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Green Portfolio

Optimization under environmental constraints

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Abstract

The aim of this thesis is to compare traditionally optimized equity portfolios to an alternative which takes the economic effects of environmental damage in to consideration. The comparison between the portfolios are made by their composition, in terms of economic sectors, and their characteristics, such as performance, size and risk. As climate considerations have increasingly become a given theme in public agenda, the interest in investing sustainably has increased. This thesis studies 199 S&P 500 constituents over a nine-year period, using conventional portfolio theory along with a method that utilizes an environmental damage function – a Green Portfolio. The latter enables investors to grasp the environmental and subsequent economic impact of their capital allocation. The results of this study have displayed varied alignment to those of previous research.

Keywords: Portfolio Selection, Sustainable Investing, Equity Portfolios, Emissions Intensity, Mean-Variance Optimization.

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1. Introduction

1.1 Background

Portfolio composition, diversification and optimization have been influential in the progress of financial markets. A major breakthrough came in 1952 when Harry Markowitz published his theory of portfolio selection (Markowitz, 1952). Using statistical measures such as expected return and standard deviation, Markowitz introduces the concept that investors should view return and risk as a coexisting relationship. The allocation of funds among investment possibilities should therefore be based on the theory of their return-risk trade-off. This discovery was important with respect to portfolio diversification. Which, instead of evaluating assets individually, the correlation between the assets becomes crucial. Additionally, Markowitz (1952) formulated the Mean-Variance-Optimization (MVO) problem, according to which investors should favor the portfolios with the lowest variance, assuming they have the same expected return. The allocation of funds among investment possibilities should, therefore, according to Markowitz, be based on the theory of the return-risk trade-off (Kolm et al. 2014).

However, much has changed since Markowitz theories were published. The promotion of countermeasures against climate change have become vital to the political agenda and consequently influenced the global, economic climate. In disregard to how investors choose to handle this transition towards a low carbon economy, the conversion will surely have an impact on the financial markets as we know them.

An example of this is the agreements reached at the Paris climate accord to keep the increase in global average temperature below 2˚ Celsius (The European Commission, 2015). With this in mind, it seems inevitable that governments will intervene even further to reduce emissions. Policies to reduce emissions may result in increasing prices on carbon, taxes based on emissions, caps and other trade mechanics which would affect investors' portfolios. It should be in an investor's interest to adjust their portfolio accordingly to new directives from policy makers. Either because of their general concern of their portfolios carbon footprint, or in fear that it may jeopardize their expected return or increase the level of risk in their portfolios.

According to a report from Morgan Stanley's department *Institute for Sustainable Investing* (2019), investors are divided as to whether or not sustainable investing brings a financial trade-off. However, a majority of the 1000 individual investors included in the survey were interested in further information about the outcome of sustainable investing (Morgan Stanley, 2019). Companies are experiencing pressure from governments and society to perform business in a sustainable way, report their emissions and educate investors in sustainable investing. However, much is left to the investor in order to define how environmentally friendly their investment really is. Hence, this paper examines how investors' portfolios adjust with consideration to their emissions.

1.2. Purpose

With climate change becoming an increasingly recurring subject in the public discourse, it has also come to influence other areas, such as investing. Historically, there has been a significant ambiguity in the discussion of sustainable investing with the general sentiment suggesting a trade-off between good performance and sustainable allocation of resources. More recently, studies have been made questioning the previously mentioned relationship. However, the results of these studies have been varying. The purpose of this bachelor's thesis is to research the differences between conventionally optimized equity portfolios, namely Minimum Variance and Maximum Sharpe Ratio and the Green Portfolio, a concept which takes the economic consequences of environmental damage in to consideration.

1.3 Disposition

This study is divided into seven parts, with the following structure. The first chapter consists of a brief introduction of modern portfolio theory, climate change, sustainability, in addition to the purpose of the study. The second chapter reviews previous research with focus on the relationship between climate change and economic loss, along with studies which analyze how sustainability influences portfolio selection. The problem and the hypotheses are described in the third section. Chapter four explains the theory associated with modern portfolio theory, such as calculations of expected return, measuring risk, optimizing equity portfolios, also a method of estimating economic loss caused by assets emissions. The fifth section clarifies the data selection and methodology of testing the hypothesis. Chapter six provides a general summary and a discussion of the results. The final section of this thesis concludes the important discoveries of the report, along with suggestions for future research.

2. Previous Research

2.1. Climate Change and Economic Loss

Previous studies primarily focus on how carbon emissions affect the climate. There are few studies about suitable methods of measuring the impact of carbon emissions on the economy. However, a pioneer in the field of measuring the impact of carbon emissions of the economy is William D. Nordhaus who, in 2018, was awarded the Nobel Prize in Economic Sciences for "integrating climate change into long-run macroeconomic analysis" (Barrage, 2019). Nordhaus proposed that climate change works as a constraint on long run growth (Nordhaus, 1974).

A modern study by Dell et al. (2012) provides information which suggests that there is, most certainly, a connection. Areas such as economic productivity, effects on health, and physical performance are all vulnerable to climate change. However, it should be noted that Dell's study only illustrates a negative relationship between rising temperatures and economic loss in poor countries. The relationship between carbon emissions and the economy in developed nations should be viewed with greater caution (Dell et al. 2012).

In 1980, Nordhaus presented the first climate-economy optimizing integrated assessment model (IAM). In the model, he includes greenhouse gas (GHG), carbon cycle, and a climate-change-damage-function into an economic growth model. The purpose of the Nordhaus model is to estimate optimal climate policy, more specifically effective carbon taxes (Nordhaus, 1980). Continuous studies by Nordhaus create a more sophisticated version: the *Dynamic Integrated Climate-Economy* model, more commonly referred to as DICE. This model was ground-breaking, since it was able to measure the output lost due to climate change (Nordhaus, 1993).

2.2. Measuring Economic Damages

Another study by Golosov et al. (2014) also investigates optimal taxes on fossil fuels, where they endeavour to modify the Nordhaus damage function. The Golosov modification measures economic damages as a percent of final-good output. The process in the damage function can be split into two steps. Firstly, it tracks the carbon concentration to climate changes, followed by climate changes to economic damages, measured as output lost. This can best be explained with the following model:

$$1 - D_t(S_t) = e^{-\psi(S_t - \bar{S})} \qquad (1)$$

This model measures the amount of carbon in the atmosphere at a specific time (S_t), and ($\bar{S}$) represents the pre-industrial era's amount. These two components provide incomprehensible numbers and in order to make them manageable, the parameter ψ works as a scale tool. Since Golosov et al. works with billions of tons of CO2, they learn that setting the scaling tool (ψ) as in Equation 2 below made a good fit for the data

$$\psi = 5.3 * 10^{-5} \qquad (2)$$

(Golosov et al. 2014).

Furthermore, another report came to the same conclusion when converting the emissions to damages, and therefore set a similar value (Hassler et al. 2016). The important discovery in these papers, which is of relevance to this thesis, was the scalar tool and the improvements the scalar tool offers to the measuring of economic damages caused by carbon emissions. With this in mind, it would be interesting to investigate how an environmental aspect would adjust an investor's portfolio selection.

Utz et al. (2013) set a framework for inverse portfolio optimization in a Markowitz model which includes an additional criterion: risk tolerance regarding ESG-score. Inverse portfolio optimization, more specifically, optimizes when the weights are known and the parameters unknown. In the study Utz et al. compares the implied risk tolerance between several conventional and socially responsible (SR) mutual funds. Surprisingly, there was no significant difference between the two classes of mutual funds. Comparing indicators such as expected return, volatility and ESG-score they only found a slight difference regarding the volatility. For which the SR-funds displayed a marginal lower result. The report includes two intriguing results; socially responsible investors were not exposed to higher levels of risk in relative to conventional investors, and that SR-funds did not invest more sustainably than their conventional counterparts (Utz et al. 2013).

On the other hand, a study by Jónsdóttir et al. (2017) examines the possibility of reducing the carbon footprint of equity portfolios while minimizing the tracking error. Their results indicate a possibility to decarbonize portfolios up to 25%, without an increase in risk or a lower expected return.

3. Problem and Hypotheses

3.1 Problem

Previous research on the subject of portfolio optimization with focus on sustainability have focused on different areas and internally reached varying results and conclusions. Also, the general sentiments towards investing and the effect of environmental considerations have been placed on a broad spectrum where misconceptions and possibly obsolete notions are prevalent. An example of the formerly mentioned misconception is that environmental considerations are considered a compromise or goodwill for the ambitious investor.

Therefore, it could be of interest to construct two portfolios of assets through conventional portfolio optimization along with a Green Portfolio, a concept which is based upon the considerations of economic loss caused by environmental damage. Analyzing these portfolios through composition and characteristics could possibly yield interesting results and address general sentiment along with possible misconceptions.

3.2 Hypotheses

The hypotheses are based on the general sentiments of how the three different equity portfolios will look in terms of two main areas: composition and characteristics.

3.2.1. Composition of three equity portfolios.

The composition of the three portfolios was primarily studied by the economic sectors that the companies within the portfolios belonged to. The performance, in terms of returns, along with the emissions of each portfolio was researched and the latter ranked. The definition of the sectors, performance and emissions will be elaborated upon in the Theory section of this study.

H#	Hypotheses of Portfolio Composition
1.	The portfolio weight of the sectors with greater emissions, relative the other sectors; will be lower in the Green Portfolio than in the other two.
2.	The number of companies in the sectors with greater emissions, relative the other sectors; will be lower in the Green Portfolio than in the other two.
3.	If the portfolio weights of a sector is lower in the Green Portfolio than the other two, the number of companies in that sector will also be lower in the Green Portfolio relative to the other two.
4.	The similarity of the top ten companies in each portfolio, in terms of portfolio weight, will be negligible between the Green Portfolio and the other two equity portfolios.
5.	The composition, in terms of portfolio sector weights, in the top ten will be very similar to that of the entire portfolio for the individual portfolio.
6.	The Green Portfolio would have the highest amount of portfolio weight in the top ten.

