QUANTITATIVE RESEARCH REPORT

Portfolio Construction & Optimization

Efficient Frontier Analysis of Equity Portfolio Allocation

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Introduction

Constructing an efficient portfolio requires balancing expected return, risk, and diversification. Investors must allocate capital across a set of assets while considering not only the standalone characteristics of individual securities, but also how those securities interact within a broader portfolio. While traditional portfolio allocation often relies on discretionary judgment or simple weighting schemes, quantitative methods provide a more systematic framework for evaluating portfolio efficiency.

Modern portfolio theory highlights that portfolio risk is not determined solely by the volatility of individual assets, but also by the correlation structure between them. As a result, assets should not be assessed in isolation. By combining securities with different return and risk characteristics, investors can construct portfolios that improve diversification and achieve stronger risk-adjusted outcomes.

This report applies quantitative portfolio analysis to a selection of Nordic equities. Using historical return data, the study evaluates the risk and return characteristics of individual assets and examines how different portfolio construction approaches influence overall portfolio performance.

Several portfolio structures are compared throughout the analysis, including the current portfolio allocation, an equal-weight portfolio, an optimized portfolio based on risk-adjusted returns, and a constrained portfolio with position limits. In addition to comparing these allocation methods, the report analyzes the correlation structure between assets and illustrates how individual securities contribute to the portfolio's overall risk-return profile.

The objective of this report is to demonstrate how quantitative portfolio construction can support more disciplined capital allocation decisions. Rather than replacing fundamental judgment, these methods should be viewed as analytical tools that strengthen portfolio design, improve risk awareness, and provide a more structured basis for investment decision-making.

Data & Methodology

Data

The analysis is based on historical price data for a selection of Nordic equities across multiple sectors, including financials, industrials, real estate, and technology. The dataset covers the period from January 2023 to February 2024 and consists of daily adjusted closing prices.

All price data was obtained from publicly available financial market data providers using the Python library yfinance, which provides access to historical price series from Yahoo Finance. Adjusted prices were used in order to account for corporate actions such as dividends and stock splits, ensuring that the return series accurately reflects the total return of each asset.

Using daily data allows for a sufficiently granular estimation of return distributions, volatility, and correlations between assets. These statistical characteristics form the foundation of quantitative portfolio construction and are widely used in empirical asset pricing and portfolio optimization research.

Daily returns were calculated using percentage price changes:

$$R_t = \frac{P_t - P_{t-1}}{P_{t-1}}$$

where P_t represents the adjusted closing price at time t.

The resulting return series forms the basis for estimating expected returns, volatility, and correlations between assets.

Estimation of Expected Returns

Expected asset returns were estimated using the historical mean of daily returns over the sample period. Historical averages are commonly used in empirical portfolio analysis as a simple estimator of expected returns, although they are known to be sensitive to the sample period.

While more advanced approaches exist, such as factor models or Bayesian estimators, the historical mean provides a transparent and easily interpretable baseline estimate of expected returns. This approach is widely used in empirical portfolio studies and serves as a standard input in mean-variance portfolio optimization frameworks.

Risk and Covariance Estimation

Portfolio risk is measured using the variance and covariance structure of asset returns. The covariance matrix captures the degree to which asset returns move together over time.

The covariance between two assets *i* and *j* is defined as:

$\mathrm{Cov}(R_i, R_j) = (1/T) \cdot \Sigma[(R_{i,t} - \bar{R}_i)(R_{j,t} - \bar{R}_j)]$

The covariance matrix plays a central role in portfolio construction because portfolio risk depends not only on the volatility of individual assets but also on their correlations with other assets.

Assets with low or negative correlations can reduce overall portfolio risk when combined. This diversification effect is one of the fundamental insights of modern portfolio theory.

Volatility for each asset was estimated using the standard deviation of returns, while the full covariance matrix was calculated using the historical return series.

