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Incorporating Corporates' Carbon Footprint in Stock Portfolio Construction

An in-depth study of the relationship between carbon footprint and financial performance

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Serge MESSEAUW

Abstract

The relationship between companies' carbon footprint and the financial performance of a portfolio composed of these companies is a highly controversial subject in the literature. With the growing importance of climate concerns, the aim of this thesis is to demonstrate whether there is indeed a relationship between companies' carbon footprint and their financial performance and, if such a link exists, what is its nature? To answer this question, we constructed a benchmark portfolio comprising the 50 companies in the EuroStoxx50, which we grouped into five quintiles based on their average carbon intensity and the trend in their management. To check whether the quintiles with a lower carbon score performed better, we constructed 5 portfolio models in each quintile and then observed their results in terms of Sharpe ratios. To verify the statistical significance of these ratio differences, we applied a Jobson-Korkie test modified by Memmel, which led us to conclude that there was a relationship between carbon footprints and financial performance, and that this relationship was negative. However, with a view to enriching our study, we also applied a second approach consisting of applying the same portfolio models but to the reference portfolio, adding a cardinality constraint requiring the selection of 10 assets. We challenged these results with a robustness test that confirmed the significance of only one model. As a result, this second approach also provided us with evidence of a relationship between carbon footprint and financial performance, but this time a positive relationship. In summary, this study has enabled us to verify the existence of a link between carbon footprints and financial performance, with uncertainty as to the nature of such a link, although the results of our first approach appear to be more robust.

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Introduction

The current climate situation, with its far-reaching effects, has become a major concern for our society, posing challenges to everyone. From the 2015 Paris Agreement to COP28 in 2023, there is a growing commitment among policy-makers to make greener decisions for a more sustainable future. This same commitment is also visible among consumers and investors. Indeed, according to a study by NielsenIQ (2022), "78% of consumers say a sustainable lifestyle is important to them and 30% are more likely to purchase products with sustainable credentials".

To adapt to these changes, the integration of Environmental, Social, and Governance (ESG) criteria into investment strategies has gained significant traction in recent years (PwC France, 2023). Among the various ESG criteria, company carbon footprints are particularly prevalent and practical in constructing equity portfolios, due to their quantitative nature. This underscores the necessity for the investment sector to evolve and incorporate such criteria. Moreover, investors will play a pivotal role in the transition to a decarbonized economy and a more sustainable world. According to the Boston Consulting Group (Oehling et al., 2023), around 150 trillion dollars will be required to achieve complete decarbonization by 2050. Investors can contribute to this goal in multiple ways while maintaining profitability.

The aim of this dissertation is to determine whether, and to what extent, incorporating the carbon footprint of companies when constructing an investment portfolio and allocating weights to the various stocks affects the portfolio's performance. To conduct our analysis, we categorized companies into five mutually exclusive groups based on their carbon score. These groups were then used to construct different model portfolios, which were compared with each other and a benchmark portfolio based on the EuroStoxx50, in order to assess the relationship between carbon footprint and portfolio returns. We will validate our findings using a secondary approach that involves constructing portfolios using a cardinality constraint, limiting the number of selected companies. Additionally, we will challenge our results with a robustness test. Finally, we will analyse whether the companies selected by the models are also found in specific quintiles.

Recent studies support the idea that investing in environmentally responsible companies does not necessarily reduce returns; on the contrary, it may enhance them. According to Benlaribi (2024), between 2018 and 2022, the carbon footprints of EuroStoxx50 companies for scope 1 and 2 decreased by 18%, while average sales increased by 17%.

We should therefore anticipate a negative relationship between lower carbon footprints and higher returns. The existing literature already provides a range of positions on the link between carbon footprints and portfolio returns. Some studies, such as those by Derwall et al. (2005), argue for a negative link between carbon footprints and returns, while others, like Bolton and Kacperczyk (2021), suggest a positive relationship. Additionally, some researchers, including Lewandowski (2015), posit that the observed link may be influenced by various factors, such as company size, given that large companies tend to have both higher output and a larger carbon footprint, but this does not mean that the link is explainable. Our study aims to contribute to this discourse by analyzing the relationship between portfolio returns and companies' carbon footprints, with a focus on pre-selecting and ranking companies based on a carbon score, and accounting for potential size-related biases through carbon intensity. For our analysis, we chose to classify the companies according to their average carbon footprint and management trends, as we want to verify the existence of a profound link between carbon footprint and financial performance. We will first test our main hypothesis, the aim of which is to define the existence of such a link: *Carbon footprints impact portfolio returns.* Following this, we will investigate our secondary hypothesis to determine the nature of this relationship: *The impact of carbon footprints on portfolio returns is positive.*

To thoroughly explore the subject, this report will be structured as follows:

- Chapter 1 introduces the concept of sustainable finance and the importance of ESG data. We will also briefly review the literature, with a focus on carbon footprint criteria.
- In Chapter 2, we will define key concepts such as carbon footprint and carbon intensity, including the different scopes used to measure them. Additionally, we will present important facts regarding carbon footprints and their current impact.
- In Chapter 3, , we will explain the concept of investment portfolios and their utility, and detail the different models employed in our study.
- In Chapter 4, we will cover the data and methodology used in our analysis. We will explain how we collected and processed the data, and demonstrate how it was utilized to build and assess our models.
- In Chapter 5, we will present the empirical results of our analysis, addressing our initial hypotheses and the research question of this dissertation based on our findings.
- In Chapter 6, we will conclude with a summary of the key insights discovered. We will also discuss the limitations of our study, and suggest potential directions for future research.

1 Literature Review

In this chapter, we will present what sustainable finance is and how the integration of ESG data can help improve the climate situation, with a particular focus on carbon footprints. We will then examine the various articles that have already been written on the link between carbon footprint and financial performance and discuss their findings.

1.1 Sustainable Finance

"Sustainable Finance is the system that ponders a holistic approach to material ESG considerations and impact when making decisions in investing, and lending with the intention to create sustained value and manage risk in the long-term." (Vargas, 2023). Sustainable finance therefore makes it possible to accommodate the financial interests of investors with societal interests, which are becoming increasingly important.

The growing popularity of sustainable finance is largely due to the issues surrounding it. Indeed, it is no longer a secret that the current climate situation is a major concern for everyone, including investors, and it is no longer possible to ignore it. This is why numerous laws have been passed to improve the situation, many of them based on investment in sustainable finance to support ecological actions and try to achieve a climate-neutral, resource-efficient and fair economy (European Commission, n.d.). What's more, there is also a growing desire among many to reduce our environmental impact and become more responsible.

In order to spread the practice of sustainable finance as widely as possible, the Global Sustainable Investment Alliance (GSIA) has defined seven investment strategies used to achieve this type of finance. We present them briefly following the definitions given by Global Sustainable Investment Alliance (2019):

1. **Negative/exclusionary screening:** the exclusion of certain sectors or companies on the basis of ESG criteria.

2. **Positive/best-in-class screening:** the decision to invest in sectors or companies with better ESG performance than their peers.

3. **Norms-based screening:** review of investments against international standards (issued by OECD, ILO, UN and UNICEF for example).

4. **ESG integration:** the inclusion of ESG criteria during financial decision.

5. **Sustainability themed investing**: investment in assets linked to sustainable development (such as clean energy, green technologies, etc.).

6. **Impact/community investing:** targeted investment to solve social problems, such as community investment, or to invest in businesses with a social or environmental objective.

7. **Corporate engagement and shareholder action:** using shareholder power to influence business behaviour, filing or co-filing shareholder proposals and proxy voting, guided by ESG standards.

1.1.1 Environmental, Social and Governance

As explained above, sustainable finance is based on ESG data. Let us explain what this data corresponds to.

ESG, which stands for environmental, social and governance, is a concept popularised in the 21^{st} century, which measures a company's environmental and social impact (Krantz & Jonker, 2024). It is based on 3 pillars:

1. **Environmental:** refers to the fact that the company's activities respect the environment and take into account environmental issues such as carbon emissions.

2. **Social:** refers to the organisation's impact on people, and how it looks after them.

3. **Governance:** refers to the way in which the company is run.

By declaring this data, companies are demonstrating their willingness to be transparent and trustworthy, which enables them to attract new investors. On the other hand, by incorporating such data into their investment decisions, investors can not only consider new business risk perspectives, but also expect to invest in companies with greater operational efficiency and expansion (Kotsantonis et al., 2016). Examples include the reputational risk, which is reduced by a more responsible and respectable corporate image, and the reduced risk associated with regulation, which is likely to become increasingly strict in ESG areas.

In summary, as part of our study, we will apply three sustainable finance strategies with ESG integration, negative screening and positive screening, when we classify companies into quintiles according to their carbon footprint. In addition, we will focus on the environmental pillar of ESG since we are only considering carbon footprints as a criterion.

1.2 Carbon Footprint and Financial Performance

Now that we have discussed the growing importance of sustainable finance and the integration of ESG criteria into our investment decisions, we will move on to the integration of carbon footprints as an environmental criterion and focus on the findings of studies that have been carried out to test the link between carbon footprint and financial performance.

When it comes to determining the existence of a link between carbon footprint and financial results, different points of view are expressed in the literature. There are numerous articles reporting a negative relationship between carbon footprint and financial performance. Derwall et al. (2005) demonstrated that a portfolio constructed from the most eco-efficient companies significantly outperformed a portfolio constructed from less eco-efficient companies between 1995 and 2003. Using the Carhart four-factor model, they found that the eco-responsible portfolio outperformed the other by almost 6% annually, even after adjusting for industry fixed effects. Similar results were obtained by Soh et al. (2017) who used the Capital Asset Princing Model (CAPM) and the Fama-French 3 and 5 factors model to determine whether a portfolio made up of carbon-efficient companies performed better than a carbon-inefficient portfolio. The results lead to the conclusion that by buying shares in a carbon-efficient portfolio and selling those in a carbon-inefficient portfolio, we could obtain an abnormal annual return of between 7.7% and 8.9%.

One of the main reasons for this link is the social enthusiasm for investing in environmentally responsible companies. In a study by Pástor et al. (2022), it was shown that when the effects of increases in climate concerns were removed, the outperformance of green stocks over brown stocks disappeared. This would indicate that without the societal will to reduce our environmental impact, the link between carbon footprint and financial performance would potentially not exist.

On the other hand, some studies show a positive relationship between emissions and performance. This is notably the case of Bolton and Kacperczyk (2021), which has shown that companies with higher carbon emissions have higher returns. They also tried to link the carbon premium to other known risk factors, but to no avail. This indicates that the higher returns with the carbon premium are directly linked to the higher carbon emissions. Oestreich and Tsiakas (2015) also discovered in their study that companies with high carbon emissions had higher returns, especially during favourable regulatory periods. In fact, in their study on the impact of the European Union's Emissions Trading Scheme (ETS) on German stock returns, they found that companies that took advantage of allowances to emit carbon emissions for free outperformed those that did not. Of course, a large part of this outperformance can be explained by the cash flow generated by allowances for free carbon emissions, but there is also the presence of a carbon risk factor, which stems from the risk associated with higher carbon footprints and therefore higher compensation for this risk.

One of the reasons for these opposing results lies in the formulation of their hypotheses. On the one hand, we have the authors in favour of a negative relationship between carbon footprint and financial performance, which focus mainly on the future costs associated with high footprints and on social pressure from investors to invest more responsibly. For the authors in favour of a positive relationship, the hypotheses focus more on the higher carbon premiums paid to investors to compensate for the risk, as well as the liquidity that is possible with the ETS market in the EU. There are also some differences in the data used, but these are not sufficient to explain the discrepancies.

Finally, a third point of view can also be found in the literature. Some authors consider the existence of such a link to be inexplicable. Lewandowski (2015) demonstrates in his study that despite the existence of a link between carbon emissions and financial results, it is not possible to clearly define the meaning of this relationship or to be able to explain it on the basis of robust financial concepts. He explains his results notably by the general contradiction in the literature on this relationship, as we saw earlier, but also by the lack of information on how carbon risk is actually integrated by investors.

As we can see, the literature on this subject is extremely varied and does not allow us to determine in advance whether low-carbon companies outperform high-carbon companies. However, we will nevertheless base our thesis on the hypothesis that low-carbon footprint companies perform better than high-carbon footprint companies. Indeed, despite the differences of opinion in the studies presented above, concerns about climate change and initiatives to reduce the global carbon footprint are growing, which should accentuate the effect highlighted by Pástor et al. (2022) that eco-efficient companies perform better during periods of heightened environmental concern.

2 Carbon Footprint

The aim of this chapter is to give some information about carbon footprints and their use. We will try to explain why they are becoming more and more important in many fields, especially in finance.

2.1 Definition

The carbon footprint is the ”amount of carbon dioxide (CO2) emissions associated with all the activities of a person or other entity” (Selin, 2024). The carbon footprint is generally expressed in tonnes of CO_2 equivalent per year. This carbon footprint metric is a component from the Ecological Footprint, developed by William Rees and Mathis Wackernagel at the University of British Columbia, which corresponds to the total area of land required to counteract pollution (Selin, 2024). The idea behind the carbon footprint is to quantify the impact that a company's activity has on our planet, and it is generally used with the aim of reducing it as much as possible.

Therefore, with the aim of measuring the carbon footprint of companies in the most appropriate way, the GHG Protocol has introduced the concept of ”Scope”. This makes it possible to delineate the different sources of emissions, which is useful for adapting to the different types of companies as well as the various legal obligations arising from them. Three scopes have been proposed by the GHG protocol (World Resources Institute & World Business Council for Sustainable Development, 2004):

1. **Scope 1:** Direct GHG emissions. This takes into account all the emissions produced directly by the company. This may, for example, be due to combustion in boilers, vehicles, etc., owned or controlled by the organisation.