Table 1: Hypotheses of Portfolio Composition

In Table 1, the authors' hypotheses of how the Green Portfolio would differ from the other equity portfolios in terms of composition are presented. The construction of the Green Portfolio, which will be elaborated upon in detail in a later section in this study, is a process which takes the emissions of a company in to consideration. This was the basis for the first two hypotheses in Table 1. The third was based on the same rationale, which was an expectation of consistency between the number of companies and weight of companies.

The fourth hypothesis was based on a rationale that the outlook of viable options for the portfolios would be fundamentally different due to environmental considerations. The fifth hypothesis was based on an in hindsight possibly arbitrary notion that the size of the sample would lead to an even distribution of companies. The sixth hypothesis stemmed for a rationale similar to that of the fourth, that the Green Portfolio, for reasons to be explained later in this study, would have less viable options and thus a greater degree of concentration in the portfolio.

3.2.2 Characteristics of the three equity portfolios

H#	Characteristic	Hypothesis
1.	**Expected Returns**	Max. Sharpe – Min. Variance - Green
2.	**Variance and Standard Deviation**	Max. Sharpe – Green – Min. Variance
3.	**Sharpe Ratio**	Max. Sharpe – Min. Variance - Green
4.	**Market Capitalization**	Min. Variance – Max. Sharpe – Green
5.	**Emissions Intensity**	Min. Variance – Max. Sharpe – Green

Table 2: The Hypotheses of Portfolio Characteristics

Table 2 above outlines the several characteristics which this thesis has studied for the three different equity portfolios and the hypotheses how the characteristics of each portfolio would be relative the others. The presentation of the hypotheses are in decreasing order, i.e. from largest to smallest.

In terms of expected returns, the hypothesis was that the Green Portfolio would have the lowest value as a consequence of the considerations to environmental damage, which was expected to lower the number of viable alternatives. The hypothesis for the expected returns can be found in Table 2.

Given the method by which the Green Portfolio is constructed, the authors' hypothesis for the risk in terms of standard deviation and variance for the portfolio was that the Green Portfolio would be in the middle of the other portfolios (as seen in Table 2) due to less viable alternatives on the expected returns side.

In light of the two hypotheses described above, the expectations for the Sharpe Ratio of the three equity portfolios was that the Green Portfolio would have the lowest. The order in its entirety would be as presented in Table 2.

When considering the expectations for the Geometric Average Market Cap, which is a measure of the size of companies in which the portfolios invests, the authors believed that the Green Portfolio would have the lowest and the complete order would be as in Table 1. Further explanations of the Geometric Average Market Cap will follow in the Theory section of this thesis.

Not unexpectedly, the authors' expected the Green Portfolio to have the lowest Weighted Average Emissions Intensity, which is also displayed in Table 2.

4. Theory

In order to test the hypotheses regarding the portfolios' composition and performance mentioned in the previous section, several theories and concepts need to be clarified. Therefore, the theory required to optimize the three equity portfolios is presented. The section also includes a general explanation about emissions, suitable metrics for emissions, important market concepts and a method for measuring economic damages caused by a company's emissions.

4.1 Returns, Expected Returns & Expected Excess Returns

The percentage return of an asset between the points of time *t-1* and *t* is calculated with the following equation

$$r_{i,t} = \frac{P_{i,t} - P_{i,t-1}}{P_{i,t-1}} \tag{3}$$

Where $r_{i,t}$ is the return of the asset, and $P_{i,t}$ *and* $P_{i,t-1}$ are the prices of an asset *i* at the points of time *t-1* and *t* respectively.

When calculating the expected return of an asset with historical data, the probabilities of occurrences are treated as equal. Therefore, the expected return of an asset is estimated as the arithmetic mean of the rates of return in the given sample (Bodie et al. 2013) as per the following equation

$$\mu_i = \frac{1}{T} \sum_{i=1}^{T} r_{i,t} \tag{4}$$

Where μ_i is the expected return of asset *i*, T is the number of observations and r is the observed return. When investing in assets, in this case stocks, an investor can expect to be compensated for possible exposure towards risk with a fitting return. Therefore, it may be deemed appropriate to consider an expected excess return R_i which is calculated as

$$R_i = (\mu_i - r_f) \tag{5}$$

The Excess Return is also known as the real return and describes the rate of return which is in excess of a risk-free alternative with the interest rate (r_f). Thus, the excess return is the return on an investment in comparison with a risk-free alternative. Commonly used risk-free alternatives are United States Treasury bills (known as T-bills), certain government bonds, money market funds, or a regular bank placement (Bodie et al. 2013).

4.1.2 Expected Returns and Expected Excess Returns for Portfolios

This thesis has utilized matrices and vectors to calculate the characteristics of the included equity portfolios. The expected returns for an equity portfolio (μ_p) is calculated as below

$$\mu_p = X^T \mu \qquad (6)$$

And the expected excess returns R_p as

$$R_p = X^T R \qquad (7)$$

Where X is a portfolio composition vector with the elements being the individual weights of portfolio companies ($X = X_1, \ldots, X_n$) that sum to one. μ is a vector of individual equity expected returns and R is a vector of individual Expected Excess returns. The reason for the vector X being raised by T implies that it is transposed (Utz et al. 2013).

4.2. Risk Measures

This thesis has utilized variance and standard deviation as risk measurement in terms of volatility. The function is common to measure financial risk, by using the historical deviation of investments from their mean. The risk method follows the normal distribution which simplifies the adoption phase of the model as a risk measure.

4.2.1 Variance and Standard Deviation for an asset

When considering risk, the likelihood of deviations from the expected return are of interest. The variance is estimated by calculating the average of squared deviations from the arithmetic mean, which is the expected return. The equation for the variance of an asset is as follows

$$\sigma_i^2 = \frac{1}{T} \sum_{i=1}^{T} (r_{i,t} - \mu_i)^2 \qquad (8)$$

The standard deviation (σ_i) is the square root of the variance, therefore the equation is as follows

$$\sigma_i = \sqrt{\frac{1}{T}\sum_{i=1}^{T}(r_{i,t} - \mu_i)^2} \qquad (9)$$

(Bodie et al. 2013).

4.2.2 Variance and Standard Deviation for a Portfolio

To calculate the variance and standard deviation of a portfolio, this essay has utilized matrix and vector multiplication. The equation for portfolio variance σ_p^2 is as follows

$$\sigma_p^2 = X^T \Omega X \qquad (10)$$

Where Ω represents a covariance matrix, with the dimensions nxn. And the standard deviation is as for the individual asset, the square root of the variance as in Equation 11 below

$$\sigma_p = \sqrt{X^T \Omega X} \qquad (11)$$

The X^T represents a transposed version of the composition weight vector, as presented earlier (Utz et al. 2013).

4.3 Sharpe Ratio

Named after William Sharpe, who conceived the ratio in 1966, the Sharpe ratio can also be called or interpreted as the reward-to-variability ratio. The ratio equals the excess return, which is the expected return deducted by the risk-free interest rate, divided by the standard deviation. The ratio aims at measuring the reward of an asset per unit of risk. Therefore, a high Sharpe ratio implies a greater reward given risk, whilst a low Sharpe ratio implies a lower reward given the risk. The asset allocation decision requires the consideration of a risk-free asset. The reason being that the Sharpe ratio which is to be maximized, is as previously defined, the returns in *excess of the risk free rate* divided by the standard deviation (Bodie et al. 2013).

4.3.1 Sharpe Ratio of an asset & portfolio

The Sharpe ratio of an asset if calculated with the below Equation 12, consistent with the above description.

$$S_i = \frac{(\mu_i - r_f)}{\sigma_i} \tag{12}$$

When using matrix multiplication for the other parts of the portfolio optimization, we will also use it to calculate the Sharpe ratio of the portfolio as below

$$S_p = \frac{R_p}{\sigma_p} \tag{13}$$

Where, as earlier presented in Equation 6, $R_p$is the expected excess return of the portfolio and σ_p is the portfolio standard deviation (Bodie et al. 2013).

4.4 Market Capitalization

Market capitalization (MC) or market cap refers to the value of a company in terms of the total value of its issued shares. It is calculated by multiplying the share price with the total number of outstanding shares:

$$Market\ Cap = Share\ Price * Total\ number\ of\ outstanding\ shares \tag{14}$$

Therefore, the market cap measures the value of a company on an open market because it reflects what investors are willing to pay for a stock (Fidelity, 2017).

4.4.1 Market Capitalization of an Equity Portfolio

The average market capitalization of an equity portfolio provides a measure of the size of the companies in which the portfolio invests. Morningstar calculates this figure as the geometric mean of the market capitalizations (GAC). This geometric average is calculated by raising the market capitalization of each stock to a power equal to that stock's weight in the equity portfolio (x_i), as below

$$GAC_p = MC_1^{x_1} * \ MC_2^{x_2}, * \dots . * MC_n^{x_n} \tag{15}$$

Where MC and x are the market capitalizations and portfolio weights respectively. A different strategy is to calculate the median market capitalization of a portfolio. The benefit of the Geometric Average Market Capitalization (GAC) is that it better identifies the "center of gravity” of the portfolio. It provides a more accurate insight into how market trends, in terms of capitalization, might affect the portfolio (Morningstar, 2020).

4.5 GICS Sectors

In order to classify securities in a transparent way, they are categorized in accordance with the Global Industry Classification Standard, usually referred to as GICS. This standardized method is common, and accepted worldwide (MSCI, 2016).

4.6 Environmental

4.6.1 Emissions

Emissions are reported as greenhouse gas (GHG) of metric tons per year. GHG per definition are those gases which contribute to the trapping of heat in the atmosphere. These are Carbon Dioxide, Methane, and Nitrous Oxide. In order for companies to get an overview and manage their emissions they are split into different categories. Direct emissions come from sources directly owned by the company, while indirect emissions have their origin from activities of the company, but occur at sources owned by another firm. Furthermore, emissions are classified into three subcategories, usually referred to as scopes in purpose to avoid companies accounting for the same emissions. Scope 1 include all direct emissions, Scope 2 all indirect emissions from sources such as electricity, heating, etc. Scope 3 includes all other indirect GHG emissions (World Business Council for Sustainable Development and World Resources Institute, 2004).