Mean-Variance Portfolio Optimization

The portfolio optimization framework used in this analysis is based on Modern Portfolio Theory, originally introduced by Markowitz (1952). The objective of mean-variance optimization is to identify the portfolio allocation that maximizes expected return for a given level of risk, or equivalently minimizes risk for a given expected return.

Portfolio expected return is calculated as the weighted average of individual asset returns:

$$E(R_p) = \sum_{i=1}^{N} w_i \mu_i$$

where:

- w_i represents the portfolio weight of asset i
- μ_i represents the expected return of asset i

Portfolio risk is determined by the covariance structure of asset returns:

$$\sigma_p^2 = w^T \Sigma w$$

where:

- w is the vector of portfolio weights
- Σ represents the covariance matrix of asset returns

The optimization procedure generates the efficient frontier, which represents the set of portfolios that achieve the highest expected return for each level of portfolio risk.

Sharpe Ratio and Risk-Adjusted Performance

To evaluate portfolio efficiency, this analysis focuses on the Sharpe Ratio, a widely used measure of risk-adjusted performance.

The Sharpe Ratio measures excess return relative to portfolio volatility and is defined as:

$$S = \frac{E(R_p) - R_f}{\sigma_p}$$

where:

- R_f The risk-free rate is proxied by the Swedish 3-month Treasury bill rate (SSVX 3M), averaging approximately 3.8% annually during the sample period.
- $E(R_p)$ represents expected portfolio return
- σ_p represents portfolio volatility

As the analysis is based on daily return data, both expected returns and volatility are annualized prior to computing the Sharpe Ratio. Daily returns are scaled by a factor of 252 and daily volatility is multiplied by √252, reflecting the approximate number of trading days in a year.

Maximizing the Sharpe Ratio identifies the portfolio with the highest expected return per unit of risk.

Portfolio Construction Approaches

To evaluate different portfolio allocation strategies, several portfolio constructions are compared in the analysis.

First, the current portfolio allocation is analyzed in order to evaluate its risk-return characteristics.

Second, an equal-weight portfolio is constructed where capital is distributed evenly across all assets. This portfolio serves as a simple benchmark strategy frequently used in empirical portfolio research.

Third, an optimized portfolio is constructed using mean-variance optimization to maximize the Sharpe Ratio.

Finally, a constrained portfolio is generated by imposing a maximum weight of 20% per asset. This constraint reflects realistic portfolio management considerations by preventing excessive concentration in a single security.

Backtesting Framework

To evaluate how different portfolio constructions would have performed historically, a backtest is conducted using the historical return series.

The backtest simulates the cumulative performance of each portfolio by applying the respective portfolio weights to the daily asset returns. Portfolio growth is measured as the cumulative return of an initial investment over the sample period. Performance is compared against the **OMX Stockholm All-Share Index (OMXPI)**, which serves as a benchmark representing the broader Swedish equity market. It is important to note that the optimization and evaluation are performed using the same historical dataset. Consequently, the backtest results should primarily be interpreted as an illustration of portfolio efficiency rather than a prediction of future performance.

Asset Correlations

Understanding the correlation structure between assets is an essential component of portfolio construction. While individual asset returns and volatility are important, the relationship between assets plays a critical role in determining overall portfolio risk. Assets that move closely together provide limited diversification benefits, whereas assets with low or negative correlations can significantly reduce portfolio volatility when combined.

To analyze the interaction between the selected equities, a correlation matrix of asset returns was constructed. The matrix measures the strength and direction of the linear relationship between each pair of assets, with correlation values ranging from -1 to 1. A correlation of 1 indicates that two assets move perfectly together, while a correlation of -1 implies that the assets move in opposite directions.

The results show that most assets in the portfolio exhibit relatively low to moderate correlations. This suggests that diversification benefits are present within the asset set. Several asset pairs display correlations close to zero, indicating largely independent return dynamics.

Some moderate positive correlations can be observed among certain assets, which is expected given that many of the companies operate within the same regional market. Market-wide factors such as macroeconomic conditions, interest rate expectations, and overall equity market sentiment often affect multiple securities simultaneously, leading to some degree of positive correlation.