2. **Scope 2:** Electricity indirect GHG emissions. This scope includes the use of electricity purchased by the company. This correspond to the electricity which is imported into the boundaries of the enterprise.

3. **Scope 3:** Other indirect GHG emissions. This final scope includes all other indirect emissions. In other words, emissions that occur as a result of the company's activity, but which come from sources that are not under the direct ownership or control of the firm. These may include, for example, emissions linked to the extraction and production of purchased materials, transport, etc.

However, while Scope 1 and 2 emissions are fairly easy to assess and report, Scope 3 emissions are often complicated and require a lot of resources from companies to measure them correctly. There are two reasons for this: firstly, Scope 3 is often larger than the other two, generally representing between 65% and 95% of a company's emissions (PwC, 2022). Secondly, they are indirect and therefore not controlled by the company itself, which makes them more difficult to measure.

Therefore, to ensure a solid basis for comparison, we have decided to focus only on Scope 1 and 2 emissions for our companies. This enables us to obtain all the information from a single source, which ensures greater consistency in the way the data is collected. Indeed, as Scope 3 emissions reports are relatively recent, there are many disparities in the way they are disclosed, which does not guarantee the consistency of the data.

2.2 Regulatory Impact

Unfortunately, for many years, human activity has increasingly strained Earth's finite resources, leading to a range of critical threats for both current and future generations, including deforestation, climate change, and the extinction of various animal and plant species (Global Footprint Network, 2023). To mitigate these issues and lessen our impact, one significant area where we can effect change is our carbon footprint. Currently, the human carbon footprint constitutes approximately 60% of humanity's overall ecological footprint, making it a crucial factor in reducing our environmental impact (Global Footprint Network, 2023).

In response to these concerns, the global population and its leaders began to focus on the state of Earth's climate, leading to a significant milestone in the pursuit of sustainability: the 2015 Paris Agreement. This international treaty, adopted by 196 countries at COP21 in Paris, aims to limit the increase in global temperatures to well below 2°C above pre-industrial levels (United Nations Framework Convention on Climate Change, n.d.). A key measure taken by member countries is the reduction of greenhouse gas emissions, which necessitates monitoring and assessing changes in carbon footprints.

Other policies have also emerged, such as the European Green Deal, which is a guide to making Europe a climate-neutral continent by 2050 (European Parliament, 2022). The Green Deal includes a number of laws designed to achieve its goals, particularly in terms of reducing the carbon footprint, which will have a major impact on European businesses. An example of such a law is the European Climate Law, which sets a target of reducing emissions by 55% by 2030 and being climate-neutral by 2050 (European Parliament, 2022). Beyond regulatory measures, the Green Deal offers numerous opportunities in terms of job creation, future income and financial support for environmentally responsible projects. These opportunities are critical considerations for investors, especially when deciding to invest in low-carbon companies.

2.3 Carbon Intensity

Often, a company's carbon footprint correlates with its size, which could create a bias in our study on the relationship between carbon footprint and portfolio returns. Indeed, a large company with several production sites will often have a higher carbon footprint than a smaller company with a single site, particularly due to the number of sites, the number of vehicles, transport, etc. Other factors, such as industry and location, can also impact carbon footprint. However, due to limited data on each company, we were unable to fully account for all potential biases.

For the purposes of our study, we therefore chose to use carbon intensity as a metric of carbon footprint, given the diverse sizes of companies in our reference portfolio. In order to compare the carbon footprints of these different companies, we needed to find a basis for comparison, which led us to normalise them. To avoid any biases due to company size, we chose to use carbon intensity, which is a company's carbon footprint (expressed in tons of CO_2 equivalent), divided by its annual turnover (expressed in millions of euros) (Bajo & Rodríguez, 2022). This measure allows us to normalise the carbon footprints of companies according to their revenues, eliminating size-related biases and facilitating a more accurate comparison.

3 Portfolio Investment

3.1 Definition

An investment portfolio involves holding a number of assets, usually financial, in the hope of growing them over the long term or generating income. (Chen, 2020). There are many different types of portfolios, with many different strategies, all of which depend on the investor's profile. A portfolio can be made up of investments in financial assets (equities, corporate and government bonds, exchange-traded funds, etc.), physical assets (property, art, gold, etc.) or financial contracts (options, derivatives, etc.). It can be managed passively, i.e. without recalculating the weights on a regular basis, in the hope of maximising the return on the basic investment, or more actively, by recalculating the weights frequently, to try to take advantage of changes in asset prices.

For the purposes of our study, we will focus on financial portfolios, and more specifically on portfolios consisting solely of stocks. Furthermore, we are only interested in the part linked to the construction of such a portfolio, given that our study focuses solely on optimisation when allocating weights.

3.2 Portfolio Models

We will now describe the different models we used during our study[1]. The choice of these models is not based on any criteria, it is completely arbitrary.

3.2.1 Equally Weighted Portfolio

This is likely one of the simplest, yet most widespread stock portfolio models. The premise is straightforward: it is a portfolio where each stock holds an equal weight, regardless of the stock's price or the company's size (Chen, 2022). The formula used to calculate the weight of each stock is as follows:

$$w_i = \frac{1}{n}$$

with:

$$w_i = \text{weight of stock i} \qquad n = \text{number of assets}$$

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[1] A sample code is available in Appendix 7. This is a basic code that we have adapted to our models on each occasion.

3.2.2 Mean Variance Portfolio

The second model we used is the Mean Variance portfolio which was introduced by Harry Markowitz in 1952. The objective of this portfolio is to find the optimal set of weights for which a certain level of expected rate of return is reached while minimizing risk (University of Washington, n.a.). It is also possible to look at this another way, by considering the set of optimal weights to be the weights that maximize returns for a given level of risk. The underlying theory behind this portfolio assumes that most investors are risk-averse, that is to say that among portfolios with the same expected returns, investors will prefer the one with the lower risk (CFI Team, n.a.).

According to Markowitz's Modern Portfolio Theory, the expected return of a portfolio is calculated as a weighted sum of the returns of the individual assets, while the portfolio's risk is measured by the standard deviation of its returns, which accounts for both the variances of the assets and their covariances (The Investopedia Team, 2023). This led us to use the following formula to compute the optimal set of weights (N. Lassance, personal communication, 2023):

$$W = \frac{\hat{\Sigma^{-1}}\hat{R}}{1_n^T \hat{\Sigma^{-1}}\hat{R}}$$

with:

$W =$ Vector of portfolio weights
$\hat{\Sigma^{-1}} =$ Estimated inverse variance-covariance matrix of returns
$\hat{R} =$ Estimated vector of mean returns
$1_n =$ Column vector of 1 of dimension n

3.2.3 Minimum Variance Portfolio

The minimum variance portfolio is a portfolio similar to the previous one, with the difference that, as the name suggests, the objective is to find the portfolio with the lowest variance, that is, the least risk . In fact, one of the biggest disadvantages of the Mean Variance portfolio comes from the difficulty in estimating the average returns, to which this type of portfolio is very sensitive (N. Lassance, personal communication, 2023). Indeed, according to DeMiguel et al. (2009), when estimating the vector of average returns, many errors can occur, which leads to poor out-of-sample performance for this type of portfolio. To counter this, some have proposed replacing the vector of mean returns with a vector of 1, which gives the Minimum Variance portfolio.

To determine the weights of our assets using the Minimum Variance Portfolio, we used the following formula (Institute for Management Science, 2023):

$$W = \frac{\hat{\Sigma^{-1}} 1_n}{1_n^T \hat{\Sigma^{-1}} 1_n}$$

with:

W = Vector of portfolio weights 1_n = Column vector of 1 of dimension n

$\hat{\Sigma^{-1}}$ = Estimated inverse variance-covariance matrix of returns

3.2.4 Minimum Variance with $l1 - l\infty$ Constraints Portfolio

The fourth model we implement is based on the Minimum Variance Portfolio, but to which we added two constraints, called l1-$l\infty$ norm constraint. The objective of the first constraint l1, is to reduce the weight of certain assets to zero when their weights fall below a predefined threshold, and to increase the weight of other assets to higher absolute values, resulting in a very sparse solution (Xing et al., 2014). On the other hand, since having only a few assets with large weights, especially negative weights, is not very favourable, the addition of a l∞ constraint makes it possible to restrict the asset weights from taking on too high absolute values (Xing et al., 2014).

To implement this portfolio model, we used the following formula and constraints, coming from Xing et al. (2014):

$$min_W W^T \hat{\Sigma} W$$

Under the constraints:

$$\begin{aligned} 1^T W &= 1, \\ ||W||_1 &\leq L1_{max}, \\ ||W||_\infty &\leq L\infty_{max} \end{aligned}$$

with:

W = Vector of portfolio weights

$\hat{\Sigma}$ = Estimated variance-covariance matrix of returns

1^T = Transposed vector of 1 of dimension n

$||W||_1$ = l1 norm

$||W||_\infty$ = l∞ norm

$L1_{max}$ = Maximum limit for the l1 norm of portfolio weights

$L\infty_{max}$ = Maximum limit for the l∞ norm of portfolio weights

In order to determine the best values for the l1 and l∞ norms, we used the grid search method, which consists of using a loop that tests several combinations of values for each norm and retains the best solution, in our case the one that minimises the variance.

3.2.5 Mean Variance Skewness Kurtosis (MVSK) Portfolio

The final portfolio model we have implemented is based on the Mean Variance Portfolio, but as well as considering the mean of returns and their variance, we also take into account skewness and kurtosis. The reason why considering these higher-order moments is beneficial comes from one of the assumptions of the Mean Variance Portfolio, which is to consider returns as being normally distributed, except that "asset returns distributions are characterised by negative skewness and excess kurtosis, and so the assumption for a normal distribution is continuously being violated", according to Aggarwal, Rao, & Hiraki (as cited in Naqvi et al., 2017).

To take account of the skewness and kurtosis of our data when determining our portfolios' weights, we used the following objective function, coming from Naqvi et al. (2017).

$$F(w_i) = \lambda_1 \sum_i w_i r_i - \lambda_2 \sum_i \sum_j w_i w_j \sigma_{ij} + \lambda_3 \sum_i w_i \gamma_i - \lambda_4 \sum_i w_i \kappa_i - 1000(\sum_i w_i - 1)^2$$

with:

w_i = Weight of asset i
σ_{ij} = Covariance between returns of assets i and j
κ_i = Kurtosis of asset i
λ_2 = Penalty for variance
λ_4 = Penalty for kurtosis

r_i = Mean return of asset i
γ_i = Skewness of asset i
λ_1 = Reward for return
λ_3 = Reward for skewness

The last term, $-1000(\sum_i w_i - 1)^2$, correspond to a penalty in case the sum of the weights are different than exactly one.

Finally, in order to determine the optimal values for the 4 lambdas that maximize the objective function, we again used the grid search method.

4 Data and Methodology

The aim of this thesis is to determine whether incorporating companies' carbon footprint when constructing an investment portfolio can improve its financial performance. In other words, to determine whether a lower carbon footprint translates into higher returns.

To determine whether such a link exists, we will examine the following hypothesis:

Carbon footprints impact portfolio returns.

This first hypothesis will then be followed by a second, which aims to determine the nature of this link and will be formulated as follows:

The impact of carbon footprints on portfolio returns is positive.

4.1 Data

In order to perform our analysis, we need different types of data. The first ones are the composition of the EuroStoxx50 at a certain moment in time. The second ones are the monthly stocks' prices of the companies present in the portfolio benchmark from 2014 to 2023, to compute the returns on these shares. Finally, we also need the carbon footprint of each company. In order to ensure consistency in the data collection method and, as explained above, to avoid biases due to companies' size, we directly collected the annual carbon intensity of each company from 2014 to 2023.

4.1.1 Sources

To obtain the composition of the EuroStoxx50, we contacted the organisation STOXX, part of the "Deutsche Börse Group". They gave us the composition of the EuroStoxx50 for the last five years. Then, regarding the stock's prices, we retrieved the data from Yahoo Finance, from December 2013 to December 2023, which enabled us to compute the returns for 2014 to 2023. To do this, we have used the formula:

$$\frac{T_2 - T_1}{T_2}$$

which allows us to calculate the rate of return. Finally, for the carbon intensity, we retrieved the data from Bloomberg. Unfortunately, data was missing for nine companies (seven had no data in 2023, one had no data in 2014 and one had no data in 2014, 2015, 2016 and 2023).

We estimated all this data using an Autoregressive Integrated Moving Average (ARIMA) model. We decided to use this model because it is recognised as one of the best performing models in terms of predicting time series and because we have already used it in previous work, and it gave us a good understanding of the model.

4.1.2 Sample Selection

The 50 organizations we selected for our benchmark portfolio are the companies making up the EuroStoxx50. We chose to use this index as a reference for two reasons. The first one is that the ESG data is more widespread in European companies. Secondly, because as a Belgian student, I felt more connected with European firms than with foreign ones.

Unfortunately, due to missing information on the share prices of certain companies, we decided to use the components of the EuroStoxx50 as it stood in June 2020. Indeed, we had to choose a period of the EuroStoxx50 for which all the companies present had share prices over a period running from December 2013 to December 2023. Moreover, the index at this date will also serve as a basis for us to build the benchmark portfolio by using the weights of the index to build a portfolio with the same weights[2].

Sector	**Number of companies**
Automobiles & Parts	3
Banks	6
Basic Resources	2
Chemicals	1
Construction & Materials	2
Consumer Products & Services	4
Energy	2
Financial Services	1
Food, Beverage & Tobacco	2
Health Care	5
Industrial Goods & Services	5
Insurance	3
Media	1
Personal Care, Drug & Grocery Stores	3
Technology	4
Telecommunications	3
Utilities	3
Total	50

Table 1: Sector classification for companies in the benchmark portfolio

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[2] The composition of the benchmark portfolio and its weights can be found in Appendix 1.

