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INTEGRATION OF CARBON GOALS INTO PORTFOLIO CONSTRUCTION: AMER REGION ANALYSIS

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ABSTRACT

This project explores the integration of carbon emission constraints into traditional portfolio construction methodologies. Specifically, this report focuses on portfolios created from firms listed in the North American region. With increasing regulatory and investor pressure to align the goals of companies with climate goals, we employ minimum variance optimisation frameworks along with value-weighted benchmarks to compare a range of portfolios' performance alongside their scope 1 and 2 emission data for portfolios created from 2014 to 2023. The core objective of this report is to asses financial trade-offs of embedding carbon reduction targets explicitly into the portfolio creation process.

We utilise the Markowitz Minimum Variance Portfolio (MVP) model and construct a long-only portfolio optimized using several covariance matrix estimation techniques, including Ledoit-Wolf shrinkage, identity shrinkage, and factor-based models. Our benchmark portfolio is value-weighted. We then introduce two climate-constrained variants: Portfolios with a fixed 50% reduction in carbon footprint relative to their unconstrained counterparts and a dynamic net-zero portfolio targeting a 10% annual reduction in carbon emissions, aligned with international climate trajectories such as the EU Paris-Aligned Benchmark.

The analysis of the 2014–2023 period reveals that carbon-reducing investment strategies can achieve significant emission reductions without compromising financial performance. The 50% carbon-reduced MVP not only matched but slightly outperformed the unconstrained MVP in terms of Sharpe ratio (0.7205 vs. 0.7011) and cumulative return, while maintaining similar levels of volatility and maximum drawdown. Similarly, a 50% constrained benchmark-tracking portfolio produced market-like return profile (12.35% vs. 12.14% cumulative return for the benchmark), while also consistently halving emissions. The net-zero portfolio maintained its emission reduction goals over the period, with minimal tracking error and a Sharpe ratio of 0.7798, demonstrating the feasibility of ambitious decarbonization paths in investment strategies.

These findings highlight that integrating carbon goals into portfolio construction can align investment practices with sustainability objectives while maintaining, or even enhancing, financial performance. The results support a growing body of literature advocating for optimized, climate-aligned investment frameworks and suggest that investors can meet decarbonization targets at low or no cost to performance, even in high-dimensional and noisy financial datasets.

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INTRODUCTION

1.1 Project Background

Sustainable finance is becoming a central pillar of investment strategy nowadays, with growing pressure on investors to align their portfolios with climate objectives. Carbon emissions have emerged as a key metric in this transition, driven by regulatory requirements and increasing awareness of climate risks (OECD, 2021). This project simulates how climate considerations, specifically carbon intensity and footprint, can be integrated into traditional portfolio construction. The analysis focuses on listed firms from the America (AMER) region, using financial data covering the period from 2004 to 2024 and carbon emission data (Scope 1 and 2) spanning from 2013 to 2023. Companies were selected based on the availability of reliable Scope 1 and Scope 2 CO_2emissions, annual revenues, market capitalizations, and monthly total return indices. A long-only minimum variance portfolio (MVP) is constructed using the classical Markowitz framework. Portfolio weights are optimized annually based on a ten-year rolling window of monthly simple return data. The performance of this MVP is then evaluated against a value-weighted benchmark portfolio across common financial metrics, including return, volatility and Sharpe ratio. Building upon this, the study introduces climate-aware strategies. These include a portfolio constrained to reduce carbon footprint by 50%, a benchmark-tracking portfolio with similar emission limits, and a net-zero portfolio designed to reduce emissions by 10% annually. Such strategies reflect real-world decarbonisation efforts while preserving investment efficiency. The project highlights the trade-offs between financial performance and carbon reduction.

1.2 Problem Statement

This project seeks to understand how climate constraints, specifically carbon emissions, influence portfolio construction and performance within a mean-variance optimization framework applied to AMER-listed firms.

1. How does the financial performance of a standard MVP compare to that of a value-weighted benchmark?
2. What is the impact of applying a 50% carbon footprint constraint to both MVP and benchmark-tracking portfolio in terms of risk, return, and emissions?
3. How does a progressive net-zero decarbonisation strategy, by reducing emissions by 10% annually, compare to other approaches?

CHAPTER II
METHODOLOGY

See Appendix 1 for a visual summary of the process flow.

2.1 Data Preparation and Filtering

This project begins with assembling and filtering a dataset to ensure regional consistency and ESG data integrity. The initial step involves loading firm-level static data from *Static.xlsx*, which includes ISIN codes, firm names, and regional classifications. The dataset is filtered to retain only firms classified in the "AMER" (Americas) region.

Environmental data is then integrated through Scope 1 (direct emissions) and Scope 2 (indirect emissions) datasets sourced from *Scope_1.xlsx* and *Scope_2.xlsx*. Using ISIN codes, emissions are mapped to firm names and filtered for AMER companies, under specific conditions: firms are required to have at least 7 years of non-missing data and at least 5 consecutive years of valid observations in both scopes. This threshold ensures sufficient historical depth and continuity for further analysis. A custom time-series consistency check is applied to validate these criteria, and firms passing this threshold are labelled as "solid_names".

Financial data are loaded next, comprising monthly returns (*DS_RI_T_USD_M.xlsx*), market capitalization (*DS_MV_T_USD_M.xlsx*), and annual revenues (*DS_REV_USD_Y.xlsx*). Since revenue data are reported annually, they are backward filled across months within the corresponding year to match the monthly structure of prices and market caps. Risk-free rate data from *Risk_Free_Rate.xlsx* are also loaded, converted from percentage to decimal format, and aligned to month-end timestamps. Firms that passed the ESG screen are further filtered to ensure they have complete financial data mentioned above.

To improve data continuity and quality, companies with more than 10% missing values (post-interpolation) are excluded. Zero values in prices, market caps, or revenues are assumed erroneous and replaced with NaNs. A linear interpolation is then performed across internal gaps, leaving leading and trailing NaNs untouched. This preprocessing step ensures smooth return computation and avoids disruptions in subsequent statistical modelling.

Finally, an additional filter is applied during the formation of each portfolio that ensures there is scope 1 and 2 carbon data for the firms entering the portfolio, this ensures the different portfolios have the same initial stock universe for comparability.

2.2 Standard Asset Allocation Process

This section details the construction of the conventional minimum-variance portfolio (MVP) using historical and ESG-screened data. The process comprises factor modelling, covariance matrix estimation using five different methods, rolling window optimization, and performance evaluation against a value-weighted benchmark.

2.2.1 Covariance Estimation Methods

To construct an MVP, a reliable estimate of the asset return covariance matrix is essential. This tests five alternative methods (see Appendix 2 for the comparison) to estimate covariance matrices. The Ledoit-Wolf shrinkage estimator regularizes the sample covariance matrix to reduce estimation noise in high-dimensional settings (Ledoit & Wolf, 2004). It applies $\widehat{\sum}_{LW} = \delta T + (1-\delta)S$ where T is the structured target matrix (e.g. identity), S is the sample covariance, and δ is the shrinkage intensity. The shrinkage to identity matrix combines the sample covariance matrix *S* with a scaled identity matrix *I* to mitigate instability from small eigenvalues. This applies $\widehat{\sum}_{ID} = (1-\lambda)S + \lambda\bar{\sigma}^2 I$, where $\bar{\sigma}^2$ is the average variance, and $\lambda \epsilon [0,1]$. The pseudo-inverse method applies the Moore-Penrose inverse to the sample covariance when the matrix is singular or ill-conditioned: $w \propto \sum^{+}1$. This method does not require optimization and directly yields closed-form weights, however, to implement the long only constraint it was necessary to feed this pseudoinverse through the optimiser as well. The factor models (1-factor and 3-factor) construct a structured covariance matrix using factor exposures, factor return covariances, and residual variances. The model follows $\widehat{\sum}_{FM} = BCov(f)B^T + D$, where *B* is the matrix of factor loadings, *Cov(f)* is the factor covariance, and *D* is the diagonal matrix of residual variances. The factors used in this project include market excess return (Mkt-Rf), size (SMB) based on market cap splits, and value (HML) based on revenue-to-market ratios (Fama & French, 1993). Factor betas are estimated using OLS regressions on at least 60 months of return history.

2.2.2 Rolling Window Setup

A 10-year (120-months) rolling window approach is implemented. For each investment year *Y*, the estimation window spans from January *Y*-10 to December *Y*-1. Assets must have at least 60 valid monthly returns in this period. This was done as there is a need to balance dataset completeness with statistical reliability, as data points with too few observations can distort the analysis. The corresponding forecast period (January to December of year Y) serves as the out-of-sample horizon for applying the optimized weights.

2.2.3 MVP Portfolio Optimization and Rebalancing

For each covariance method and each year, the MVP weights *w* are derived through quadratic optimization. This optimization minimizes portfolio variance subject to long-only constraints and full-investment constraints, formulated as: $\min_{w} w^T \sum w$ subject to $\sum_{i=1}^{N} w_i = 1,\ w_i \geq 0\ \forall i$, where $\sum$ is the estimated covariance matrix, and w is the vector of portfolio weights. The optimization is carried out using CVXPY, a convex optimization framework. For each investment year *Y*, this optimization is performed separately for each covariance estimation method, producing distinct MVP weight vectors. These weight vectors are then stored and used for out-of-sample return evaluation in the following calendar year. Portfolio rebalancing occurs annually at the start of each year. That is, for a given year *Y*, the weights optimized using data from the previous 10 years (up to December *Y*-1) are applied to the monthly returns from January to December of year *Y*. Throughout the year, weights are updated monthly via buy-and-hold logic: returns are reinvested proportionally based on asset performance, simulating a realistic passive investment strategy without interim rebalancing.

2.2.4 Value-Weighted (VW) Benchmark Portfolio Construction

In parallel, a Value-Weighted (VW) Benchmark Portfolio is constructed as a reference strategy. For each month *t*, the portfolio weights are computed based on the market capitalizations observed in the previous month *t* - 1. To avoid return inflation, the returns were calculated using beginning of period weights. This approach reflects a realistic and investable passive strategy commonly used in academic and institutional settings.

2.2.5 Ex-Post Performance Evaluation

An evaluation is then conducted using several key metrics: annualized average return, annualized volatility, Sharpe ratio, cumulative return, minimum and maximum monthly returns, and maximum drawdown (see Appendix 3 for definitions). Finally, cumulative return series from both strategies are plotted to visually compare growth.

2.3 Allocation with a 50% Reduction in Carbon Emissions

This section describes the construction of portfolio with a 50% reduction in carbon emissions.

