Risk Modeling and Optimization of a Diversified Portfolio: Financial Services, Technology, and Real Estate Sectors

Sokpheanal Huynh[1]

[1] Harrisburg University of Science and Technology

Author Note

Correspondence concerning this article should be addressed to Sokpheanal Huynh, 326 Market St, Harrisburg, PA 17101. E-mail: shuynh@myhu.harrisburgu.edu

Abstract

This paper explores quantitative portfolio management strategies focusing on equally weighted and risk-parity approaches. The study evaluates sector performance across Technology, Financial Services, and Real Estate by analyzing cumulative returns and risk-return trade-offs. Intra-sector and inter-sector correlations are assessed to understand diversification benefits, and sector-level risk is compared using tail risk analysis via Extreme Value Theory (EVT). The study employs ARIMA models to forecast returns for individual securities, comparing accuracy across sectors, and revealing how different sectors respond to market conditions. Portfolio optimization is achieved using the Markowitz mean-variance model, allowing for optimized security weights calculation, and robust methods are applied to enhance portfolio resilience. The impact of market volatility is incorporated, providing a comprehensive view of the risks and rewards associated with different portfolio strategies. The findings provide practical insights into optimizing portfolios through statistical and machine learning techniques, helping investors make data-driven decisions in volatile markets. Visualizations clarify sector dynamics and highlight key performance trends, guiding investment strategy development.

Keywords: Risk, ARIMA, EVT, Markowits Mean-Variance Optimization, Suitable Distribution for Returns

Word count: 161

Risk Modeling and Optimization of a Diversified Portfolio: Financial Services, Technology, and Real Estate Sectors

Contents

In today's dynamic financial landscape, portfolio management strategies have evolved to incorporate advanced statistical methods and machine learning techniques. Investors and portfolio managers constantly seek methods that balance risk and return, enhancing portfolio performance across different market sectors. Traditional approaches, such as equally-weighted portfolios, have been complemented by sophisticated techniques like risk-parity and mean-variance optimization, which account for sector-specific risk exposures and volatility patterns.

This paper aims to explore and compare two prominent portfolio strategies—equally weighted and risk-parity—by assessing their cumulative returns, sector correlation, and risk-return trade-offs. It delves into sector-specific analyses across Technology, Financial Services, and Real Estate, evaluating their risk profiles and correlation structures. In addition to traditional measures, tail risk is quantified using Extreme Value Theory (EVT) to provide insights into the impact of rare, extreme market events.

Furthermore, the study incorporates ARIMA-based return forecasting for individual securities within each sector, allowing for a comprehensive evaluation of forecast accuracy and its implications for sector performance. The results of these analyses form the basis for portfolio optimization, with a focus on short selling and robust optimization techniques to enhance portfolio resilience under volatile market conditions.

In analyzing portfolio returns, identifying a suitable distribution for returns is critical for effective risk modeling. Traditional models often assume that asset returns follow a normal distribution, but empirical evidence suggests that financial returns typically exhibit fat tails and skewness that normal distributions cannot capture. This study investigates the suitability of Generalized Hyperbolic (GHYP) and Normal Inverse Gaussian (NIG) distributions for modeling the returns of individual securities in the portfolio. By fitting these distributions to the return series of securities from the Financial Services, Technology, and Real Estate sectors, the study aims to provide a more accurate representation of risk, particularly during extreme market conditions. The use of fat-tailed distributions like GHYP allows for better modeling of extreme events, which is essential for risk management and portfolio optimization in volatile markets. This approach enhances the ability to forecast and manage risks, improving the robustness of the portfolio in response to tail events.

By leveraging quantitative tools and machine learning, this research provides actionable insights into optimizing portfolios, helping investors make data-informed decisions in a constantly evolving market environment.

Methods

This study utilizes a combination of quantitative tools, time series analysis, and portfolio optimization methods to evaluate and compare various portfolio strategies. The following steps outline the methods employed in each section of the analysis:

The analysis focuses on six securities representing three sectors: Financial Services (JPM, GS), Technology (AMZN, NVDA), and Real Estate (CCI, AMT). Historical adjusted closing prices were obtained using the `quantmod` package in R. Returns for individual securities were calculated based on the log difference of daily adjusted closing prices.

Two portfolio strategies were compared: Equally Weighted and Risk-Parity. The Equally Weighted strategy allocates equal weights to each security, while the Risk-Parity strategy adjusts the weights to equalize the risk contribution of each asset. Cumulative returns were calculated for both strategies to assess performance over time.

Sector correlations were computed using the correlation matrix of returns within and across sectors. Intra-sector and inter-sector correlations were visualized using correlation matrices and scatter plots. The average correlation for each sector was computed to assess the relationship between securities within each sector.

The risk associated with each sector was quantified using the standard deviation of returns. Tail risk was evaluated using Extreme Value Theory (EVT) to estimate the portfolio's exposure to rare, extreme market events. The fExtremes, evir, and ismev packages in R were used to fit generalized extreme value (GEV) distributions to sector returns.

ARIMA models were applied to individual securities using the forecast package in R to predict future returns. The model order (1,1,1) was manually selected based on stationary and residual analysis. Forecasts were evaluated by calculating accuracy metrics such as RMSE, MAE, and MAPE for each sector.

Markowitz Mean-Variance Optimization was performed using the quadprog package to compute optimized portfolio weights, with the option to allow for short selling (negative weights). Sector-level weights were calculated by aggregating the optimized weights of individual securities within each sector.

The risk-return trade-off was visualized by plotting the standard deviation (risk) against the mean return for each sector, enabling comparison between the Technology, Real Estate, and Financial Services sectors.

To identify the most suitable distribution for the returns of individual securities, Generalized Hyperbolic (GHYP) and Normal Inverse Gaussian (NIG) distributions will be fitted. Each security's return series will be analyzed using these fat-tailed distributions to better capture the skewness and kurtosis often observed in financial data. The fitting process was performed using the `fit.ghypuv()` and `fit.NIGuv()` functions, which estimate the parameters of these distributions. The goodness of fit was evaluated by comparing the empirical distribution of returns to the theoretical distributions. These models allow for more accurate representations of asset return behavior, particularly in capturing tail risks that are not well-modeled by normal distributions. The use of these methods ensures a more realistic understanding of risk, which is crucial for portfolio optimization and risk management.

Data Analytics Plan

1. Data Manipulation Using Security Prices:

- The raw stock prices for JPM, GS, AMZN, NVDA, CCI, and AMT will be collected and manipulated into returns data. This involves calculating daily and monthly price returns for each stock.
- R Tools: `quantmod`, `xts`

2. Calculating Individual Security Returns:

- Daily returns for each security will be computed from price data. These returns will serve as the basis for further risk and return analysis.
- R Tools: `quantmod`, `xts`

3. Calculating Portfolio Returns:

- The returns for the overall portfolio will be calculated using both equal weights and optimized weights (derived from Markowitz mean-variance optimization).
- R Tools: `quantmod`, `xts`

4. Analyzing Portfolio Risks:

- The portfolio's risk will be assessed using standard deviation (volatility), Value at Risk (VaR), and Conditional Value at Risk (CVaR).
- R Tools: `xts`

5. Finding Suitable Distribution for Returns:

- The distribution of stock and portfolio returns will be tested to identify the best-fitting distribution. The goodness of fit will be evaluated to select an appropriate model.
- R Tools: `FRAPO`, `ghyp`, `timeSeries`, `fBasics`

6. Checking through Extreme Value Theory (EVT):

- Using EVT, the tail risk of the portfolio will be assessed. EVT will be used to evaluate the portfolio's exposure to extreme losses in rare market events.
- R Tools: `fExtremes`, `evir`, `ismev`

7. Create ARIMA Models:

- ARIMA models will be applied to forecast returns for each sector. Comparisons will be made to see how well the ARIMA model predicts returns for Financial Services, Technology, and Real Estate sectors, and their forecast accuracy will be evaluated.
- R Tools: `forecast`, `tseries`

8. Optimize the Portfolio Using the Markowitz Mean-Variance Optimization:

- The portfolio will be optimized to maximize return for a given level of risk. Mean-variance optimization will be applied to calculate the optimal portfolio weights.
- R Tools: `zoo`, `quadprog`

9. Find the Suitable Distribution for Returns:

- The distribution of each security's returns will be fitted using the Generalized Hyperbolic (GHYP) and Normal Inverse Gaussian (NIG) distributions to better capture the characteristics of fat tails and skewness in financial returns. The goodness of fit will be assessed to select the most appropriate model for each security's returns.
- R Tools: `FRAPO`, `ghyp`, `fBasics`, `timeSeries`

Data

The dataset used in this analysis consists of the adjusted closing prices of six publicly traded stocks from three different sectors: Financial Services, Technology, and Real Estate. These sectors are represented by the following stocks:

Financial Services

- JPMorgan Chase & Co. (JPM)
- Goldman Sachs Group, Inc. (GS)

Technology

- Amazon.com, Inc. (AMZN)
- NVIDIA Corporation (NVDA)

Real Estate

- Crown Castle Inc. (CCI)
- American Tower Corporation (AMT)

Each stock's adjusted closing prices were sourced using the R package `quantmod`, which provides a streamlined method of retrieving financial data directly from sources such as Yahoo Finance. The data spans a multi-year period, with daily frequency, capturing the price movements and volatility of the stocks within their respective sectors.

