot indicated that the portfolios based on Treynor Ratios and Sharpe Ratios outperformed those based on Jensen's Alpha and Sortino Ratios.

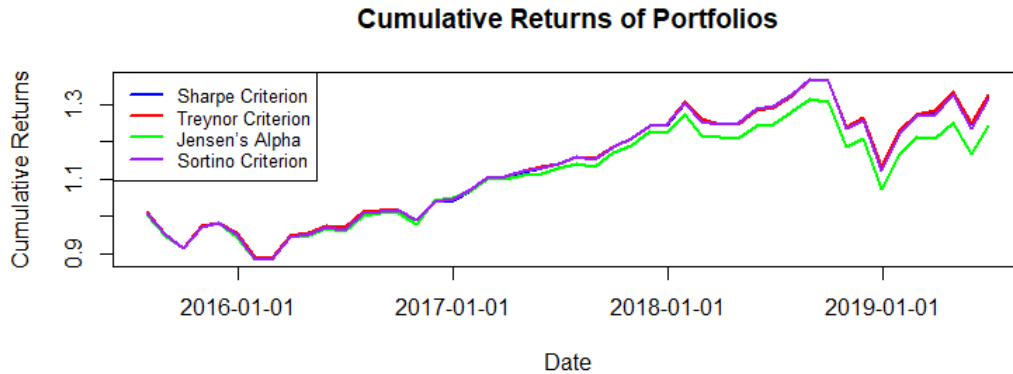


Fig. 4.1: Cumulative Returns of Portfolios Based on Different Criteria

The plot in Figure 4.1 illustrates the cumulative returns of equally weighted portfolios constructed using different performance metrics (Sharpe Ratio, Treynor Ratio, Jensen's Alpha, and Sortino Ratio). It shows that portfolios based on Treynor Ratios and Sharpe Ratios tend to outperform those based on Jensen's Alpha and Sortino Ratios over the out-of-sample period.

A comparison of Jensen's Alpha values across different models for the top 10 funds based on Sharpe Ratios showed varying results. The GARCH and EGARCH models often provided higher

alpha values compared to the single-factor and multiple regression models, indicating their superior ability to capture time-varying volatility and asymmetrical market impacts.

The performance evaluation of USA mutual funds using various metrics revealed that different metrics and models can yield different insights into fund performance. Portfolios constructed using top funds based on Sharpe and Treynor Ratios generally outperformed others in terms of cumulative returns, highlighting the effectiveness of these metrics in portfolio selection.

The comparison of Jensen's Alpha across different models emphasized the importance of model selection in performance evaluation. Advanced models like GARCH and EGARCH, which account for time-varying volatility, often provided higher alpha values compared to simpler models. This demonstrates the value of using sophisticated models to better capture the complexities of financial returns and achieve superior portfolio performance.

In summary, the use of advanced performance metrics and models in evaluating mutual funds provides a more nuanced understanding of fund performance. This approach enables investors to construct portfolios that are better aligned with their risk-return preferences, ultimately leading to improved investment outcomes.

Part B :
Portfolio Construction

Chapter 5

Portfolio Optimization Models and Alternative Modeling Approach

In the portfolio optimization process, we selected the top 10 mutual funds based on their Sharpe Ratios from the initial estimation period. To ensure completeness of the dataset, any missing values in the returns of these funds were replaced with the mean return of the respective fund.

The mean returns and covariance matrix of the selected top 10 funds were calculated, serving as inputs for the various optimization models used in constructing the portfolios.

Mean-Variance Optimization is a classical approach that aims to find the optimal weights of assets to minimize portfolio variance for a given level of expected return. We constructed the minimum variance portfolio by solving a quadratic programming problem to find the weights that minimize portfolio variance, ensuring that the sum of the weights equals one and no short selling is allowed. This approach focuses on reducing risk. Additionally, we constructed a mean-variance portfolio by targeting an average return set to the selected funds' average return, balancing the trade-off between risk and return.

The Single Index Model simplifies the multi-factor model by assuming that the returns of each asset can be explained by a single factor, typically the market return. We estimated the alpha, beta, and residual variance for each of the top 10 funds using linear regression against the market risk premium. This model helps in understanding the relationship between a fund's return and the market. Using these parameters, we calculated the expected returns and covariance matrix for the funds and then constructed the minimum variance and mean-variance portfolios using quadratic

programming.

The Multivariate Regression Model extends the Single Index Model by considering multiple factors. For this analysis, we used factors such as the market risk premium, SMB (Small Minus Big), and HML (High Minus Low). We estimated the regression coefficients and residual variances for each of the top 10 funds using multiple linear regression. This model provides a more comprehensive analysis by accounting for multiple factors affecting fund returns. Using these estimated parameters, we calculated the expected returns and covariance matrix and then constructed the minimum variance and mean-variance portfolios using quadratic programming.