2.3.1 Weighted-Average Carbon Intensity (WACI) and Carbon Footprint (CF)

This section outlines the computation of two carbon metrics for the Minimum Variance Portfolio (MVP): the Weighted-Average Carbon Intensity (WACI) and the Carbon Footprint (CF). These are evaluated annually over the period 2014–2023, using portfolio weights $w_{i,Y}$ derived at the end of year *Y* and applied to year *Y*+1. Total emissions for each firm *i* in year *Y* are computed by aggregating Scope 1 and Scope 2 emissions as $E_{i,Y} = Scope1_{i,Y} + Scope2_{i,Y}$. Annual revenues and market capitalizations are extracted as of December each year to align with the rebalancing schedule. Only firms with complete emissions, revenue, and market cap data are included in a given year to ensure consistency. The portfolio's carbon footprint (CF) in year *Y*+1 is calculated $CF_{Y+1}^{(p)} = \sum_{i=1}^{N} w_{i,Y} \left(\frac{E_{i,Y+1}}{Cap_{i,Y+1}} \right)$, which expresses the total emissions per unit of capital invested in tons of CO_2 equivalent per million USD. Meanwhile, the WACI is calculated as $WACI_{Y+1}^{(p)} = \sum_{i=1}^{N} w_{i,Y} \left(\frac{E_{i,Y+1}}{Rev_{i,Y+1}/1000} \right)$, reflecting the portfolio's emissions intensity relative to firm revenues, also expressed per million USD.

2.3.2 MVP Tracking Portfolio with 50% Carbon Footprint Reduction

This section extends the standard MVP (Ledoit-Wolf) by incorporating a carbon constraint aimed at reducing the portfolio's carbon footprint by 50% relative to the original MVP. The methodology applies annually from 2013 to 2023 using a rolling-window framework, with performance evaluated out-of-sample in year *Y*+1 using weights optimized at the end of year *Y*. Firm-level carbon intensities are calculated for each year *Y* as $c_{i,Y} = \frac{E_{i,Y}}{Cap_{i,Y}}$, where $E_{i,Y}$ is the total Scope 1 and Scope 2 emissions, and $Cap_{i,Y}$ is the market capitalization of firm *i.* These intensities are stored as annual vectors c_Y. The carbon footprint of the baseline MVP is also computed each year as $CF_Y^{(p_{oos}^{mv})} = \sum_{i=1}^{N} \alpha_{i,Y} c_{i,Y}$ where $\alpha_{i,Y}$ are the MVP weights for year *Y*. The portfolio optimization is formulated to minimize portfolio variance, subject to standard constraints and an additional carbon constraint. For each year *Y*, the optimization problem follows: $\underset{w}{min}\ w^T \widehat{\sum}_Y w$ subject to $\sum_{i=1}^{N} w_i = 1,\ w_i \geq 0\ \forall i,\ w_i \leq 1\ \forall i,\ \sum_{i=1}^{N} w_i c_{i,Y} \leq 0.5 \cdot CF_Y^{(p_{oos}^{mv})}$. Here, $\widehat{\sum}_Y$ is the covariance matrix estimated using the Ledoit-Wolf shrinkage method over a 10-year lookback window (120 months of monthly returns). Only firms with at least 60 valid monthly returns in the window are considered. The resulting constrained weights are applied to compute out-of-sample monthly returns from January to December of year *Y*+1, simulating a passive investment strategy with annual rebalancing. Monthly returns are compounded using a buy-and-hold logic. The portfolio's carbon footprint is recalculated each year as $CF_Y^{(p)} = \sum_{i=1}^{N} w_i c_{i,Y}$ to verify compliance with the 50% reduction threshold.

2.3.3 VW Tracking Portfolio with 50% Carbon Footprint Reduction

This part describes the construction of a decarbonized portfolio, denoted $p_{oos}^{vw}(0.5)$, designed to track the performance of a value-weighted (VW) benchmark while achieving a 50% reduction in carbon footprint. The methodological framework mirrors that used in Section 2.3.2, with adjustments to the benchmark and constraint reference. The VW benchmark portfolio, P^{vw}, is constructed using end-of-year market capitalizations: $w_{i,Y}^{vw} = \frac{Cap_{i,Y}}{\sum_{j=1}^{N} Cap_{j,Y}}$. Hence, the benchmark's carbon footprint is calculated as $CF_Y^{vw} = \frac{\sum_{i=1}^{N} E_{i,Y}}{\sum_{i=1}^{N} Cap_{i,Y}}$. This value serves as the carbon intensity threshold for the optimized portfolio, which must satisfy $\sum_{i=1}^{N} w_i c_{i,Y} \leq 0.5 \cdot CF_Y^{vw}$, where $c_{i,Y}$ represents firm-level carbon intensities as previously defined. The portfolio optimization minimizes the tracking error variance relative to the VW benchmark, subject to the same long-only, full investment, and carbon footprint constraints described in Section 2.3.2. The objective function is $\underset{w}{min}\ (w - w^{vw})^T \widehat{\sum}_Y (w - w^{vw})$, where $\widehat{\sum}_Y$ is the Ledoit-Wolf covariance matrix estimated over the 10-year rolling window.

2.3.4 Performance Evaluation and Comparison

The next step is to evaluate the performance of the two carbon-constrained tracking portfolios: the $p_{oos}^{mv}(0.5)$ which tracks the MVP, and the $p_{oos}^{vw}(0.5)$ which tracks the value-weighted benchmark. Each portfolio is constructed annually using optimized weights w_Y applied to year *Y*+1. Within each year, portfolio weights evolve via a passive buy-and-hold approach. That is, starting with the optimized weights in January, monthly returns are reinvested proportionally based on asset performance: $w_{i,t+k} = \frac{w_{i,t+k-1}(1+R_{i,t+k-1})}{1+ R_{p,t+k-1}}$, where $R_{i,t+k-1}$ is the return of asset i, and $R_{p,t+k-1}$ is the return of the overall portfolio in the previous month. A time series of monthly returns $\{R_{p,t+k-1}, \dots, R_{p,T}\}$ is generated for each strategy, and standard financial performance metrics (as previously mentioned in Section 2.2.5) are computed. The actual carbon footprint of each portfolio is also monitored annually, following $CF_{Y+1}^{p} = \sum_{i=1}^{N} w_{i,Y} \cdot c_{i,Y+1}$, then compared to its respective constraint: $0.5 \times CF_{Y+1}^{mw}$ for the MVP-tracking portfolio and $0.5 \times CF_{Y+1}^{vw}$ for the VW-tracking portfolio. Finally, both portfolios are benchmarked against their unconstrained counterparts p_{oos}^{mv} and p_{oos}^{vw}, in order to assess the cost of carbon reduction in terms of financial performance. This helps clarify the implications of adopting climate-aware investment strategies across both active (MVP-based) and passive (VW-based) management style.

2.4 Portfolio Construction with a Net Zero Objective

This part describes the procedures taken to construct a minimum-variance portfolio that cumulatively reduces its carbon emissions by following a Net Zero pathway. The strategy targets a 10% annual reduction in the portfolio's carbon footprint relative to a 2013 base year benchmark, using a rolling optimization and out-of-sample evaluation.

2.4.1 Net Zero Portfolio Construction

The Net Zero portfolio $p_{oos}^{vw}(NZ)$ is designed to minimize the tracking error relative to a value-weighted (VW), benchmark portfolio, while meeting a dynamic carbon reduction constraint. The optimization is repeated annually for the investment years 2014-2023, based on data and calculations from the prior 10 years. The carbon footprint of the VW benchmark in the base year $Y_0 = 2013$, denoted $CF_{Y_0}^{vw}$, is computed as $CF_{Y_0}^{vw} = \frac{\sum_{i=1}^{N} E_{i,Y_0}}{\sum_{i=1}^{N} Cap_{i,Y_0}}$, where E_{i,Y_0} is the total Scope 1 and 2 emissions of firm *I*, and Cap_{i,Y_0} is its market capitalization. The annual carbon constraint for each year *Y* is computed using exponential decay as follows: $CF_{Y}^{target} = (1-\theta)^{Y-Y_0+1} \cdot CF_{Y_0}^{vw}, \theta = 0.10$. Using a 10-year rolling window of monthly returns, a covariance matrix $\widehat{\sum}_Y$ is estimated via Ledoit-Wolf shrinkage. The optimization problem minimizes tracking error against the VW benchmark, which follows $\underset{w}{min} (w - w^{vw})^T \widehat{\sum}_Y (w - w^{vw})$, subject to $\sum_{i=1}^{N} w_i = 1$, $w_i \geq 0 \; \forall i$, $w_i \leq 1 \; \forall i$, $\sum_{i=1}^{N} w_i c_{i,Y} \leq CF_{Y}^{target}$.

2.4.2 Performance Evaluation and Comparison

The optimized weights w_Y are applied to year *Y*+1, forming a buy-and-hold strategy throughout that year. Monthly returns are accumulated to compute the total return time series for the Net Zero portfolio. Each year, the portfolio's actual carbon footprint is computed as $CF_{Y}^{p} = \sum_{i=1}^{N} w_i \cdot c_{i,Y}$. This is compared to the target CF_{Y}^{target} to ensure compliance with the Net Zero trajectory. Financial performance metrics (as mentioned in Section 2.2.5) are computed for $p_{oos}^{vw}(NZ)$ and benchmarked against p^{vw} and p_{oos}^{vw}. Cumulative return plots and summary statistics are also visualized, allowing for comparison across the three strategies, highlighting both financial trade-offs and carbon footprint reduction effectiveness.

CHAPTER III
RESULTS AND DISCUSSION

3.1 Standard Asset Allocation

In this section, we analyze the out-of-sample performance of five minimum-variance portfolios (MVPs), each built using a different technique to estimate the covariance matrix, along with the value-weighted (VW) benchmark portfolio for comparison. The methods used include: Ledoit-Wolf shrinkage, pseudo-inverse, 1-factor model, 3-factor model, and shrinkage towards the identity matrix. The comparison is based on cumulative returns, risk-adjusted metrics (like the Sharpe ratio), and performance stability over the 2014–2023 period, as shown in Table 1 below.

Table 1 Financial metrics comparison between covariance estimation methods

	Annualized Average Return	Annualized Volatility	Cumulative Total Return	Sharpe Ratio	Minimum Monthly Return	Maximum Monthly Return	Maximum Drawdown
Ledoit-Wolf	0.0912	0.1209	1.3930	0.6878	-0.0883	0.1199	-0.1657
Pseudoinverse	0.1127	0.1637	1.9082	0.6649	-0.1612	0.1452	-0.2560
1-factor	0.0716	0.1340	0.9974	0.4970	-0.1082	0.1141	-0.1699
3-factor	0.0719	0.1287	1.0019	0.5142	-0.1077	0.1105	-0.1902
Identity	0.0911	0.1191	1.3923	0.6960	-0.0854	0.1170	-0.1629
Value-weighted	0.1214	0.1483	2.1444	0.7712	-0.1183	0.1248	-0.2081

Among the minimum-variance approaches considered, the Ledoit-Wolf shrinkage estimator emerges as the most reliable and well-suited for our dataset. Since our data are high-dimensional (more than 200 assets over 120 months) and include missing values, traditional methods for estimating the covariance matrix face serious challenges.

