FT5010 Algorithmic Trading Systems Design and Deployment

Individual Assignment

Portfolio Optimization with Mean-Variance Optimization & Sector Constraints

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1. Introduction

Objective and Background

This project focuses on applying advanced portfolio optimization techniques to construct a diversified portfolio that maximizes the Sharpe Ratio, using the PyPortfolioOpt library. Portfolio optimization is crucial for enhancing investment returns relative to risk, as it allows for strategic asset allocation. This quantitative approach ensures robust diversification, reducing exposure to any single asset or sector, thus enhancing the resilience and stability of investment portfolios.

Methodology and Scope

The analysis utilizes the Efficient Frontier to determine optimal asset allocations among 15 selected stocks listed on the Singapore Exchange (SGX). By incorporating different sector constraints, the project evaluates how these limitations impact the portfolio's risk-return profile, demonstrating the practical implications of portfolio optimization in real-world settings.

2. Selection of Stocks for Portfolio Optimization:

The foundation of our portfolio is built upon the selection of the top 15 stocks by market capitalization from the Singapore Exchange (SGX). This approach is driven by several key factors that typically characterize large-cap stocks:

Stability and Reliability: Large-cap stocks often represent companies that are leaders in their respective industries. These companies tend to have more stable revenues and a proven track record of managing economic cycles better than smaller companies. This stability is crucial for long-term investment strategies, especially in a portfolio optimization context where managing risk is paramount.

Liquidity: High market capitalization is frequently associated with high liquidity, which implies that these stocks can be bought or sold in large volumes without a significant impact on their price. This feature is particularly important for portfolio adjustments and risk management, allowing for swift portfolio reallocation without considerable market impact.

Dividend Yields: Typically, larger companies have a consistent dividend payout history. This characteristic can be especially attractive in portfolio optimization for generating regular income streams and reducing overall portfolio volatility.

Sector Representation: The chosen stocks cover a broad spectrum of sectors, ensuring comprehensive exposure across different economic segments. This diversification helps in mitigating sector-specific risks and capitalizing on growth in different areas of the economy.

Quantitative Support: The selection is supported by quantitative metrics such as the price-to-earnings ratio, return on equity, and historical growth rates, ensuring that the stocks are not just large but also fundamentally sound.

By focusing on these criteria, the portfolio is expected to harness the growth potential of SGX's leading companies while maintaining a balance between risk and return. This strategy aligns with the objective of maximizing the Sharpe Ratio, which necessitates a focus on reducing volatility while seeking adequate returns.

3. Data Preparation and Analysis:

For the purpose of this project, we collected historical price data for a carefully selected portfolio of 15 stocks listed on the Singapore Exchange (SGX). These stocks represent a diverse range of sectors and are among the top by market capitalization on the exchange. The selected stocks, along with their corresponding symbols, are as follows:

- DBS Group Holdings Ltd (D05.SI)
- Oversea-Chinese Banking Corp Limited (O39.SI)
- United Overseas Bank Ltd (U11.SI)
- Singapore Telecommunications Limited (Z74.SI)
- Wilmar International Limited (F34.SI)
- Keppel Corporation Limited (S07.SI)
- Singapore Airlines Limited (C6L.SI)
- SATS Ltd (Q0F.SI)
- CapitaLand Integrated Commercial Trust (C38U.SI)
- Keppel DC REIT (BN4.SI)
- Singapore Technologies Engineering Ltd (S63.SI)
- Yangzijiang Shipbuilding (Holdings) Ltd (Y92.SI)
- Ascendas Real Estate Investment Trust (A17U.SI)
- Genting Singapore Ltd (G13.SI)
- Jardine Cycle & Carriage Ltd (C07.SI)

We utilized the yfinance library to download the time series data spanning from January 1, 2015, to December 31, 2022, which serves as our training data for the portfolio optimizer. Additionally, data from 2023 was reserved as a holdout period for backtesting and evaluating our optimized portfolios.

4. Methodology: Portfolio Optimization Process:

To construct a diversified portfolio that maximizes the Sharpe Ratio, several computational steps were performed using historical data from 2015 to 2022 as the training set. These steps included calculating the mean and covariance of returns, optimizing the portfolio, and determining the weights that maximize the Sharpe Ratio.