Adjusted Closing Price: The adjusted closing price reflects the stock's closing price, taking into account all corporate actions, such as dividends and stock splits, making it a more accurate reflection of the stock's value over time.

Daily Returns: From the adjusted closing prices, daily log returns were calculated. These represent the percentage change in stock prices from one day to the next and are a key metric used in portfolio analysis, risk assessment, and forecasting.

Sector Groupings

Financial Services Sector: Consists of JPM and GS, two major banks in the U.S., both of which are highly liquid and prone to market shifts based on macroeconomic factors such as interest rates and banking regulations.

Technology Sector: Includes AMZN and NVDA, two dominant players in e-commerce and semiconductor industries, respectively. Their returns are influenced by technological advancements, market demand, and competitive landscapes.

Real Estate Sector: Comprised of CCI and AMT, two large real estate investment trusts (REITs) focused on communication infrastructure. They are sensitive to interest rates and real estate market trends.

This dataset is utilized for various analyses including portfolio strategy comparisons, sector correlation studies, risk assessments, and forecasting future returns based on historical performance. Each stock's data will be used to construct cumulative returns, perform sector-level analyses, and apply advanced statistical methods such as ARIMA for forecasting.

Time Scope

The time frame for this study will span from December 1st, 2015, to September 21st,

2024. However, we will use the risk-free rate of 4.53% (Board, 2024) September 23rd, 2024, as the original end date was a Saturday. This period covers multiple economic cycles, including the impact of the COVID-19 pandemic, giving the analysis insight into how each sector and security performs during different macroeconomic conditions.

Data Description

The individual securities' data will be downloaded using the `quantmod` package as time series. Each security will each have 2,216 observations, six attributes; Open, High, Low, Close, Volume, and Adjusted. All prices are of numeric data type. For the analysis, Adjusted Price will be used.

Results

Portfolio Strategies Return Comparison

Figure 1 illustrates the cumulative returns for two portfolio strategies: Equally Weighted and Risk Parity. Both strategies demonstrated steady growth over the analyzed period, with the Equally Weighted portfolio slightly outperforming the Risk Parity portfolio. The final cumulative returns presented in Table 2 show that the Equally Weighted strategy achieved a return of 6.93%, while the Risk Parity strategy yielded a return of 6.82%.

Correlations

Intra-sector correlations, depicted in Figure 2 and summarized in Table 3, reveal that Real Estate had the highest average correlation (0.83), followed by Financial Services (0.82) and Technology (0.54). These values suggest strong within-sector relationships, especially in Real Estate and Financial Services.

Figure 3 and Table 4 highlight the inter-sector correlations. The Financial Services and Technology sectors had a moderate correlation (0.41), while Real Estate exhibited weaker correlations with both Financial Services (0.35) and Technology (0.33). These results indicate diversification potential across sectors, especially when combining Technology with Real Estate or Financial Services.

Risk and Tail Risk Analysis

Table 5 shows the sector risk values, with Technology having the highest standard deviation (0.02304), followed by Financial Services (0.01720) and Real Estate (0.01545). Tail risk, assessed via Value at Risk (VaR) and Conditional Value at Risk (CVaR), is presented in Tables 6 and 7. Technology exhibited the highest VaR (0.03706) and CVaR (0.05241), indicating greater exposure to extreme losses compared to other sectors.

ARIMA Forecasting Accuracy

The accuracy of ARIMA forecasts for individual securities is shown in Tables 12 to 17. Across sectors, the training set errors (e.g., RMSE, MAE) demonstrate varying degrees of forecast accuracy. For example, Amazon (AMZN) in the Technology sector achieved an RMSE of 2.41, while JPMorgan (JPM) in Financial Services had an RMSE of 1.83, indicating relatively better forecast performance for Financial Services.

Risk-Return Trade-Off

The risk-return trade-off, as depicted in Figure 4, shows that Real Estate exhibited the lowest risk, with a standard deviation of 0.01545, while Technology had the highest risk (0.02304). However, in high-volatility periods (Table 18), both Technology and Financial Services showed negative returns, whereas Real Estate maintained a positive, albeit minimal, return. Real Estate, understandably, also has the lowest risk during periods of high volatility (0.03045).

Portfolio Optimization by Makowitz Mean-Variance Method

The optimized portfolio weights, calculated using Markowitz Mean-Variance Optimization, are shown in Table 10. The optimization allocated the largest weight to

JPMorgan (37.21%), with notable negative weights in Goldman Sachs (-7.48%) indicating a short position. Sector-level weights (Table 11) were also optimized, with Real Estate receiving the highest allocation (38.41%) and Financial Services the lowest (29.74%).

Suitable Distribution for Returns

The plots provided in Figures 9 through 14 show the comparison of two fitted distributions: the Generalized Hyperbolic (GHYP) and the Normal Inverse Gaussian (NIG) for the returns of each security (JPM, GS, NVDA, AMZN, AMT, and CCI).

JPM Suitable Distribution (Figure 9) shows the returns for JPM fit well with both GHYP and NIG distributions, though the GHYP model provides a slightly better fit in capturing the tail behavior, which is crucial for risk modeling. GS Suitable Distribution (Figure 10) shows that for GS, both distributions seem to follow the central tendencies well, but the NIG distribution appears to under-perform in the tails compared to GHYP. This suggests GHYP may be more effective in modeling extreme events for GS.

NVDA Suitable Distribution (Figure 11) is similar to GS. NVDA's return distribution demonstrates that GHYP performs better at capturing the distribution's tails, indicating its strength in modeling risks in highly volatile stocks like NVDA. AMZN returns are best captured by the GHYP distribution, with both models aligning in the central distribution but GHYP showing better tail behavior Figure 12.

Figure 13 - AMT Suitable Distribution shows that for AMT, both GHYP and NIG seem to perform comparably in the central region, with GHYP slightly better in capturing the extremes. CCI Suitable Distribution (Figure 14) shows the distribution of returns for CCI is similarly modeled better by GHYP compared to NIG, especially in the tails, which is important for assessing risk. In summary, for all securities, GHYP consistently outperforms NIG in capturing the tail risks, which are vital for portfolio risk management. This demonstrates GHYP's utility in providing a more robust representation of returns, particularly in extreme market conditions.

Discussion

The analysis provided several key insights into the performance, risk, and optimization of a diversified portfolio consisting of Financial Services, Technology, and Real Estate sectors.

Among the three sectors, the Technology sector exhibited the highest risk with a standard deviation of 0.02304, as detailed in Table 5. This higher level of volatility is consistent with the sector's exposure to innovation cycles, market competition, and regulatory pressures. The Real Estate sector, in contrast, showed the lowest risk, making it a more stable component of the portfolio during the assessment period.

Optimization with Robust Methods: Using Markowitz mean-variance optimization, the highest portfolio weight was allocated to JPMorgan (JPM) in the Financial Services sector, while Goldman Sachs (GS) received a negative weight, indicating a short position. The optimized sector-level weights, as seen in Table 11, show that Real Estate received the highest allocation (38.41%), followed by Technology and Financial Services. These results suggest that, given the portfolio's risk-return profile, Real Estate was favored for its stability, while short-selling GS helped to balance the portfolio.

Correlation analysis revealed that Financial Services stocks (JPM and GS) had a higher intra-sector correlation of 0.82 (Table 3) compared to Technology (AMZN, NVDA) and Real Estate (CCI, AMT). This stronger correlation indicates that the Financial Services sector was more internally homogeneous, which could affect diversification strategies within the sector. Inter-sector correlations (Table 4) show that Technology and Real Estate had weaker correlations with Financial Services, suggesting that diversification benefits can be achieved by combining sectors.

The Technology sector, despite its higher risk, provided higher potential returns compared to Real Estate (Figure 4). However, the Sharpe ratios in Table 9 indicate that Real Estate had a more favorable risk-return trade-off than Technology, making it an attractive sector for risk-averse investors.

During periods of high market volatility, both the Technology and Financial Services sectors experienced negative returns, whereas Real Estate demonstrated resilience by maintaining positive returns (Table 18). This reinforces the view that Real Estate offers more stability in turbulent markets, while Technology and Financial Services are more vulnerable to market fluctuations.