However, the overall correlation structure remains sufficiently dispersed to allow for meaningful diversification. This is particularly relevant for portfolio optimization, as the presence of low correlations enables the construction of portfolios that achieve lower overall risk relative to holding individual assets.

The correlation matrix therefore provides important insights into how the assets interact within the portfolio and serves as a key input for the portfolio optimization framework presented in the following sections.

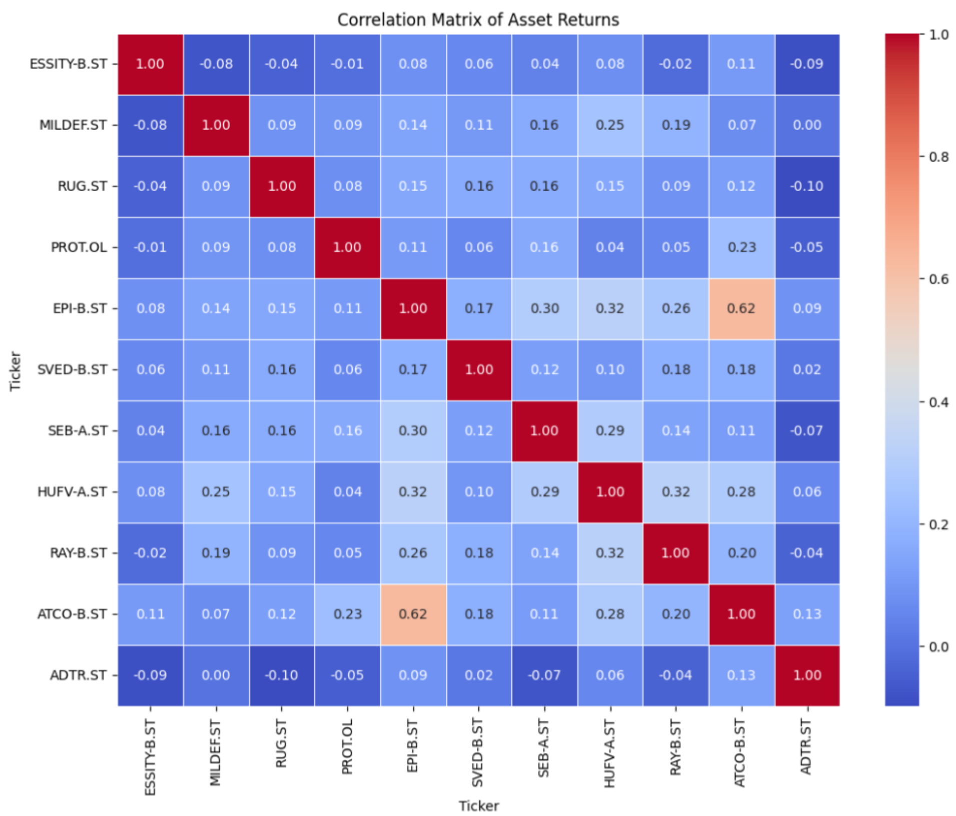

Figure 1: Correlation matrix of daily asset returns for the selected Nordic equities

Risk-Return Characteristics

Understanding the relationship between risk and return is a fundamental principle in portfolio theory. Investors generally require higher expected returns as compensation for taking on higher levels of risk. Examining the risk–return characteristics of individual assets therefore provides important insight into how securities behave before they are combined in a portfolio.

To visualize this relationship, each asset is plotted in risk–return space, where the horizontal axis represents annualized volatility and the vertical axis represents expected annual return. Volatility serves as a proxy for risk and reflects the variability of asset returns over time, while expected return is estimated using the historical mean return over the sample period.

The scatter plot reveals notable differences in the risk–return profiles of the selected equities. Some assets exhibit relatively high volatility while offering only moderate returns, whereas others provide stronger return performance relative to their level of risk. These differences illustrate that not all assets contribute equally to portfolio efficiency when evaluated on a standalone basis.