To check that our sample is representative, we classified the 50 companies by sector. Table 1 shows us all the sectors of activity represented in our sample of companies. We can see that, despite the limited number of companies, only 50, this portfolio is made up of organisations present in 17 of the 20 supersectors, which makes this portfolio an accurate representation of the general economy. The supersectors are part of the classification system proposed by the Industry Classification Benchmark (ICB), which is one of the two classification systems recognised and used worldwide, including by Euronext (Kenton, 2023).

Next came the problem of choosing the frequency of our data. For carbon intensity, the frequency was annual and for the composition of the EuroStoxx50, it was quarterly. But we still had to decide whether to use daily, weekly, monthly or annual data for the returns. We quickly eliminated the annual data option because it did not represent sufficient historical data to carry out relevant statistical tests. In the end, we decided to use monthly data for two reasons:

- Firstly, unlike daily and weekly data, they present much less noise and fluctuations which are not useful for our study, since we are looking for an underlying trend between carbon footprints and returns.
- Secondly, as the other two data sources are quarterly and annual, it was easier to match them all with monthly data.

4.2 Methodology

In order to determine the link between carbon footprints and portfolio performance, we used two approaches. For each approach, we had to group the 50 companies into five quintiles of equal size using a carbon score.

4.2.1 Carbon Score

To ascertain whether the integration of carbon footprints into equity portfolio management impacts the performance of such portfolios, we chose to categorize our 50 companies into five equally sized groups. The objective was to rank the firms based on their carbon intensity. Specifically, the first group comprised companies with the best carbon intensity, the second group included those with slightly higher carbon intensities than the first group but better than the third group, and so on.

In order to be able to classify these companies, we first thought about a comparison metric. Our first option was to standardise the data, which would have provided a good distribution and allowed us to select five separation thresholds. Unfortunately, this methodology didn't quite fit with our objective for this study. We therefore decided to use a composite score. This is a score constructed from several criteria. For this study, we used two criteria:

- The mean
- The trend

We used the average because it is a good representation of a company's carbon impact. In addition, as the aim of this thesis is to determine whether there is a deep and significant relationship between carbon footprint and returns, we also felt it was important to take into account each company's tendency to manage its carbon footprint, in order to represent the long-term component of this link in our classification system. We would have liked to include a third component, taking into account a score comparing companies in the same sector. Unfortunately, with only 50 companies, some sectors had only one or two firms, which did not allow for a proper ranking.

Subsequently, to ensure that the parameters had comparable values, we normalized them using the following formula:

$$X_{Normalised} = \frac{(X - X_{min})}{(X_{max} - X_{min})}$$

with:

$X_{Normalised}$ = Normalized score of a company

X = Basic score of a company

X_{min} = Minimum score in all the companies

X_{max} = Maximum score in all the companies

Once normalization was completed, we assigned a weight of 0.5 to each parameter, resulting in a score for each company. Based on this score, we classified the 50 companies into five quintiles, each containing 10 companies [3].

4.2.2 First Approach

In our initial approach, we aimed to construct five distinct portfolio models for each of the five clusters. It was essential to have multiple points of comparison with the reference portfolio, rather than relying on a single portfolio model, to examine the potential correlation between

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[3] The composition of each quintile as well as the mean, the trend and the score of each company can be found in Appendix 2

carbon footprint and returns. The primary objective is to determine whether portfolios constructed in a low carbon intensity quintiles outperform those in high intensity quintiles. The results derived from this analysis are intended to demonstrate the existence of a link between carbon footprint and portfolio returns. Identifying this link and drawing meaningful conclusions from its performance is imperative.

To this end, we will measure the Sharpe ratio of each model and compare it across different quintiles. The primary objective is to determine whether there is a real difference in Sharpe ratios, indicating a potential link. But in order to determine whether this difference statistically significant or merely due to chance, we will also apply a Jobson-Korkie test modified by Memmel, which will enable us to check the accuracy of the differences between Sharpe ratios (Auer & Schuhmacher, 2013). It is important to note that each Sharpe ratio result may be influenced by factors such as the chosen time window, the sample size, etc.

The results of the Jobson-Korkie test will allow us to address our first hypothesis, which is: *Carbon footprint impacts portfolio returns?* To test our second hypothesis, we will compare the Sharpe ratios of our portfolio models across the different quintiles and then determine whether the portfolios with the best results are in the low-carbon quintiles or not.

4.2.3 Second Approach

For our second approach, we wanted to find another way to detect a link between carbon footprint and performance. To do this, instead of classifying companies based on their carbon intensity and then applying the portfolio models, we left the 50 companies as is. We took four of the five portfolio models used in the first approach and applied them to all 50 available assets (i.e. without taking into account the clusters based on the carbon score). However, we added a cardinality constraint which requires each of the models to select only 10 companies among the 50 available. This constraint takes the form of a large penalty that is added to the objective functions if they select more than 10 companies. We then used either evolutionary algorithms or quadratic solver, depending on the portfolio model, to find best solution.

The reason why we only have four portfolio models instead of five is that we were unable to implement the cardinality constraint on the Equally Weighted portfolio. Since the latter has no objective function other than to give the same weight to all the companies, we could not optimise this portfolio to select only the 10 companies that give the best results in terms of objective function.

Ultimately, the goal is to compare the 10 companies selected by each model with the 10 companies in each cluster without considering carbon footprints. Each portfolio must maximize or minimize its objective function with the constraint of including no more than 10 companies with non-zero weights. This method will therefore allow us to confirm or refute the results obtained with our first approach. Indeed, by examining the companies selected with the cardinality constraint, we can draw conclusions on the possible existence of a link between carbon footprint and portfolio returns.

4.2.3.1 Robustness Test

With the aim of verifying the accuracy of our models and results, we will again apply our four portfolio models to our 50 companies, but this time without the cardinality constraint. Once the weight optimisation problem has been finalised, we will keep only the 10 companies whose weights have the largest absolute values. We take the absolute value because, from the outset, we have not imposed a positivity constraint on our weights. A negative weight therefore means that the company in question is performing very poorly and that we are better off selling it.

Finally, if the 10 best companies correspond to those selected with our cardinality constraint, this will prove that our results are solid and allow us to confirm our findings.

4.2.4 In-Sample and Out-of-Sample

In order to train our different models and test their performance, we decided to use two methods called in-sample and out-of-sample. The first method consists of training our models on all the available data and then testing them on the same data. The reason for using a second method and not just this one is that the in-sample method presents a risk of overfitting, which means that the models will be adapted to the test data, even over-adapted, but may not work well once we want to use them on new data (Rapach & Wohar, 2006). However, the aim of building a portfolio is to add new data regularly. This is where the out-of-sample method comes into its own. This consists of training the models on part of the data and testing them on another, completely different, part.

To further our analysis, we decided to use the out-of-sample method combined with a rolling window approach. This method involves training the models on a small window of data and then testing them on another small segment of the data. The process is repeated, but each time the window used is moved forward by a certain period. After multiple iterations, we ended up with nine different sets of weights and nine sets of returns and Sharpe ratios. Since we had to choose in order to be able to compare our results, we chose to retain the value corresponding to the average of the nine Sharpe ratios.

Finally, of the five portfolio models we used, four were developed using both in-sample and out-of-sample methods. The only model for which we have only applied the in-sample method is the Equally Weighted portfolio because, given that the weights are identical for all stocks, there is no point in optimising the allocation of weights via a rolling window. We will nevertheless use it in the out-of-sample comparisons in our report, as it provides a valuable benchmark for performance evaluation.

4.2.5 Financial Metrics

In order to measure the performance of each of our models and to subsequently compare them, we have defined 5 financial performance metrics, based on both returns and risks. In order to answer our hypotheses, the measure that is most important to us is the Sharpe ratio. However, we have also calculated additional financial metrics for informational purposes only.

4.2.5.1 Mean Rate of Returns

This is a financial metric used to assess the performance of financial investments, in our case the performance of equity portfolios. One of its definitions is that it "refers to the mean rate of gain or loss on an investment over a specified period of time" (Swoop Funding, n.d.). We chose to use the term "rate of returns", instead of just "returns", to emphasize that we are measuring returns in percentages rather than monetary amounts.

4.2.5.2 Standard Deviation of the Returns

Standard deviation is used to measure the extent to which an asset's returns deviate from its average return (DeNicola, n.d.). This is a good indicator of the volatility of an asset and therefore it can be used to partially measure the risk undertaken by an investor, since an asset with higher volatility generally carries greater risk.

4.2.5.3 Sharpe Ratio

The Sharpe ratio was first introduced by William F. Sharpe in 1966. It is a risk-adjusted return measure of the performance of a portfolio and it is based on the formula (Baldridge, 2024):

$$\text{Sharpe ratio} = \frac{\text{Mean return} - \text{Risk free rate}}{\text{Standard deviation}}$$

The numerator represents the market risk premium, which is the return an investor can gain in addition to the return on a risk-free asset (Baldridge, 2024). The risk free rate corresponds to the rate of return an investor can expect from an asset with zero risk. On the other hand, the denominator is composed of the standard deviation and, as we have seen before, it can be used to measure risk. In other terms, the Sharpe ratio represents the compensation an investor can expect for the extra risk taken (Wikipedia, n.d.). When comparing two portfolios, the one with the higher Sharpe ratio offers better return than the other one for the same level of risk.

We decided to use it as the benchmark for our study because it is one of the most widely recognized and utilized indicators in the financial world. Therefore, it seemed appropriate to employ it to closely align with real-world practices.

Finally, for the purposes of our study, we have considered the 10 Year Treasury yields of the U.S.A. as the annual risk-free rate, which is equal to $r_f = 4.28\%$, as of 06/07/2024 (Bloomberg, n.d.). This corresponds to a monthly risk-free rate of 0.3498%.

4.2.5.4 Maximum Drawdown

Before defining maximum drawdown (MDD), let's first explain what a drawdown is. It corresponds to a fall in the value of an investment measured from a spike to the trough that follows it on the curve (Mitchell, 2024). If we consider the maximum drawdown, this is the difference in value between the highest peak and the lowest trough that follows it, up to the next peak, expressed as a percentage (Hayes, 2024). Maximum drawdown are often considered by investors to be a good indicator of the risk incurred by an investment, as they show how volatile the investment has been in the past through the value of the MDD (a larger MDD means greater volatility, and vice versa). The formula used to calculate the maximum drawdown is as follows (Wall Street Prep, 2024):

$$\text{Maximum drawdown} = \frac{\text{Peak value} - \text{Trough value}}{\text{Peak value}}$$

4.2.5.5 Calmar Ratio

Finally, the last measure we have chosen to use is the Calmar ratio. It was first introduced by Terry W. Young in 1996 (Kenton, 2024). It is a risk-adjusted measure that compares an investor's income with the biggest risk he has taken (because a higher Calmar ratio means that the portfolio has had better returns than the maximum loss, and vice versa) (Fowls, 2023). The difference with the Sharpe ratio comes from the denominator. Indeed, for the Sharpe ratio, the denominator represents the total volatility of the portfolio, whereas for the Calmar ratio, it only represents the maximum loss the investor could have faced in the past.

$$\text{Calmar ratio} = \frac{\text{Mean rate of return} - \text{Risk free rate}}{\text{Maximum drawdown}}$$

4.2.6 Carbon Intensity Measure

Finally, to gain an understanding of the carbon footprint differences among the various portfolios, and more importantly, to measure the disparity between each portfolio and the benchmark, we will also use the Weighted Average Carbon Intensity (WACI). This metric allows us to measure the carbon efficiency of a portfolio and has the advantage of being comparable across portfolios of different sizes and over time, as it uses normalized data for its calculation (European Central Bank, 2023). The WACI value is expressed in tonnes of CO2 equivalent per million euros of revenue ($tCO_2e/M\ revenue$).

The formula used to compute this measure is (Bajo & Rodríguez, 2022):

$$\text{WACI} = \sum_{i=1}^{n} w_i CI_i$$

with:

$$w_i = \text{Weight of asset i} \qquad CI_i = \text{Carbon intensity of asset i}$$

4.2.7 Statistical Testing

In the course of our research, we identified two tests that are most commonly used to test the difference in Sharpe ratios, namely the Jobson-Korkie test modified by Memmel, and the Ledoit-Wolf test (Auer & Schuhmacher, 2013). The Jobson-Korkie test modified by Memmel has the advantage of requiring less computing power and being easier to implement. In addition, this is the test most commonly used to compare Sharpe ratios in the last decades (Auer & Schuhmacher, 2013). The Ledoit-Wolf test has the advantage of being better suited to data with a time dependency and a non-normal distribution.

In order to determine the most appropriate test for our study, we decided to test each time series of data and check whether it showed any time dependency. We therefore applied the Ljung-Box test, which detects the presence of time dependency and, of the 50 companies tested, only six obtained a p-value greater than 0.05. This means that the majority of the data do not show time dependency, which leads us to prefer the Jobson-Korkie test, for its ease of implementation and its reputation.

The Jobson-Korkie test modified by Memmel tests the null hypothesis that the two Sharpe ratios are equal and therefore that their difference is equal to zero. The alternative hypothesis consists in the difference of the Sharpe ratio value.

$$H_0 : \mathit{\Delta} = Sh_i - Sh_n = 0$$
$$H_1 : \mathit{\Delta} = Sh_i - Sh_n \neq 0$$

where Sh_i and Sh_n are the 2 Sharpe ratios to be compared. If the results of the test lead to the rejection of the null hypothesis, this indicates that one of the portfolios has really performed better than the other (Auer & Schuhmacher, 2013).

Finally, to find out whether the null hypothesis is rejected or retained, we will check the p-value of the test. This corresponds to the probability that our data exists under the null hypothesis (the smaller the p-value, the greater the chance of rejecting the null hypothesis) (Simplilearn, 2023). In statistical tests, it is often compared to an α significance level, which we have defined, for the purposes of our study, at 3 different levels, respectively $\alpha = 0.01$, $\alpha = 0.05$ and $\alpha = 0.1$. Finally, if our p-value is less than α, we reject the null hypothesis, but if the p-value is greater, then we cannot reject it.