The equally weighted portfolio slightly outperformed the risk-parity portfolio in terms of cumulative returns (Table 2). However, the risk-parity approach provided more stable returns with reduced volatility, indicating that it might be more suitable for risk-averse investors who prioritize stability over higher returns.

Extreme Value Theory (EVT) and Conditional Value at Risk (CVaR) results (Tables 6 and 7) showed that the Technology sector had the highest tail risk, meaning it is more susceptible to extreme losses. This is consistent with its higher volatility. Real Estate, once again, had the lowest tail risk, demonstrating its strength in minimizing exposure to rare, extreme market events.

The ARIMA models applied to forecast returns revealed varying levels of accuracy across sectors. Financial Services had relatively better predictive performance with lower RMSE values compared to Technology and Real Estate (Tables 12–17). This suggests that Financial Services returns are more predictable, while Technology and Real Estate may require more sophisticated models for accurate forecasting.

In this study, the suitability of return distributions was explored to better capture the underlying characteristics of financial returns, particularly the presence of fat tails and skewness, which are commonly observed in financial data. Using Generalized Hyperbolic (GHYP) and Normal Inverse Gaussian (NIG) distributions, the return data was fitted for each security across the portfolio. The results revealed that both GHYP and NIG distributions provided a better fit compared to the traditional normal distribution, particularly for securities exhibiting higher levels of volatility. For example, securities in the Technology and Real Estate sectors demonstrated pronounced tail behavior, underscoring the importance of using flexible distribution models. The findings suggest that models assuming normally distributed returns may underestimate extreme movements in stock prices, potentially leading to sub-optimal risk management strategies. By incorporating these more sophisticated distributions, the analysis accounted for extreme market events more accurately, improving the overall robustness of the portfolio's risk assessment.

Conclusion

This study explored the performance and risk of a diversified portfolio composed of stocks from the Financial Services, Technology, and Real Estate sectors, utilizing various quantitative methods including portfolio optimization, risk analysis, and forecasting. Through the integration of tools like Markowitz mean-variance optimization, Extreme Value Theory (EVT), and ARIMA modeling, the analysis provided valuable insights into the dynamics of sector-specific returns and risks.

Key findings revealed that the Technology sector, while offering the potential for higher returns, also carried the highest risk, as evidenced by its elevated volatility and tail risk. In contrast, the Real Estate sector demonstrated stability and lower risk exposure, making it an attractive option for conservative investors, particularly during periods of high market volatility. Financial Services stocks showed strong intra-sector correlations, impacting diversification opportunities within the sector.

The optimized portfolio favored a higher allocation to Real Estate and recommended a short position in Goldman Sachs (GS) to mitigate risk, demonstrating the effectiveness of robust optimization methods. Moreover, the equally weighted portfolio strategy slightly outperformed the risk-parity portfolio in terms of returns, although the latter offered more stability.

Forecasting efforts using ARIMA models highlighted that Financial Services returns were more predictable compared to the more volatile Technology and Real Estate sectors. These findings emphasize the importance of sector-specific strategies in portfolio management and the need for a balanced approach to maximize returns while mitigating risks in varying market conditions.

One of the key contributions of this study was identifying the suitable distribution for returns. By fitting Generalized Hyperbolic (GHYP) and Normal Inverse Gaussian (NIG) distributions, the fat tails and skewness in return distributions was modeled more effectively. These distributions captured the extreme behavior in returns, providing a more accurate measure of risk, particularly in volatile market conditions. This highlights the importance of moving beyond the assumption of normally distributed returns to improve the robustness of financial models in portfolio management.

The study's findings provide actionable insights for investors looking to optimize portfolios in volatile and uncertain market environments, using both traditional risk measures and more advanced statistical techniques.

Future Directions

Building upon the findings of this study, several avenues for future research and practical application emerge. First, more advanced machine learning models, such as neural networks or support vector machines, could be explored to improve the accuracy of return forecasts, especially for sectors like Technology and Real Estate, where ARIMA models showed limitations in predictability. Integrating these models into the portfolio optimization process could enhance the robustness of the investment strategies, particularly in volatile market environments.

Second, the use of multi-factor models could be expanded to include additional macroeconomic variables such as interest rates, inflation, or geopolitical events, which may further explain sector-specific risks and returns. A deeper analysis of how these factors influence tail risk and extreme events could provide insights into better hedging strategies during rare market shocks.

Another potential direction involves dynamic portfolio re-balancing, where the portfolio is continuously adjusted based on real-time data. This would allow for adaptive strategies that respond to sudden changes in market conditions, thereby minimizing risk and improving returns over time.

Lastly, future studies could assess the performance of sustainable and ESG (Environmental, Social, and Governance) investments in these sectors. As investor demand for socially responsible investments grows, understanding the risk-return profile of ESG-integrated portfolios will become increasingly relevant.

By further refining models, incorporating more diverse data inputs, and expanding the scope of portfolio optimization strategies, future research can offer more nuanced and resilient approaches to navigating complex financial markets.

References

Board, F. R. (2024). *H. 15 selected interest rate.* https://www.federalreserve.gov/datadownload/Build.aspx?rel=H15