Several assets stand out in the risk–return space. **PROT.OL** exhibits the highest expected return in the sample while maintaining only moderate volatility. This positions the asset near the upper region of the risk–return distribution and suggests strong historical performance relative to risk. Similarly, **SVED-B.ST** demonstrates a favorable balance between return and volatility, offering relatively strong returns without excessively high risk.

Other assets appear less attractive when evaluated individually. **MILDEF.ST** and **ADTR.ST** display comparatively high volatility while delivering only moderate returns. These securities are positioned further to the right in the risk–return space, indicating a weaker risk–return trade-off. Assets with such characteristics may increase overall portfolio risk without proportionally improving expected returns.

Some securities also exhibit relatively low expected returns given their level of volatility. For example, **ESSITY-B.ST** and **HUFV-A.ST** appear in the lower region of the risk–return distribution, indicating weaker historical performance relative to risk. While these assets may seem less attractive in isolation, they may still provide diversification benefits when combined with other securities that exhibit different return dynamics.

Despite these individual differences, evaluating assets solely based on their standalone risk–return characteristics does not fully capture their role in a diversified portfolio. Even assets with less favorable individual profiles may contribute positively to portfolio efficiency if they exhibit low correlations with other assets. This highlights the importance of considering both individual asset behavior and cross-asset relationships when constructing portfolios. The distribution of assets in risk–return space therefore provides an important foundation for portfolio optimization. The efficient frontier, illustrated in the figure for reference, represents the set of portfolios that achieve the highest expected return for a given level of risk. The following section builds on this analysis by applying mean–variance optimization to identify optimal portfolio allocations along the efficient frontier.