5 Results and Discussion

In this section, we will analyse and interpret the results obtained during our study. We will begin by presenting the results obtained by each portfolio across the quintiles following our first approach. The next step will be to check the Sharpe ratio differences with the results of the statistical test. We will conclude our first approach by interpreting the results to determine the nature of the link between carbon footprint and performance. To challenge our results, we will also analyse the 10 companies selected by each of our models in our second approach and compare them with the companies in the quintiles. Finally, we will check our results from this second approach using our robustness test.

Moreover, for the sake of brevity and to avoid overwhelming the reader with results, we will focus our analysis on annualised out-of-sample performance metrics, such as Sharpe ratio. Indeed, carbon footprints (and carbon intensity) are expressed in annual values, so this will enable us to make a better comparison. In-sample and monthly results are available for informational purposes in Appendix 3, 4 and 5 respectively.

5.1 First Approach Results

In this section, we will present the results obtained using our first methodology, which consists of comparing the results of the models between each quintile

We begin here with Table 2 showing the performance metrics of our benchmark portfolio. These values will be used later for comparison with the different portfolios we will be analysing.

Metrics	**Benchmark Portfolio**
Mean rate of returns	9.5%
Standard deviation	0.1623
Sharpe ratio	0.3216
Max drawdown	0.2355
Calmar ratio	0.4033691
WACI	156.4965 $tCO_2e/M\ revenue$

Table 2: Performance metrics of the benchmark portfolio; the mean rate of returns, the standard deviation of the returns, the Sharpe ratio, the maximum drawdown, the Calmar ratio and the WACI.

We can also observe the Calmar ratios of the different portfolios through the five quintiles in Table 3. The performance measure allows us to measure the extent to which this portfolio has benefited us in exchange for the maximum potential loss we have incurred.

Models	1^{st} **Q**	2^{nd} **Q**	3^{rd} **Q**	4^{th} **Q**	5^{th} **Q**
Equally Weighted	0.2076	0.1166	0.1871	0.0370	0.1215
Mean Variance	1.2073	3.6331	0.3558	0.4570	0.4823
Minimum Variance	0.5510	0.4053	0.3312	-0.0689	0.7509
M.V. l1 - l_∞ Constraint	0.3031	0.1422	0.1960	-0.0225	0.1012
MVSK	0.7442	0.1919	0.0782	0.0800	0.2999

Table 3: Calmar ratios of the 5 portfolio models in each of the 5 quintiles

When we take a closer look at the data for this ratio, we notice that for the majority of data, the first quintiles obtained a higher ratio than the others, which means that for a certain maximum drawdown, the portfolios in the first quintiles provide us with better returns. The only exception is the Minimum Variance portfolio. However, we cannot draw any precise conclusions from this ratio as we have not verified its statistical significance. We have therefore provided this table for informational purposes only.

Table 4 shows the WACI obtained by each portfolio model in the five quintiles. This measure should enable us to check whether the portfolios in the first quintiles do indeed have a lower carbon intensity than the models in the last quintiles and compared with the benchmark portfolio.

Models	1^{st} **Q**	2^{nd} **Q**	3^{rd} **Q**	4^{th} **Q**	5^{th} **Q**
Equally Weighted	105.4270	3.0660	3.7410	20.0201	482.0428
Mean Variance	361.3343	-2.2537	6.1818	-70.6893	643.0157
Minimum Variance	182.7725	3.8093	8.0768	30.3423	841.9904
M.V. l1 - l_∞ Constraint	67.2637	2.1016	4.9016	19.9298	475.7094
MVSK	1.2588	3.6042	11.7390	12.4234	322.6944

Table 4: WACI of the 5 portfolio models in each of the 5 quintiles, expressed in tCO_2e/M *revenue*

Nevertheless, as can be seen from the values of the majority of models, the 1^{st} quintile has a higher WACI than the 2^{nd}, the 3^{rd} and the 4^{th} quintiles. The reason why the 1^{st} quintile does not always have a lower WACI than the others is that our companies are ranked according to a score based both on their average carbon intensity and on the trend in their carbon intensity management. This results in companies with a high carbon intensity but a strong downward trend in the first quintile. Since the WACI is only based on carbon intensities, without taking into account the trend in the data, it does not give us results that corroborate our expectations. However, when we look at the extreme quintiles, we can see that there is a decrease in the WACI between the 1^{st} and 5^{th} quintile. We will therefore focus more on their comparison than on the others, as they best reflect the difference in carbon footprints.

It might be interesting to check in several years if the WACI of the first quintile has become the lowest WACI when new data is added. Indeed, since we have selected companies with a strong downward trend in carbon footprints, we should expect to see companies with increasingly smaller carbon footprints. This would allow us to check whether the carbon score used to classify companies was a good methodology to follow or not.

5.1.1 First Results

The next data we present in Table 5, corresponds to the Sharpe ratios of each portfolio model within the five quintiles. In order to find this Sharpe ratio, we calculated the average ratio among those obtained via our rolling windows. Below each ratio, we have also added its standard deviation, which will allow us to better compare the performance of each model across all quintiles. The standard deviation will tell us which quintile has the most stable ratios, which is a good indicator of performance. On the other hand, those with a larger standard deviation indicate more volatility in Sharpe ratio values, which corresponds to more risk. The only exception is the Equally Weighted portfolio, since the weights are always the same, we don't apply an out-of-sample methodology.

Models	1^{st} **Q**	2^{nd} **Q**	3^{rd} **Q**	4^{th} **Q**	5^{th} **Q**
Equally Weighted	0.1123	0.1974	0.2917	0.0672	0.1988
Mean Variance	0.4723	0.4332	0.5387	-0.1462	-0.3592
	(0.9658)	(1.1836)	(0.8917)	(1.7183)	(1.2407)
Minimum Variance	0.7030	-0.2819	0.3248	0.0395	0.0251
	(1.4603)	(0.9949)	(0.7332)	(0.8506)	(1.3321)
l1 - l_∞ Constraint	0.2876	0.3802	0.4476	-0.0408	0.2227
	(1.1468)	(1.1919)	(1.1793)	(0.9077)	(0.9440)
MVSK	1.0098	0.4703	0.3629	0.1127	0.1145
	(1.2604)	(1.0886)	(0.4318)	(1.1896)	(0.9475)

Table 5: Sharpe ratios of the 5 portfolio models in each of the 5 quintiles

Looking at these initial results, we can see that, in general, the top quintile performs better than the bottom, except for the Equally Weighted model. The behaviour of the middle quintiles is quite divergent, with some following the general trend and others presenting more extreme values. If we take a closer look at the standard deviations, we can see that the majority have fairly high values, which does not allow us to draw any conclusions.

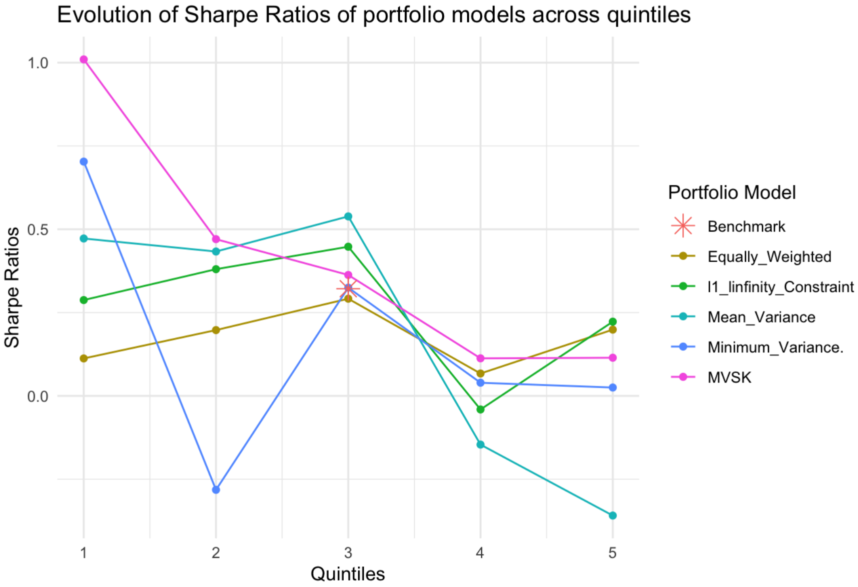

Figure 1: Evolution of the values of the Sharpe ratio of each portfolio model across the 5 quintiles

In order to get a better idea, we have used a graph, Figure 1, showing in line graph form the evolution of Sharpe ratio values for each model across the five quintiles. We have also added the Sharpe ratio value of the benchmark portfolio in order to be able to compare if there is a difference in the performance of the quintiles.

By looking at this chart, we can easily identify a downward trend in Sharpe ratio performance across quintiles. Nevertheless, this trend is far from being linear, since, despite a lower Sharpe Ratio in the last quintile than in the first, the values between these two points are quite dispersed and do not show any particular trend. However, we are concentrating mainly on the comparison between the 1^{st} quintile and the 5^{th}, as these are the most extreme and therefore the ones that will give us the best indication of the trend in the link between carbon footprint and financial performance.

Another piece of information to consider is the comparison of the performance of the models with that of the benchmark portfolio. The most obvious fact is that most of the models perform better than the benchmark portfolio when they use companies from the first quintiles, and therefore when they only use companies with a better carbon score.

5.1.2 Statistical Testing

The next step in our analysis is to verify the statistical significance of the differences between the Sharpe ratio of the models across each quintile. To do this, we analyze the results from the Jobson-Korkie test modified by Memmel to all the differences. We compare the Sharpe ratio of each model in each quintile against the values obtained by the same model in the other quintiles. In order to provide the best information, we used a star system to show which differences are significant. The classification is as follows:

- 3 stars = significant at 1%
- 2 stars = significant at 5%
- 1 star = significant at 10%
- 0 star = not significant

So, if one of the differences has no star, this means that it is considered insignificant since it does not reject the null hypothesis stipulating that the two ratios are equal.

We therefore applied our statistical test to our models across each quintile. These results are presented from Table 6 to Table 10, in the form of a double entry matrix. Each cell of the matrix corresponds to the difference between the Sharpe ratio of the quintile in the row and that of the quintile in the corresponding column. There is a table for each of the 5 portfolio models.

However, there is a lot of data to compare at the same time, which makes it difficult to identify a trend. To make the results easier to read, we have added a final column, corresponding to the mean of the differences for each row. This will give us a classification of which quintiles performed best and worst, which should help us to see a trend in the data.

Quintiles	1^{st} **Q**	2^{nd} **Q**	3^{rd} **Q**	4^{th} **Q**	5^{th} **Q**	**Mean**
1^{st} **Q**	-	-0.0851*	-0.1793***	0.0452	-0.0865*	**-0.0764**
2^{nd} **Q**	0.0851*	-	-0.0943**	0.1303**	-0.0014	**0.0299**
3^{rd} **Q**	0.1793***	0.0943**	-	0.2245***	0.0929*	**0.1478**
4^{th} **Q**	-0.0452	-0.1303**	-0.2245***	-	-0.1316**	**-0.1329**
5^{th} **Q**	0.0865*	0.0014	-0.0929*	0.1316**	-	**0.0317**

Table 6: Difference between Sharpe ratios for the Equally Weighted portfolio across the 5 quintiles.

This first portfolio model shows that company classification has not improved the Sharpe ratio of the portfolio. In fact, the best performing portfolio is in the 3^{rd} quintile, followed by the 5^{th}. These initial results do not allow us to draw any conclusions about the existence of a link between performance and carbon footprint.

Quintiles	1^{st} **Q**	2^{nd} **Q**	3^{rd} **Q**	4^{th} **Q**	5^{th} **Q**	**Mean**
1^{st} **Q**	-	0.0391	-0.0664	0.6185***	0.8315***	**0.3557**
2^{nd} **Q**	-0.0391	-	-0.1054	0.5794***	0.7924***	**0.3068**
3^{rd} **Q**	0.0664	0.1054	-	0.6849***	0.8978***	**0.4386**
4^{th} **Q**	-0.6185***	-0.5794***	-0.6849***	-	0.2129	**-0.4175**
5^{th} **Q**	-0.8315***	-0.7924***	-0.8978***	-0.2129	-	**-0.6837**

Table 7: Difference between Sharpe ratios for the Mean Variance portfolio across the 5 quintiles

For our second model, the Mean Variance, the quintile at the top of the list is the 3^{rd}, followed by the 1^{st}. The 5^{th} quintile is the worst performer. Despite the fact that the results for the 3^{rd} quintile disrupt the analysis, if we focus on the extremes, we can still see a downward trend as we move up the quintiles. This model therefore supports our hypothesis of a negative relationship between Sharpe ratio and carbon footprint.

Quintiles	1^{st} **Q**	2^{nd} **Q**	3^{rd} **Q**	4^{th} **Q**	5^{th} **Q**	**Mean**
1^{st} **Q**	-	0.9850***	0.3782**	0.6635***	0.6780***	**0.6762**
2^{nd} **Q**	-0.9850***	-	-0.6067***	-0.3214**	-0.3070*	**-0.5550**
3^{rd} **Q**	-0.3782**	0.6067***	-	0.2853*	0.2997*	**0.2034**
4^{th} **Q**	-0.6635***	0.3214**	-0.2853*	-	0.0144	**-0.1533**
5^{th} **Q**	-0.6780***	0.3070*	-0.2997*	-0.0144	-	**0.1713**

Table 8: Difference between Sharpe ratios for the Minimum Variance portfolio across the 5 quintiles

The results we obtain with this third model are more or less the same as those obtained previously. The 1^{st} quintile performed best, followed by the 3^{rd} and then the 5^{th}. However, the 2^{nd} and 4^{th} quintile performed the worst, contrary to what we might have expected. But all the same, there is still a downward trend between the two extremes.