Appendix

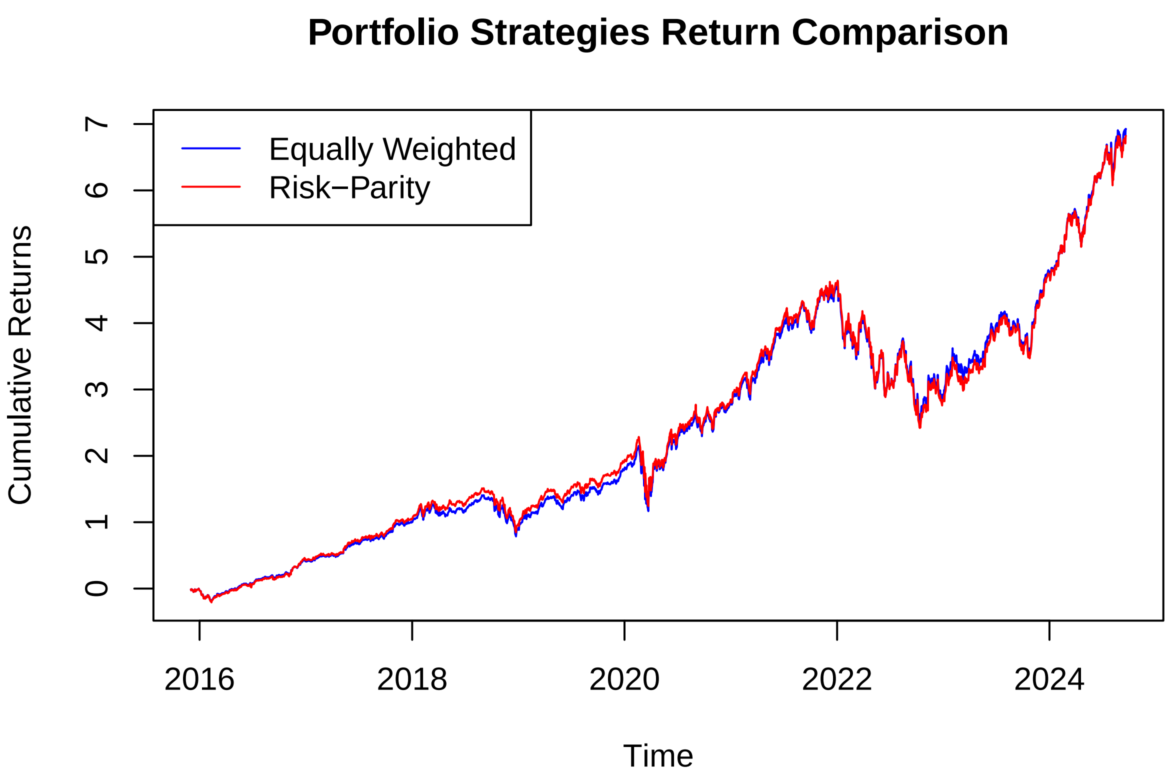


Figure 1. Portfolio Strategies Return Comparison Plot

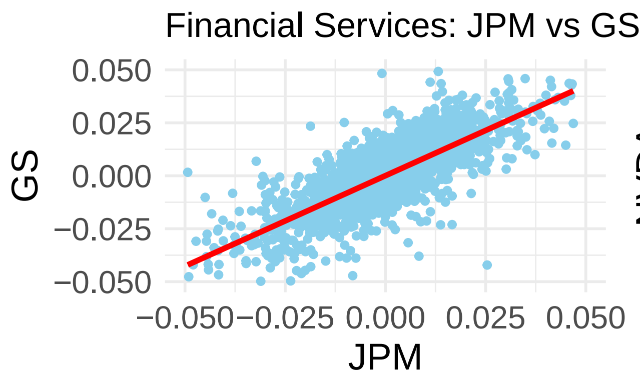


Figure 2. Intra−Sector Correlations

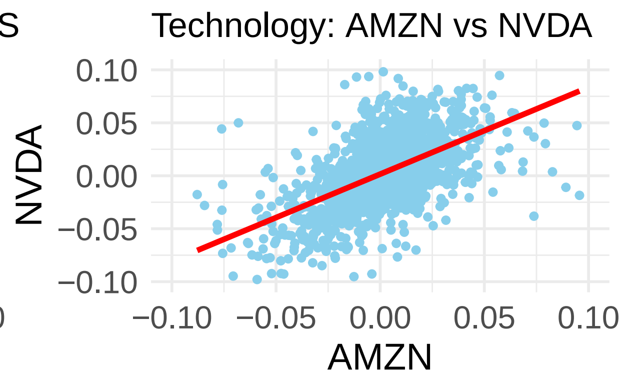


Figure 2. Intra−Sector Correlations

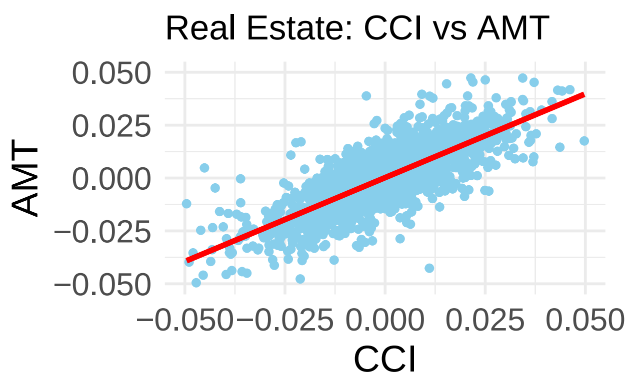


Figure 2. Intra−Sector Correlations