4.6.2 Emissions Intensity

Total emissions in their absolute form are difficult to comprehend, thus they are commonly converted with respect to a relevant economic figure. An example is MSCI´s *Security Carbon Emission Intensity*, defined as (Emissions/Sales), if any data is missing the result will be null. These calculations generate results that are suitable for comparison between companies of different sizes (MSCI, 2018). Further development of the model results in the *Weighted Average Carbon Intensity*. The formula is as follows

$$Weighted\ Average\ Carbon\ Intensity = \sum_{i=1}^{n} x_i * \left(\frac{Issuers\ emissions_i}{Issuers\ Sales_i}\right) \qquad (16)$$

In the formula above, x_i represents the weight of company i in the portfolio. The formula captures a portfolio's total carbon intensity. Issuer´s emissions is given as tons of CO2, and includes previously mentioned Scope 1 and Scope 2, sales are given as USD in millions. This approach simplifies the process of identifying which equities contribute the most to the portfolios overall, in this case carbon, emission intensity. Additionally it's convenient for establishing the portfolios associated emissions. Moreover, the formula can be altered to compute the intensity of other emissions classes (MSCI, 2020).

4.6.3 Environmental Damage and Adjusted Excess Returns

In order to make the emissions applicable to the optimization problem, a parameter which converts the data is necessary. Such a parameter is the already mentioned scalar tool used by Hassler et al. (2016) and Golosov et al. (2014), which henceforth will be referred to as *Scion*. *Scion* has given good approximations about the economic damages caused by emissions, and should therefore be suitable for converting companies emissions. Referring to previous research, the following value is set for *Scion*, as demonstrated before in Equation 2:

$$\psi = 5.3 * 10^{-5} \qquad (2)$$

In order to illustrate the economic damages caused by an asset, an environmental adjusted excess return is required. In the formula below, m represent a company´s emission intensity, which is scaled with *Scion*. The estimations of the economic damages are acting as an additional risk-free rate. Therefore, companies with higher emission intensity will be less attractive prospects for the environmentally friendly investor. In light of the above, an environmentally adjusted expected excess return for an asset i, $\tilde{R}_i$ is introduced as in Equation 17 below

$$\tilde{R}_i = (\mu_i - r_f - \psi m_i) \qquad (17)$$

The environmentally adjusted excess returns $\tilde{R}_p$ for a portfolio is as in equation below

$$\tilde{R}_p = X^T \tilde{R} \qquad (18)$$

$\tilde{R}$, is a vector of individual environmentally adjusted excess returns, and X^T is the transposed weights. From the above adjusted excess return, a similar equation to the Sharpe ratio of a portfolio is constructed as in equation 19 below and will be known as the optimal ratio, G_p, for Green Portfolio (Fischer et al. 2020):

$$G_p = \frac{\tilde{R}_p}{\sigma_p} \quad (19)$$

4.7 Portfolio Optimization

The calculations of the equity portfolios, the foundation of which is matrix computation, are subject to short sale constraints. The implication of which is that no individual company weight within the portfolio can be negative, i.e. the portfolio may not have short positions in the shares of any company.

4.7.1 Minimum Variance Portfolio

The minimum variance portfolio (MV) is the portfolio composition of stock-weights that amounts to the lowest variance given the covariance matrix Ω. The minimum variance portfolio is the solution to the following minimization problem:

$$\text{Min } \sigma_p^2 = X^T \Omega X \qquad \text{s.t. } X^T e = 1 \quad \text{or} \quad \sum_{i=1}^{n} x_i = 1 \quad (20)$$

Where e is a vector of consisting of ones, the implication of which is that the sum of the portfolio weights must be 1, i.e. 100% (Kempf et al. 2006).

4.7.2 Maximum Sharpe Ratio

When optimizing capital allocation (Bodie et al. 2013) the objective is to work with the capital allocation line (CAL) which offers the highest slope and subsequently, the highest/maximum Sharpe ratio. The higher the Sharpe ratio, the greater the expected return corresponding to any given level of volatility. The solution to the optimization problem can therefore be formally written as:

$$\text{Max } S_p = \frac{R_p}{\sigma_p} \qquad \text{s.t . } X^T e = 1 \quad \text{or} \qquad \sum_{i=1}^{n} x_i = 1 \quad (21)$$

4.7.3 Green Portfolio

The optimal green portfolio is a portfolio created with respect to the environmental damages caused by selected assets. To construct the Green Portfolio, the environmentally adjusted Sharpe ratio is utilized. By using the previously mentioned environmental adjusted excess return in a maximization problem, the portfolio diverges from the original Sharpe portfolio. A portfolio composition is established by finding the optimal Sharpe ratio, and including emissions negative effect, more precisely the economic damages. In order to follow the concept of the green portfolio, it can be viewed in three steps. Firstly, the damage function presented in previous research include *Scion*, a suitable scalar-tool to measure economic loss caused by emissions. Secondly, by taking advantage of *Scion* and companies emissions intensity a new adjusted excess return is computed.

Finally, an optimal Green Portfolio is established, which enables investors to incorporate an environmental aspect in their decision making. The optimization problem is as follows (Fischer et al. 2020):

$$\text{Max } G_p = \frac{\tilde{R}_p}{\sigma_p} \qquad \text{s.t. } X^T e = 1 \quad \text{or} \quad \sum_{i=1}^{n} x_i = 1 \qquad (22)$$

5. Data & Methodology

Data for annual closing prices and emissions have been retrieved from Bloomberg through their terminal. In order to secure a sufficient amount of annual reports, the whole S&P 500 constituent list was downloaded from the time period 2010.12.31 to 2018.12.31, resulting in a total period of nine years. In this essay, we have used the average quote of one-year U.S. T-bills on the last day of each year from the year 2009 to 2018 as a measurement of the risk-free rate. United States Treasury Bills are by a general consensus considered to be the government bond with the least risk, which is the reason for the choice.

5.1 Sample Selection

The initial sample downloaded from the Bloomberg Terminal was the entire list of constituents of the S&P 500 at the time when it was retrieved (December, 2019). The index, where the number of constituents amount to 505, was filtered in to sample which could be utilized for this study. Companies were excluded from the selection based on the availability of relevant data.

The first exclusion from the data selection was based on the emissions data, any company that had failed to report emissions for at least five of the nine years was excluded. The rationale for this measure is that the sample would be more realistic if reporting was conducted for at least half of or more of the entire time period. Throughout this study, Microsoft Excel with its Solver software, was utilized for optimization operations along with other relevant calculations. The limitations of the program was the basis for further exclusions of companies from the sample. To compute a correct covariance matrix, companies with missing closing prices were excluded, after which 226 companies remained. Due to the Excel Solver's limit of 200 variables in optimization, 27 of the remaining companies were excluded from the sample based on the market capitalization of the companies, resulting in 199 companies in the selection. The full list of companies in the selection can be found in Appendix A. It should be noted that excluding companies by their market capitalization size could affect the results, but the authors weighted the alternatives and found the method as the most rationale.

The format of annual emissions was collected as (Total GHG Emissions/Million Sales, or if not available Total CO2 Emissions/Million Sales) in order to link company's emissions to their sales, these results was also retrieved directly from Bloomberg terminal. The emissions retrieved from Bloomberg only includes scope 1 and scope 2, for the reason that companies rarely report emissions related to scope 3 and because it may result in counting emissions twice.

The scope includes both upstream and downstream emission that take place in the value chain. For example, including scope 3 emissions from a company and their subcontractor in a portfolio, will result in twice the correct amount.

For the reason that emissions collected from Bloomberg are given as GHG or CO2, depending on which data was available, it could be confusing and difficult to interpret which group the results are referring to. Thus, for the rest of this study, all results regarding emissions will henceforth be presented with the term *Greenhouse Gases (GHG)* and/or *emissions.* Relevant formulas and calculations presented in the Theory section will be adjusted to accommodate this data.

Furthermore, the annual average of the company's annual total emissions/millions sales have been computed. This method was selected in order to present the emissions of the companies on equal terms. In the following section (results & analysis), sectors are ranked according to their emission intensity in the entire sample. If a sector is ranked as number one, this alludes that the sector in question has the highest emission intensity in the sample. Obviously, a higher ranking implies a lower emission intensity. In pursuit of obtaining a diversified result, and including several sectors and companies in the optimal portfolios, another criteria was created. The optimal portfolios had to allocate their funds in at least fifty different companies, in order to prevent placement in a few top performers, and generate a more useful result. This was ensured by setting an additional constraint in the solver optimization, similar to setting the sum of weights to 1, but with the number of assets to fifty. In summary, the report includes the previously mentioned 199 companies out of the original 505 companies downloaded.

6. Result & Analysis

In this selection, the results in terms of composition and characteristics are presented. By way of clarification, it is useful to note that any variable that is presented for an individual sector is calculated from the data selection in its entirety, i.e. 199 companies.