The Ledoit-Wolf approach addresses these by shrinking the sample covariance matrix toward a structured and well-conditioned target, effectively reducing estimation noise and improving matrix stability. This results in more robust and implementable portfolio weights.

By contrast, the pseudo-inverse method, while showing a higher annual return (11.27%), is affected by very high volatility (16.37%) and a large maximum drawdown (–25.6%), both of which reflect its numerical instability and extreme sensitivity to missing or irregular data. These issues make the method unreliable in practice, particularly in real-world scenarios like ours where data imperfections are frequent.

The factor-based models, both 1-factor and 3-factor, showed the weakest performance among the methods tested. In theory, these models can capture market dynamics using factors like market, size, and value. However, their effectiveness depends on having long and complete historical data, which our dataset lacks due to limited ESG coverage and gaps in firm-level return histories. As a result, the factors explain less of the return variation, and the portfolios built with these models are less accurate and less stable. This is reflected in their performance: cumulative returns below 1.00, Sharpe ratios under 0.52, and return trajectories that diverge significantly from the benchmark, with more noise and irregular patterns.

Finally, the shrinkage-to-identity method follows a similar idea to Ledoit-Wolf but uses a fixed shrinkage level. This makes it less flexible and less responsive to the actual data. While it performs well in terms of efficiency (annual return: 9.11%; Sharpe ratio: 0.696; volatility: 11.91%), it lacks the adaptive quality of the Ledoit-Wolf approach. Because Ledoit-Wolf adjusts the shrinkage level based on the data, it produces more realistic and reliable estimates, making it the most accurate and suitable choice for high-dimensional, noisy datasets like ours.

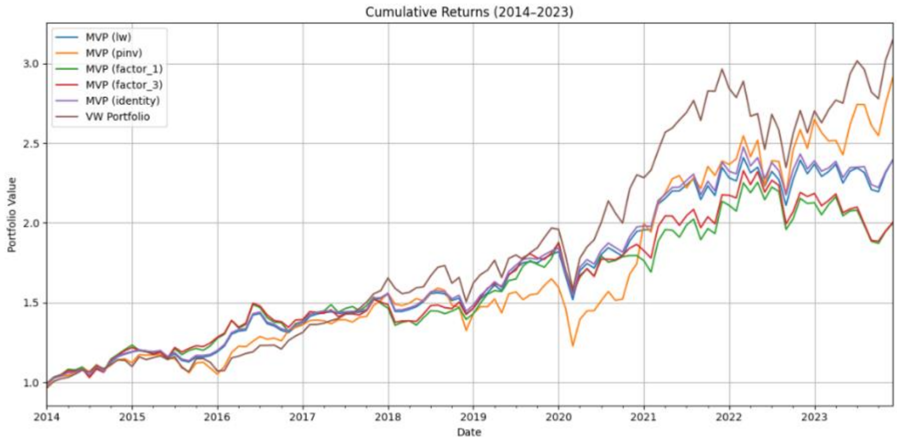

Figure 1 Cumulative return comparison method covariance estimation methods

Given its strong theoretical foundation and consistent performance, the MVP built with the Ledoit-Wolf estimator is compared to the VW portfolio, highlighting two contrasting approaches to portfolio construction. The MVP, focused on risk minimization, shows lower volatility (12.09%) and a respectable return (9.12%), whereas the VW portfolio, driven by market-cap weighting, achieves a higher return (12.14%), higher volatility (14.83%), and the best Sharpe ratio (0.7712).

This difference reflects how the two portfolios are built: the MVP, based only on U.S. stocks, invests in defensive companies from low-volatility sectors like utilities, consumer staples, and healthcare, frequently including stocks like PG&E, General Mills, Quest Diagnostics, and Capitol Federal Financial. In contrast, the VW portfolio is heavily exposed to large-cap growth stocks in the U.S. market, such as Apple, Microsoft, Amazon, Nvidia, and JPMorgan, with a strong concentration in big tech companies, which represent about 20% of total market capitalization each year.

The MVP's composition is also more dynamic, with 37 unique stocks entering its top 10 holdings over 10 years, compared to 19 for VW. This higher turnover reflects the MVP's sensitivity to changes in the covariance matrix, which is a feature that supports adaptability, but could lead to higher transaction costs. Notably, Walmart is the only stock to appear consistently among the top holdings of both portfolios, due to its rare combination of size and stability.

Performance attribution highlights further contrasts. Between 2014 and 2023, a small number of high-weight, high-return stocks drove results. The MVP benefited from stable companies like PG&E, Hershey, and Southern Co., with occasional boosts from top performers such as Eli Lilly and Edwards Lifesciences. At the same time, it was negatively affected by more volatile stocks such as Barrick Gold or Range Resources.

The VW portfolio, meanwhile, benefited strongly from the post-Covid tech boom: in 2021, for example, Apple and Microsoft delivered returns of 52% and 34%. However, the portfolio also struggled during market corrections, as shown by Amazon's losses in 2022 and 2023, and the weak performance of commodity-related stocks like Freeport-McMoRan.

During times of crisis, like the COVID-19 crash in 2020, the MVP showed greater resilience thanks to its low exposure to cyclical sectors such as energy and financials, and the protective effect of defensive stocks. This confirms its ability to reduce risk compared to the VW. In contrast, during bullish markets, especially the tech rebound in 2021–2022, where the VW strongly outperformed, fully benefiting from its high exposure to growth stocks. The MVP, by design, underweights volatile assets and thus captured only part of the upside, leading to a performance gap despite similar long-term growth trends.

These findings underscore the importance of portfolio design and risk profile, showing how sector allocation, turnover, and exposure to growth versus defensive stocks play a critical role in shaping performance across varying market conditions.

3.2. Allocation with a Carbon Emissions Reduction of 50%

This section examines and compares the carbon characteristics of the unconstrained portfolio alongside the $p_{oos}^{mv}(0.5)$ and $p_{oos}^{vw}(0.5)$ portfolios.

3.2.1 Carbon Profile of the Unconstrained Portfolio

Covering the years 2014 – 2023, the discussion traces how the unconstrained portfolio's carbon profile has evolved, drawing on two common sustainability indicators: **carbon footprint** (t CO_2e per USD million invested) and **weighted-average carbon intensity** (WACI, t CO_2e per USD million revenue). Together, these indicators offer a comprehensive view of the portfolio's environmental profile from both an asset allocation and operational efficiency perspective.

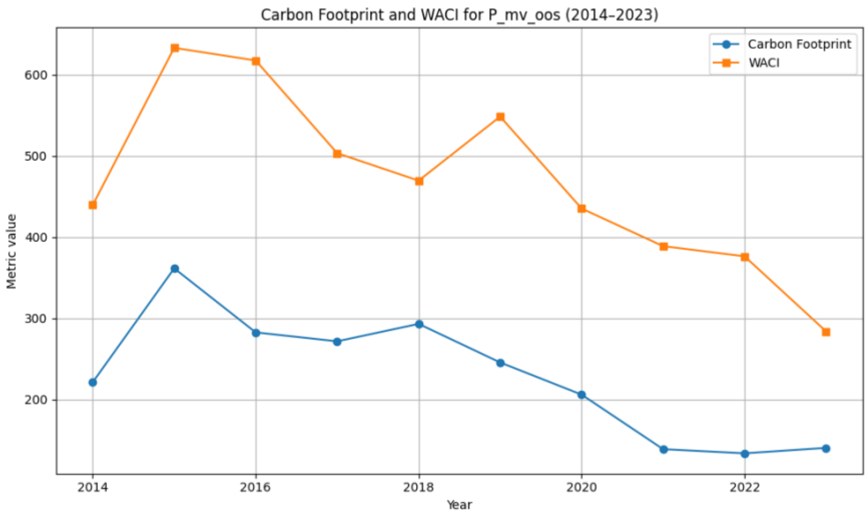

Figure 2: Carbon Footprint (tons CO_2e per million USD invested) and WACI (tons CO_2e per million USD revenue) of the Unconstrained Portfolio (2014–2023).

The portfolio's carbon footprint, which is defined as the **financed emissions per million dollars invested**, experienced significant fluctuation across the sample period. Starting at 143.16 in 2014, the footprint surged sharply to 364.19 in 2015, indicating a strong tilt toward carbon-intensive sectors, likely including fossil fuels, heavy industry, or utilities. This is supported by the portfolio analysis with PPL co. and Southern co., large gas and coal companies, entering the top 10 weights, with Southern co.'s emissions totaling more than 2014's entire top 10. This sharp increase signals elevated environmental risk from an investor's perspective, particularly during a period marked by growing awareness of climate-related financial exposures. However, from its 2015 peak, the carbon footprint declined steadily over the subsequent years, reaching a low of 134.16 in 2022. This suggests a gradual shift either in the underlying asset composition, which favors less carbon-intensive sectors, or in the emission profiles of the portfolio's holdings. The slight uptick to 140.55 in 2023 interrupts this trend, mainly due to temporary sector rotations or increased exposure to high-emitting firms and may raise concerns for investors monitoring long-term decarbonization consistency.

A similar pattern is observed in the portfolio's WACI, which measures **emissions relative to revenue** and reflects the carbon efficiency of the companies held. The WACI peaked at 639.63 in 2015, highlighting the portfolio's exposure to firms with high emissions relative to their output, which is a less attractive feature for sustainability-oriented investors. Encouragingly, this metric also trended downward over the decade, reaching 276.57 by 2023. The consistent decline suggests either improvements in corporate emission efficiency or portfolio shifts toward companies with lower carbon intensity. The analysis of data confirms the latter with the 2023 portfolio having 1 oil and gas company in its top 10 weights compared to 3 in 2015. Nevertheless, WACI also exhibited notable year-to-year volatility, for instance, a pronounced rebound to 548.42 in 2019, indicating that the portfolio's carbon efficiency gains were neither linear nor fully stable. This inconsistency is attributable to changing market dynamics or reactive reallocations that temporarily undermined sustainability goals.

Taken together, the trends in both metrics point to an overall **improvement in the portfolio's environmental performance** between 2015 and 2023, marked by reduced financed emissions and enhanced carbon efficiency. However, the presence of interim spikes and the absence of a binding constraint suggest that the observed reductions were market-driven rather than the result of systematic decarbonization. For sustainability-minded investors, this raises an important consideration: while the unconstrained portfolio shows a positive long-term trajectory, its carbon profile remains highly sensitive to market movements and lacks explicit alignment with climate targets such as those embedded in Paris-Aligned or Net Zero benchmarks. As such, additional screening or constraints may be required to meet institutional climate commitments with greater consistency.