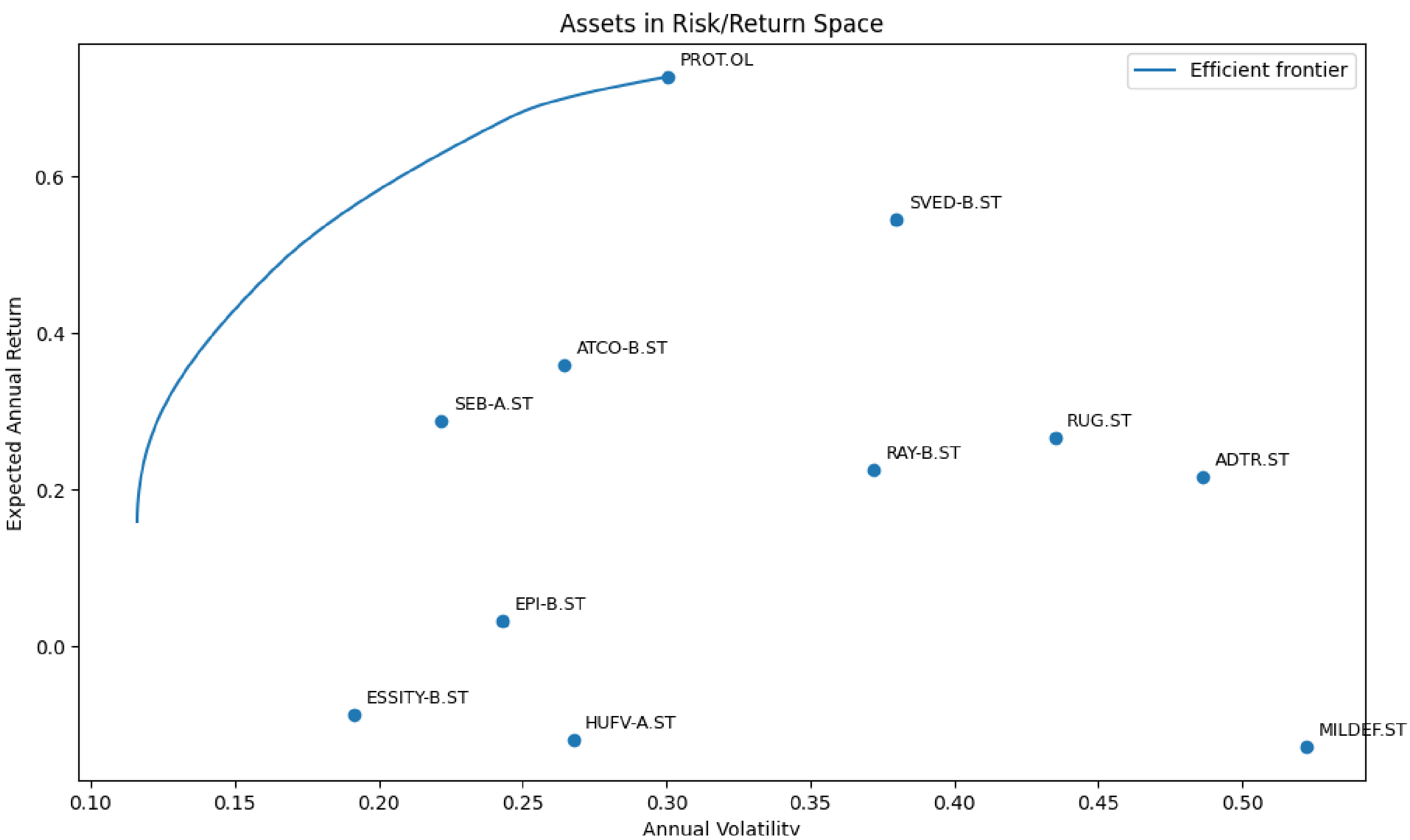

Figure 2: Risk-return characteristics of the selected equities. Each point represents an asset plotted by expected annual return and annualized volatility.

Portfolio Optimization

Portfolio construction aims to identify asset allocations that balance expected return and risk in an efficient manner. While individual securities may exhibit different risk–return characteristics, combining assets within a portfolio can significantly improve risk-adjusted performance through diversification. To analyze this relationship, the mean–variance optimization framework introduced by Markowitz (1952) is applied.

Using the return and risk framework defined in the Methodology section, a large set of possible portfolio allocations can be evaluated to determine the combinations of assets that deliver the highest expected return for a given level of risk. The set of optimal portfolios forms the efficient frontier, which represents the upper boundary of attainable risk–return combinations.

The efficient frontier is illustrated in Figure 3 together with several portfolio alternatives. These include the current portfolio allocation, an equal-weight portfolio, an optimized portfolio that maximizes the Sharpe ratio, and a constrained portfolio where individual asset weights are limited to a maximum allocation of 20%.

The optimized portfolio seeks to maximize the Sharpe ratio, defined as the ratio of excess return to portfolio volatility:

$$S = \frac{E(R_p) - R_f}{\sigma_p}$$

where R_f represents the risk-free rate.

Comparing the different portfolio allocations relative to the efficient frontier provides insight into how efficiently capital is currently allocated. Portfolios that lie below the frontier are considered inefficient, as higher expected returns could theoretically be achieved at the same level of risk through improved diversification and asset weighting.

The results show that optimized portfolios move significantly closer to the efficient frontier compared to simple allocation strategies such as equal weighting. This highlights the potential benefits of quantitative portfolio construction in improving risk-adjusted returns.

The next section evaluates how these portfolio strategies would have performed historically through a backtest analysis.