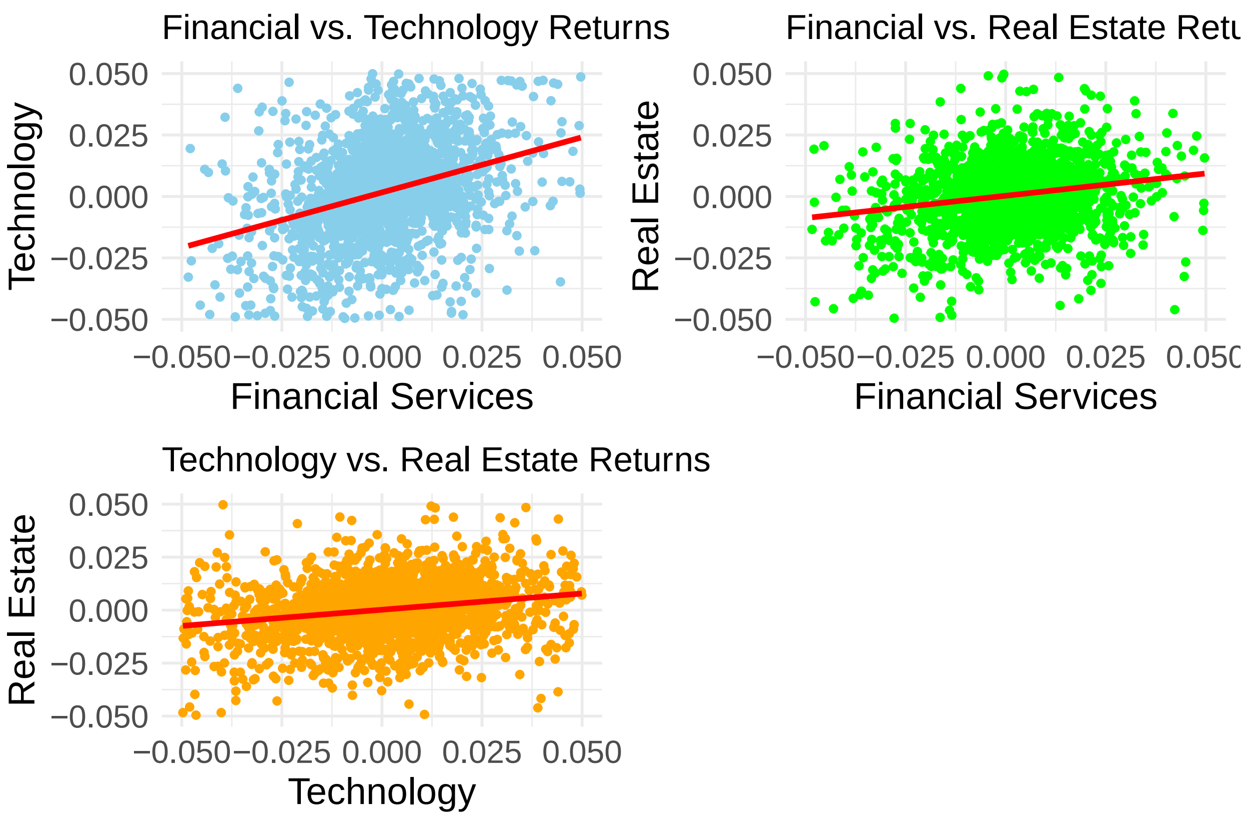


Figure 3. Inter−Sector Correlations

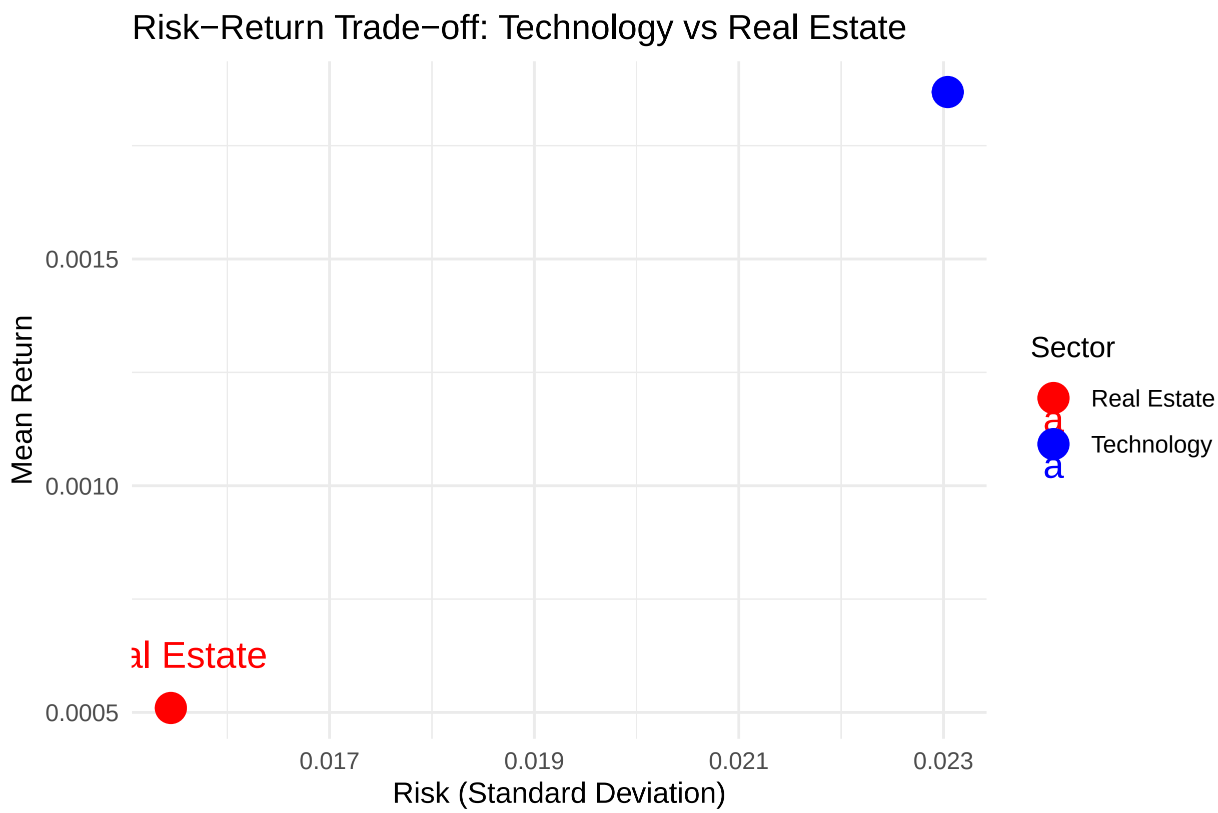


Figure 4. Risk−Return Trade−Off

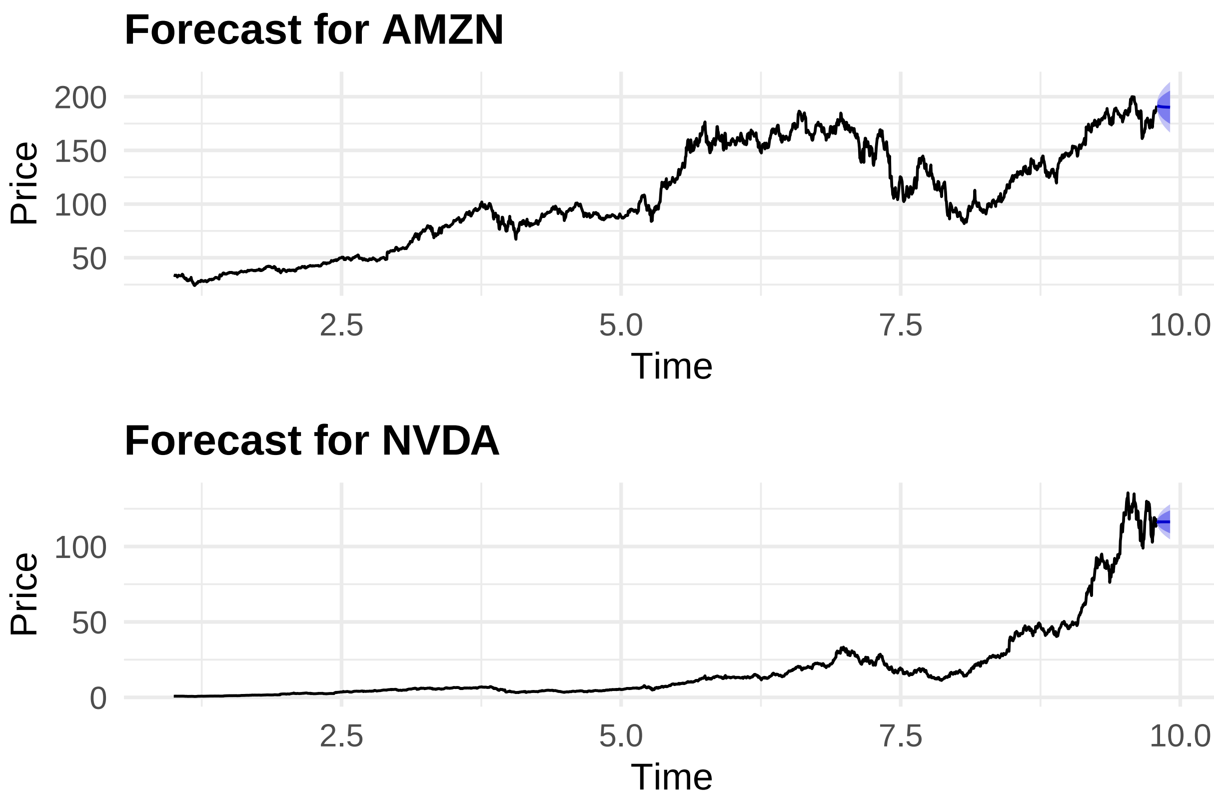


Figure 5. Technology Sector Forecasts

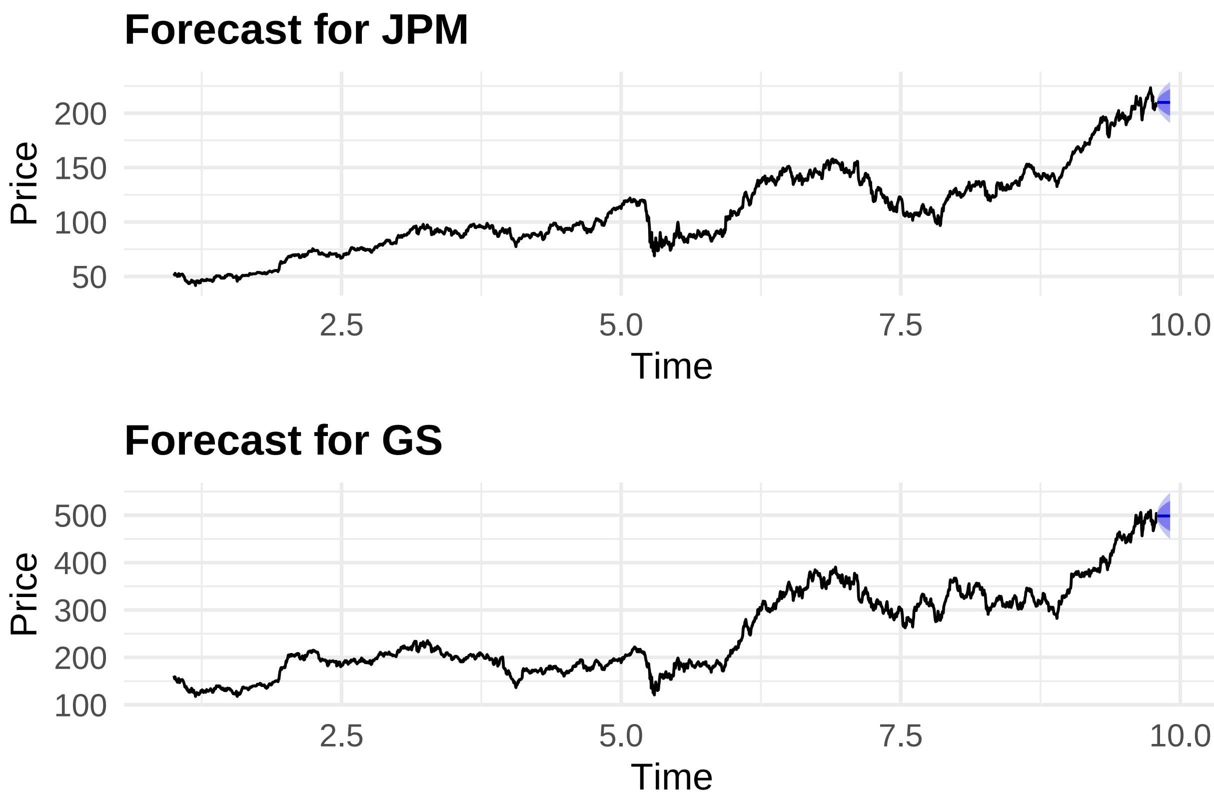


Figure 6. Financial Services Sector Forecasts