6.1 Portfolio Composition

6.1.1 Weights and number of companies by GICS sector

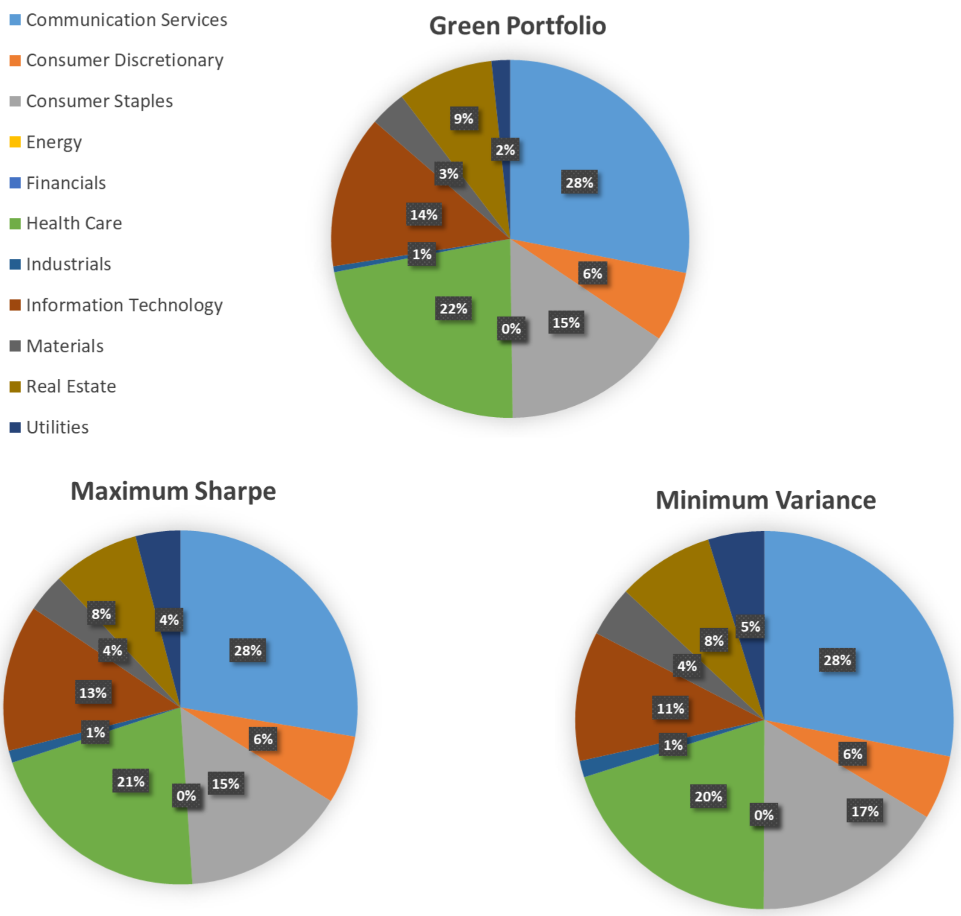


Figure 1: GICS Sector Composition of the three equity portfolios

The composition in terms of GICS Sectors for the three portfolios are displayed in the pie charts in Figure 1. For clarification purposes, Table 3 below demonstrates the weights of the sectors in the three portfolios as a percentage along with GHG ranking and expected return (μ) for each of the sectors.

Sectors	Green	Minimum σ^2	Maximum SR	GHG Ranked	µ
Communication Services	28,05%	28,09%	27,65%	10	10,8%
Consumer Discretionary	6,35%	5,48%	6,23%	5	18,0%
Consumer Staples	15,38%	16,48%	15,04%	7	13,5%
Energy	0,00%	0,00%	0,00%	2	1,4%
Financials	0,00%	0,00%	0,00%	11	12,8%
Health Care	22,24%	20,05%	21,02%	9	17,5%
Industrials	0,53%	1,41%	1,11%	4	18,0%
Information Technology	13,81%	11,08%	13,39%	8	17,2%
Materials	3,28%	4,31%	3,53%	3	14,9%
Real Estate	8,68%	8,28%	7,93%	6	11,0%
Utilities	1,68%	4,81%	4,08%	1	12,6%

Table 3: GICS Sector Composition of the equity portfolios compared to GHG ranking and expected returns

The expected returns in this case is the average expected return of all the companies in the selection. The same applies to the emissions intensity ranking. The emissions intensity ranking is computed as the arithmetic mean of emission intensity between the companies in a GICS sector. As previously described, the GICS sector with the rank 1 has the highest average emissions intensity and the sector with the ranking 11 has the lowest. Also note that the sole sector to not be included in any of the portfolios is Energy. Financials is displayed as zero in Table 3 but is in fact a very low number. A curious observation to be made in regards to the GICS Sector *Financials* is the sector's low weights in each of the three portfolios despite having an adequate expected return for the sector as a whole. Given the sector's expected returns and low emissions intensity ranking, the weights in the Green Portfolio in comparison to the others did not amount to the authors' expectations. Possible explanations for this occurrence may stem from limitations in the dataset as outlined in the previous chapter.

As expected, the Green Portfolio has lower weights in the sectors with the greatest emission intensity relative to the conventionally optimized portfolios. This observation is substantiated by the below graph in Figure 2, where the vertical axis represents the average change in terms of increase and decrease from the Minimum Variance and Maximum Sharpe portfolios to the

Green Portfolio. The horizontal axis represents the sector's emissions intensity ranking. The lines in Figure 2 are trendlines for the scatterplot fitting the previously described figure.

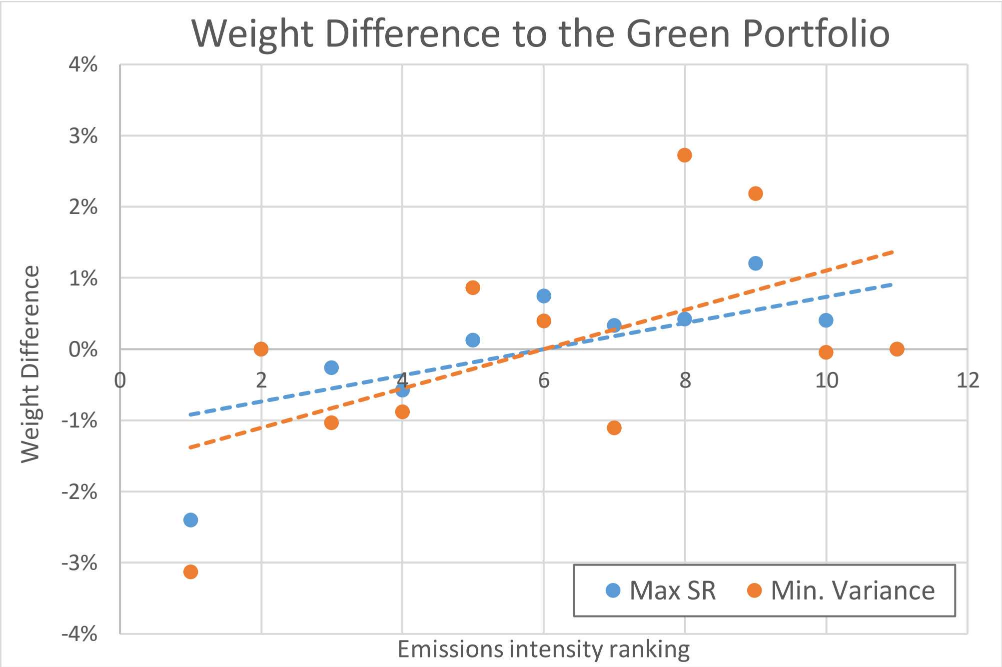


Figure 2: The difference between the sector weights in the Green Portfolio in comparison to conventionally optimized, and the Emissions Ranking illustrated with trendlines. Negative values imply a lower weight in the Green Portfolio and positive values imply a higher weight in the Green Portfolio.

The graph displays a positive relationship between the shift in fund allocation and lower emissions intensity, i.e. the Green Portfolio allocates a lesser share of the portfolio total, the higher the sector's emissions intensity. The graphs in Figure 2 are trendlines to a scatterplot where the vertical axis is the weight difference as described in the caption of the figure, and the horizontal axis is the emissions intensity ranking. The purpose of the graph is to make the results of Table 3 more tangible for the reader. When analyzing the results, a pivotal limitation can be observed by looking at the numbers for the Energy Sector, which was 0% in each portfolio. In the utilized selection, the energy sector had the lowest average expected returns by a large margin, as seen in Table 3.

The resulting differences to portfolio composition in terms of number of companies were as displayed in the Table 4.

No. Companies per sector	Min. Variance	Max. SR	Green	GHG	# of companies in selection
Communication Services	3	2	2	10	6
Consumer Discretionary	3	5	5	5	19
Consumer Staples	9	8	9	7	22
Energy	0	0	0	2	11
Financials	1	1	1	11	21
Health Care	12	12	12	9	24
Industrials	2	1	4	4	30
Information Technology	7	7	7	8	23
Materials	2	2	2	3	13
Real Estate	4	4	5	6	13
Utilities	7	8	3	1	17

Table 4: The number of companies by sector in the portfolios compared to emissions ranking and total number of companies in the selection.

At first glance, it would seem as if the number of companies per sector corresponds with the development in portfolio weights demonstrated in Table 3 and Figure 2. As a whole, the amount of companies decreases on average from the portfolios in sectors with a higher emissions intensity ranking. However, after further considerations it became evident that the largest change in sector, which was utilities, was possibly distorting the results.

In terms of the authors' hypothesis regarding portfolio composition, the result for the sample as a whole was in line with the expectations, i.e. the number of companies and the portfolio weights respectively decreased in the more emission intensive sectors.

GICS SECTOR	Portfolio Weights	Number of Companies	GHG Rank
Communication Services	MV > Green > SR	MV > SR =Green	10
Consumer Discretionary	Green > SR > MV	Green = SR >MV	5
Consumer Staples	MV > Green > SR	MV = Green > SR	7
Energy	0	0	2
Financials	=	=	11
Health Care	Green > SR > MV	=	9
Industrials	MV > SR > Green	Green > MV > SR	4
Information Technology	Green > SR > MV	=	8
Materials	MV > SR > Green	=	3
Real Estate	Green > MV > SR	Green > MV=SR	6
Utilities	MV > SR > Green	SR > MV > Green	1

Table 5: Relative Sector Composition Summarized and compared with GHG rank

However, when observing Table 5 above, it can be seen that in some cases, such as in the GICS sector *Industrials,* the results differed. To clarify; the number of companies in the sector was higher for the Green Portfolio despite the Green Portfolio having a lower weight in this sector. This discovery was not in line with the authors' hypotheses and proved an interesting result. After the results have been presented, it can be argued that this occurs because the Green Portfolio aims to minimize the total emissions intensity of the portfolio.