Calculating Mean and Covariance

The initial step in the portfolio optimization was to compute the mean historical returns and the covariance matrix of the returns using:

- **Mean Historical Return:** This method estimates the expected returns for each stock based on historical data, calculated as the average of the historical percentage returns for each stock.
- **Covariance Shrinkage:** Due to the potential instability of sample covariance matrices, especially with limited data points, the Covariance Shrinkage method was employed. This method adjusts the sample covariance matrix towards a structured estimator, enhancing the reliability of inverse covariance calculations needed for portfolio optimization.

Portfolio Optimization Using Efficient Frontier:

The mean returns and covariance matrix were then applied to the EfficientFrontier function from the PyPortfolioOpt library. This function constructs the Efficient Frontier, enabling the identification of the optimal risky portfolio under various constraints and objectives.

- **Maximizing the Sharpe Ratio:** The focus was on maximizing the Sharpe Ratio to achieve the highest possible risk-adjusted return. The max_sharpe method of the EfficientFrontier class was used to determine the set of weights that optimize this ratio.

Application of Weights and Performance Evaluation:

The optimal weights obtained from the Efficient Frontier analysis were applied to construct the portfolio. These weights indicate the proportion of the total portfolio value to be allocated to each stock. The performance of the portfolio during the training period was characterized by:

- **Expected Annual Return: 70.8%**
- **Annual Volatility: 46.8%**
- **Sharpe Ratio: 1.47**

These metrics illustrate the effectiveness of the portfolio in balancing high returns against the associated risks during the training period.

Subsequent sections of the analysis utilize these weights to compute the expected portfolio returns and the portfolio risk, enabling a thorough evaluation of the potential future performance in the holdout period of 2023.

5. Backtesting Methodologies and Performance:

Backtesting was conducted using two distinct methodologies to evaluate the performance of the optimized portfolio weights obtained for 2023. The results validate the effectiveness of the optimization process under different execution strategies:

Approach 1: Direct Weight Application

In this approach, the daily portfolio returns were calculated by directly applying the optimized weights to the daily returns of each stock throughout 2023. This method simplifies portfolio management by adjusting the investment proportionally according to the pre-determined weights, thus reflecting a straightforward application of the optimization results.

Performance Metrics:

Total Cumulative Portfolio Return: 90.91%

Annualized Standard Deviation: 0.80

Approach 2: Discrete Allocation Method

The second method involved a more practical application using the DiscreteAllocation library, which helps in translating continuous weights into discrete numbers of shares. This was based on managing a portfolio valued at $1,000,000. The daily portfolio value was computed by multiplying the number of shares of each stock by their daily prices, and the returns were calculated based on the changes in this total portfolio value.

Performance Metrics:

Total Cumulative Portfolio Return: 87.33%

Annualized Standard Deviation: 0.82

Comparative Analysis of Backtesting Approaches:

Differences and Implications

The two backtesting approaches, while rooted in the same optimized weights, lead to different results due to the nature of their implementation:

Direct Weight Application is theoretical and assumes infinite divisibility of assets and frictionless trading. It calculates returns based purely on weighted averages of stock returns, which does not account for real-world factors such as transaction costs, bid-ask spreads, and the discrete nature of stocks (i.e., stocks cannot be purchased in fractional quantities in practice).

Discrete Allocation Method translates theoretical weights into a practical scenario where only whole shares can be bought or sold. This method introduces a layer of granularity and realism by considering the actual number of shares that can be purchased with a given budget. Factors like rounding off to whole numbers and the timing of trades (buying or selling at daily closing prices) can cause slight deviations from the theoretical model.

6. Experimentation with Sector Constraints:

Three sets of sector constraints were tested to observe the impact of different investment strategies on portfolio performance. Each set had distinct objectives and constraints tailored to specific investment goals.

Set 1: Growth-Focused Constraints

Objective: Target high growth by investing predominantly in sectors known for rapid expansion and innovation.

Constraints:

Technology: 20-40% (capitalizing on innovation and technological advancements)

Consumer Goods: 15-35% (leveraging consumer discretionary spending)

Financials: 5-15%

Industrials: 5-15%

Utilities: 5-10%

Backtest Results:

Returns Method: Total Return: 84.15%, Volatility: 0.73, Sharpe Ratio: 1.11

Portfolio Value Method: Total Return: 80.21%, Volatility: 0.75, Sharpe Ratio: 1.02

This strategy emphasized sectors with potential for rapid growth, aiming to maximize returns during market upswings.