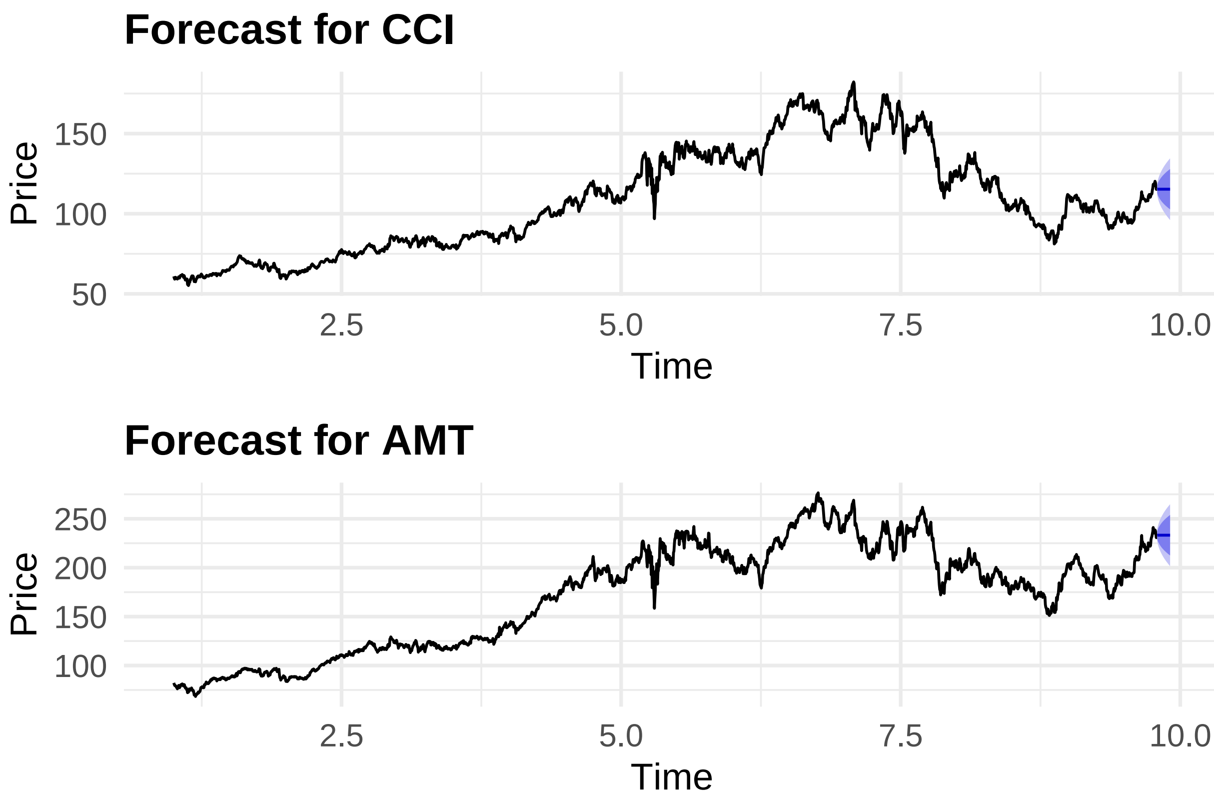


Figure 7. Real Estate Sector Forecasts

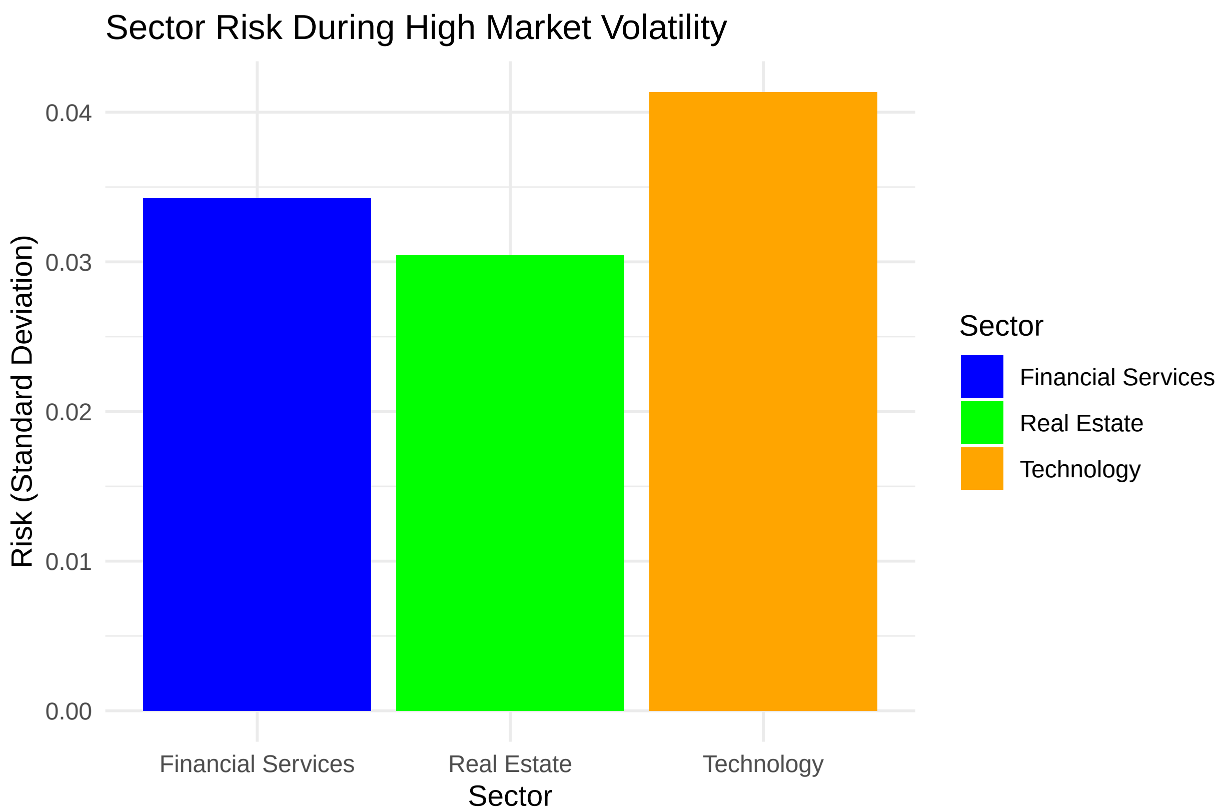


Figure 8. Sector Risk During High Market Volatility

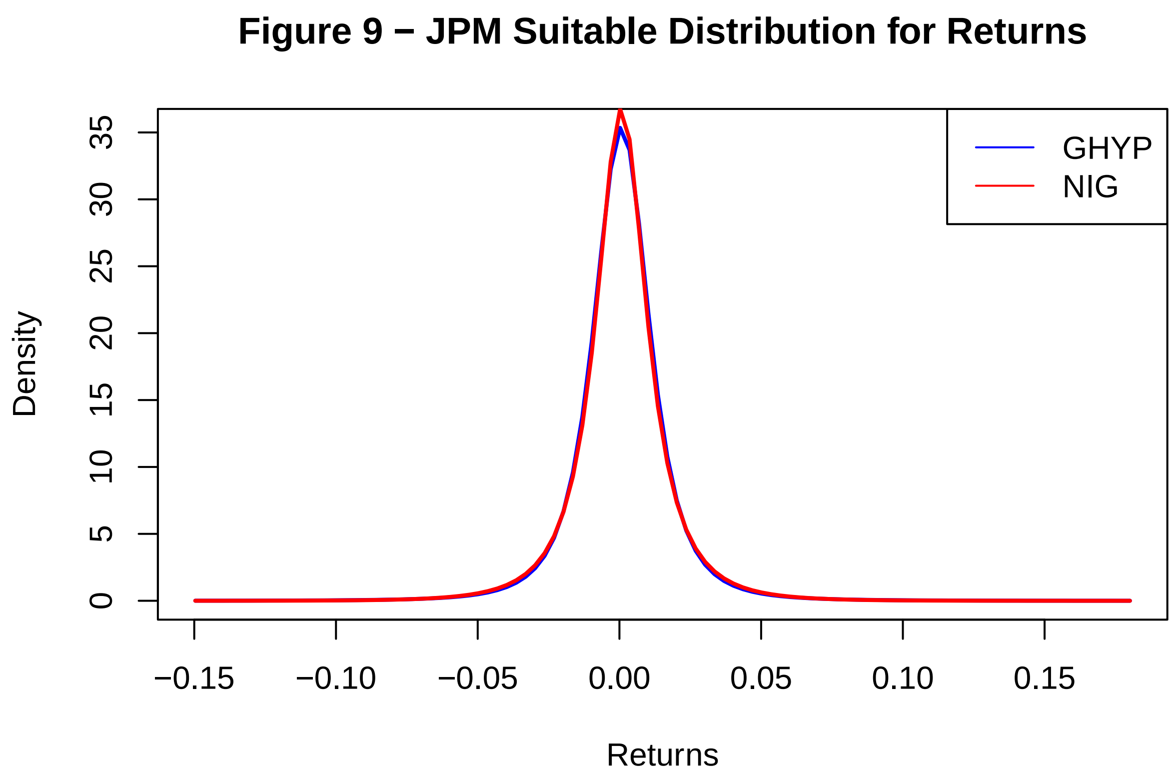


Figure 9 − JPM Suitable Distribution for Returns
GHYP
NIG
Density
Returns
0
5
10
15
20
25
30
35
−0.15
−0.10
−0.05
0.00
0.05
0.10
0.15