6.1.2 Top Ten Companies in Equity Portfolios

	Top Ten Holdings					
	Green		Maximum SR		Minimum Variance	
#	**Company**	**Weight**	**Company**	**Weight**	**Company**	**Weight**
1	Verizon Inc.**	26,4%	Verizon Inc.**	26,0%	Verizon Inc.**	25,8%
2	Eli Lilly & Co.**	6,9%	Eli Lilly & Co.**	6,8%	Eli Lilly & Co.**	6,7%
3	McCormick & Co.**	4,2%	McCormick & Co.**	4,2%	McCormick & Co.**	4,0%
4	Edwards Lifesciences Corp**	3,9%	Edwards Lifesciences Corp**	3,7%	Newmont Corp	3,4%
5	NVIDIA Corp.*	3,3%	Hormel Foods Corp.**	3,4%	Hormel Foods Corp.**	3,4%
6	Hormel Foods Corp.**	3,2%	NVIDIA Corp.*	3,0%	McDonald's Corp.**	2,9%
7	Visa Inc*	3,0%	Starbucks Corp.**	3,0%	Edwards Lifesciences Corp**	2,9%
8	Church & Dwight Co.*	3,0%	Church & Dwight Co.*	2,9%	PPL Corp.	2,6%
9	Starbucks Corp.**	2,9%	Visa Inc*	2,8%	Pfizer Inc.	2,5%
10	McDonald's Corp.**	2,7%	McDonald's Corp.**	2,7%	Starbucks Corp.**	2,3%
Sum		59,6%		58,4%		56,4%
GAC($B)		16,0		15,1		14,9

Table 6: Top Ten Companies in the Three Portfolios by weight

The above (Table 6) describes the portfolio composition in terms of the top ten companies in each of the three equity portfolios. The asterix after the company names are meant to demonstrate how similar the top ten companies in the portfolios are. Two asterixis imply that the company is in each of the three portfolios, one asterixis in two portfolios and no asterixis in one portfolio. With that in mind, an interesting observation to be made is that the Green Portfolio and Maximum Sharpe portfolio contain the same ten companies. The Minimum Variance portfolio contained all but three.

The result was not in line with the authors' hypotheses. The authors had made several hypotheses in regards to the composition. The authors believed that the market capitalizations (GAC) would follow the same order as the complete portfolios. To some extent, they did. However, the exception proved to be that the Maximum Sharpe Ratio had a higher GAC than the Minimum Variance, which was not the case for the entire portfolios. The authors also expected the Minimum Variance portfolio to have the lowest share of its entire weight in the top ten holdings, a hypothesis that proved to be correct. The entire list of companies included in each portfolio can be found in Appendix C.

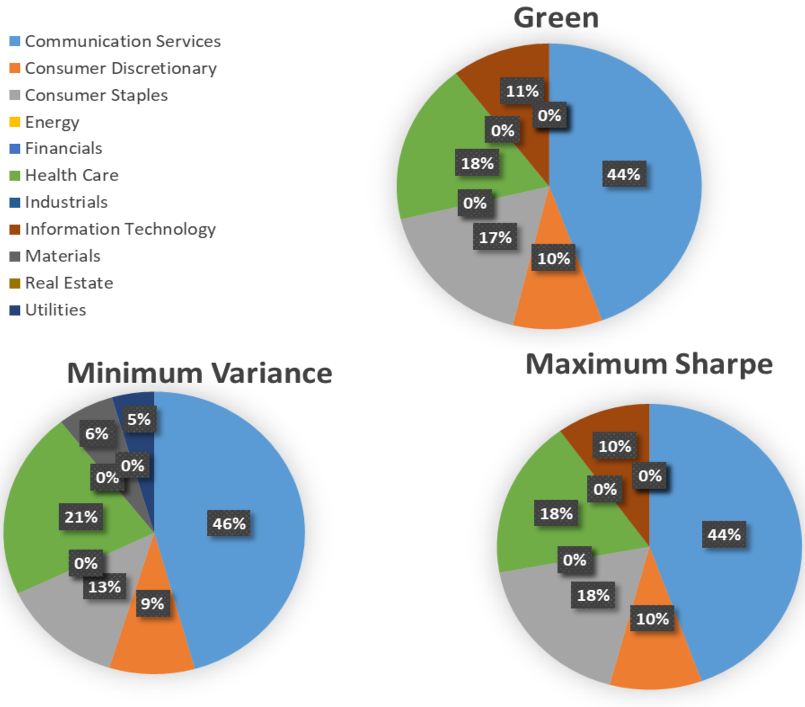


Figure 3: Top Ten Companies in each portfolio by GICS sector

The pie charts in Figure 3 above demonstrate the composition in terms of GICS sector within the top ten companies in each of the portfolios. As predicted, they followed a similar composition as the entire portfolios, but with a higher concentration than the authors' had anticipated, leading to a visible difference.

6.2 Portfolio Performance Measures and Characteristics

Performance Measures	Green	Minimum Variance	Maximum Sharpe
Variance	0,008%	0,006%	0,007%
Standard Deviation	0,87%	0,79%	0,83%
Expected Returns	17,2%	15,5%	16,9%
Expected Excess Returns	16,5%	14,8%	16,2%
Sharpe Ratio	18,9	18,8	19,4
GAC($Billion)	86,4	84,9	84,2

Table 7: Characteristics of the three portfolios.

The above Table 7 demonstrates the characteristics and performance measures of the three observed equity portfolios and the results will be discussed in the coming section. The above results are calculated as outlined in the theory section of this study.

6.2.1 Portfolio Variance and Standard Deviation

As observed in Table 7 the Green Portfolio has the highest variance and standard deviation among the three portfolios, thereby implying that the Green Portfolio had the highest risk in terms of volatility. Unsurprisingly, the minimum variance portfolio had the lowest values of variance and standard deviation and therefore lower risk in terms of volatility, followed by the Maximum Sharpe Ratio portfolio. The resulting Portfolio Variance and Standard deviation was contrary to the authors' hypothesis. An explanation for this result can be drawn from the fact that the Green Portfolio had a lower number of viable options in the selection, as many of the companies in the sectors yielded substantially less returns when they were calculated as Green Excess Returns with considerations to the GHG footprints. Therefore, the Green Portfolio had less of an ability to diversify its risk in terms of volatility.

6.2.2 Portfolio Expected Return and Expected Excess Return

In direct contrast to the authors' hypotheses, the Green Portfolio had the highest expected return of the three portfolios, as demonstrated in Table 7. The authors had expected the Green Portfolio to have the lowest levels of expected returns with the Maximum Sharpe followed by the Minimum Variance on top. An intuitive explanation to the fact that the Green Portfolio had the highest return can be that it also had the highest risk in terms of volatility (variance and standard deviation). Moreover, the decrease in viable companies to invest in due to environmental considerations had implications for the Portfolio's ability to diversify and therefore attained a higher degree of portfolio returns in order to maximize the environmentally adjusted Sharpe ratio.

Beyond the possibly intuitive explanations outlined above, questions were raised whether there was in fact a counterintuitive answer. Building on this line of questioning and previous unforeseen results, the authors endeavored to test if there was in fact a negative relationship between expected returns and emissions intensity. Therefore, a regression analysis was conducted to investigate the possible connection. The results are outlined in the following section.

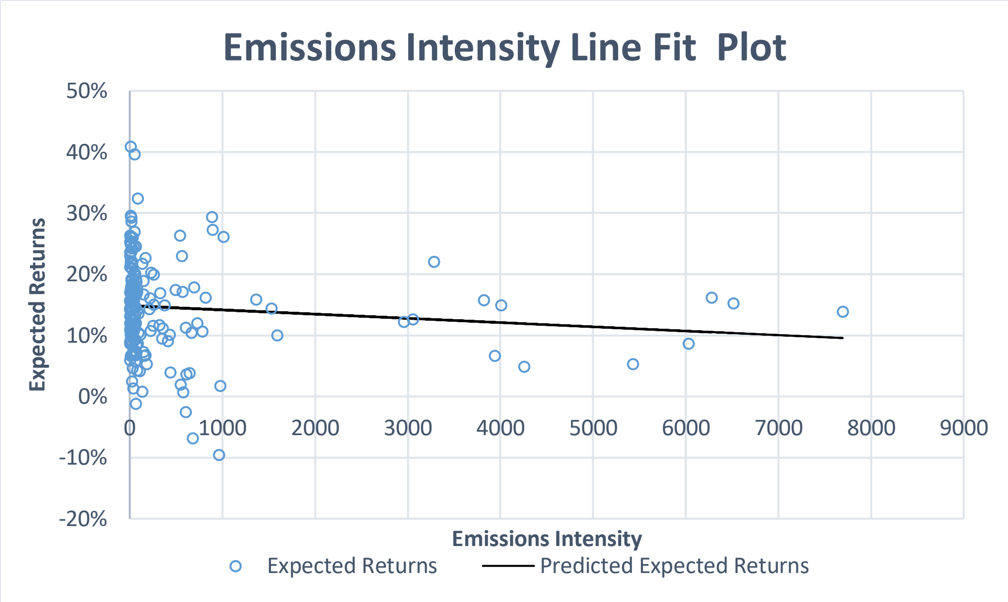


Figure 4: Fitted Line Plot between expected returns and emission intensity

The figure above illustrates the regression with expected return as the dependent variable, and emissions intensity as the explanatory variable. Multiple R have a value of 0.1094808 and since the coefficient is negative this implies a weak negative relationship. R Square gives us a value of 0.011986 which is the variation in expected returns explained by emission intensity. However, the explanatory variable does have a p-value of 0.123727 making it insignificant at the 5% level. Even though the observed result differed from the authors' initial hypotheses regarding the positive relationship between expected returns and emission intensity, the regression that was to enforce this shortcoming proved to be statistically insignificant, as demonstrated below.