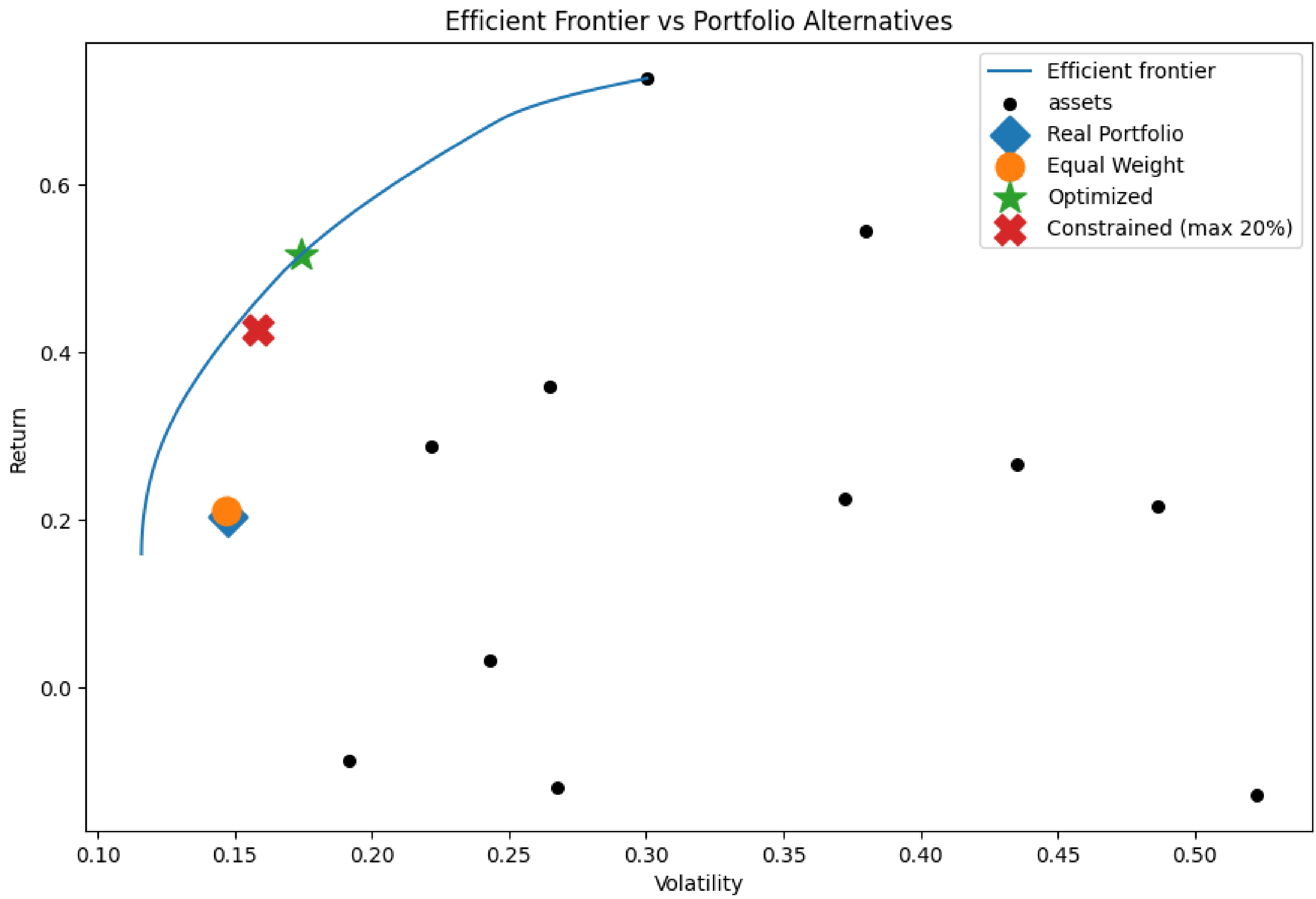

Figure 3: Efficient frontier and portfolio alternatives. The figure compares the real portfolio, equal-weight portfolio, optimized portfolio and constrained portfolio in risk-return space.

Backtest Analysis

To evaluate how the different portfolio strategies would have performed in practice, a historical backtest was conducted. The purpose of this analysis is to compare the performance of several portfolio constructions over time and assess how quantitative optimization affects portfolio returns and risk.

The backtest is based on daily returns over the period from January 2023 to February 2024. For each strategy, portfolio performance was calculated by applying the respective portfolio weights to the historical asset return series. The cumulative performance of each portfolio was normalized to a starting value of 1, allowing for a clear comparison of relative growth over the sample period.