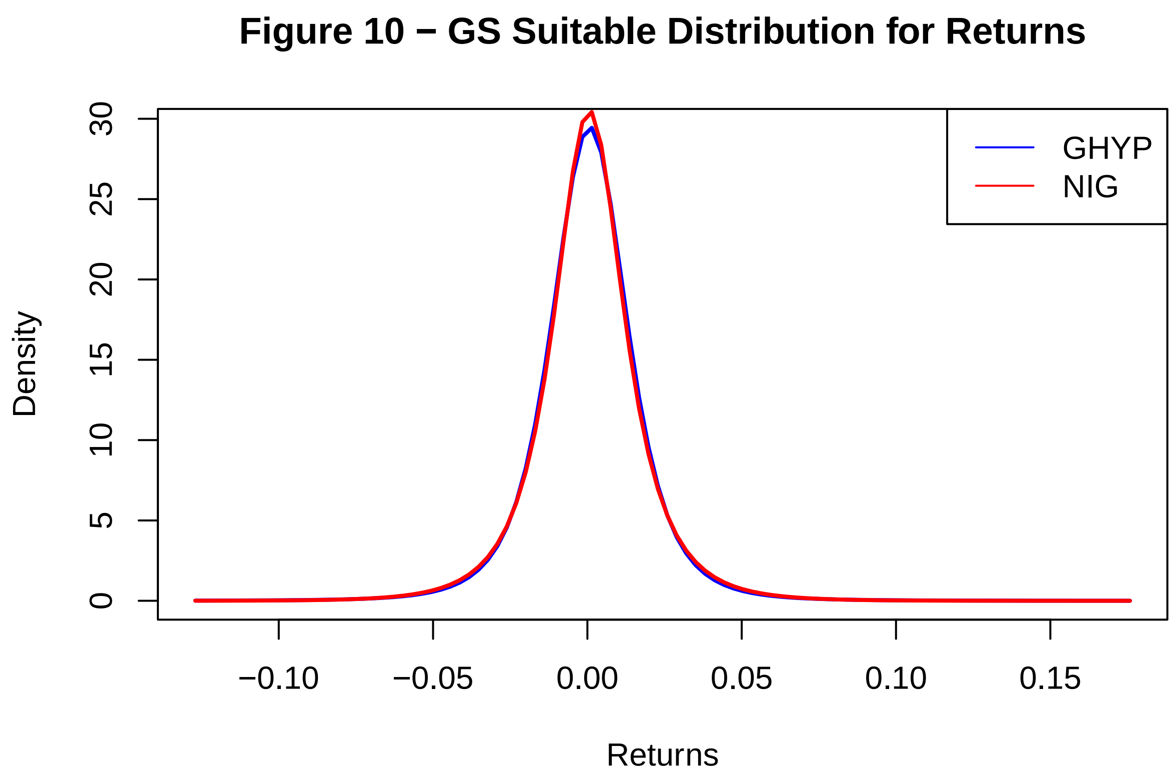


Figure 10 − GS Suitable Distribution for Returns
Density
30
25
20
15
10
5
0
−0.10
−0.05
0.00
0.05
0.10
0.15
Returns
GHYP
NIG

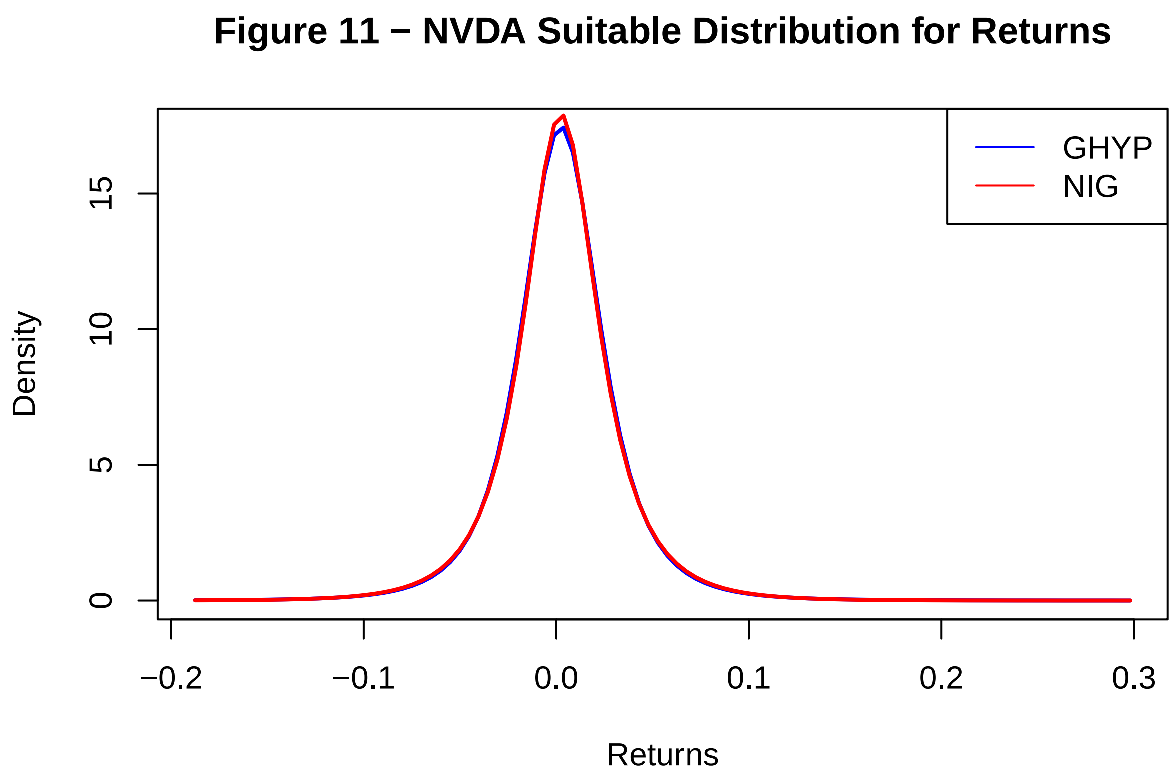
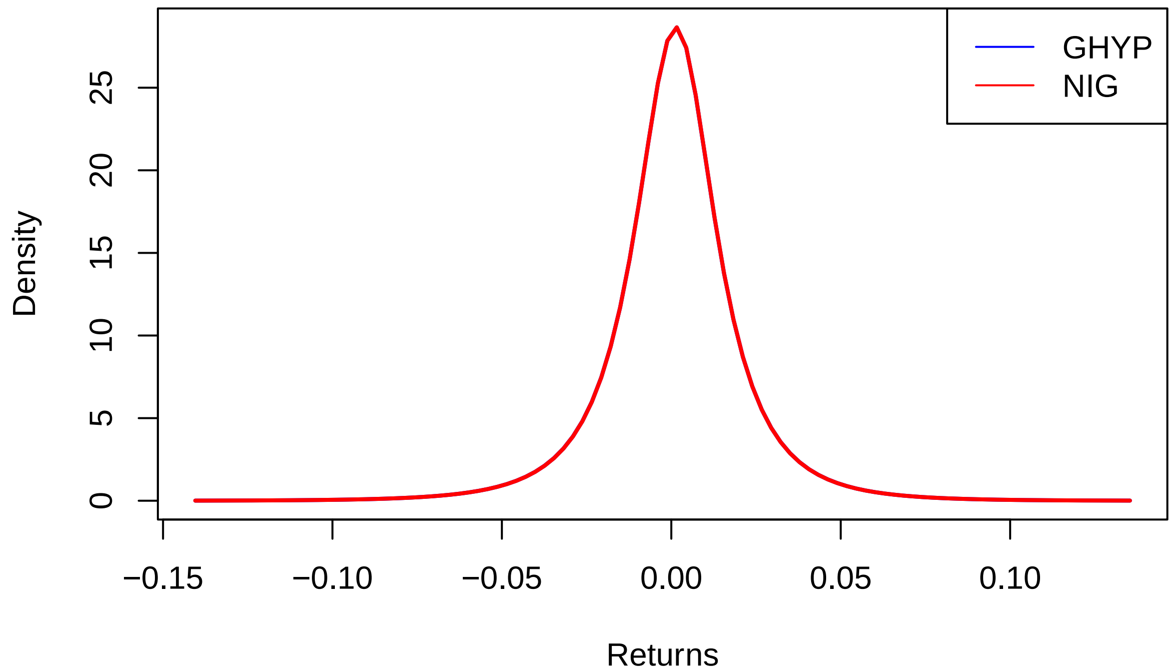


Figure 11 − NVDA Suitable Distribution for Returns
GHYP
NIG
Density
0
5
10
15
−0.2
−0.1
0.0
0.1
0.2
0.3
Returns