Quintiles	1^{st} **Q**	2^{nd} **Q**	3^{rd} **Q**	4^{th} **Q**	5^{th} **Q**	**Mean**
1^{st} **Q**	-	-0.0927*	-0.1601**	0.3284***	0.0649	**0.0351**
2^{nd} **Q**	0.0927*	-	-0.0674**	0.4210***	0.1576*	**0.1510**
3^{rd} **Q**	0.1601**	0.0674**	-	0.4884***	0.2250***	**0.2352**
4^{th} **Q**	-0.3284***	-0.4210***	-0.4884***	-	-0.2634***	**-0.3753**
5^{th} **Q**	-0.0649	-0.1576*	-0.2250***	0.2634***	-	**-0.0460**

Table 9: Difference between Sharpe ratios for the Minimum Variance l1-l∞ Constraint portfolio across the 5 quintiles

Regarding the results of the Minimum Variance with $l1 - l\infty$ Constraint model, we can see that the 3^{rd} quintile is the best performer, followed by the 2^{nd} and the 1^{st}. Once again, there is a downward trend between the two extreme quintiles, but it seems much less pronounced, as the difference between the average score of the two quintiles is very small.

Quintiles	1^{st} **Q**	2^{nd} **Q**	3^{rd} **Q**	4^{th} **Q**	5^{th} **Q**	**Mean**
1^{st} **Q**	-	0.5395***	0.6469***	0.8971***	0.8953***	**0.7447**
2^{nd} **Q**	-0.5395***	-	0.1075	0.3576*	0.3558*	**0.0703**
3^{rd} **Q**	-0.6469***	-0.1075	-	0.2502*	0.2484*	**-0.0640**
4^{th} **Q**	-0.8971***	-0.3576*	-0.2502*	-	-0.0018	**-0.3767**
5^{th} **Q**	-0.8953***	-0.3558*	-0.2484*	0.0018	-	**-0.3744**

Table 10: Difference between Sharpe ratios for the Mean Variance Skewness Kurtosis portfolio across the 5 quintiles.

Our final model, the Mean Variance Skewness Kurtosis, provides results that strongly support our hypothesis of a negative relationship between carbon footprint and financial performance. In fact, we can see that the further you move up the quintiles, the lower the value of the average difference in the Sharpe ratios.

Finally, in order to bring all these results together for comparison, we plotted the performance in terms of the average of the differences between the Sharpe ratios of each model across the five quintiles in a line graph. To achieve this, we estimated a linear regression on the average Sharpe ratio differences data for each model. This gave us Figure 2.

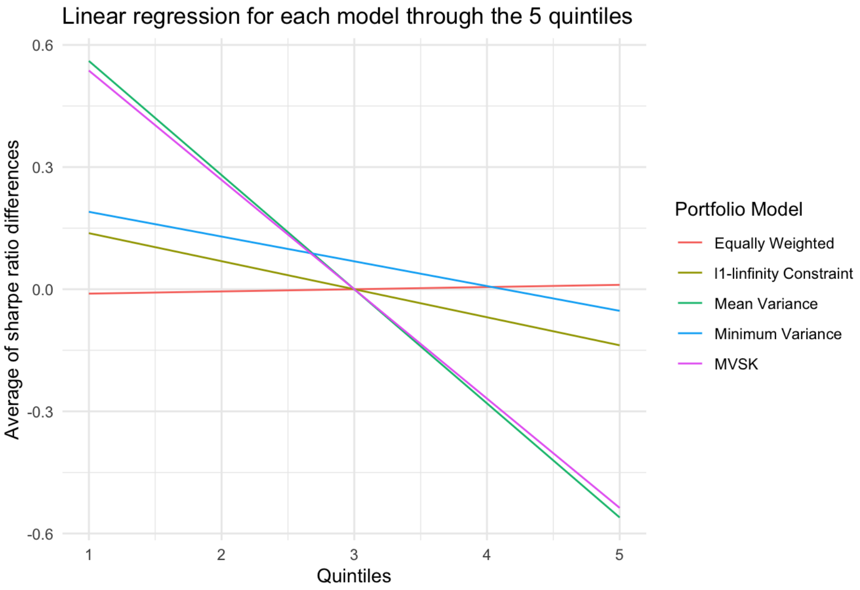

Figure 2: Mean of the differences in Sharpe ratios for each portfolio model through the 5 quintiles.

Examining the graph, we can immediately see that, generally speaking, there is a downward trend in Sharpe ratio performance as we move up the quintiles. As we saw earlier, the only exception to this trend is the Equally Weighted portfolio, which has more or less a horizontal trend. The Mean Variance and MVSK portfolios are the two models showing the steepest slope and therefore the biggest trend. The Minimum Variance and $l1 - l\infty$ Constraint portfolios, on the other hand, show smaller yet noticeable slopes.

These results indicate that there is a negative relationship between carbon intensity and risk-adjusted returns. In other words, companies that are more environmentally-friendly tend to outperform those that are not. To get an idea of the order of magnitude of this relationship, we have indicated the slope of the linear regression for each of the model in Table 11.

Model	**Slope**
Equally Weighted	0.0054
Mean Variance	-0.2803
Minimum Variance	-0.0608
M.V. $l1 - l\infty$ Constraint	-0.0689
MVSK	-0.2685

Table 11: Slopes of the linear regressions for the 5 portfolio models

However, even though its slope coefficient is very low, the Equally Weighted portfolio remains significant. When equal weights are assigned to all the companies, the Sharpe ratio is almost completely independent of the carbon footprint. Conversely, when we start taking risk and performance measures into account when constructing portfolios, the Sharpe ratio improves as the carbon footprint decreases. This suggests avenues for future research to explore the cause of this negative relationship, in particular to verify whether a small level of carbon footprint correlates with lower risk or higher returns, or both.

5.2 Second Approach Results

In our second approach, we applied our models to a portfolio containing the 50 companies, but added a cardinality constraint requiring the selection of exactly 10 of them. Our objective with this method is to see whether, by using a completely different approach, without involving any information linked to carbon footprints, the models still give priority to companies with low footprints in order to optimise their results. If this hypothesis is confirmed, it will support our previous findings, indicating that companies with low carbon footprints are preferred to companies with high footprints.

The results we obtained using this second approach are presented in Figure 3 in the form of a bar graph. Each bar represents the number of companies selected by the model for the corresponding quintile. The bars are both in the positive values, corresponding to the companies selected with positive weight, but also in the negative values, representing the companies to which a negative weight has been assigned. We also calculated the average selection value per quintile and then represented them via a line of averages.

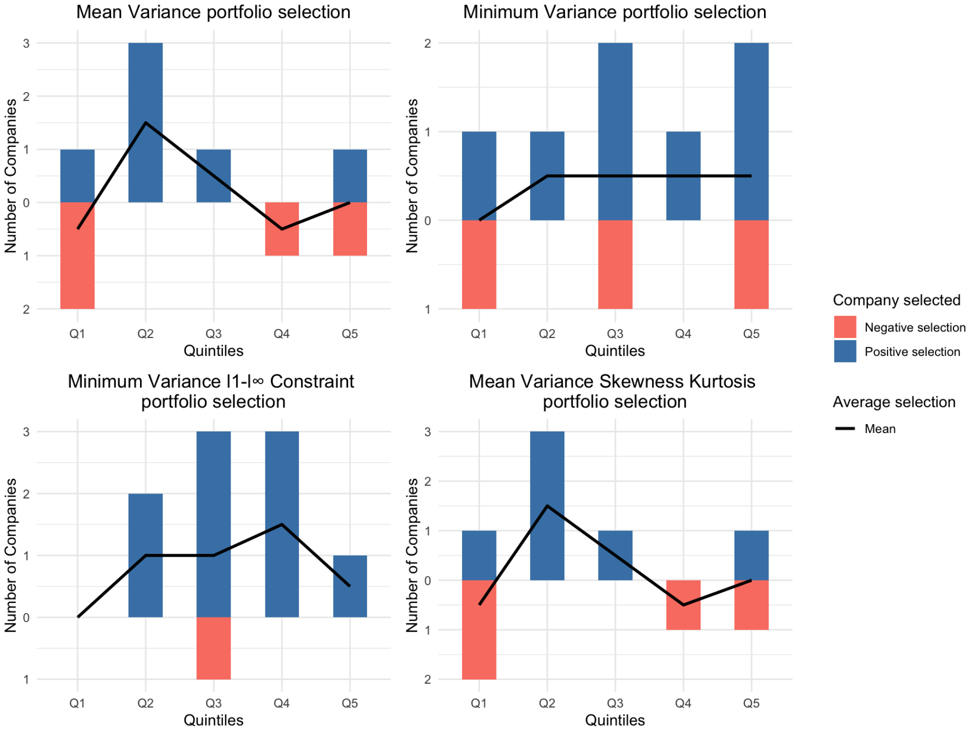

Figure 3: Companies selected by the cardinality constraint of the 4 portfolio models compared with the composition of the quintiles

Overall, these results are not what we expected. Our initial approach, based on quintile classification, indicated a negative relationship between carbon footprint and financial results. The results of this second approach are much less supportive of this hypothesis.

We first have the Mean Variance and Mean Variance Skewness Kurtosis models, for which it is very difficult to define any relationship at all. Based on these results, there is apparently no link between carbon footprint and financial performance. Secondly, we also have the results of the Minimum Variance and Minimum Variance with $l1 - l\infty$ Constraint models, which, according to these graphs, show a rather positive trend between carbon footprints and the number of companies selected. These results therefore completely contradict those obtained in our first approach.

Such discrepancies can be attributed to several factors, two of which are particularly significant: the first concerns the algorithms used to solve the cardinality constraint. For three of our models, we had to use evolutionary heuristic algorithms which can support the cardinality constraint in addition to the other constraints specific to each model. However, these algorithms need many iterations to obtain the most convincing results. Unfortunately, we did not have sufficient computational power to implement such a high number of iterations. We therefore had to limit the number of iterations, which may have led to a bias in our data. The use of different algorithms or greater computational power could lead to different results.

The second reason concerns the data periods used. We noticed during our various tests that the companies selected changed when we moved from one window to another in our out-of-sample results. The use of a larger historical database could make it possible to increase the size of the windows and potentially reduce the changes in companies.

Let us now verify whether our models have indeed had an impact on the results with our robustness test.

5.2.1 Robustness Test

Figure 4 shows the results we obtained during our test. We have chosen to present them in the same form as those obtained previously with the cardinality constraint, in order to better see the differences and similarities. However, to get a clearer idea of the impact of each model with the cardinality constraint on their results, we have also calculated the percentage differences between the two methodologies.

As a reminder, the purpose of this test is to indicate whether the choice of our models with cardinality constraints has had a significant impact on our previous results. A high percentage of similarities indicates a low impact on our data and therefore robust results, whereas a lower percentage would indicate a greater impact of our models on the results obtained, indicating weaker and therefore less relevant findings.

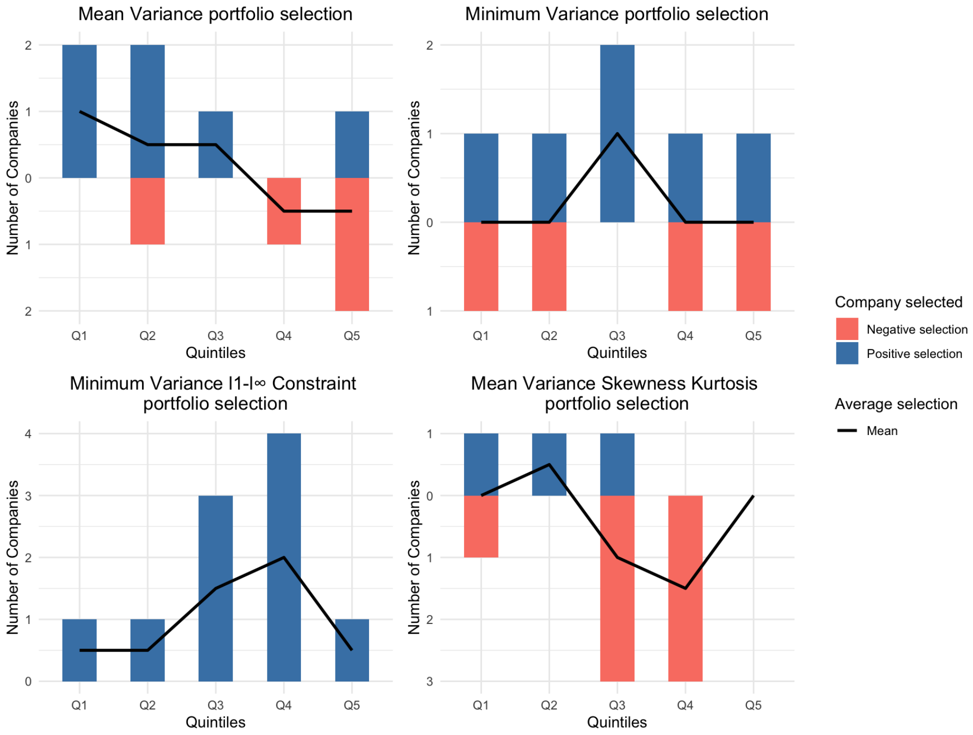

Figure 4: Top 10 companies selected with the 4 portfolio models compared with the composition of the quintiles

When we look at the results for each model in the Figure 4, we can see some differences with those obtained with the cardinality constraint in Figure 3, particularly for the Mean Variance and Minimum Variance models, for which the trend in the data is quite different. This time, we have a Mean Variance model showing a downward trend in the selected companies when the carbon footprints are increased. The Minimum Variance model, on the other hand, no longer shows any relationship between carbon footprint and performance. Our last two models present results more similar to those obtained previously.