Regression Statistics	
Multiple R	0,1094808
R Square	0,011986
Adjusted R Square	0,0069707
Standard Error	0,0745054
Observations	199

Variables	Expected Returns	Emissions Intensity
Coefficients	0,148	0,000
Standard Error	0,006	0,000
t Stat	26,368	-1,546
P-value	0,000	0,124
Lower 95%	0,137	0,000
Upper 95%	0,160	0,000
Lower 95,0%	0,137	0,000
Upper 95,0%	0,160	0,000

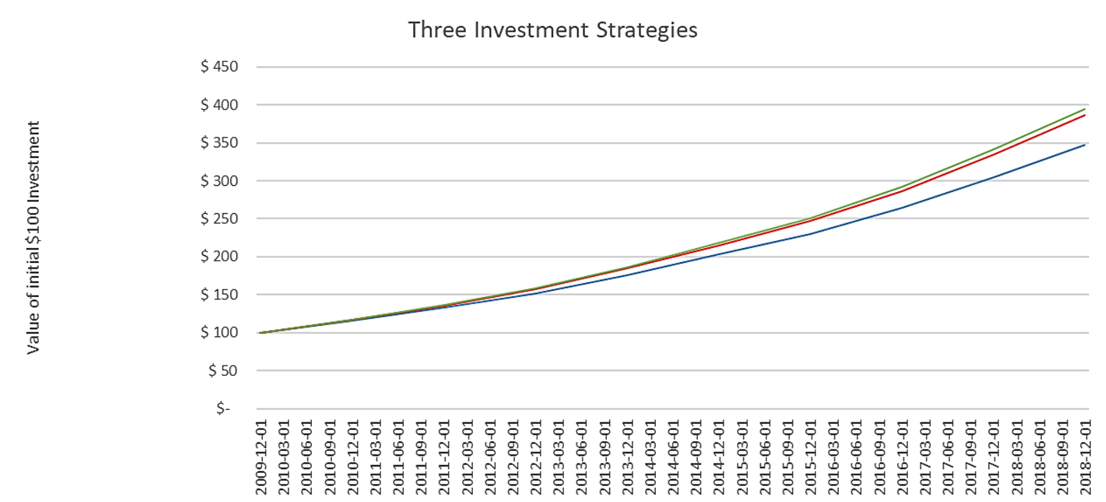
	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	0,013266459	0,013266	2,389897	0,123726573
Residual	197	1,093558569	0,005551		
Total	198	1,106825028			

Table 8: Regression statistics

6.2.3 Portfolio Sharpe Ratio

The Sharpe ratios of the three different equity portfolios was partly consistent with the authors' hypotheses. The authors had expected the Maximum Sharpe Ratio Portfolio to have the highest Sharpe ratio, followed by the Minimum Variance Portfolio and the Green Portfolio. Instead the Green Portfolio followed the Maximum Sharpe Ratio.

6.2.4 The Three Portfolios as Investment Strategies



	2009-12-31	2010-12-31	2011-12-30	2012-12-31	2013-12-31	2014-12-31	2015-12-31	2016-12-30	2017-12-29	2018-12-31
Minimum Variance Portfolio	$ 100	$ 116	$ 133	$ 152	$ 176	$ 203	$ 230	$ 264	$ 305	$ 347
Max Sharpe Portfolio	$ 100	$ 117	$ 136	$ 157	$ 185	$ 215	$ 247	$ 287	$ 335	$ 386
Green Portfolio	$ 100	$ 117	$ 136	$ 158	$ 186	$ 218	$ 251	$ 292	$ 342	$ 395

Figure 5: The three equity portfolios as investment strategies

Unexpectedly to the authors, the green portfolio proved to have the greatest return among the three equity portfolios in question. Therefore, the authors endeavored to compare the three as investment strategies. A hypothetical $100 investment on 2009-12-31 has been utilized to demonstrate the value increase of the three equity portfolios. As graphically displayed in Figure 5, the Green Portfolio comes out on top. However, it is incremental to note that the graphically illustrated investment strategies are not entirely realistic. The reasons for this is the fact that the returns are computed on a yearly basis, thus failing to illustrate the volatility of the portfolios and the true market movements in an appropriate manner. Also, it could be argued that the variation in fiscal cycles is inadequate.

The $100 dollar investment in the respective portfolios from 2009-12-31 to 2018-12-31 would have yielded the results in the table below.

Investment Strategies:	Green	Minimum Variance	Maximum Sharpe
$100 Investment	$394,81	$347,13	$ 386,02
Total Return	295%	247%	286%

Table 9: The excess return of the three equity portfolios

The yearly returns were calculated as the weighted excess return of the portfolio holdings. I.e. the excess return of each year, times weight of each company in the respective portfolios.

6.2.5 Portfolio Market Capitalization

In terms of Geometric Average Market Capitalization (GAC), the three equity portfolios were in the following order from highest to lowest; Green Portfolio – Minimum Variance – Maximum Sharpe Ratio. The authors had expected the Green Portfolio to have the lowest GAC, the Minimum Variance portfolio as the highest and the Maximum Sharpe in between. Thus, implying a significant contrast between the expected and observed GAC of the Green Portfolio in particular.

6.2.6 Portfolio Emissions

The utilized formula for emissions intensity was an alteration to the Weighted Average Carbon Intensity that was outlined in the Theory section. The purpose of the alteration was to adhere to the appropriate data, the composition of which is explained in the Data section. The term Weighted Average Emissions Intensity will therefore be utilized.

	Green	Minimum Variance	Maximum Sharpe
Tons Emissions /$M Sales	78,9	255,1	202,1

Table 10: Weighted Average Emission Intensity of the three portfolios

As seen in Table 10 above, the Green Portfolio had the lowest Weighted Emissions Intensity, the Minimum Variance had the highest, followed by the Maximum Sharpe Ratio portfolio. This was in line with the authors' hypotheses due to the minimization process in the Green Portfolio optimization. However, the authors had not expected such a stark contrast between the three equity portfolios in terms of Weighted Average Emission Intensity.

The magnitude of how much higher the Weighted Average Emissions Intensity is in the Minimum Variance and Maximum Sharpe Ratio portfolios can seem puzzling at first glance. However, as noted earlier in the results, the number of companies increased in the GICS sectors which the weight as a percentage decreased (with the exception of utilities). These sectors had a higher average emission intensity than the ones that increased. A possible explanation for this could be the lowering of total emission intensity by investing in more, smaller companies with a lower degree of emission intensity despite decreasing the portfolio weight in these areas.

6.3 Collective Results & Discussion

In terms of composition, the initial hypotheses are compared with the results in Table 9. The shortcomings of the second and third hypotheses is rooted in a rationale that was initially overlooked by the authors. This rationale was that the companies in the Green Portfolio would diversify in the areas in which the weight decreased. These companies were emission intensive in terms of sector classification, implying the aversion of large holdings in emission intensive companies.

H#	Hypotheses of Portfolio Composition	Results
1	The portfolio weight of the sectors with greater emissions, relative the other sectors; will be lower in the Green Portfolio than in the other two.	Correct. The result was in line with the hypothesis.
2	The number of companies in the sectors with greater emissions, relative the other sectors; will be lower in the Green Portfolio than in the other two.	Partially correct. The number of companies was in some cases higher.
3	If the portfolio weights of a sector is lower in the Green Portfolio than the other two, the number of companies in that sector will also be lower in the Green Portfolio relative to the other two.	Partially correct. In some cases the number of companies was higher in a sector in the Green Portfolio even though the portfolio weight in the sector was lower than the others.
4	The similarity of the top ten companies in each portfolio, in terms of portfolio weight, will be negligible between the Green Portfolio and the other two equity portfolios.	False. The equity portfolios shared the majority of top ten companies. The Maximum SR and Green Portfolio had the same companies in top ten.
5	The composition, in terms of portfolio sector weights, in the top ten will be very similar to that of the entire portfolio for the individual portfolio.	Partially correct. More concentrated.
6	The Green Portfolio would have the highest amount of portfolio weight in the top ten.	Correct.

Table 11: The Hypotheses vs Results in terms of composition

The shortcomings of the fourth hypothesis in Table 11 stemmed from the authors' proven misconception that emission intensive companies would yield higher returns (when not environmentally adjusted) and therefore be excluded from the Green Portfolio.

		Hypothesis	Result
H#	**Characteristic**	***1 - 2 - 3***	***1 - 2 - 3***
1.	**Expected Returns**	Max. Sharpe – Min. Variance - Green	Green – Max. Sharpe – Min. Variance
2.	**Variance and Standard Deviation**	Max. Sharpe – Green – Min. Variance	Green – Max. Sharpe – Min. Variance
3.	**Sharpe Ratio**	Max. Sharpe – Min. Variance - Green	Max. Sharpe – Green – Min. Variance
4.	**Market Capitalization**	Min. Variance – Max. Sharpe – Green	Green – Max. Sharpe – Min. Variance
5.	**Emissions Intensity**	Min. Variance – Max. Sharpe – Green	Min. Variance – Max. Sharpe – Green

Table 12: Hypotheses vs Results in terms of characteristics

The above Table 12 summarizes the Hypotheses and corresponding results for the characteristics of the equity portfolios. As previously discussed in further detail, general observations can be made in regards to the successes and shortcomings of authors' hypotheses. The subsequent total failure of the hypotheses 1, 3 and 4 can be explained by the overconfidence in the performance of large companies who also are large emitters. The authors' belief was that large companies would become exponentially more emission intensive while growing in size, instead of the opposite. This proved to be incorrect in an absolute value, leading to the fact that the Green Portfolio had the largest market capitalization as measured by GAC. A possible explanation for the Green Portfolio having the greatest returns could be the manner in which the portfolio is constructed. Since the number of viable options decreased (also affecting the volatility of the portfolio), the Green maximization problem had to resort to higher returns to improve its optimal ratio. Somewhat cynically, one could also argue that there is an apparent relationship between higher risks and higher rewards.

When analyzing the results of this study in comparison to the previous research, the consistency between the two was varying. For example, the results of the Jónsdóttir et al. (2017) study implied that there was a possibility to decarbonize an equity portfolio while maintaining the expected returns and level of risk. This result was consistent to the results of this study, were the Green Portfolio even showed higher returns. The Utz et al. (2013), who studied ESG sustainable funds, suggested that there negligible differences between regular funds and ESG funds in terms of expected returns (among others). The results outlined by Utz et al suggest, however, that sustainable funds have a lower degree of volatility - a result which further contributed to the lack of consistency to the findings of this study.

The study in itself has produced interesting results that were in line with the authors' purpose of the essay, namely to compare the characteristics and composition of conventionally optimized equity portfolios and a Green Portfolio, which takes in to account the economic effects of environmental damage.