The following portfolio strategies are evaluated in the backtest:

- **Real Portfolio** – the actual portfolio based on the observed asset allocations.
- **Equal Weight Portfolio** – a portfolio where all assets receive identical weights.
- **Optimized Portfolio** – the portfolio obtained by maximizing the Sharpe ratio using mean–variance optimization.
- **Constrained Portfolio** – an optimized portfolio where individual asset weights are limited to a maximum allocation of 20%.
- **OMXPI Benchmark** – a broad Swedish equity index used as a reference for overall market performance.

The results, illustrated in Figure 4, reveal notable differences between the portfolio strategies. The optimized portfolio demonstrates the strongest performance over the sample period and clearly outperforms both the equal-weight portfolio and the real portfolio. This suggests that the optimization process is able to identify more efficient combinations of assets based on their risk and return characteristics.

The equal-weight portfolio performs relatively similarly to the real portfolio, indicating that the current allocation does not deviate substantially from a simple diversification strategy. However, both portfolios remain below the optimized alternatives, suggesting that improvements in capital allocation could potentially enhance risk-adjusted returns.

The constrained optimization, which restricts individual asset weights to a maximum of 20%, produces slightly lower returns than the fully optimized portfolio but still maintains a clear improvement relative to the simpler allocation strategies. This demonstrates how realistic portfolio constraints may influence the outcome of optimization models.

Comparing the strategies to the OMXPI benchmark provides additional context for the results. During the sample period, the optimized portfolios outperform the benchmark index, indicating that the model has the potential to generate excess returns through more efficient asset allocation.

It is important to note that this backtest is subject to in-sample bias, as the optimization was performed on the same data used for evaluation. The optimizer has full knowledge of the historical return distribution, which inflates performance metrics relative to what could realistically be achieved out-of-sample. The results should therefore be interpreted as an upper bound on portfolio efficiency rather than an expectation of future performance. An out-of-sample or walk-forward test would be required to validate these results more rigorously.