Model	**Slope**
Mean Variance	70%
Minimum Variance	60%
M.V. $l1 - l\infty$ Constraint	20%
MVSK	50%

Table 12: Percentage differences between the companies selected by the cardinality constraint and those selected during the robustness test

These percentage differences confirm what we observed earlier when comparing our graphs. The Mean Variance, Minimum Variance and MVSK models all exhibit relatively high percentage differences. This indicates that our results obtained with the cardinality constraint are probably biased by the models we used, making them statistically less reliable.

In contrast, the Minimum Variance with $l1 - l\infty$ Constraint model has a very low percentage difference. With only a 20% difference between the two methods, this model provides more robust results. We should therefore focus more on this portfolio when examining the results obtained using the cardinality constraint. The reasons for this outperformance may be linked to the pre-existing constraints, which have strengthened the model and reduced the potential bias in the data. On the one hand, we have the $l1$ constraint, which imposes a limit on the number of assets selected, and on the other hand the $l\infty$ constraint, which imposes a maximum weight on the assets, in order to ensure that the $l1$ constraint does not overly restrict the number of stocks selected too much.

By adding the cardinality constraint, we have essentially strengthened the l1 constraint by explicitly requiring the model to select only 10 companies. For our other models, however, the cardinality constraint was entirely new, bringing about a major change in the resolution of the models, which may have had a bigger impact on their results.

6 Conclusion

The aim of this thesis was to define the existence of a relationship between companies' carbon footprint and their financial performance and, if such a link existed, to try to determine its nature. To achieve this, we used the 50 companies in the EuroStoxx50 as a benchmark portfolio, which we grouped into five quintiles based on a carbon score derived from their average carbon intensity and the trend in their management. These quintiles formed the basis of our study, serving as a point of comparison for verifying the existence of the relationship in our two approaches.

As previously stated, we supported the hypothesis that companies with lower carbon footprints perform better than those with higher footprints. Indeed, despite the many divergences on the subject in the current literature, we believe that the growing general concern about the climate situation will drive climate-conscious companies to outperform others. This study provides empirical results, which have been rigorously challenged in order to verify their robustness, enabling us to respond to this hypothesis.

In our first approach, which involved applying portfolio models across the five quintiles, we discovered that the models performed better for the quintiles with a low carbon score than for those with a high score. Furthermore, when compared with the benchmark portfolio, the latter performed less well than the portfolios in the first quintiles. The only exception was the Equally Weighted model, which showed no discernible trend across quintiles. To check the statistical significance of our results, we also tested our differences in Sharpe ratios using the Jobson-Korkie test modified by Memmel, testing the null hypothesis that our Sharpe ratios are equal. For a large number of our results, we were able to reject this null hypothesis at the 10% significance level. Finally, in our linear regression estimation on our data, we obtained a negative trend in the relationship between carbon footprint and financial performance. Once again, with the exception of the Equally Weighted portfolio, our models showed a negative relationship, thereby confirming our initial hypothesis.

In order to challenge our initial results and check their reliability, we used a second methodology consisting of applying our models to the benchmark portfolio but adding a cardinality constraint imposing the selection of exactly 10 assets. Once we had the results for each model, we compared the selected companies with the quintiles. Unexpectedly, the results were not as explicit as before. Out of four of our models, two no longer showed any relationship, and the other two showed a fairly positive relationship between carbon footprint and performance. However, being aware that the cardinality constraint could have a major impact on the results of this method, we also used a robustness test to check their reliability. The results of this test were quite negative, since only the Minimum Variance with $l1 - l\infty$ Constraint model presented sufficiently robust results. We therefore took into account only the results obtained by this model for our second approach, which led us to conclude that there was a positive relationship between carbon footprint and financial performance, in this specific context.

The rather contradictory results obtained by the two approaches can be explained by several factors, in particular the differences in the methodologies used in the two approaches, the limitations of our models, and the impact, to a greater or lesser extent, of the cardinality constraint. However, all these differences only serve to demonstrate the complexity of integrating carbon footprints into the construction of financial portfolios and, above all, of capturing the essential information linked to carbon emissions that can improve the performance of such portfolios.

In conclusion, despite these differences, our study has enabled us to highlight the existence of a relationship between companies' carbon footprint and their financial performance. Unfortunately, we were unable to clearly define the nature of this relationship via our results because of the discrepancies in our findings. However, due to its higher statistical significance, we consider the results obtained from our first approach to be more robust, leading us to believe that the relationship is still following a negative trend. Nonetheless, these results are promising and pave the way for us to continue improving the integration of carbon footprints into our investment decisions. Future research will therefore be necessary to overcome our limitations and improve the robustness of our models.

6.1 Limits of the Study

When reading this dissertation, the reader should not forget to take into account that we had to face several limitations, which may significantly impact our results. The main limitations we faced are the following ones:

- The sample size of the data was quite restricted. Indeed, we only included 50 enterprises with 120 monthly historical data points in our benchmark portfolio. This small sample size limits the ability to draw general conclusions. Increasing the number of companies and the amount of historical data will improve the accuracy and generalizability of this study.

- The availability of the data was quite limited. Unfortunately, we couldn't access several databases, particularly for collecting carbon footprint data, which led us to select only a limited number of companies and to extrapolate some of the missing data.
- The historical data we used to calculate share returns included the Covid-19 period, which we did not analyze separately. It should not be forgotten that Covid-19 had a major impact on economic activity and companies' carbon footprint, which could influence our results.
- The choice of models we used may also have a considerable impact on our results. We have chosen these models on the basis of their reputation and characteristics, but other models could give completely different results.
- The cardinality constraint also posed a number of limitations, particularly in terms of the difficulty of integrating it into our models and the increase in computational power it entailed.

6.2 Further Research

For the purposes of deepening our study and challenging our results, future research should attempt to overcome our limitations, primarily by using a larger database with more historical data. Utilizing a broader base portfolio, such as the EuroStoxx600, could be more representative and better reflect the reality of this link. This study could even be applied to indexes from other continents, such as the S&P500, or even global indexes, such as the MSCI World Index, in order to verify the differences between continents.

Furthermore, we have chosen to use the Sharpe ratio as the main measure for our different portfolios, which implies that we base our results on a specific metric. It might be interesting to try other performance metrics, which take into account other factors, in order to determine whether the discovered link is rather related to the risk side of the Sharpe ratio or whether companies with better carbon footprints are just better performers.

The use of other portfolio models with greater computational power could also be beneficial, in order to check whether our results are linked to the choices of our models or whether there is a robust link between returns and carbon footprints.

Lastly, our decision to rank companies based on a score composed of half the average of carbon footprints and half their trend significantly impacted our results. Exploring alternative ranking methods could yield different insights, which would be valuable to study.

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8 Appendices

8.1 Appendix 1: Benchmark Portfolio Composition

Company name	**Weights**
Adidas AG	1.86311‰
Ahold Delhaize NV	1.15622%
Air Liquide SA	2.63184%
Airbus SE	1.5951%
Allianz SE	3.2831%
Amadeus IT Group	0.90468%
Anheuser-Busch InBev SA/NV	1.6025%
ASML Holding NV	6.02486%
AXA SA	1.667%
Banco Bilbao Vizcaya Argentaria SA	0.8846%
Banco Santander SA	1.56463%
BASF SE	1.98365%
Bayer AG	2.79852%
Bayerische Motoren Werke AG	0.78835%
BNP Paribas SA	1.76606%
CRH	1.056%
Danone SA	1.72951%
Deutsche Boerse AG	1.3249%
Deutsche Telekom AG	2.09823%
DHL Group	1.38491%
Enel SpA	2.58254%
Engie	0.88568%
Eni SpA	0.93382%
EssilorLuxottica SA	1.46746%
Fresenius	0.78542%
GRP Societe Generale	0.54685%
Iberdrola SA	2.63657%
Industria de Diseno Textil SA	1.13422%
ING Groep NV	1.04675%
Intesa Sanpaolo SpA	1.20387%
Kering SA	1.56295%
L'Oreal SA	3.01436%
Linde	4.4982%
LVMH Moet Hennessy Louis Vuitton SE	4.49235%
Mercedes-Benz Group AG	1.31383%

Continued on next page

Company name	**Weights**
Muenchener Rueckversicherungs-Gesellschaft AG in Muenchen	1.40368%
Nokia Oyj	0.95192%
Orange	0.91255%
Philips	1.64586%
Safran SA	1.3736%
Sanofi SA	4.46624%
SAP SE	5.89005%
Schneider Electric SE	2.35885%
Siemens AG	3.39441%
Telefonica	0.85748%
TotalEnergies SE	3.82754%
Unilever NV	2.8064%
Vinci SA	1.97369%
Vivendi	0.85549%
Volkswagen AG	1.06961%
Total	100%

Table 13: Benchmark porftolio composition. Data retrieved from STOXX

8.2 Appendix 2: Quintiles Composition and Carbon Score

Company name	**Mean**	**Trend**	**Carbon score**
ASML Holding NV	12.4920	-2.8766	0.4892
Bayer AG	134.3610	-22.6397	0.4818
Deutsche Telekom AG	28.4400	-6.9200	0.4847
Enel SpA	1103.1340	-156.9894	0.4782
Engie	1134.8520	-202.2975	0.3786
Iberdrola SA	637.0940	-102.2331	0.4559
Industria de Diseno Textil SA	19.5330	-5.1042	0.4861
Kering SA	6.5780	-1.5588	0.4904
Philips	10.0200	-3.4189	0.4870
Telefonica	21.3390	-3.2866	0.4911

Table 14: Composition of the 1^{st} quintile with the mean, the trend and the carbon score

Company name	**Mean**	**Trend**	**Carbon score**
Banco Bilbao Vizcaya Argentaria SA	5.8340	-1.1179	0.4912
Banco Santander SA	2.6090	-0.4452	0.4918
Bayerische Motoren Werke AG	10.7000	-1.4636	0.4920
BNP Paribas SA	3.8150	-0.5313	0.4920
L'Oreal SA	3.3480	-0.4794	0.4920
LVMH Moet Hennessy Louis Vuitton SE	7.3140	-1.0595	0.4919
Mercedes-Benz Group AG	14.3480	-2.0390	0.4918
SAP SE	8.3520	-1.1324	0.4920
Siemens AG	16.8870	-2.5885	0.4914
Vivendi	5.9640	-0.8720	0.4919

Table 15: Composition of the 2^{nd} quintile with the mean, the trend and the carbon score

Company name	**Mean**	**Trend**	**Carbon score**
Allianz SE	1.5120	-0.1899	0.4921
Amadeus IT Group	6.7580	-0.6954	0.4926
AXA SA	0.9140	-0.0948	0.4921
Deutsche Boerse AG	2.3600	-0.1302	0.4925
ING Groep NV	0.7260	-0.0731	0.4921
Intesa Sanpaolo SpA	3.1710	-0.1607	0.4927
Muenchener Rueckversicherungs-Gesellschaft AG in Muenchen	1.3560	-0.1476	0.4921
Sanofi SA	21.4720	-2.7983	0.4924
Schneider Electric SE	14.4210	-1.5169	0.4931
Unilever NV	25.2990	-3.1797	0.4927

Table 16: Composition of the 3^{rd} quintile with the mean, the trend and the carbon score

Company name	**Mean**	**Trend**	**Carbon score**
Adidas AG	4.4620	0.3241	0.4943
Ahold Delhaize NV	50.2430	-4.1918	0.4986
Airbus SE	14.7880	-0.3109	0.4962
Danone SA	52.9008	-3.9344	0.5001
Fresenius	39.5750	-4.9596	0.4932
GRP Societe Generale	23.5933	-0.7131	0.4982
Nokia Oyj	17.4850	-0.9969	0.4954
Orange	31.9970	-0.8397	0.5006544
Safran SA	26.8950	-1.8944	0.4964
Volkswagen AG	34.5910	-2.9235	0.4965

Table 17: Composition of the 4^{th} quintile with the mean, the trend and the carbon score

Company name	**Mean**	**Trend**	**Carbon score**
Air Liquide SA	1498.5780	3.1812	1.0000
Anheuser-Busch InBev SA/NV	109.1518	-10.5053	0.5029
BASF SE	316.2270	-10.9747	0.5709
CRH	1322.8970	-36.4155	0.8450
DHL Group	100.6680	-0.9833	0.5232
Eni SpA	577.8840	-17.2593	0.6429
EssilorLuxottica SA	46.5700	-2.6053	0.5012
LINDE	1466.4700	-0.7176	0.9798
TotalEnergies SE	299.9990	-20.1915	0.5430
Vinci SA	52.2310	-3.4969	0.5009

Table 18: Composition of the 5^{th} quintile with the mean, the trend and the carbon score

8.3 Appendix 3: Monthly Performance of the Benchmark Portfolio

Metrics	**Benchmark Portfolio**
Mean rate of returns	0.7592%
Standard deviation	0.04685897
Sharpe ratio	0.08737024
Max drawdown	0.2355
Calmar ratio	0.2217
WACI	156.4965 $tCO_2e/M\ revenue$

Table 19: Performance metrics of the benchmark portfolio; the mean rate of returns, the standard deviation of the returns, the Sharpe ratio, the maximum drawdown, the Calmar ratio and the WACI.