However, it is vital to identify the shortcomings and limitations of this thesis' analysis. The limitations of the sample used for the thesis is that it lacks the diversity, size, complexity, and perhaps the necessary depth to identify perfectly realistic results. The rationale behind the mentioned limitations is the use of American, S&P 500 companies, filtered for the data availability. The time series and corresponding data is perhaps not long enough either. Another limitation is related to the possible lack of complexity and depth, which is probably based on the fact that the thesis is at Bachelor level, implying that exhaustive results and conclusions require authors with a higher level of technological and/or environmental science and/or economic aptitude.

7. Conclusion

In conclusion, the characteristics and composition of an equity portfolio that takes the economic effects of environmental damage in to considerations were to some degree surprising and to a lesser degree expected. The Green Portfolio demonstrated higher market capitalization and expected returns than its traditionally optimized counterparts, an observation which challenges the notions of environmental damage being a prerequisite for successful investing and the authors' misconception of marginally increasing environmental damage of S&P 500 companies. The Green Portfolio also demonstrated a higher degree of volatility and an unforeseen similarity in terms of top ten holdings to its conventionally optimized counterparts. The findings of the thesis were diverse and consistent with the purpose of the study, which was to research the composition and characteristics of the three studied equity portfolios.

However, in light of the limitations of the analysis which were highlighted in the final part of the previous chapter, it can be argued that the findings of this study are inconclusive and possibly even unrealistic. Therefore, further research in the subject of portfolio optimization with considerations to environmental effects is needed. Future research could enhance the complexity, depth and significance of the results along with the development of tangible financial methodology for the subject.

8. Bibliography

Barrage, L. (2019). The Nobel Memorial Prize for William D. Nordhaus. *Scand. J. of Economics 121(3), 884-924* https://onlinelibrary.wiley.com/doi/pdf/10.1111/sjoe.12383 (Accessed 12 December 2019)

Bodie, Zvi – Kane, Alex – Marcus, Alan J. (2013). *Investments*, McGraw Hill, Global Edition, 10th edition.

Dell, M., Jones, B. F., Olken, B, A. (2012). Temperature Shocks and Economic Growth: Evidence from the Last Half Century. *American Economic Journal: Macroeconomics, 4(3):66-95* https://pubs.aeaweb.org/doi/pdfplus/10.1257/mac.4.3.66 (Accessed 19 December 2019)

Fidelity. (2017). *Understanding market capitalization.* https://www.fidelity.com/learning-center/trading-investing/fundamental-analysis/understanding-market-capitalization (Accessed 5 January 2020)

Fischer, T., Lundtofte, F. (2020*). Green portfolios.* Mimeo.

Golosov, M., Hassler, J., Krussel, P., Tsyvinski, A. (2014). Optimal Taxes On Fossil Fuel In General Equilibrium. *Econometrica, Vol. 82, No. 1, 41-88* http://hassler-j.iies.su.se/PAPERS/ECTA.pdf (Accessed 12 December 2019)

Hassler, J., Krussel, P., Smith Jr, A.A. (2016). Environmental Macroeconomics. *Handbook of Macroeconomics Vol. 2, 1893-2008* https://www.sciencedirect.com/science/article/pii/S1574004816300076?via%3Dihub (Accessed 12 December 2019)

Jónsdóttir, H. S., Palmelind, S. (2017). *Reducing the Carbon Footprint of Equity Portfolios.* https://gupea.ub.gu.se/bitstream/2077/53121/1/gupea_2077_53121_1.pdf (Accessed 9 January 2020)

Kempf, A., Memmel, C. (2006). Estimating the Global Minimum Variance Portfolio. *Schmalenbach Business Review, 58(4), 332-348.* https://link.springer.com/article/10.1007/BF03396737 (Accessed 6 January 2020)

Kolm, P. N., Tütüncü, R., & Fabozzi, F. J. (2014). 60 years of portfolio optimization: practical challenges and current trends. *European Journal of Operational Research, 234(2), 356-371.* http://doi:10.1016/j.ejor.2013.10.060 (Accessed 14 December 2019)

Markowitz, H. (1952). *The Journal of Finance, Vol.7, No.1.77-91.* https://www.jstor.org/stable/2975974?seq=1#metadata_info_tab_contents (Accessed 14 December 2019)

Morgan Stanley. (2019). *Interest and Adoption of Sustainable Investing Continue to Grow* https://www.morganstanley.com/ideas/sustainable-investing-growing-interest-and-adoption (Accessed 10 January)

Morningstar. (2020). *Using the Portfolio Snapshot Report with Clients.* http://advisor.morningstar.com/enterprise/VTC/PortfolioSnapshotReport.pdf *(*Accessed 5 January 2020)

MSCI, (2016). *Global Industry Classification Standard (GICS).* https://www.msci.com/documents/10199/4547797/GICS+Sector+definitions-Sep+2016.pdf/7e5236a8-2ddd-4e29-a8bf-18f394c7f0fb (Accessed 6 January 2020)

MSCI. (2018). *MSCI Carbon Footprint Index Ratios Methodology.* https://www.msci.com/documents/1296102/6174917/MSCI+Carbon+Footprint+Index+Ratio+Methodology.pdf/6b10f849-da51-4db6-8892-e8d46721e991 (Accessed 9 January 2020)

MSCI, (2020). *Weighted Average Carbon Intensity*. https://www.msci.com/index-carbon-footprint-metrics (Accessed 3 January 2020)

Nordhaus, W. D. (1974). Resources as a Constraint on Growth. *The American Economic Review, 64 (2), 22-26.* https://www.jstor.org/stable/1816011?seq=1#metadata_info_tab_contents (Accessed 16 December 2019)

Nordhaus, W. D. (1980). Thinking about Carbon Dioxide: Theoretical and Empirical Aspects of Optimal Control Strategies. *Cowles Foundation Discussion Paper 565,* Yale University. http://cowles.yale.edu/sites/default/files/files/pub/d05/d0565.pdf (Accessed 16 December 2019)

Nordhaus, W. D. (1993). Reflections on the Economics of Climate Change. *Journal of Economic Perspectives, 7(4), 11-25.* https://pubs.aeaweb.org/doi/pdfplus/10.1257/jep.7.4.11 (Accessed 16 December 2019)

The European Commission. (2015). *The Paris Protocol – A blueprint for tackling global climate change beyond 2020*

https://ec.europa.eu/clima/sites/clima/files/international/paris_protocol/docs/com_2015_81_en.pdf (Accessed 15 December 2019)

Utz, S., Wimmer, M., Hirschberger, M., Steuer, R, E. (2013). Tri-criterion inverse portfolio optimization with application to socially responsible mutual funds. *European Journal of Operational Research 234(2), 491-498.* https://www.sciencedirect.com/science/article/pii/S037722171300605X (Accessed 17 December 2019)

World Business Council for Sustainable Development, World Resources Institute. (2004). *The Greenhouse Gas Protocol*. https://wriorg.s3.amazonaws.com/s3fs-public/pdf/ghg_protocol_2004.pdf (Accessed the 8 December 2019)

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Appendix

Appendix A: List of companies in the selection

VZ UN Equity
BA UN Equity
CAT UN Equity
JPM UN Equity
CVX UN Equity
KO UN Equity
DIS UN Equity
XOM UN Equity
GE UN Equity
HPQ UN Equity
HD UN Equity
IBM UN Equity
JNJ UN Equity
MCD UN Equity
MRK UN Equity
MMM UN Equity
AWK UN Equity
BAC UN Equity
PFE UN Equity
PG UN Equity
T UN Equity
UTX UN Equity
WMT UN Equity
CSCO UW Equity
INTC UW Equity
MSFT UW Equity
CI UN Equity
C UN Equity
HON UN Equity
MO UN Equity
IP UN Equity
ABT UN Equity
APD UN Equity
RCL UN Equity
AEP UN Equity
HES UN Equity
APA UN Equity
AVY UN Equity
BLL UN Equity
BK UN Equity
BAX UN Equity
BDX UN Equity
BBY UN Equity
BSX UN Equity
BMY UN Equity
BF/B UN Equity
CPB UN Equity
KSU UN Equity
CCL UN Equity
CTL UN Equity
CLX UN Equity
CL UN Equity
CMA UN Equity
CAG UN Equity
ED UN Equity
SLG UN Equity
CMI UN Equity
TGT UN Equity
D UN Equity
ETN UN Equity
ECL UN Equity
PKI UN Equity
EMR UN Equity
ETR UN Equity
FDX UN Equity
FMC UN Equity
F UN Equity
FCX UN Equity
GD UN Equity
GIS UN Equity
HAL UN Equity
PEAK UN Equity
HSY UN Equity
HRL UN Equity
HUM UN Equity
ITW UN Equity
IR UN Equity
IFF UN Equity
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KMB UN Equity
KIM UN Equity
KSS UN Equity
KR UN Equity
LLY UN Equity
LNC UN Equity
LOW UN Equity
HST UN Equity
XRX UN Equity
SPGI UN Equity
MDT UN Equity
CVS UN Equity
MSI UN Equity
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NBL UN Equity
NSC UN Equity
ES UN Equity
NOC UN Equity
WFC UN Equity
PVH UN Equity
OXY UN Equity
OMC UN Equity
PPL UN Equity
COP UN Equity
PNW UN Equity
PNC UN Equity
PPG UN Equity
PEG UN Equity
RTN UN Equity
EIX UN Equity
SLB UN Equity
SHW UN Equity
SO UN Equity
LUV UN Equity
TXT UN Equity
TIF UN Equity
TJX UN Equity
JCI UN Equity
UNP UN Equity
MRO UN Equity
VFC UN Equity
VNO UN Equity
WY UN Equity
WHR UN Equity
WEC UN Equity
ADBE UW Equity
AES UN Equity
AMGN UW Equity
AAPL UW Equity
ADSK UW Equity
TAP UN Equity
MKC UN Equity
COST UW Equity
TSN UN Equity
AMAT UW Equity
CAH UN Equity
EXPD UW Equity
WELL UN Equity
BIIB UW Equity
NTRS UW Equity
QCOM UW Equity
SBUX UW Equity
KEY UN Equity
STT UN Equity
USB UN Equity
NLOK UW Equity
WM UN Equity
AGN UN Equity
ALK UN Equity
INTU UW Equity
MS UN Equity
MCHP UW Equity
CB UN Equity
ALL UN Equity
SPG UN Equity
EMN UN Equity
AVB UN Equity
PRU UN Equity
UPS UN Equity
MCK UN Equity
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COF UN Equity
WAT UN Equity
HIG UN Equity
IRM UN Equity
EL UN Equity
ROK UN Equity
BXP UN Equity
ACN UN Equity
PLD UN Equity
AEE UN Equity
NVDA UW Equity
CTSH UW Equity
RSG UN Equity
EBAY UW Equity
GS UN Equity
SRE UN Equity
AKAM UW Equity
DVN UN Equity
GOOGL UW Equity
A UN Equity
DTE UN Equity
PM UN Equity
CRM UN Equity
MET UN Equity
EW UN Equity
CBRE UN Equity
LDOS UN Equity
TEL UN Equity
V UN Equity
RMD UN Equity
MTD UN Equity
ALB UN Equity
CHD UN Equity
MHK UN Equity
URI UN Equity
DAL UN Equity
LVS UN Equity