In conclusion, although the unconstrained portfolio demonstrates progress in carbon metrics over the sample period, its environmental profile remains **volatile** and only **partially aligned with sustainability objectives**. The data suggest that without dedicated constraints, improvements in carbon performance are neither stable nor assured, which limits the portfolio's appeal for investors with explicit decarbonization mandates.

3.2.2 Characteristics of $p_{oos}^{mv}(0.5)$

Following the comparison between carbon footprint and the weighted average carbon intensity (WACI), this section examines the effects of a 50% carbon-emissions constraint on the minimum-variance portfolio (MVP) benchmark. We compare the **unconstrained MVP** against the **50% carbon-constrained MVP** over the period 2014–2023. The carbon constraint is defined such that the constrained MVP targets half the carbon footprint (carbon intensity) of the unconstrained portfolio. Performance is evaluated in terms of carbon emissions and risk-return metrics (annualized return, Sharpe ratio, volatility, and maximum drawdown). In what follows, we focus exclusively on the unconstrained and 50% carbon-constrained MVPs, while value-weighted or other portfolios are considered later.

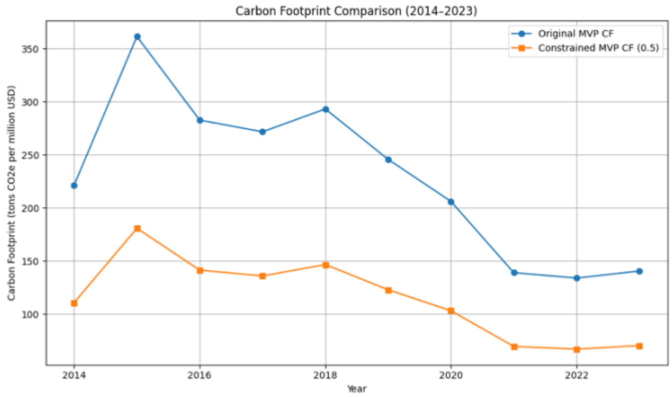

Figure 2: Carbon footprint (tons CO_2e per million USD) of the unconstrained MVP (blue) and 50% carbon-constrained MVP (orange) (2014-2023).

The constrained portfolio maintains roughly half the carbon intensity of the unconstrained MVP in each year. Over the decade, both portfolios' carbon footprints decline as lower-carbon assets gradually enter the portfolio, but the constrained MVP's footprint remains substantially lower at all times. For example, in 2014 the unconstrained portfolio emits on the order of 143.16 tons CO_2e per million USD, whereas the constrained MVP emits 71.58 tons CO_2e, consistent with the 50% reduction target. By 2023 the unconstrained MVP has fallen to about 140.55, while the carbon-constrained MVP is near 70.28. Thus, the 50% carbon reduction constraint effectively and consistently lowered portfolio emissions. However, the overall reduction across the entire time span was minimal. As observed in the previous task, a significant increase occurred in 2015, which was gradually offset over the subsequent eight years. Taking the results from 2015 onwards, they align with the portfolio design: by penalizing high-emission assets in the optimization, the constrained MVP shifts weight toward cleaner stocks, achieving roughly half the carbon exposure with minimal turnover. Importantly, the carbon constraint does not necessarily imply higher risk. In fact, recent research finds that low-carbon constraints can halve emissions with "virtually no loss in Sharpe ratio" for reasonable constraint levels (Anquetin, Coqueret, Tavin, & Welgryn, 2022).

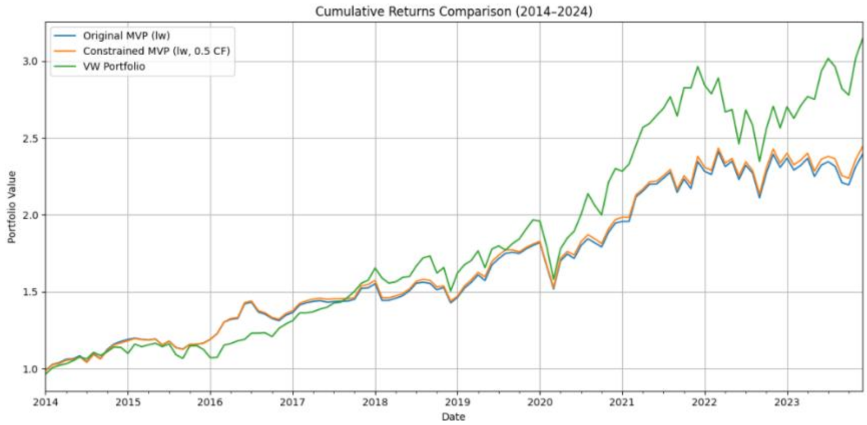

Figure 3: Cumulative return of the unconstrained MVP (blue) and 50% carbon-constrained MVP (orange) (2014-2023).

Both portfolios exhibit very similar return trajectories. As shown, the constrained MVP closely tracks the performance of the unconstrained MVP year by year. By the end of 2023, both portfolios have nearly increased by a factor of 2.5 in value (a cumulative return of about 150%), implying comparable compound growth. For most of the period the orange line (50% carbon constraint) lies almost on top of the blue line (unconstrained MVP), with only very small divergences. The largest drawdowns occur around the early-2020 market crash, where both portfolios decline by roughly 20–25% peak-to-trough, thereafter both recover on a similar path.

Quantitatively, the key performance metrics of the two portfolios are similar, but the constrained portfolio outperformed. The **annualized return** (CAGR) of the unconstrained MVP is at 9.28% per year over 2014–2023, and the constrained MVP's annualized return is 22bps higher at 9.50%. In other words, imposing the 50% carbon target did meaningfully increase long-term returns. Likewise, their **volatilities** are almost the same at 12.07% (unconstrained) and 12.02% (constrained), while this results in a higher **Sharpe ratio** for the constrained portfolio at 0.7205 (0.0194 higher than unconstrained). The difference in Sharpe ratios between the unconstrained and constrained portfolios is only a few hundredths at most, and thus effectively negligible in practice. This is consistent with the literature: Anquetin et al. (2022) report that one can "cut emission intensities in half" with "virtually no loss in Sharpe ratio" under reasonable carbon constraints (papers.ssrn.com). Similarly, the maximum drawdowns are very close. Both portfolios experienced a **maximum drawdown** on the order of 20–25% (driven largely by the 2020 COVID market drop), and neither portfolio shows a materially different worst-case loss. In short, annual return is slightly higher for the constrained approach, while the volatility stays nearly the same, which results in a higher Sharpe ratio for carbon reduced approach.

The upshot is that the 50% carbon constraint dramatically reduces emissions while preserving the risk-return profile of the MVP. This outcome makes sense. The unconstrained MVP tends to overweight low-volatility sectors (often utilities or stable industries) which may also be relatively carbon-intensive. By limiting carbon, the constrained MVP shifts toward cleaner but similarly low-volatility assets. In this case, those alternative assets turned out to have comparable returns, so the overall portfolio performance was nearly unaffected. In other words, the low-carbon tilt did not sacrifice diversification or significantly increase volatility. General theory warns that constraints can raise MVP volatility by pulling it toward the market portfolio (researchaffiliates.com), but here the constraint merely swapped in different low-risk stocks, leaving total risk similar. Indeed, the small uptick in Sharpe ratio suggests that the constrained MVP's risk-adjusted return is even better.

Overall, the analysis reveals no material performance trade-off from the 50% carbon constraint. The constrained MVP achieves a 50% reduction in carbon footprint each year (as intended) while yielding better cumulative return path and same risk metrics as the unconstrained MVP. This finding is in line with prior research on carbon-smart portfolios. In particular, scholars have emphasized that moderate carbon constraints can greatly cut emissions without harming portfolio efficiency papers.ssrn.com researchaffiliates.com. Thus our results corroborate the view that a low-carbon MVP can be implemented at near-zero cost to return and volatility.

3.2.3 Characteristics of $p_{oos}^{vw}(0.5)$

Both the carbon-constrained tracking portfolio (denoted $p_{oos}^{vw}(0.5)$) and the value-weighted benchmark (p^{vw}) delivered very similar financial performance over 2014–2023. The tracking portfolio was designed to closely mimic the market index while maintaining a carbon footprint 50% lower than the benchmark each year. As a result, its return profile closely *tracked* the benchmark: the two portfolios' cumulative return lines are nearly indistinguishable.

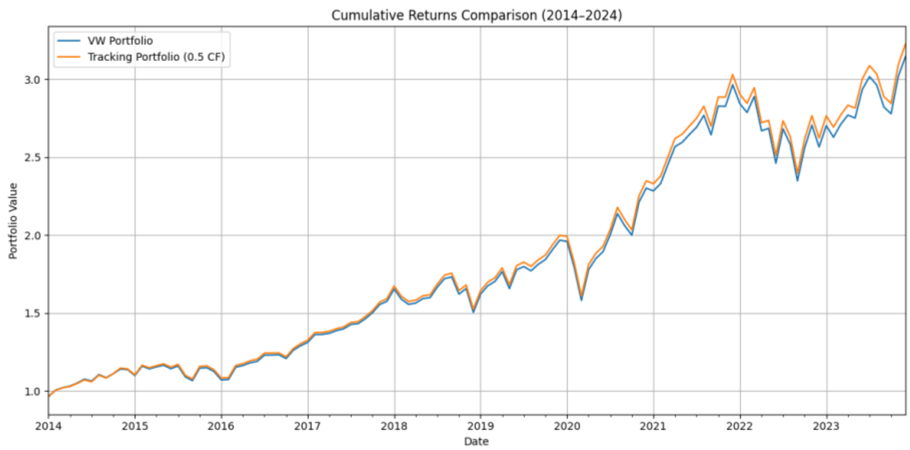

Figure 4: Cumulative return of p^{vw} and $p_{oos}^{vw}(0.5)$ (2014–2024).

Over the full period, the tracking portfolio achieved an annualized total return of **12.35%**, virtually the same as the benchmark at 12.14%. Volatility was likewise comparable (on the order of 14.83% annualized, with the tracking portfolio 1bp higher), leading to a small but higher Sharpe ratio for the carbon reduced portfolio at **0.7836** (Benchmark at 0.7712). This slight outperformance can be attributed to normal tracking error and favourable sector tilts rather than a structural return advantage. Importantly, both portfolios endured similar drawdowns during market stress periods. For instance, during the COVID-19 shock in early 2020, the tracking portfolio's peak-to-trough drawdown was on the same order (~30%) as that of the broad market, indicating no significant increase in downside risk from the carbon constraint. Overall, the financial metrics, including returns, volatility, Sharpe ratio, and maximum drawdown, show that the 50% carbon-constrained portfolio delivered **market-like performance with no material deviation** from the benchmark.