8.4 Appendix 4: In-sample Annual Portfolio Results

8.4.1 Calmar Ratios

Models	1^{st} **Q**	2^{nd} **Q**	3^{rd} **Q**	4^{th} **Q**	5^{th} **Q**
Equally Weighted	0.2076	0.1166	0.1871	0.0370	0.1215
Mean Variance	1.6371	0.9467	0.7271	0.7199	1.3065
Minimum Variance	0.6335	0.1613	0.3202	-0.0222	0.5849
M.V. l1 - l_∞ Constraint	0.6028	0.1979	0.3088	-0.0190	0.5280
MVSK	0.3068	-0.0124	0.0479	-0.0607	0.0358

Table 20: Calmar ratios of the 5 portfolio models in each of the 5 quintiles

8.4.2 Sharpe Ratios

Models	1^{st} **Q**	2^{nd} **Q**	3^{rd} **Q**	4^{th} **Q**	5^{th} **Q**
Equally Weighted	0.1123	0.1974	0.2917	0.0672	0.1988
Mean Variance	2.2659	1.0823	0.7061	1.0671	1.2241
Minimum Variance	0.4544	0.2960	0.3700	-0.0481	0.6111
M.V. l1 - l_∞ Constraint	0.4518	0.3438	0.3642	-0.0399	0.5769
MVSK	0.3848	-0.0268	0.0774	-0.1543	0.0789

Table 21: Sharpe ratios of the 5 portfolio models in each of the 5 quintiles

8.4.3 Differences in Sharpe Ratio Values

Quintiles	1^{st} **Q**	2^{nd} **Q**	3^{rd} **Q**	4^{th} **Q**	5^{th} **Q**	**Mean**
1^{st} **Q**		-0.0851*	-0.1793***	0.0452	-0.0865*	**-0.0764**
2^{nd} **Q**	0.0851*		-0.0943**	0.1303**	-0.0014	**0.0299**
3^{rd} **Q**	0.1793***	0.0943**		0.2245***	0.0929*	**0.1478**
4^{th} **Q**	-0.0452	-0.1303**	-0.2245***		-0.1316**	**-0.1329**
5^{th} **Q**	0.0865*	0.0014	-0.0929*	0.1316**		**0.0317**

Table 22: Difference between Sharpe ratios for the Equally Weighted portfolio across the 5 quintiles.

Quintiles	1^{st} **Q**	2^{nd} **Q**	3^{rd} **Q**	4^{th} **Q**	5^{th} **Q**	**Mean**
1^{st} **Q**		1.1836***	1.5598***	1.1988***	1.0418***	**1.2460**
2^{nd} **Q**	-1.1836***		0.3762***	0.0152	-0.1418	**-0.2335**
3^{rd} **Q**	-1.5598***	-0.3762***		-0.3610***	-0.5180***	**-0.7038**
4^{th} **Q**	-1.1988***	-0.0152	0.3610***		-0.1570	**-0.2525**
5^{th} **Q**	-1.0418***	0.1418	0.5180***	0.1570		**-0.0563**

Table 23: Difference between Sharpe ratios for the Mean Variance portfolio across the 5 quintiles.

Quintiles	1^{st} **Q**	2^{nd} **Q**	3^{rd} **Q**	4^{th} **Q**	5^{th} **Q**	**Mean**
1^{st} **Q**		0.1584*	0.0844	0.5025***	-0.1567*	**0.1472**
2^{nd} **Q**	-0.1584*		-0.0740	0.3442***	-0.3151***	**-0.0508**
3^{rd} **Q**	-0.0844	0.0740		0.4181***	-0.2411***	**0.0417**
4^{th} **Q**	-0.5025***	-0.3442***	-0.4181***		-0.6593***	**-0.4810**
5^{th} **Q**	0.1567*	0.3151***	0.2411***	0.6593***		**0.3431**

Table 24: Difference between Sharpe ratios for the Minimum Variance portfolio across the 5 quintiles.

Quintiles	1^{st} **Q**	2^{nd} **Q**	3^{rd} **Q**	4^{th} **Q**	5^{th} **Q**	**Mean**
1^{st} **Q**		0.1081*	0.0877	0.4918***	-0.1250*	**0.1406**
2^{nd} **Q**	-0.1081*		-0.0204	0.3837***	-0.2331***	**0.0055**
3^{rd} **Q**	-0.0877	0.0204		0.4041***	-0.2127***	**0.0310**
4^{th} **Q**	-0.4918***	-0.3837***	-0.4041***		-0.6168***	**-0.4741**
5^{th} **Q**	0.1250*	0.2331***	0.2127***	0.6168***		**0.2969**

Table 25: Difference between Sharpe ratios for the Minimum Variance $l1 - l\infty$ Constraint portfolio across the 5 quintiles.

Quintiles	1^{st} **Q**	2^{nd} **Q**	3^{rd} **Q**	4^{th} **Q**	5^{th} **Q**	**Mean**
1^{st} **Q**		0.4116***	0.3074***	0.5391***	0.3059**	**0.3910**
2^{nd} **Q**	-0.4116***		-0.1042	0.1275	-0.1057	**-0.1235**
3^{rd} **Q**	-0.3074***	0.1042		0.2317*	-0.0015	**0.0068**
4^{th} **Q**	-0.5391***	-0.1275	-0.2317*		-0.2332*	**-0.2829**
5^{th} **Q**	-0.3059**	0.1057	0.0015	0.2332*		**0.0086**

Table 26: Difference between Sharpe ratios for the Mean Variance Skewness Kurtosis portfolio across the 5 quintiles.

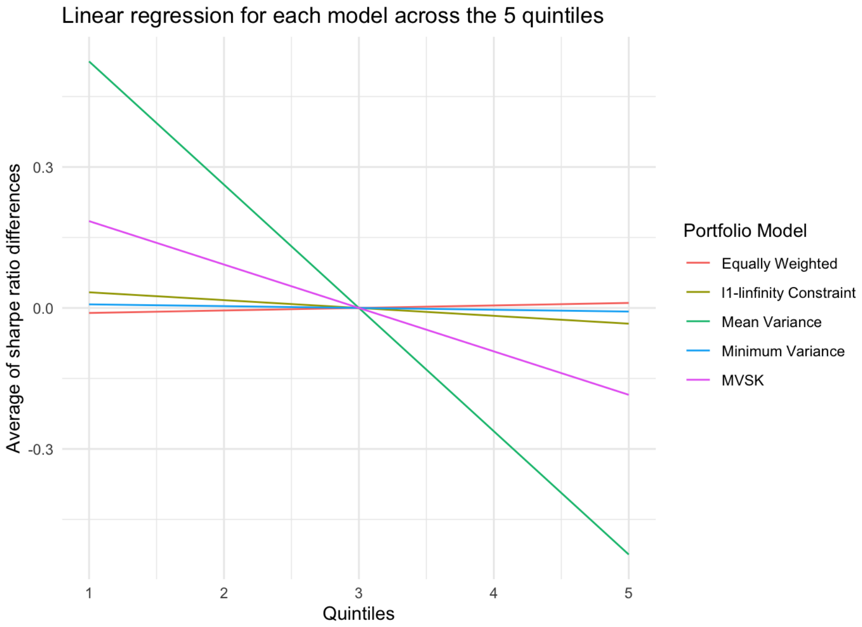

Figure 5: Mean of the differences in Sharpe ratios for each portfolio model through the 5 quintiles

8.5 Appendix 5: Monthly Portfolio Results

8.5.1 In-Sample Results

8.5.1.1 Calmar Ratios

Models	1^{st} **Q**	2^{nd} **Q**	3^{rd} **Q**	4^{th} **Q**	5^{th} **Q**
Equally Weighted	0.0168	0.0092	0.0147	0.0030	0.0096
Mean Variance	0.0994	0.0675	0.0554	0.0487	0.0941
Minimum Variance	0.0502	0.0127	0.0252	-0.0018	0.0451
M.V. l1 - l_∞ Constraint	0.0478	0.0155	0.0243	-0.0015	0.0408
MVSK	0.0239	-0.0010	0.0038	-0.0049	0.0028

Table 27: Calmar ratios of the 5 portfolio models in each of the 5 quintiles

8.5.1.2 Sharpe Ratios

Models	1^{st} **Q**	2^{nd} **Q**	3^{rd} **Q**	4^{th} **Q**	5^{th} **Q**
Equally Weighted	0.0310	0.0259	0.0792	0.0186	0.0544
Mean Variance	0.4687	0.2672	0.1863	0.2502	0.3053
Minimum Variance	0.1225	0.0807	0.1007	-0.0134	0.1633
M.V. l1 - l_∞ Constraint	0.1218	0.0934	0.0991	-0.0111	0.1545
MVSK	0.1021	-0.0075	0.0214	-0.0434	0.0217

Table 28: Sharpe ratios of the 5 portfolio models in each of the 5 quintiles

8.5.1.3 Differences in Sharpe ratio values

Quintiles	1^{st} **Q**	2^{nd} **Q**	3^{rd} **Q**	4^{th} **Q**	5^{th} **Q**	**Mean**
1^{st} **Q**		0.0050	-0.0483	0.0124	-0.0235	**-0.0136**
2^{nd} **Q**	-0.0050		-0.0533*	0.0074	-0.0285	**-0.0199**
3^{rd} **Q**	0.0483	0.0533*		0.0606*	0.0248	**0.0468**
4^{th} **Q**	-0.0124	-0.0074	-0.0606*		-0.0359	**-0.0291**
5^{th} **Q**	0.0235	0.0285	-0.0248	0.0359		**0.0158**

Table 29: Difference between Sharpe ratios for an Equally Weighted portfolio across the 5 quintiles.

Quintiles	1^{st} **Q**	2^{nd} **Q**	3^{rd} **Q**	4^{th} **Q**	5^{th} **Q**	**Mean**
1^{st} **Q**		0.2016*	0.2824***	0.2185*	0.1634	**0.2165**
2^{nd} **Q**	-0.2016*		0.0809	0.0170	-0.0381	**-0.0355**
3^{rd} **Q**	-0.2824***	-0.0809		-0.0639	-0.1190	**-0.1366**
4^{th} **Q**	-0.2185*	-0.0170	0.0639		-0.0551	**-0.0567**
5^{th} **Q**	-0.1634	0.0381	0.1190	0.0551		**0.0122**

Table 30: Difference between Sharpe ratios for the Mean Variance portfolio across the 5 quintiles.

Quintiles	1^{st} **Q**	2^{nd} **Q**	3^{rd} **Q**	4^{th} **Q**	5^{th} **Q**	**Mean**
1^{st} **Q**		0.0418	0.0218	0.1359*	-0.0408	**0.0397**
2^{nd} **Q**	-0.0418		-0.0199	0.0941	-0.0826	**-0.0126**
3^{rd} **Q**	-0.0218	0.0199		0.1141	-0.0626	**0.0124**
4^{th} **Q**	-0.1359*	-0.0941	-0.1141		-0.1767**	**-0.1302**
5^{th} **Q**	0.0408	0.0826	0.0626	0.1767**		**0.0907**

Table 31: Difference between Sharpe ratios for the Minimum Variance portfolio across the 5 quintiles.

Quintiles	1^{st} **Q**	2^{nd} **Q**	3^{rd} **Q**	4^{th} **Q**	5^{th} **Q**	**Mean**
1^{st} **Q**		0.0284	0.0227	0.1329*	-0.0326	**0.0379**
2^{nd} **Q**	-0.0284		-0.0057	0.1045	-0.0610	**0.0024**
3^{rd} **Q**	-0.0227	0.0057		0.1102	-0.0554	**0.0095**
4^{th} **Q**	-0.1329*	-0.1045	-0.1102		-0.1656**	**-0.1283**
5^{th} **Q**	0.0326	0.0610	0.0554	0.1656**		**0.0787**

Table 32: Difference between Sharpe ratios for the Minimum Variance $l1 - l\infty$ Constraint portfolio across the 5 quintiles.

Quintiles	1^{st} **Q**	2^{nd} **Q**	3^{rd} **Q**	4^{th} **Q**	5^{th} **Q**	**Mean**
1^{st} **Q**		0.1096	0.0807	0.1456	0.0804	**0.1041**
2^{nd} **Q**	-0.1096		-0.0289	0.0360	-0.0292	**-0.0329**
3^{rd} **Q**	-0.0807	0.0289		0.0648	-0.0004	**0.0032**
4^{th} **Q**	-0.1456	-0.0360	-0.0648		-0.0652	**-0.0779**
5^{th} **Q**	-0.0804	0.0292	0.0004	0.0652		**0.0036**

Table 33: Difference between Sharpe ratios for the Mean Variance Skewness Kurtosis portfolio across the 5 quintiles.