Figure 12 − AMZN Suitable Distribution for Returns



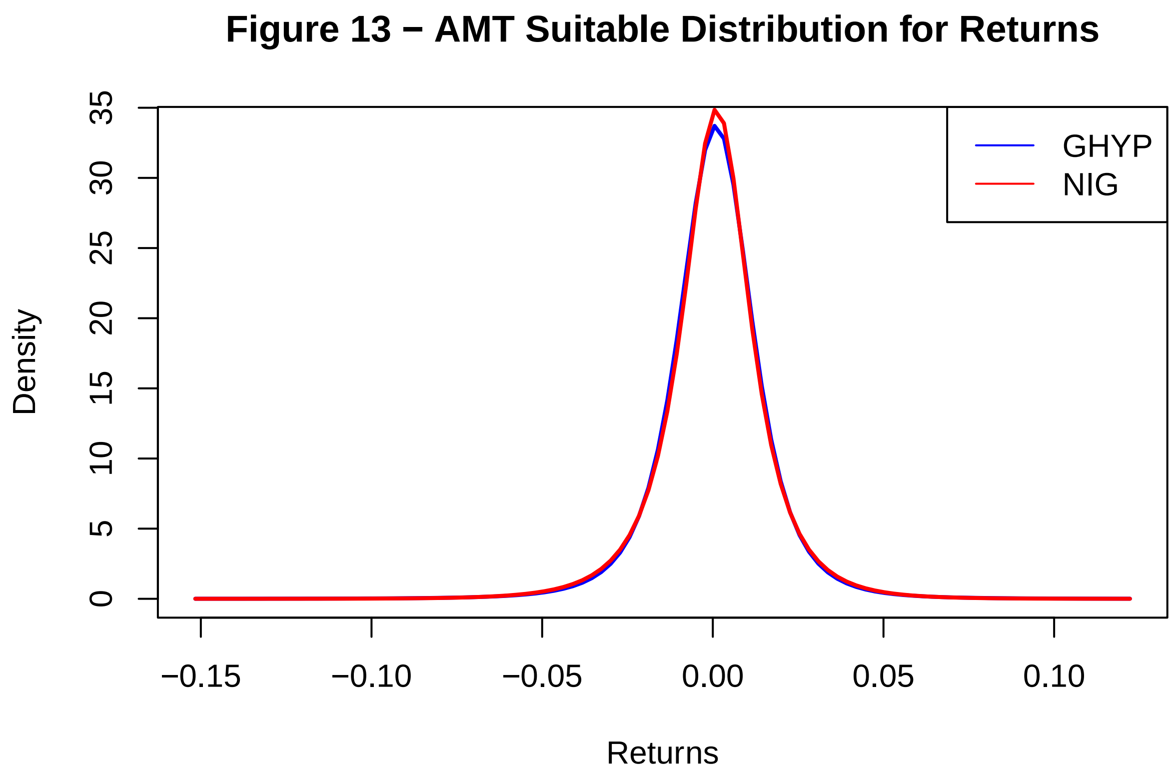


Figure 13 − AMT Suitable Distribution for Returns
GHYP
NIG
Density
Returns
0
5
10
15
20
25
30
35
−0.15
−0.10
−0.05
0.00
0.05
0.10

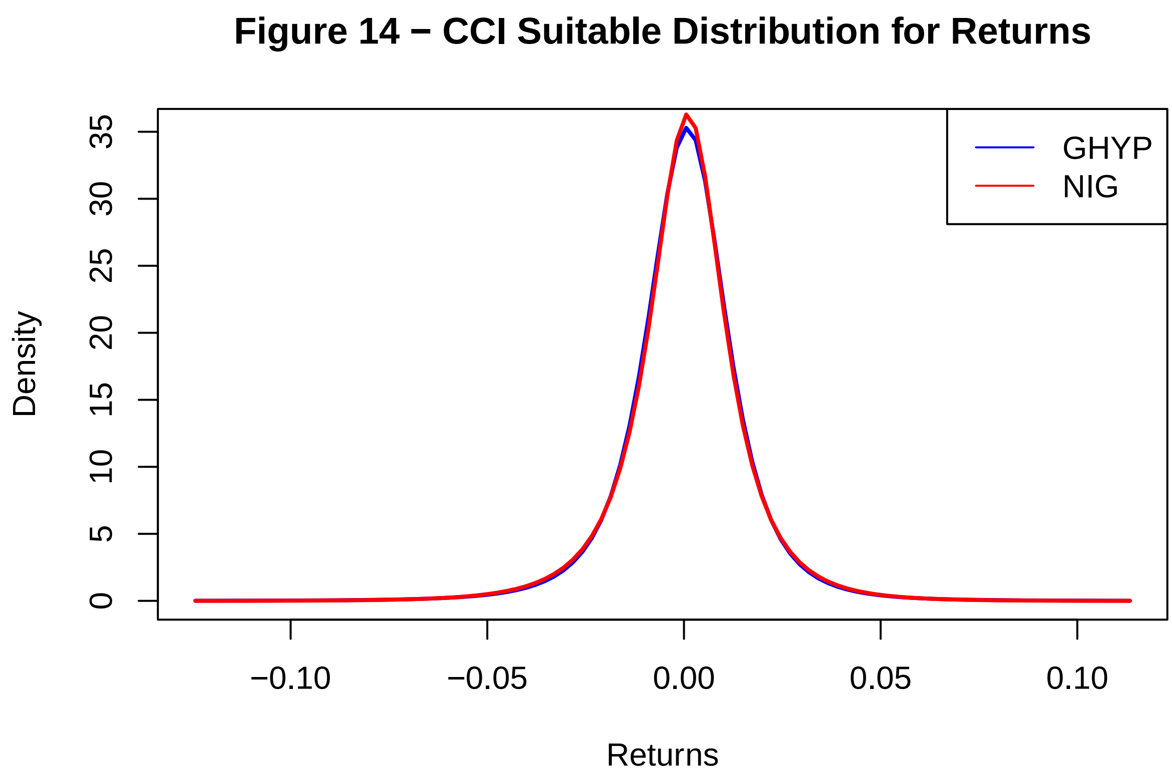


Figure 14 − CCI Suitable Distribution for Returns
GHYP
NIG
Density
0
5
10
15
20
25
30
35
−0.10
−0.05
0.00
0.05
0.10
Returns

Table 1

Returns Matrix

JPM	GS	AMZN	NVDA	CCI	AMT
-0.01405126	-0.01455420	-0.004491508	-0.007633891	-0.016613273	-0.016902200
-0.01290143	-0.02659524	-0.014437626	-0.002153878	-0.012466213	-0.015785159
0.03176295	0.02586387	0.009590993	0.040703272	0.004129442	-0.003473252
-0.01310954	-0.02368522	-0.004177543	-0.018962745	0.015626421	0.001435294

Table 2

Cumulative Returns Comparison Between Portfolio Strategies

Strategy	Cumulative Return
Equally Weighted	6.92538
Risk Parity	6.82218

Table 3

Intra-Sector Average Correlations

Sector	Average Correlation
Financial Services	0.82216
Technology	0.53914
Real Estate	0.82988

Table 4

Inter-Sector Correlation Matrix

	Financial Services	Technology	Real Estate
Financial Services	1.00000	0.40927	0.35247
Technology	0.40927	1.00000	0.32565
Real Estate	0.35247	0.32565	1.00000

Table 5

Sector Risks

Sector	Risk
Financial Services	0.01720
Technology	0.02304
Real Estate	0.01545

Table 6

Value at Risk (VaR) by Sector

Sector	VaR
Financial Services	0.02525
Technology	0.03706
Real Estate	0.02444

Table 7

Conditional Value at Risk (CVaR) by Sector

Sector	CVaR
Financial Services	0.03878
Technology	0.05241
Real Estate	0.03491

Table 8

EVT-based Tail Risk Summary for Each Sector

Sector	VaR (95%)	CVaR (95%)
Technology	0.95	0.04296
Real Estate	0.95	0.02382
Financial Services	0.95	0.02631

Table 9

Sector Performance Summary

Sector	Mean Return	Risk	Sharpe Ratio
Technology	0.00187	0.02304	-1.88489
Real Estate	0.00051	0.01545	-2.89943

Table 10

Optimized Portfolio Weights Using Markowitz Mean-Variance Optimization

Stock	Weights
JPM	0.37211
GS	-0.07477
AMZN	0.16392
NVDA	0.15466
CCI	0.11566
AMT	0.26842

Table 11

Optimized Sector Weights Using Markowitz Mean-Variance Optimization

Sector	Weight
Financial_Services	0.29735
Technology	0.31857
Real_Estate	0.38408

Table 12

AMZN Accuracy Metrics

Metric	ME	RMSE	MAE	MPE	MAPE	MASE	ACF1
Training set	0.08151	2.40737	1.56532	0.06571	1.43587	0.04752	-0.00229

Table 13

NVDA Accuracy Metrics

Metric	ME	RMSE	MAE	MPE	MAPE	MASE	ACF1
Training set	0.0553	1.14448	0.47805	0.18678	2.21056	0.03876	0.00794

Table 14

CCI Accuracy Metrics

Metric	ME	RMSE	MAE	MPE	MAPE	MASE	ACF1
Training set	0.02601	1.89412	1.25446	0.01712	1.11513	0.05922	0.0014

Table 15

AMT Accuracy Metrics

Metric	ME	RMSE	MAE	MPE	MAPE	MASE	ACF1
Training set	0.07168	3.09457	2.04185	0.03555	1.1426	0.06749	0.00779

Table 16

JPM Accuracy Metrics

Metric	ME	RMSE	MAE	MPE	MAPE	MASE	ACF1
Training set	0.07376	1.82571	1.22307	0.04911	1.15563	0.0467	0.01381

Table 17

GS Accuracy Metrics

Metric	ME	RMSE	MAE	MPE	MAPE	MASE	ACF1
Training set	0.14813	4.43324	3.12438	0.03284	1.28878	0.05707	-0.00143

Table 18

Sector Performance During High Volatility Period

Sector	Mean Return	Risk High Volatility
Technology	-0.00264	0.04134
Real Estate	0.00013	0.03045
Financial Services	-0.00192	0.03425