These findings demonstrate that a substantial reduction in portfolio carbon exposure can be achieved **without sacrificing financial returns or incurring excessive risk**. The tracking portfolio was explicitly constructed to minimize its tracking error relative to the market index, and the results confirm that its ex-post tracking error remained very low. This aligns with prior research by asset managers as shown in Appendix 4. The robust performance of our tracking portfolio corroborates these insights: by optimally rebalancing rather than simply divesting, the portfolio was able to **maintain market-like returns** despite a drastic cut in emissions. In summary, the 50% carbon-constrained strategy achieved its climate objective with negligible impact on traditional performance metrics, a result consistent with the broader literature on low-carbon indexes and enhanced index strategies ((LGIM), 2025) (Blitz, Mutsaers, & Jansen, 2023).

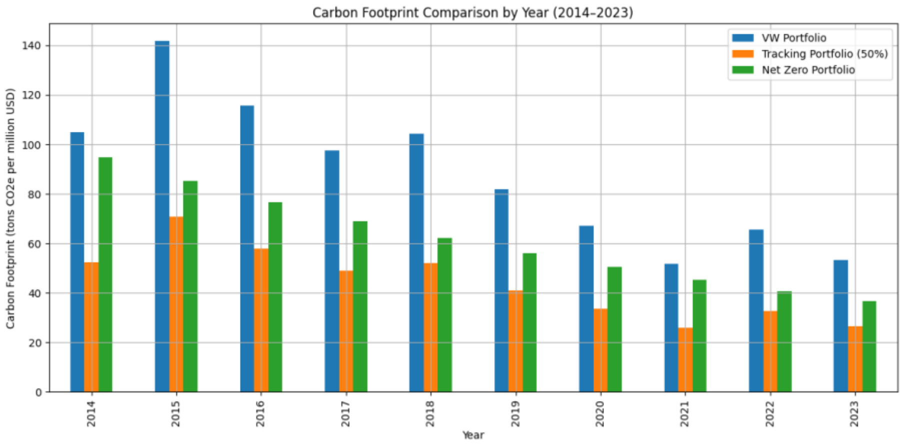

Figure 5: Annual carbon footprint comparison between p^{vw}, $p^{vw}_{oos}(0.5)$, $p^{vw}_{oos}(NZ)$, *measured in* tons CO_2e per million USD invested (2014–2023).

The tracking portfolio successfully maintained a carbon footprint approximately **50% lower** than that of the benchmark in each year of the sample. As shown above, the benchmark's carbon intensity (blue bars) steadily declined from 141.71 tons CO_2e per \$1M in 2015 to 53.18 tons by 2023, reflecting general decarbonization trends in the market. The 50% constrained portfolio (orange bars) consistently came in around half these levels, for example 70.85 tons vs. 141.71 in 2015, and 26.59 vs. 53.18 in 2023. This translates to a **50% reduction in financed emissions** compared to the standard index, even as the market's carbon intensity declined. As shown in the chart, the climate goal was met every year. In 2018, the benchmark's footprint was 104.31tons/\$1M vs 52.16 for the constrained portfolio. By 2021 it was 51.60 vs. 25.80. These annual reductions compounded to a significant climate impact over the decade.

Moving over, Achieving the 50 percent carbon reduction required careful reweighting of holdings relative to the benchmark. From 2014 to 2023, the portfolio consistently underweighted high-emission sectors such as oil and gas. Firms like ExxonMobil and Chevron remained in the portfolio but at reduced weights, especially by 2022 when energy sector risks were more pronounced. Meanwhile, allocation increased to lower-carbon sectors such as technology. In 2019, Microsoft's weight was notably raised, while Apple remained overweighted throughout much of the decade. These gradual tilts helped reduce emissions without sacrificing diversification or increasing tracking error.

It is worth emphasizing that these portfolio tilts were generally incremental (often a few tenths of a percentage point in weight) rather than wholesale exclusions. This subtle reallocation approach is why the portfolio achieved such low tracking error. By design, the optimization avoided extreme deviations, for example, completely dropping a top index constituent like Exxon would have introduced non-trivial active risk, so instead the portfolio held a smaller position in ExxonMobil rather than zero. The outcome is a portfolio that **mirrors the benchmark's sector and stock exposures closely**, with just enough adjustment to cut the carbon footprint in half. The experience from this case aligns with best practices noted in sustainable investing literature: replacing high-emission stocks with lower-emission alternatives requires careful balancing. If done naively (simply excluding polluters and pro-rata increasing others), one might unintentionally end up with large overweight positions in tech names like Apple or Microsoft, thereby incurring significant tracking error (Blitz, Mutsaers, & Jansen, 2023). Our strategy consciously mitigated that risk by optimizing the weight replacements. Indeed, the chosen approach ensured that even though the portfolio was biased *slightly* toward tech and away from energy, it remained well-diversified and sector-constrained. This is reflected in its steady performance. In hindsight, tilting toward technology firms proved beneficial during 2014–2023 (especially from 2020 onwards, a period when tech stocks outperformed, and fossil fuel stocks faced headwinds for much of the decade), which explains the tracking portfolio's mild outperformance. However, the construction was **not** reliant on any specific sector bet, the portfolio's success came from broad-based risk parity with the index, with climate considerations delicately folded in.

3.2.4 Trade-Off Analysis between p_{oos}^{mv}, $p_{oos}^{mv}(0.5)$, p^{vw}, $p_{oos}^{vw}(0.5)$

We compare the four portfolios with respect to return and emissions. As shown in detail in previous paragraph, the value-weighted benchmark p^{vw} generated moderate returns with full carbon (normalized to 100%), while its 50%-carbon portfolio $p_{oos}^{vw}(0.5)$ halved the carbon footprint by design while only slightly lowering performance. In our analysis the constrained VW portfolio achieved 50% lower carbon intensity at nearly the same Sharpe ratio (e.g. 0.7836 vs. 0.7712). This shows even **better results,** than S&P Global's findings, where a low-carbon S&P500 portfolio had Sharpe 0.725 vs. 0.703 and just ~30% lower carbon. In other words, cutting carbon in a passive index can usually be done with negligible drag on returns or even upside, consistent with evidence that ESG tilts can maintain or even raise risk-adjusted returns (Jondeau, Mojon, & da Silva, 2021).

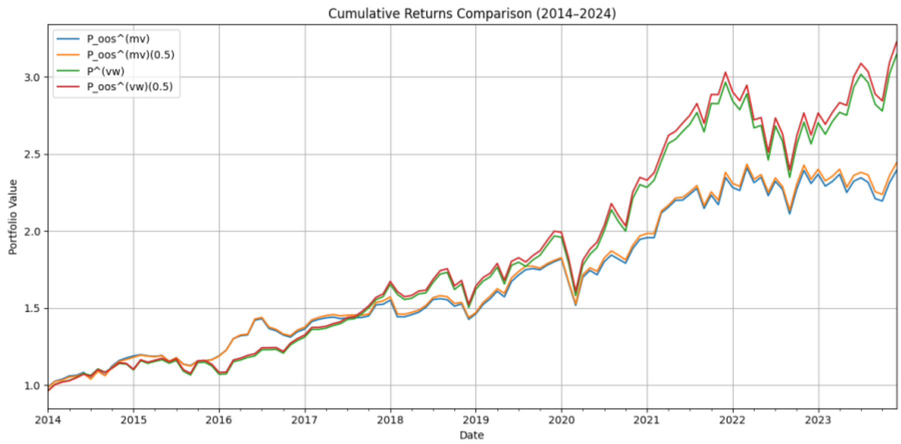

Figure 6: Cumulative returns of p^{mv}_{oos}, $p^{mv}_{oos}(0.5)$, p^{vw}, $p^{vw}_{oos}(0.5)$ *(2014-2024).*

In the minimum-variance (MV) case, the unconstrained MV portfolio p^{mv}_{oos} achieved very low volatility (Sharpe 0.7011 in our sample). Imposing the 50% carbon cap $p^{mv}_{oos}(0.5)$ cut carbon in half and even showed modestly better return and slightly decrease in volatility, so the Sharpe ratio increase to 0.7205. This illustrates an interesting result: optimization increased return/risk performance with achieving the carbon goal. Notably, even with the strict carbon limit the VW strategy outperformed the MV approach on a risk-adjusted basis.

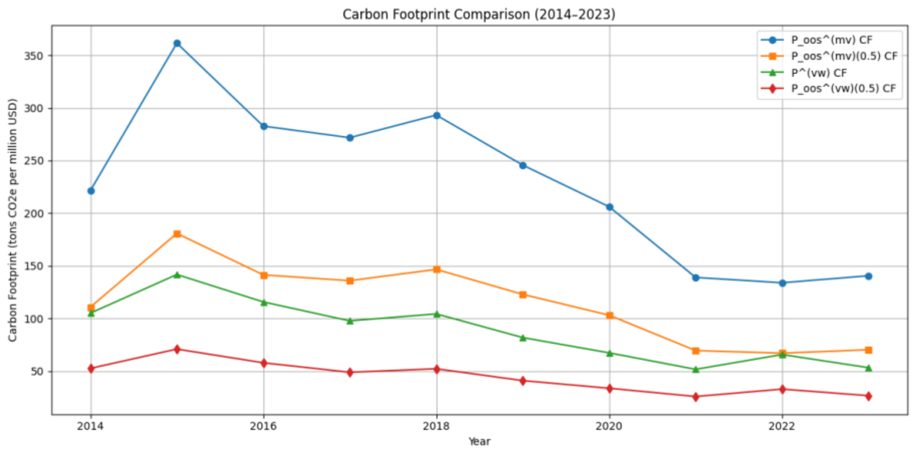

Figure 7: Carbon footprint comparison between p^{mv}_{oos}, $p^{mv}_{oos}(0.5)$, p^{vw}, *and* $p^{vw}_{oos}(0.5)$, *measured in tons* CO_2 *per $M revenue (2014-2023)..*

Overall, all four strategies exhibit the same pattern (see Figure 4 below): the carbon-constrained versions achieve 50% lower emissions and even increased risk/return performance. In fact, literature shows that even very aggressive carbon screens often leave returns unchanged or higher. Academic research report that excluding high-carbon firms produced returns at least as high as the benchmark and even *higher* Sharpe ratios, with only minor tracking error (Jondeau, Mojon, & da Silva, 2021). Our results echo this: the carbon-limited MV and VW portfolios both halved emissions while experiencing higher Sharpe ratios to their unconstrained values. This confirms that the portfolio optimization framework effectively balances the dual objectives, yielding substantial carbon reduction with achieving a modest positive impact on financial performance (Jondeau, Mojon, & da Silva, 2021).