Appendix B: Number of companies per sector in the selection

Number of companies in selection	
Communication Services	6
Consumer Discretionary	19
Consumer Staples	22
Energy	11
Financials	21
Health Care	24
Industrials	30
Information Technology	23
Materials	13
Real Estate	13
Utilities	17
Sum	199

Appendix C: Portfolios

	minvarweights	srweights	greenweights
VZ UN Equity	0,257610067	0,259653	0,264495
BA UN Equity	0	0	0
CAT UN Equity	0	0	0
JPM UN Equity	0	0	0
CVX UN Equity	0	0	0
KO UN Equity	0,005496558	0,000765	0,000842
DIS UN Equity	0	0	0
XOM UN Equity	0	0	0
GE UN Equity	0	0	2,36E-09
HPQ UN Equity	0	0	0
HD UN Equity	0	0,000994	0,002304
IBM UN Equity	0	0	0
JNJ UN Equity	0	0	0
MCD UN Equity	0,028887131	0,027391	0,027369
MRK UN Equity	0,01975596	0,020344	0,021006
MMM UN Equity	0	0	0
AWK UN Equity	0,007705875	0,01279	0,013918
BAC UN Equity	0	0	0
PFE UN Equity	0,024989541	0,0262	0,026752
PG UN Equity	0	0	0
T UN Equity	0,00085593	0	0
UTX UN Equity	0	0	0
WMT UN Equity	0	0	0
CSCO UW Equity	0,019541459	0,013265	0,014748
INTC UW Equity	0	0	0
MSFT UW Equity	0,015738604	0,013677	0,014601
CI UN Equity	0	0	0
C UN Equity	0	0	0
HON UN Equity	0	0	0
MO UN Equity	0	0	0
IP UN Equity	0	0	0
ABT UN Equity	0,021465613	0,022213	0,023394
APD UN Equity	0	0	0
RCL UN Equity	0	0	0
AEP UN Equity	0,000694696	0,001633	0
HES UN Equity	0	0	0
APA UN Equity	0	0	0
AVY UN Equity	0	0	0
BLL UN Equity	0,008825845	0,010996	0,011413
BK UN Equity	0	0	0
BAX UN Equity	0,014781963	0,010863	0,011436
BDX UN Equity	0	0	0
BBY UN Equity	0	0	0

BSX UN Equity	0,001198595	0	0
BMY UN Equity	0	0	0
BF/B UN Equity	0	0	0
CPB UN Equity	0,002479462	0	0
KSU UN Equity	0	0	0
CCL UN Equity	0	0	0
CTL UN Equity	0	0	0
CLX UN Equity	0,019056458	0,015238	0,015578
CL UN Equity	0	0	0
CMA UN Equity	0	0	0
CAG UN Equity	0	0	0
ED UN Equity	0,001608996	0,000774	0,001722
SLG UN Equity	0	0	7,11E-10
CMI UN Equity	0	0	0
TGT UN Equity	0	0	0
D UN Equity	0	0	0
ETN UN Equity	0	0	0
ECL UN Equity	0	0	0
PKI UN Equity	0,00387681	0,002118	0,000743
EMR UN Equity	0	0	0
ETR UN Equity	0,002268441	0	0
FDX UN Equity	0	0	0
FMC UN Equity	0	0	0
F UN Equity	0	0	0
FCX UN Equity	0	0	0
GD UN Equity	0	0	0
GIS UN Equity	0	0	0
HAL UN Equity	0	0	0
PEAK UN Equity	0,022029583	0,018256	0,01923
HSY UN Equity	0	0	0
HRL UN Equity	0,033625645	0,033535	0,03248
HUM UN Equity	0	0,005857	0,009033
ITW UN Equity	0	0	0
IR UN Equity	0	0	0
IFF UN Equity	0	0	0
K UN Equity	0,018673644	0,008155	0,008649
KMB UN Equity	0,008782461	0,006252	0,006575
KIM UN Equity	0	0	0
KSS UN Equity	0	0	0
KR UN Equity	0	0	0,001899
LLY UN Equity	0,067293798	0,067852	0,069231
LNC UN Equity	0	0	0
LOW UN Equity	0	0	0
HST UN Equity	0	0	0
XRX UN Equity	0	0	0
SPGI UN Equity	0	0	0

MDT UN Equity	0,007839412	0,004429	0,006014
CVS UN Equity	0	0	0
MSI UN Equity	0,017311618	0,022043	0,022183
NEM UN Equity	0,034262894	0,024348	0,021366
NKE UN Equity	0	0,002529	0,002857
NI UN Equity	0	0,003285	0
NBL UN Equity	0	0	0
NSC UN Equity	0	0	0
ES UN Equity	0	0	0
NOC UN Equity	0	0	0
WFC UN Equity	0	3,58E-09	0
PVH UN Equity	0	0	0
OXY UN Equity	0	0	0
OMC UN Equity	0	0	0
PPL UN Equity	0,025628973	0,017663	0,001172
COP UN Equity	0	0	0
PNW UN Equity	0	0	0
PNC UN Equity	0	0	0
PPG UN Equity	0	0	0
PEG UN Equity	0,005417058	0,001731	0
RTN UN Equity	0	0	0
EIX UN Equity	0	0	0
SLB UN Equity	0	0	0
SHW UN Equity	0	0	0
SO UN Equity	0,004751036	0,002352	0
LUV UN Equity	1,69617E-09	0	2,84E-09
TXT UN Equity	0	0	0
TIF UN Equity	0	0	0
TJX UN Equity	0	0	0
JCI UN Equity	0	0	0
UNP UN Equity	0	0	0
MRO UN Equity	0	0	0
VFC UN Equity	0	0	0
VNO UN Equity	0	0	0
WY UN Equity	0	0	0
WHR UN Equity	0	0	0
WEC UN Equity	0	0	0
ADBE UW Equity	0,018751278	0,020235	0,020457
AES UN Equity	0	0	0
AMGN UW Equity	0,001525825	0,005628	0,008029
AAPL UW Equity	0	0	0
ADSK UW Equity	0	0	0
TAP UN Equity	0	0	0
MKC UN Equity	0,040396583	0,042297	0,041768
COST UW Equity	0,013883853	0,015474	0,016187

TSN UN Equity	0	0	0
AMAT UW Equity	0	0	0
CAH UN Equity	0	0	0
EXPD UW Equity	0	0	0
WELL UN Equity	0,021155521	0,021514	0,024386
BIIB UW Equity	0	0	0
NTRS UW Equity	0	0	0
QCOM UW Equity	0	0	0
SBUX UW Equity	0,022897084	0,029629	0,029179
KEY UN Equity	0	0	0
STT UN Equity	0	0	0
USB UN Equity	0	0	0
NLOK UW Equity	0	0	0
WM UN Equity	0	0	0
AGN UN Equity	0	0	0
ALK UN Equity	0	0	0
INTU UW Equity	0	0	0
MS UN Equity	0	0	0
MCHP UW Equity	0	0	0
CB UN Equity	0	0	0
ALL UN Equity	0	0	0
SPG UN Equity	0,019281492	0,020802	0,022502
EMN UN Equity	0	0	0
AVB UN Equity	0,020358977	0,018775	0,020673
PRU UN Equity	0	0	0
UPS UN Equity	0	0	8,59E-10
MCK UN Equity	0	0	0
LMT UN Equity	0	0	0
COF UN Equity	0	0	0
WAT UN Equity	0,006522785	0,001282	0,001292
HIG UN Equity	1,9606E-09	0	0
IRM UN Equity	0	0	0
EL UN Equity	0	0	0
ROK UN Equity	0	0	0
BXP UN Equity	0	0	0
ACN UN Equity	0	0	0
PLD UN Equity	0	0	0
AEE UN Equity	0	0,000604	0
NVDA UW Equity	0,020062972	0,030135	0,03262
CTSH UW Equity	0	0	0
RSG UN Equity	0,014100397	0,011095	0,005331
EBAY UW Equity	0,003043837	0,001718	0,001805
GS UN Equity	0	0	3,12E-09
SRE UN Equity	0	0	0

AKAM UW Equity	0	0	0
DVN UN Equity	0	0	0
GOOGL UW Equity	0,022475312	0,016855	0,016038
A UN Equity	0	0	0
DTE UN Equity	0	0	0
PM UN Equity	0	0	0
CRM UN Equity	0,000666162	0,006448	0,003589
MET UN Equity	0	0	0
EW UN Equity	0,028747774	0,036809	0,039399
CBRE UN Equity	0	0	0
LDOS UN Equity	0	0	0
TEL UN Equity	0	0	0
V UN Equity	0,018750386	0,028117	0,029934
RMD UN Equity	0,002495333	0,006648	0,006024
MTD UN Equity	0	0	0
ALB UN Equity	0	0	0
CHD UN Equity	0,0224303	0,02873	0,02978
MHK UN Equity	0	0	0
URI UN Equity	0	0	0
DAL UN Equity	0	0	0
LVS UN Equity	0	0	0