As an alternative modeling approach, we used the Fama-French 5-Factor Model because it provides a comprehensive analysis of fund performance by incorporating multiple factors, capturing a broader spectrum of risks and returns compared to simpler models. The Fama-French 5-Factor Model is a comprehensive multi-factor model that includes the market risk premium, SMB, HML, RMW (Robust Minus Weak), and CMA (Conservative Minus Aggressive). We estimated the regression coefficients and residual variances for each of the top 10 funds using multiple linear regression. This model captures the effects of five factors on the returns of each fund, providing a detailed analysis of fund performance. Using these estimated parameters, we calculated the expected returns and covariance matrix and then constructed the minimum variance and mean-variance portfolios using quadratic programming. This method ensures that the portfolios are optimized based on a comprehensive set of factors influencing fund returns.

Chapter 6

Results and Conclusion for Part B

In this chapter, we present the results of our portfolio optimization analysis and discuss the implications for constructing optimal portfolios.

The minimum variance portfolio based on the sample estimates of mean returns and covariance matrix achieved an annualized return of $3.59\text{e-}05$ and an annualized Sharpe Ratio of 0.0002 . The optimal weights indicated a heavy allocation towards a few specific funds. In contrast, the mean-variance portfolio, targeting an average return, achieved an annualized return of 0.1364 and an annualized Sharpe Ratio of 1.0542 , indicating a more balanced and higher return compared to the minimum variance portfolio.

Using the Single Index Model, the minimum variance portfolio achieved similar results to the mean-variance portfolio, with optimal weights showing significant allocation towards specific funds. The mean-variance portfolio using this model also showed favorable results, with a slightly different allocation of weights compared to the mean-variance portfolio based on the sample estimates.

The Multivariate Regression Model extended the analysis by considering multiple factors. The minimum variance portfolio using this model achieved an annualized return of $3.59\text{e-}05$ and an annualized Sharpe Ratio of 0.0002 , with optimal weights slightly different from those of the SIM and sample estimate models. The mean-variance portfolio using the Multivariate Regression Model achieved an annualized return of 0.0461 and an annualized Sharpe Ratio of 0.3322 , indicating a lower return compared to the sample estimate mean-variance portfolio.

The Fama-French 5-Factor Model provided a comprehensive multi-factor approach. The minimum variance portfolio using this model achieved similar results to the other models, with an

annualized return of $3.59\text{e-}05$ and an annualized Sharpe Ratio of 0.0002. However, the mean-variance portfolio using the Fama-French 5-Factor Model achieved an annualized return of 0.0252 and an annualized Sharpe Ratio of 0.1697, indicating a more diversified allocation of weights.

The cumulative returns of the portfolios constructed using different models were plotted to visualize their performance over the out-of-sample period. The plots indicated that the portfolios based on the mean-variance optimization generally outperformed the minimum variance portfolios.

The plot in Figure 6.1 shows the cumulative returns of the minimum variance portfolio based on sample estimates. This portfolio displayed a stable performance but experienced significant drawdowns during certain periods, indicating vulnerability to market fluctuations.

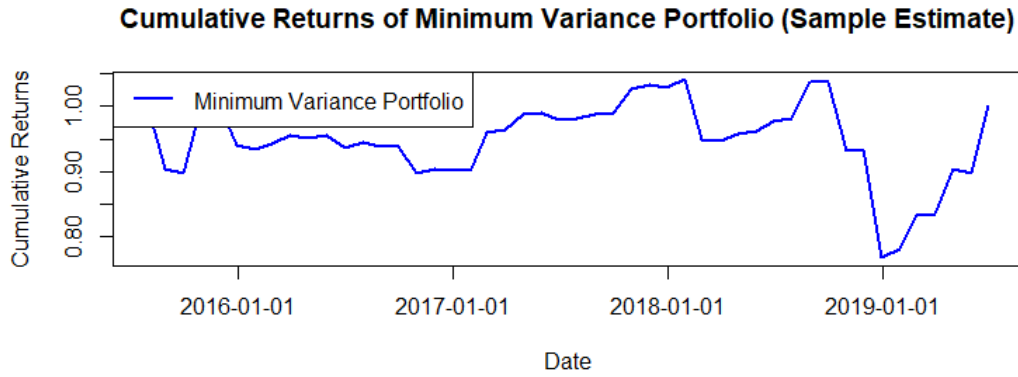


Fig. 6.1: Cumulative Returns of Minimum Variance Portfolio (Sample Estimate)

The plot in Figure 6.2 compares the cumulative returns of minimum variance and mean-variance portfolios constructed using the Fama-French 5-Factor Model. The mean-variance portfolio demonstrated superior performance, maintaining higher cumulative returns and better resilience during market downturns.