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3.3 Allocation with a Net Zero Objective

This section discusses the characteristics of $p_{oos}^{vw}(NZ)$ and compares the performance with two other portfolios: p^{vw} and $p_{oos}^{vw}(0.5)$.

3.3.1 Net Zero Tracking Portfolio ($\boldsymbol{p_{oos}^{vw}(NZ)}$)

We consider the "net-zero" tracking portfolio **P$_{oos}$^(vw)(NZ)**, obtained by solving the same minimum-variance tracking-error problem as in Section 2.3 but with a progressively tightening carbon constraint. In particular, starting from a 2013 baseline carbon footprint, the portfolio is rebalanced each year so that its footprint falls by 10% per annum. This ensures a "net-zero pathway" consistent with a 2050 zero-emissions goal. In practice, the optimization is identical to the passive tracking problem (minimize tracking error to the value-weighted benchmark) except for this annualized carbon budget. The resulting net-zero portfolio gradually shifts weight toward low-emission firms while remaining close to the benchmark. Over the 10 years, the top 10 weighted stocks matched exactly in 7 years and 9/10 in the remaining 3, showing the NZ portfolio tracked the benchmark well. Oil and gas companies like Exxon and Chevron were consistently underweighted, while cleaner tech stocks like Apple and Microsoft moved from underweighted in 2014 to neutral over overweighted by 2023.

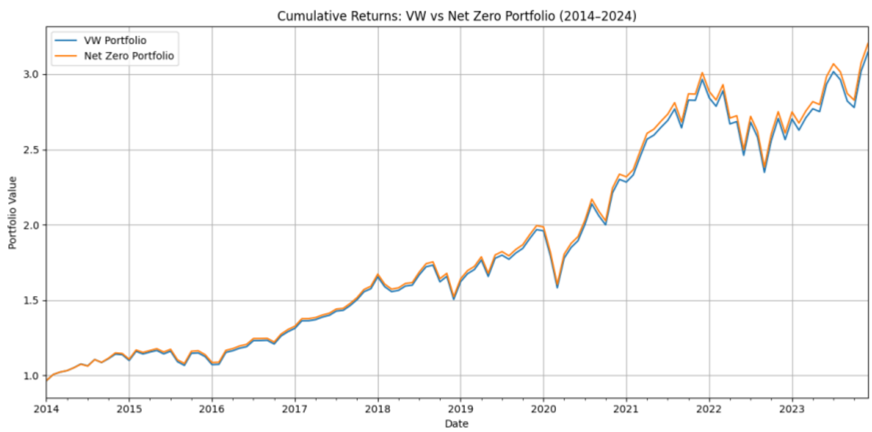


Figure 8: Cumulative return of the p^{vw} *and* $p_{oos}^{vw}(0.5)$ *(2014-2024).*

In summary statistics, the net-zero portfolio achieved a **robust financial performance** over 2014–2023. Its cumulative return more than tripled the initial value (close to the benchmark) over the decade, with an annualized return of **12.28%** and volatility (annual standard deviation) in the mid-teens at 14.83, aligning with the benchmark and the 50% carbon reduced portfolio. The Sharpe ratio remains healthy at 0.7798, indicating that the risk-adjusted return is outperforming compared to the unmanaged benchmark. Drawdowns are also similar in timing and magnitude to the overall market and 50% carbon reduced portfolio: the portfolio saw a significant decline (~20–25% from peak) during the early-2020 COVID crash and smaller peaks-to-trough drops (on the order of 10–15%) in late 2021/2022. Importantly, these performance metrics are achieved **with small overperformance**: the net-zero portfolio's cumulative return lead the benchmark by a few percentage points over the period, demonstrating that imposing the 10%/yr carbon budget had a modest positive cost in return. In other words, the financial drag of net-zero decarbonization appears positive. Overall, the net-zero tracking strategy preserved a high Sharpe ratio and acceptable drawdowns, indicating that it offered a better risk-return profile while achieving significant emissions cuts.

The **carbon footprint** of the net-zero portfolio fell dramatically, but not as much as the 50% carbon reduced portfolio. In 2013 (baseline year), the portfolio's footprint was set to a given level. By construction, the portfolio achieved roughly a 60% reduction by 2023 compared to the 2013 baseline. Concretely, the chart above shows annual carbon intensity (tons CO_2e per million USD revenue) dropping from 92.27 in 2014 to 36.72 by 2023 for the net-zero strategy. This trajectory essentially matches the ideal geometric path of a 10% per year decay: after 9 years at –10%/yr, one expects ≈(0.90)^9 ≈ 40% of the original level, which is consistent with the observed footprint (36.72 in 2023). In percentage terms, this corresponds to about a **61.21% reduction from 2013 to 2023**.

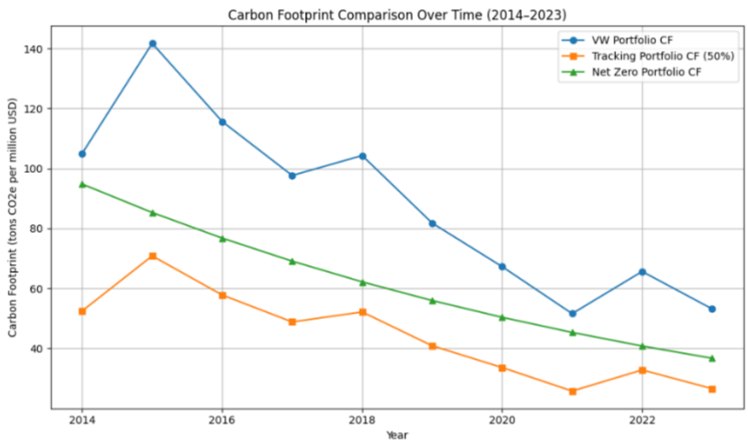


Figure 9: Carbon footprint comparison by year between p^{vw}, $p^{vw}_{oos}(0.5)$, $p^{vw}_{oos}(NZ)$, measured in tons CO_2 per $M revenue (2014-2023).

From a climate perspective, this achievement is substantial. For comparison, the EU's Paris-Aligned Benchmark rules call for an index to follow approximately a 7% annual reduction in carbon intensity (Handbook of Climate Transition Benchmarks and Paris-Aligned Benchmarks (Version 2), 2025). The net-zero portfolio's 10%/yr path is significantly steeper than that baseline, reflecting an exceptionally ambitious decarbonization trajectory. Moreover, major institutional initiatives targeting 1.5°C alignment typically set intermediate goals of similar scale: for example, the UN Net-Zero Asset Owner Alliance (representing major pension and insurance funds) commits members to reach net-zero by 2050 (consistent with 1.5°C) and targets roughly 40–60% emissions cuts by 2030 (UNEP Finance Initiative, 2025). Our net-zero portfolio's reductions over 2014–2023 already approach the lower end of that interim goal (> 60% by 2023 extrapolated), indicating feasibility. In short, the portfolio's decarbonization meets or exceeds many forward-looking climate benchmarks (e.g. EU PAB, IPCC 1.5°C pathways (Handbook of Climate Transition Benchmarks and Paris-Aligned Benchmarks (Version 2), 2025) and is in line with large asset owners' stated targets (UNEP Finance Initiative, 2025).

In terms of **feasibility and ambition**, the net-zero strategy demonstrates that a passive investor can indeed meet aggressive climate targets gaining little financial upside simultaneously. The 10%/yr reduction rule is more ambitious than regulatory minima (7%/yr) (Handbook of Climate Transition Benchmarks and Paris-Aligned Benchmarks (Version 2), 2025) and aligns with recommendations for 1.5°C; the fact that the portfolio achieved this while delivering over-benchmark returns suggests that such a decarbonization path is practical. The willingness of the optimization to continue small adjustments each year (rebalancing to lower-emitting firms) avoids any single-year shock and keeps tracking error low, which is why performance impact is minimal. One caveat is that this result assumes historical return patterns and does not address potential sectoral concentration or long-term structural shifts; nevertheless, the results indicate no severe trade-off.

3.3.2 Net Zero Portfolio Cost vs. Benchmark and 50% Strategy

The out-of-sample cumulative returns from 2014–2023 show that the unconstrained value-weighted portfolio (p^{vw}) surprisingly underperformed the decarbonized strategies, with the half-footprint portfolio ($p^{vw}_{oos}(0.5)$) gaining the highest risk/return outcome and the Net Zero portfolio ($p^{vw}_{oos}(NZ)$) slowly lagging behind. In fact, all three portfolios more than **tripled** its value over the period, whereas the benchmark portfolios return was slightly lower and volatility remained roughly constant over all three methods (1bp higher for 50% carbon-constrained portfolio). This performance gap reflects the impose of the cost by the tighter carbon constraint: $p^{vw}_{oos}(0.5)$ and $p^{vw}_{oos}(NZ)$ achieved cumulative gains higher than the benchmark. This finding is not consistent with research showing that highly aggressive decarbonization can incur substantial tracking-error costs. For example, compared to a business-as-usual benchmark, "the tracking-error cost may be relatively high, especially for equity portfolios" when enforcing net-zero emissions (Bolton, Kacperczyk, & Samama, 2021). In other words, the NZ constraint effectively imposes a "**decarbonization premium**" that depresses total return, which we cannot confirm with our findings.