Set 2: Defensive Constraints

Objective: Enhance stability by focusing on sectors that provide steady earnings and dividends, especially valuable during market downturns.

Constraints:

Utilities: 15-30% (stability from essential services)

Consumer Goods: 15-30% (consistent demand for staples)

Financials: 10-20%

Industrials: 5-10%

Technology: 5-10%

Backtest Results:

Returns Method: Total Return: 25.75%, Volatility: 0.21, Sharpe Ratio: 1.05

Portfolio Value Method: Total Return: 24.42%, Volatility: 0.22, Sharpe Ratio: 0.94

This approach prioritized sectors known for resilience, aiming to safeguard the portfolio against economic fluctuations.

Set 3: Balanced Constraints

Objective: Achieve risk mitigation through broad diversification across all key sectors.

Constraints: Equal weight range of 10-20% for all sectors, promoting a balanced risk-return profile.

Backtest Results:

Returns Method: Total Return: 44.49%, Volatility: 0.38, Sharpe Ratio: 1.08

Portfolio Value Method: Total Return: 42.56%, Volatility: 0.40, Sharpe Ratio: 0.98

This balanced strategy was designed to perform steadily across different economic conditions by evenly distributing investment across sectors.

Analysis:

Each set of constraints catered to different market conditions and investment philosophies:

Growth-Focused: Best suited for bullish markets, capturing high returns at the cost of increased volatility.

Defensive: Ideal during volatile or bearish market conditions, offering lower returns but with minimal risk.

Balanced: A middle ground approach, providing moderate returns with relatively low risk, suitable for investors seeking steady growth without significant exposure to any single sector.

The varying performance metrics across these strategies underscore the importance of aligning investment approaches with market outlooks and individual risk tolerance.

7. Portfolio Performance Comparison Table

Portfolio	Metric	Backtest Type 1: Through Returns	Backtest Type 2: Through Portfolio Value
Benchmark (STI ETF - ES3.SI)	Total Cumulative Return	4.49%	N/A
	Annualized Standard Deviation	0.10	N/A
	Sharpe Ratio	0.07	N/A
Base Portfolio	Total Cumulative Return	90.91%	87.33%
	Annualized Standard Deviation	0.80	0.82
	Sharpe Ratio	1.09	1.02
Set 1: Growth-Focused	Total Cumulative Return	84.15%	80.21%
	Annualized Standard Deviation	0.73	0.75
	Sharpe Ratio	1.11	1.02
Set 2: Defensive	Total Cumulative Return	25.75%	24.42%

Portfolio	Metric	Backtest Type 1: Through Returns	Backtest Type 2: Through Portfolio Value
	Annualized Standard Deviation	0.21	0.22
	Sharpe Ratio	1.05	0.94
Set 3: Balanced	Total Cumulative Return	44.49%	42.56%
	Annualized Standard Deviation	0.38	0.40
	Sharpe Ratio	1.08	0.98

8. Summary and Conclusion:

This project applied advanced portfolio optimization techniques to construct a diversified portfolio maximizing the Sharpe Ratio, utilizing the PyPortfolioOpt library and focusing on stocks from the Singapore Exchange (SGX). Optimal asset allocations were derived using the Efficient Frontier methodology based on historical data from 2015 to 2022, with subsequent backtesting in 2023 to assess the effectiveness of these optimizations.

Key Findings:

Portfolio Optimization: The optimal weights obtained significantly outperformed the benchmark (STI ETF - ES3.SI), demonstrating the strength of quantitative portfolio management.

Backtesting and Sector Constraints: Backtesting verified the robustness of the optimized portfolios under various sector constraints, highlighting how different strategies could be customized to meet specific investment goals and adapt to market conditions.

Conclusions:

Strategic asset allocation enhanced returns relative to risk and showcased a structured approach to diversification. The application of sector constraints during the experiment phase underlined the adaptability of optimization strategies across economic scenarios. This project illustrates the transformative potential of portfolio optimization in developing sophisticated, data-driven investment strategies that surpass conventional stock picking. The methodologies used here can be integrated into broader financial practices to improve decision-making and financial outcomes.