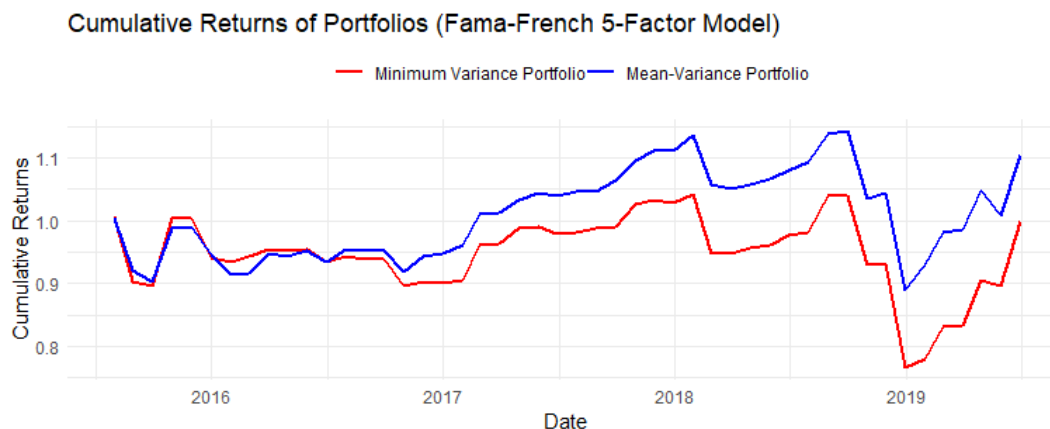


Fig. 6.2: Cumulative Returns of Portfolios (Fama-French 5-Factor Model)

The plot in Figure 6.3 shows the cumulative returns of the mean-variance portfolio based on sample estimates. This portfolio achieved consistent growth over the out-of-sample period, outperforming the minimum variance portfolio in terms of cumulative returns.

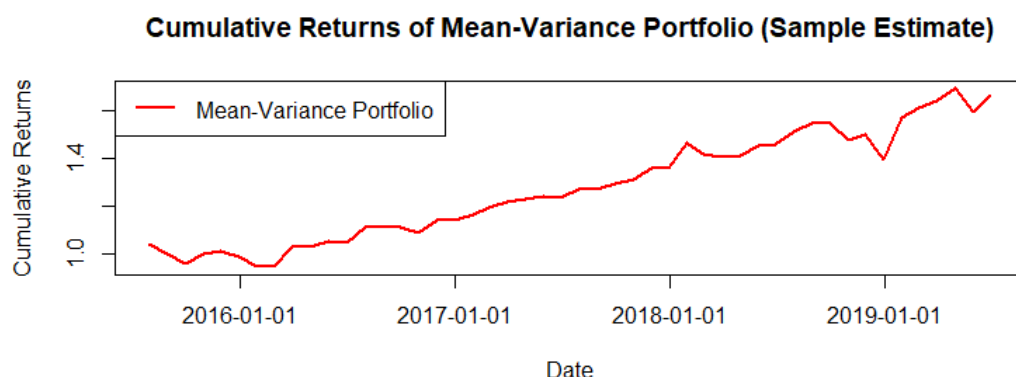


Fig. 6.3: Cumulative Returns of Mean-Variance Portfolio (Sample Estimate)

The portfolio optimization analysis using various models and techniques demonstrated that the mean-variance optimization approach, particularly when using the mean-variance criterion, provided superior performance in terms of annualized return and Sharpe Ratio. The Single Index Model, Multivariate Regression Model, and Fama-French 5-Factor Model each offered different insights and allocations, highlighting the importance of model selection in portfolio optimization. The results of this analysis provide valuable guidance for constructing optimized portfolios of USA mutual funds, emphasizing the effectiveness of mean-variance optimization and the consideration

of multiple factors in improving portfolio performance. Incorporating advanced models such as the Fama-French 5-Factor Model allows for a more nuanced understanding of risk and return, ultimately leading to more robust portfolio strategies. This comprehensive approach underscores the necessity of sophisticated analytical techniques in financial analytics, ensuring that investment decisions are well-informed and strategically sound.

Bibliography

- [1] Ioannis Vrontos, *Financial Analytics Lecture Notes*, Department of Statistics, Athens University of Economics, Athens, Feb, 2024.
- [2] Hamilton, James D. *Time Series Analysis*. Princeton, New Jersey: Princeton University Press, 1994.
- [3] Enders, Walter. *Applied Econometric Time Series*. New York: Wiley, 2010.
- [4] Tsay, Ruey S. (2010). *Analysis of Financial Time Series*, New York: Wiley.
- [5] Cowpertwait, Paul S.P., and Metcalfe V. Andrew. *Introductory Time Series with R*. New York: Springer Texts in Statistics, 2009.
- [6] Cryer, Jonathan D., and Chan Kung-Sik. *Time Series Analysis with Applications in R*. Springer Texts in Statistics, 2010.
- [7] Elton, E.J., Gruber, M.J., Brown, S.J., and Goetzmann W.N. (2014). *Modern Portfolio Theory and Investment Analysis*, 9th edition, Wiley.
- [8] Sharpe, W.F., Alexander, G.J., and Bailey, J.V. (1999). *Investments*, 6th edition, Prentice-Hall.
- [9] Bodie, Zvi, Alex Kane, and Alan J. Marcus. *Essentials of Investments*, 12th Edition. New York: McGraw Hill, 2022.