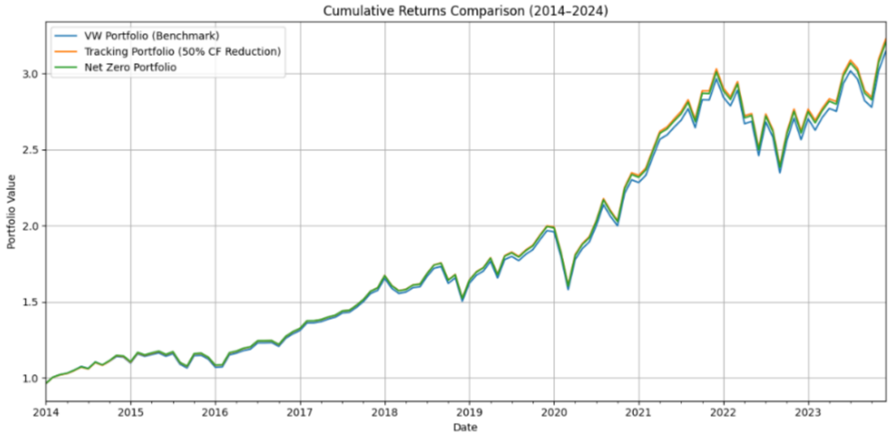


Figure 10: Cumulative return of p^{vw}*,* $p_{oos}^{vw}(0.5)$*, and* $p_{oos}^{vw}(NZ)$ *(2014-2024).*

While the portfolio with a 50% carbon-footprint reduction exhibits a marginal positive performance increase. This aligns with prior findings that moderate carbon-cuts need not sacrifice performance. As (UBS Investment Bank, 2025) reports, a low-carbon-intensity strategy "performed in-line with or slightly better than the benchmark," implying that investors "could have reduced the carbon intensity of their portfolios without sacrificing returns". In fact, UBS finds that one can "**drastically reduce the carbon intensity**" of a portfolio "**without underperforming**" and even achieve outperformance (UBS Investment Bank, 2025). Our results mirror this pattern: the 50% reduction rule halves portfolio emissions while achieving upside in total return. The Net Zero rule, however, forces a more extreme sector tilt. It systematically under weighs high-emission industries that historically offered strong returns and over weighs low-carbon sectors, which historically have been less rich in "cheap" value stocks (Chow, Li, & Polychronopoulos, 2022). And still this aggressive reallocation method shows no significant underperformance in our study. However, due to the natural decline in carbon emissions within the benchmark, the Net Zero portfolio's carbon reductions relative to year 1 have not produced a sharp emission divergence yet. In 2023, the Net Zero emissions were only approximately 30% below the benchmark, making the constraint less extreme than the 50% tracking portfolio. The "decarbonization premium" mentioned by Bolton, Kacperczyk, & Samama (2021) probably will not be significant until the portfolio's carbon reduction relative to the benchmark becomes more extreme and falls below the 50% reduction level, something likely to occur over time by design of the portfolio.

While the Net Zero portfolio does exhibit a lower cumulative return relative to the benchmark, the true costs of this strategy are primarily technical in nature. The requirement to rebalance annually in line with the 10% decarbonization trajectory leads to higher turnover and, consequently, increased transaction costs. These implementation frictions introduce a significant cost burden that is not directly visible in conventional performance metrics such as total return or the Sharpe ratio. Therefore, the net cost of the Net Zero strategy lies less in its ex-post risk–return profile and more in the operational complexity and expense of maintaining strict decarbonization compliance year over year.

CHAPTER IV
CONCLUSION

This project examined how climate constraints, specifically carbon emissions (Scope 1 and 2), influence portfolio construction and performance within a mean-variance o framework applied to listed firms in the AMER region. Three research questions were posed, and each is answered below based on our findings.

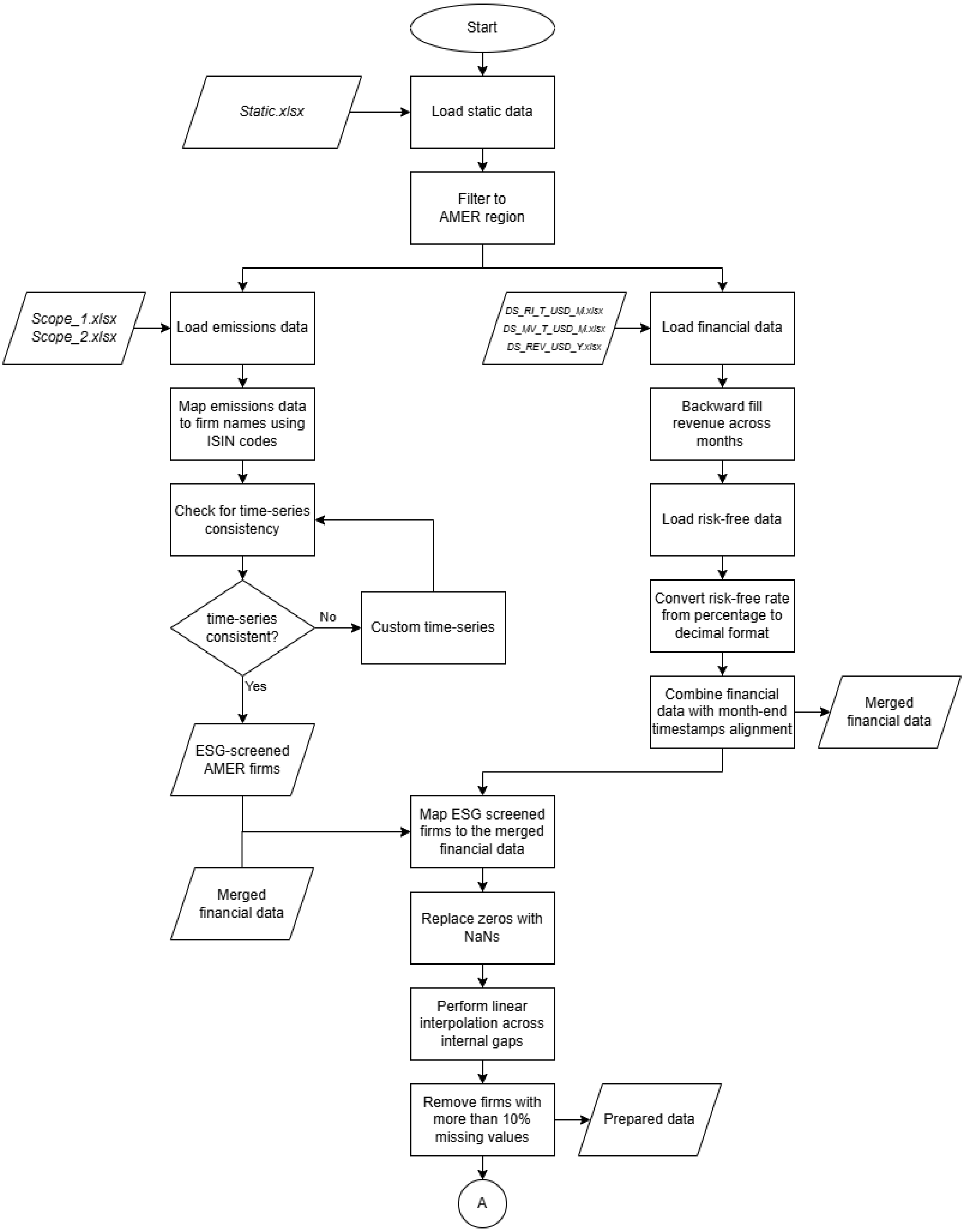
1. **How does the financial performance of a standard MVP compare to that of a value-weighted benchmark?**
   The Value-Weighted (VW) benchmark outperformed the unconstrained Minimum Variance Portfolio (MVP) in terms of total return and Sharpe ratio over the period 2014–2023. The VW portfolio achieved an annualized return of 12.14% and Sharpe ratio of 0.7712, compared to the MVP's return of 9.12% and Sharpe of 0.6878 (Ledoit-Wolf). This performance difference is largely attributed to the VW's exposure to large-cap tech stocks such as Apple, Microsoft, and Nvidia, which drove strong returns, especially post-COVID. Nonetheless, the MVP delivered lower volatility and more stable drawdowns, confirming its role as a risk-minimizing strategy.

2. **What is the impact of applying a 50% carbon footprint constraint to both MVP and benchmark-tracking portfolios in terms of risk, return, and emissions?**
   Applying a 50% carbon footprint constraint to the MVP ($p_{oos}^{mv}(0.5)$) significantly reduced emissions without sacrificing financial performance. The constrained MVP closely tracked the unconstrained version in returns, with a marginally higher Sharpe ratio (0.7205 vs. 0.7011) and nearly identical volatility. Likewise, the carbon-constrained benchmark-tracking portfolio ($p_{oos}^{vw}(0.5)$) preserved the market-like return of the VW benchmark (12.35% vs. 12.14%) while maintaining a Sharpe ratio of 0.7836 and cutting emissions by half in every year. These results confirm that climate-aware strategies can meet ambitious emission reduction goals while sustaining or even improving risk-adjusted performance.

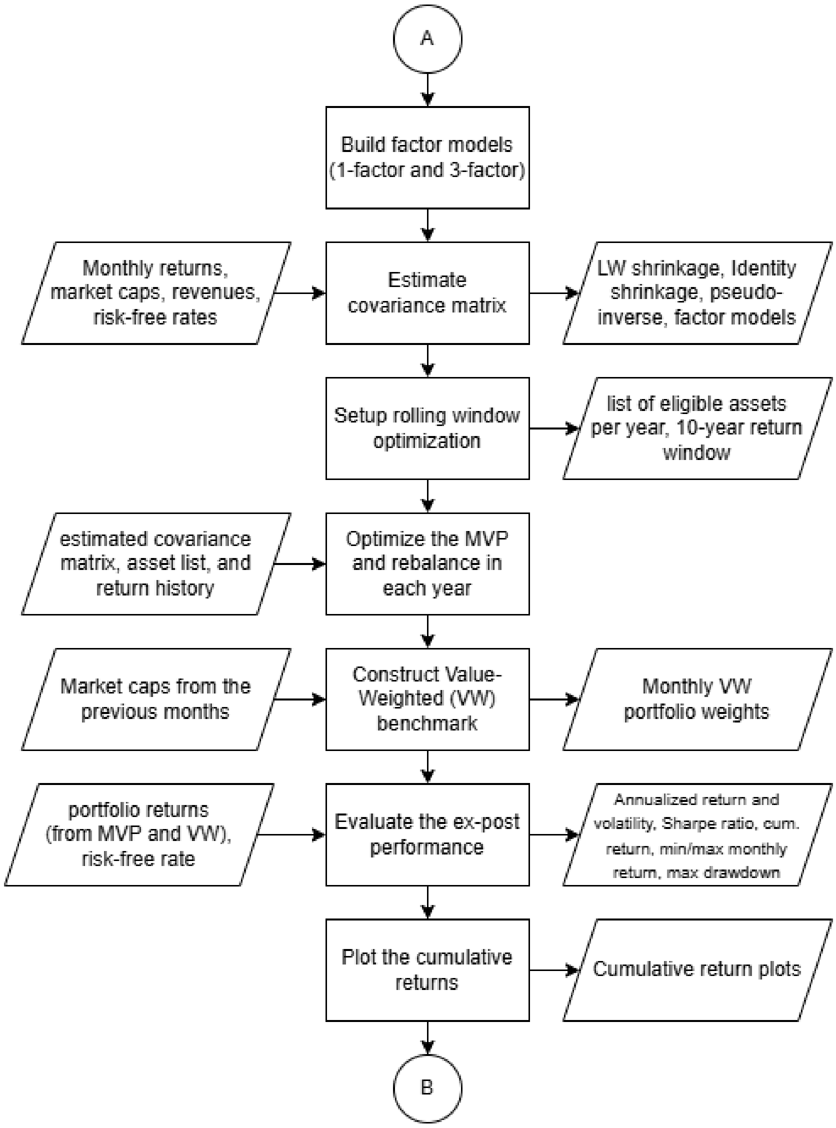
3. **How does a progressive net-zero decarbonisation strategy, by reducing emissions by 10% annually, compare to other approaches?**
   The net-zero tracking portfolio ($p_{oos}^{vw}(\text{NZ})$) succeeded in reducing carbon intensity by approximately 61% between 2013 and 2023, consistent with its 10% annual reduction target. Financially, it performed close to the VW benchmark, with an annualized return of 12.28%, volatility of 14.83%, and Sharpe ratio of 0.7798. While it trailed the 50% constrained portfolio slightly in cumulative return, it remained competitive and delivered better downside protection than the benchmark. The net-zero approach proved more ambitious than standard regulatory targets (e.g., EU PAB's 7%/year) and aligned well with global decarbonization pathways.