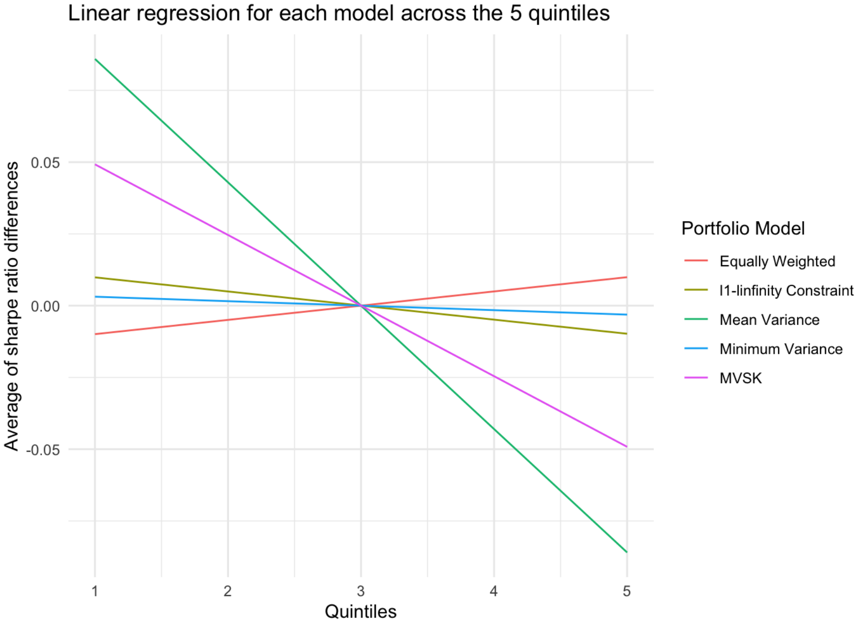

Figure 6: Mean of the differences in Sharpe ratios for each portfolio model through the 5 quintiles

8.5.2 Out-of-Sample Results

8.5.2.1 Calmar Ratios

Models	1^{st} **Q**	2^{nd} **Q**	3^{rd} **Q**	4^{th} **Q**	5^{th} **Q**
Equally Weighted	0.0168	0.0092	0.0147	0.0030	0.0096
Mean Variance	0.0757	0.1322	0.0266	0.0278	0.0337
Minimum Variance	0.0425	0.0313	0.0260	-0.0056	0.0573
M.V. l1 - l_∞ Constraint	0.0242	0.0112	0.0154	-0.0018	0.0080
MVSK	0.0552	0.0149	0.0062	0.0063	0.0233

Table 34: Calmar ratios of the 5 portfolio models in each of the 5 quintiles

8.5.2.2 Sharpe Ratios

Models	1^{st} **Q**	2^{nd} **Q**	3^{rd} **Q**	4^{th} **Q**	5^{th} **Q**
Equally Weighted	0.0310	0.0259	0.0792	0.0186	0.0544
Mean Variance	0.1363	0.1251	0.1555	-0.0422	-0.1037
Minimum Variance	0.2029	-0.0814	0.0938	0.0114	0.0072
M.V. l1 - l_∞ Constraint	0.0830	0.1098	0.1292	-0.0118	0.0643
MVSK	0.2915	0.1358	0.1047	0.0325	0.0330

Table 35: Sharpe ratios of the 5 portfolio models in each of the 5 quintiles

8.5.2.3 Differences in Sharpe ratio values

Quintiles	1^{st} **Q**	2^{nd} **Q**	3^{rd} **Q**	4^{th} **Q**	5^{th} **Q**	**Mean**
1^{st} **Q**		0.0050	-0.0483	0.0124	-0.0235	**-0.0136**
2^{nd} **Q**	-0.0050		-0.0533	0.0074	-0.0285	**-0.0199**
3^{rd} **Q**	0.0483	0.0533		0.0606	0.0248	**0.0468**
4^{th} **Q**	-0.0124	-0.0074	-0.0606		-0.0359	**-0.0291**
5^{th} **Q**	0.0235	0.0285	-0.0248	0.0359		**0.0158**

Table 36: Difference between Sharpe ratios for the Equally Weighted portfolio across the 5 quintiles.

Quintiles	1^{st} **Q**	2^{nd} **Q**	3^{rd} **Q**	4^{th} **Q**	5^{th} **Q**	**Mean**
1^{st} **Q**		0.0113	-0.0192	0.1786	0.2400	**0.1027**
2^{nd} **Q**	-0.0113		-0.0304	0.1673	0.2287	**0.0886**
3^{rd} **Q**	0.0192	0.0304		0.1977	0.2592*	**0.1266**
4^{th} **Q**	-0.1786	-0.1673	-0.1977		0.0615	**-0.1205**
5^{th} **Q**	-0.2400	-0.2287	-0.2592*	-0.0615		**-0.1974**

Table 37: Difference between Sharpe ratios for the Mean Variance portfolio across the 5 quintiles.

Quintiles	1^{st} **Q**	2^{nd} **Q**	3^{rd} **Q**	4^{th} **Q**	5^{th} **Q**	**Mean**
1^{st} **Q**		0.2843*	0.1092	0.1915	0.1957	**0.1952**
2^{nd} **Q**	-0.2843*		-0.1751	-0.0928	-0.0886	**-0.1602**
3^{rd} **Q**	-0.1092	0.1751		0.0824	0.0865	**0.0587**
4^{th} **Q**	-0.1915	-0.0928	-0.0824		0.0042	**-0.0906**
5^{th} **Q**	-0.1957	-0.0886	-0.0865	-0.0042		**-0.0938**

Table 38: Difference between Sharpe ratios for the Minimum Variance portfolio across the 5 quintiles.

Quintiles	1^{st} **Q**	2^{nd} **Q**	3^{rd} **Q**	4^{th} **Q**	5^{th} **Q**	**Mean**
1^{st} **Q**		-0.0268	-0.0462	0.0948*	0.0187	**0.0101**
2^{nd} **Q**	0.0268		-0.0195	0.1215***	0.0455	**0.0436**
3^{rd} **Q**	0.0462	0.0195		0.1410**	0.0649	**0.0679**
4^{th} **Q**	-0.0948*	-0.1215***	-0.1410**		-0.0761	**-0.1084**
5^{th} **Q**	-0.0187	-0.0455	-0.0649	0.0761		**-0.0133**

Table 39: Difference between Sharpe ratios for the Minimum Variance $l1 - l\infty$ Constraint portfolio across the 5 quintiles.

Quintiles	1^{st} **Q**	2^{nd} **Q**	3^{rd} **Q**	4^{th} **Q**	5^{th} **Q**	**Mean**
1^{st} **Q**		0.1557	0.1868	0.2590***	0.2585*	**0.2150**
2^{nd} **Q**	-0.1557		0.0310	0.1032	0.1027	**0.0203**
3^{rd} **Q**	-0.1868	-0.0310		0.0722	0.0717	**-0.0185**
4^{th} **Q**	-0.2590***	-0.1032	-0.0722		-0.0005	**-0.1087**
5^{th} **Q**	-0.2585*	-0.1027	-0.0717	0.0005		**-0.1081**

Table 40: Difference between Sharpe ratios for the Mean Variance Skewness Kurtosis portfolio across the 5 quintiles.

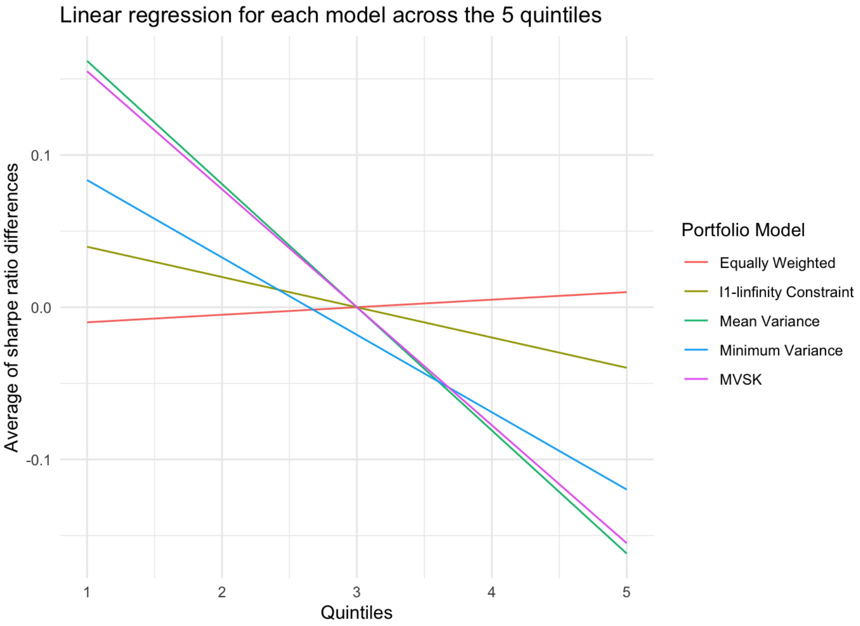

Figure 7: Mean of the differences in Sharpe ratios for each portfolio model through the 5 quintiles

8.6 Appendix 6: Template Code for Portfolio Models

```
##First Quintile of Carbon Footprint: Mean Variance Portfolio##
#Out of Sample#
#Define the function to compute weights
Mean_Var_Function <- function(returns) {
  Mean_Var_Returns <- colMeans(returns)
  Cov_Mean_Var_Matrix <- cov(returns)
  num_assets <- ncol(returns)
  Inv_Cov_Matrix <- solve(Cov_Mean_Var_Matrix)
  ones <- rep(1, num_assets)
  Weights_Mean_Var = as.numeric(solve(ones%*%Inv_Cov_Matrix%*%Mean_
     Var_Returns))*(Inv_Cov_Matrix %*% Mean_Var_Returns)
  return(as.vector(Weights_Mean_Var))
}

#Define rolling window parameters
Window_Size <- 30
```

```
Step_Size <- 10

#Lists to store results
Weights_Mean_Var_OOS_10 <- list()
Return_Mean_Var_OOS_10 <- c()
Sharpe_Ratios_Test_Mean_Var_OOS_10 <- numeric()

#Rolling window computation
for (start_index in seq(1, nrow(Return_Quintile_1) - Window_Size, by = Step_Size)) {
  end_index <- start_index + Window_Size - 1
  in_sample_data <- Return_Quintile_1[start_index:end_index,]

  #Compute in-sample weights
  weights <- Mean_Var_Function(in_sample_data)
  Weights_Mean_Var_OOS_10[[length(Weights_Mean_Var_OOS_10) + 1]] <- weights

  #Apply weights to the next out-of-sample period
  if (end_index + Step_Size <= nrow(Return_Quintile_1)) {
    out_of_sample_data <- Return_Quintile_1[(end_index + 1):(end_index + Step_Size),]
    out_of_sample_data <- as.matrix(out_of_sample_data)
    weights <- as.numeric(weights)
    portfolio_return <- out_of_sample_data * weights
    portfolio_return_sum <- rowSums(portfolio_return)
    mean_portfolio_return <- mean(portfolio_return_sum)
    portfolio_standard_dev <- sd(portfolio_return_sum)
    Return_Mean_Var_OOS_10 <- c(Return_Mean_Var_OOS_10, portfolio_return)

    #Sharpe ratios
```

```
    sharpe <- sharpe_ratio_monthly_function(mean_portfolio_return, portfolio_standard_dev)
    Sharpe_Ratios_Test_Mean_Var_OOS_10 <- c(Sharpe_Ratios_Test_Mean_Var_OOS_10, sharpe)
  }
}

#Compute mean and standard deviation of sharpe ratios
Mean_Sharpe_Ratio_Mean_Var_10 <- mean(Sharpe_Ratios_Test_Mean_Var_OOS_10)
SD_Sharpe_Ratio_Mean_Var_10 <- sd(Sharpe_Ratios_Test_Mean_Var_OOS_10)
Mean_Sharpe_Ratio_Mean_Var_10
SD_Sharpe_Ratio_Mean_Var_10
Return_Sharpe_Mean_Var_10 <- row_means(matrix(Return_Mean_Var_OOS_10, nrow = 90, ncol = 10, byrow = TRUE))
Mean_Annual_Sharpe_Ratio_Mean_Var_10 <- Mean_Sharpe_Ratio_Mean_Var_10 * sqrt(12)
SD_Annual_Sharpe_Ratio_Mean_Var_10 <- SD_Sharpe_Ratio_Mean_Var_10 * sqrt(12)
Mean_Annual_Sharpe_Ratio_Mean_Var_10
SD_Annual_Sharpe_Ratio_Mean_Var_10

#Find the best weights
Sharpe_Ratios_Test_Mean_Var_OOS_10
Best_Mean_Var_10 <- 3
Best_Weights_Mean_Var_10 <- Weights_Mean_Var_OOS_10[[Best_Mean_Var_10]]
Best_Weights_Mean_Var_10 = matrix(rep(Best_Weights_Mean_Var_10,120), nrow = 120, ncol = 10, byrow = TRUE)

#Compute returns
```

```r
Best_Return_Mean_Var_10 <- rowSums(Best_Weights_Mean_Var_10 * Return_Quintile_1)

#Performance
#Not annualized
Mean_Return_Mean_Var_OOS_10 <- mean(Best_Return_Mean_Var_10)
SD_Return_Mean_Var_OOS_10 <- sd(Best_Return_Mean_Var_10)
Sharpe_Ratio_Mean_Var_OOS_10 <- sharpe_ratio_monthly_function(Mean_Return_Mean_Var_OOS_10,SD_Return_Mean_Var_OOS_10)
Max_Drawdowns_Mean_Var_OOS_10 <- maxDrawdown(Best_Return_Mean_Var_10)
Calmar_Ratio_Mean_Var_OOS_10 <- calmar_ratio_monthly_function(Mean_Return_Mean_Var_OOS_10, Max_Drawdowns_Mean_Var_OOS_10)
Mean_Return_Mean_Var_OOS_10
SD_Return_Mean_Var_OOS_10
Sharpe_Ratio_Mean_Var_OOS_10
Max_Drawdowns_Mean_Var_OOS_10
Calmar_Ratio_Mean_Var_OOS_10

#Annualized
Mean_Annual_Return_Mean_Var_OOS_10 <- (1+Mean_Return_Mean_Var_OOS_10)^12 - 1
SD_Annual_Return_Mean_Var_OOS_10 <- sd(Best_Return_Mean_Var_10)*sqrt(12)
Sharpe_Ratio_Annual_Mean_Var_OOS_10 <- sharpe_ratio_annual_function(Mean_Annual_Return_Mean_Var_OOS_10, SD_Annual_Return_Mean_Var_OOS_10)
Max_Drawdowns_Annual_Mean_Var_OOS_10 <- maxDrawdown(Best_Return_Mean_Var_10)
Calmar_Ratio_Annual_Mean_Var_OOS_10 <- calmar_ratio_annual_function(Mean_Annual_Return_Mean_Var_OOS_10, Max_Drawdowns_Annual_Mean_Var_OOS_10)
```

```
Mean_Annual_Return_Mean_Var_OOS_10
SD_Annual_Return_Mean_Var_OOS_10
Sharpe_Ratio_Annual_Mean_Var_OOS_10
Max_Drawdowns_Annual_Mean_Var_OOS_10
Calmar_Ratio_Annual_Mean_Var_OOS_10

#WACI for December 2023
WACI_Mean_Var_OOS_10 <- sum(Best_Weights_Mean_Var_10[120,] * Carbon_
   Quintile_1[120,])

WACI_Mean_Var_OOS_10
```

Listing 1: Portfolio models R code template

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