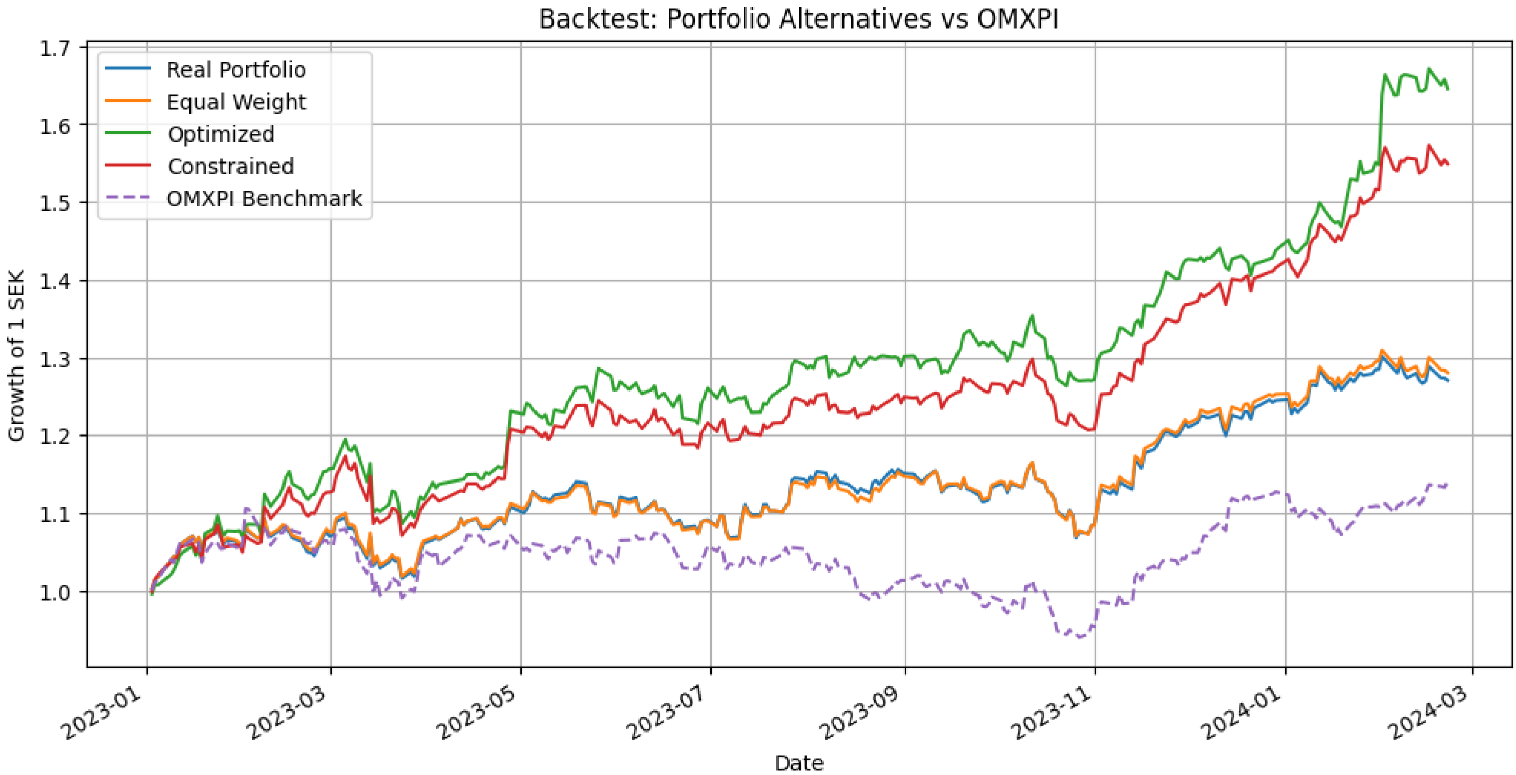

Figure 4: Historical performance of different portfolio stratgies compared with the OMXPI benchmark. Portfolio values are normalized to a starting value of 1 to illustrate relative growth over the sample period

Conclusion

This report analyzed the risk–return characteristics of a portfolio of Nordic equities and evaluated how quantitative portfolio optimization can improve portfolio efficiency. Using historical return data, the analysis examined asset correlations, individual risk–return profiles, and optimal portfolio allocations within a mean–variance optimization framework.

The results highlight the fundamental role of diversification in portfolio construction. While individual assets exhibit varying levels of risk and expected return, combining assets with different volatility and correlation structures allows investors to construct more efficient portfolios. This principle is clearly illustrated by the efficient frontier, which represents the set of portfolios that deliver the highest possible expected return for a given level of risk.

Among the analyzed allocations, the optimized portfolio that maximizes the Sharpe ratio lies closest to the efficient frontier and therefore represents the most efficient risk–return combination within the analyzed asset universe. This finding illustrates how quantitative portfolio optimization can improve portfolio efficiency compared to simpler allocation approaches such as equal weighting or discretionary portfolio construction.

However, the analysis also highlights several important limitations of purely quantitative models. Portfolio optimization relies heavily on historical data and statistical assumptions, which makes the results sensitive to the estimation of expected returns, volatility, and correlations. In practice, financial markets are influenced by a wide range of external factors that are difficult to capture within mathematical frameworks.

For example, macroeconomic developments, geopolitical events, or structural industry shifts can significantly affect asset performance in ways that are not reflected in historical return distributions. Defense-related companies such as MILDEF, for instance, may experience substantial performance changes due to geopolitical tensions or shifts in government spending, factors that are not directly incorporated in a purely statistical optimization model.

For this reason, quantitative models should not be interpreted as precise forecasts of future performance. Instead, they should be viewed as analytical tools that help investors better understand the structure of risk and return within a portfolio. The efficient frontier provides a powerful framework for identifying theoretically optimal allocations, but real-world portfolio construction often requires additional considerations such as liquidity, transaction costs, and fundamental company analysis.

Overall, the analysis demonstrates that quantitative portfolio optimization can provide valuable insights into portfolio construction and risk management. When combined with broader market awareness and fundamental analysis, these tools can support more informed investment decisions and help investors build more efficient portfolios over time.

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