APPENDIX

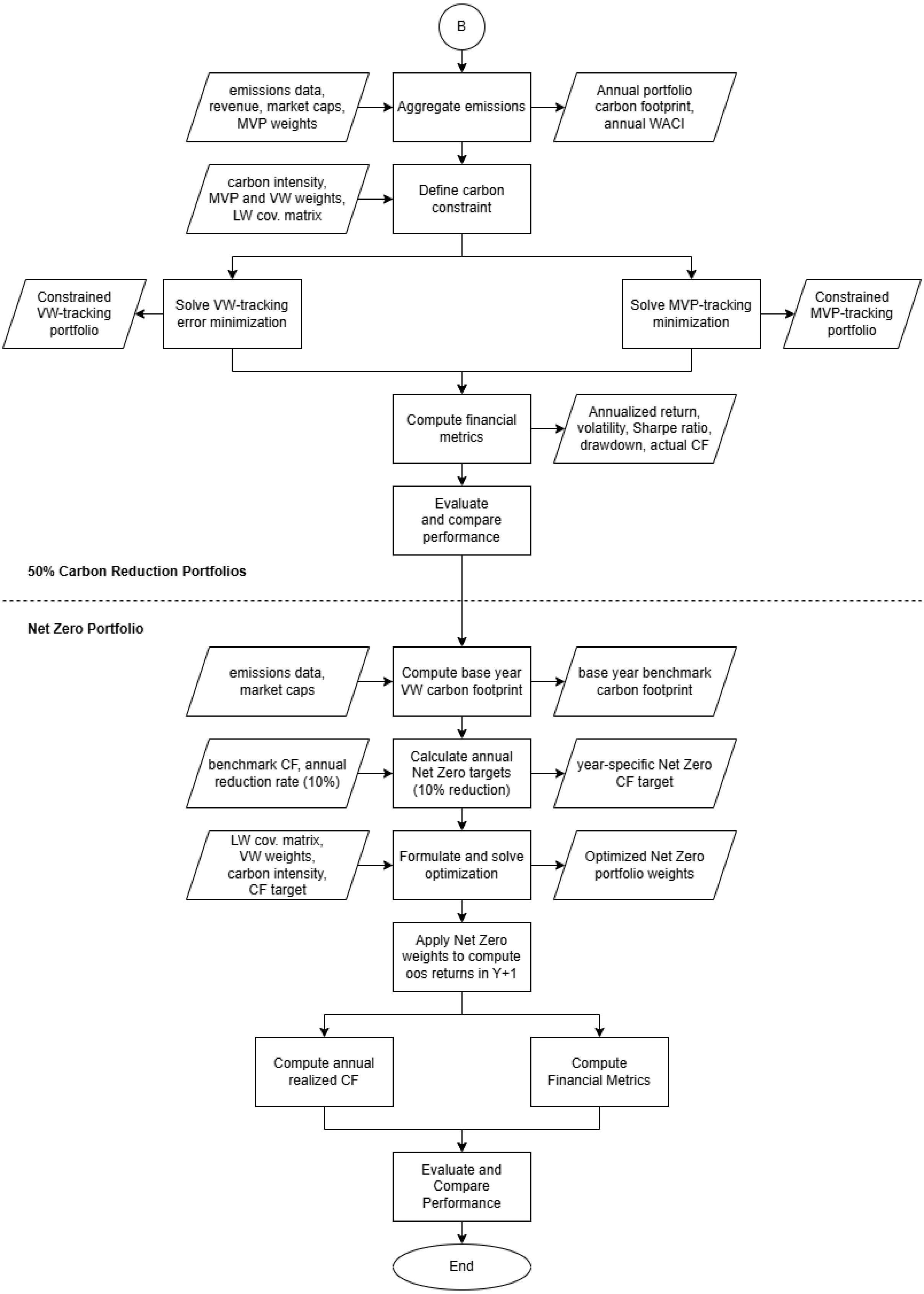
Process Flowchart – Data Preparation



Process Flowchart – Standard Asset Allocation (continued)



Process Flowchart – Portfolios with Carbon Constraints (continued)



Covariance Estimation Methods

Method	Formula	Assumptions	Strengths	Limitations
Ledoit-Wolf Shrinkage	$\Sigma = \delta T + (1 - \delta)S$	Shrinkage toward structured matrix; assumes shrinkage improves estimation	Reduces estimation error; robust in high-dimensional settings	Requires choosing appropriate shrinkage target and intensity
Identity Shrinkage	$\Sigma = (1 - \lambda)S + \lambda\sigma^2 I$	Shrinks toward average variance identity matrix	Guards against small eigenvalues; stabilizes estimation	May oversimplify true asset relationships
Pseudo-Inverse	$w \propto \Sigma^{+}1$	Sample covariance matrix may be singular	Closed-form solution; no optimization needed	Not suitable for constrained problems; unstable when matrix is near-singular
1-Factor Model	$\Sigma = B\ \mathrm{Cov}(f)\ B^T + D$	Returns explained by market excess return	Parsimonious; reduces dimensionality	Omits non-market risk factors
3-Factor Model	$\Sigma = B\ \mathrm{Cov}(f)\ B^T + D$	Returns explained by Market, SMB, and HML factors (Fama-French 1993)	Captures multiple risk sources; improves estimation stability	Factor assumptions must hold; estimation depends on factor construction and data sufficiency

Key Financial Metrics

Metric	Definition	Formula
Annualized Average Return	The geometric average of monthly returns, compounded to reflect annual growth.	$r\_annual = (\prod(1 + r_t))^\wedge(12/n) - 1$
Annualized Volatility	Standard deviation of monthly returns scaled by √12 to annualize.	$\sigma\_annual = std(r_t) \times \sqrt{12}$
Cumulative Return	Total portfolio return over the full investment horizon.	$\prod(1 + r_t) - 1$
Sharpe Ratio	Risk-adjusted return, calculated as the ratio of excess return over risk-free rate to portfolio volatility.	$SR = (mean(r_t - r\_f)) / std(r_t) \times \sqrt{12}$
Minimum Monthly Return	The lowest monthly return observed in the evaluation period.	$min(r_t)$
Maximum Monthly Return	The highest monthly return observed in the evaluation period.	$max(r_t)$
Maximum Drawdown	The largest percentage drop from a peak to a trough in cumulative return, representing downside risk.	$max\_drawdown = min((P_t - max(P_{s \leq t})) / max(P_{s \leq t}))$ where P_t is cumulative return at time t

Prior Studies on Low-Carbon Portfolio Strategies

Researcher / Institution	Year	Topic	Key Implications
Legal & General Investment Mgmt	2021	Optimized carbon reduction	~50% carbon cut feasible with minimal tracking error (~15 bps) if constraints are applied
Robeco	2022	Naïve exclusion vs. optimized strategy	Naïve exclusion leads to 2–4% losses/year; optimized approach reduces tracking volatility by 50–70%
UBS	2021	Low-carbon intensity strategy	Carbon reduction possible without sacrificing returns; may even yield outperformance
Ben Slimane et al.	2022	Net-zero and tracking error trade-offs	Aggressive net-zero cuts can incur high tracking error and depress performance

Example Excel Output Example

These statistics are outputted to an Excel document for every year and every portfolio from the code and are used throughout the analysis for industry and stock specific stats

Minimum Variance Portfolio -Ranked by top and bottom 10 Net Effect: return x weight

2021						
ISIN	**Weight**	**Weight Rank**	**Return**	**Volatility**	**Hist. Vol (10y)**	**Net Effect**
ELI LILLY	4.06%	5	66.08%	34.58%	17.84%	2.68%
LOBLAW	3.30%	9	69.32%	20.88%	17.54%	2.29%
MICROSOFT	2.81%	12	52.48%	20.81%	20.14%	1.47%
MOTOROLA SOLUTIONS	2.14%	20	61.91%	15.28%	20.58%	1.32%
CROWN CASTLE	3.60%	8	35.08%	24.04%	15.54%	1.26%
FTI CONSULTING	3.18%	10	37.33%	24.89%	30.22%	1.19%
PUBLIC STORAGE	1.50%	32	66.62%	23.41%	17.57%	1.00%
HAWAIIAN ELECTRIC INDS.	4.61%	3	21.27%	32.27%	15.00%	0.98%
FIRSTENERGY	1.91%	22	41.78%	19.33%	20.90%	0.80%
LINDSAY	3.83%	7	19.27%	20.77%	23.38%	0.74%
RANGE RES.	0.00%	543	166.12%	78.43%	66.39%	0.00%
UNITED NATURAL FOODS	0.00%	550	207.33%	77.75%	52.61%	0.00%
SM ENERGY	0.00%	538	382.15%	87.93%	115.72%	0.00%
BIOGEN	1.39%	33	-2.02%	42.16%	32.23%	-0.03%
VERTEX PHARMS.	0.71%	41	-7.08%	23.20%	40.10%	-0.05%
CAPITOL FED.FINL.	5.54%	1	-2.00%	15.14%	15.91%	-0.11%
EQUITY COMMONWEALTH	2.56%	15	-5.06%	9.68%	25.07%	-0.13%
BARRICK GOLD (NYS)	1.10%	36	-13.37%	32.24%	45.05%	-0.15%
CLOROX	1.58%	29	-11.52%	20.29%	16.19%	-0.18%
FLUTTER ENTERTAINMENT	2.86%	11	-22.88%	42.90%	28.96%	-0.65%

Minimum Variance Portfolio - Top 10 Firms

2021	
Company	**Weight**
CAPITOL FED.FINL.	5.54%
EMPIRE 'A'	5.47%
HAWAIIAN ELECTRIC INDS.	4.61%
DOMINION ENERGY	4.32%
ELI LILLY	4.06%
WALMART	3.95%
LINDSAY	3.83%
CROWN CASTLE	3.60%
LOBLAW	3.30%
FTI CONSULTING	3.18%

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