SCHOOL OF ECONOMICS AND MANAGEMENT

Environmental Impact and Stock Returns

Investigating the Risk-Adjusted Returns from Portfolios of More and Less Environmentally Sustainable Companies

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Abstract

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Keywords: Sustainability, ESG, Sharpe ratios, Portfolios, Stocks

Objective: The objective of this study is to examine whether more environmentally sustainable stocks exhibit higher risk-adjusted returns than less sustainable stocks.

Method: The question is examined through two-sided significance tests, comparing daily Sharpe ratios for pairwise portfolios consisting of the top and the bottom quantiles of companies as ranked by several sustainability metrics. These tests are performed both within sectors, and over all sectors, for 2110 global stocks in the years 2006 to 2019.

Results: The results show significant support of the more sustainable companies exhibiting higher risk-adjusted returns in many of the tests performed, especially in sectors with the largest environmental impact by the metrics used. On the other hand, there are some noteworthy differences between the companies that do report and the companies that do not report sustainability metrics.

Conclusions: While the results show support of the more sustainable companies outperforming the less sustainable, there are some limitations to the generalisation of the results.

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Glossary

Alpha (Carhart four-factor model): Represents the excess returns and is the intercept in the Carhart four-factor model.

CSR: Stands for Corporate Social Responsibility and is the way in which a company lives up to the expectations of, and responsibilities to, the economy, the environment, society, and stakeholders.

ESG: Stands for Environmental, Social and Corporate Governance and refers to the three main factors often discussed related to company sustainability and responsibility.

EU Taxonomy: A framework developed by EU to help investors and companies know how to act responsibly and how to determine who is acting responsibly.

Hard data: Verifiable facts from reliable sources, in contrast to soft data that is based on qualitative information, such as ratings or polls.

Market cap: The value of all shares of stock from a company.

Python: A high-level programming language used for many purposes, including data science and machine learning.

Risk-free rate: A theoretical rate of return, meant to represent the return an investor could expect from an investment bearing no risk for a specified period.

Scope 1 and 2 (emissions): The sum of all direct emissions from the activities of an organisation (scope 1) and all indirect emissions from electricity purchased by the organisation (scope 2). Excludes other indirect emissions from sources not controlled or owned by the organisation (scope 3).

SDG: Stands for Sustainable Development Goals and refers to the 17 goals set as a part of the 2030 Agenda for Sustainable Development.

Sharpe ratios: A commonly used metric of risk-adjusted returns, measuring the expected excess return of an asset in relation to its standard deviation.

SRI: Stands for Socially Responsible Investing and is a means of seeking financial returns while using the money to improve social and environmental factors.

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1 Introduction

The climate is changing, for Mother Nature as well as for the financial markets. The last five years, 2015 to 2019, hold the top five position of warmest years in the record of data since 1880, according to the US National Centers for Environmental Information, NOAA (2020). And with ten years to go before the intended achievement of the 2030 Agenda, including the 17 Sustainable Development Goals (SDGs), change is becoming more prominent in the financial and business arena. In March 2020, the EU Taxonomy was published as a tool and a set of recommendations that aims to help companies and investors to act responsibly, both in terms of increasing positive contributions and in terms of minimising harm done, socially as well as to the environment (EU TEG, 2020). With the Taxonomy follows some new regulations, among others requiring mutual funds that claims to be sustainable to prove this through explicit alignment to the Taxonomy (European Parliament, 2020).

While there may be many reasons to invest in sustainable companies going beyond the expectation of returns, such as trying to have a positive environmental impact, the question of returns is likely to have a large impact on investor decisions. Investors that place their trust in the Modern Portfolio Theory may hesitate to take sustainability factors into consideration, as this according to the theory would lead to worse performance due to less efficient diversification and a divergence from the efficient frontier (Markowitz, 1952). The question whether concern of sustainability in the portfolio selection results in lower returns has been investigated by many over the last few years, with various conclusions. Some, such as Kempf and Osthoff (2007) show that companies with higher sustainability rankings exhibit higher returns, while others, such as Halbritter and Dorfleitner (2015) show that these results heavily depend on the ranking agency, company sample and period of investigation. What these studies do have in common is that they base tests on rankings such as ESG-rates (Environmental, Social and Governance), which pose a great threat to the interpretation of the results. Many recent studies, such as Chatterji et al. (2016) and Berg, Koelbel and Rigobon (2020), show that the leading rating agencies diverge not only in their methods of rating companies, but more troublesome also in what their conclusions are about which companies are more and less sustainable. If not even the leading ESG-ranking agencies can agree on what constitutes a sustainable company, it is a staggering task for individual investors to understand how to invest in a sustainable manner.

Why would the more sustainable companies be better investments? Some argue that the risks stemming from climate changes are not fully priced in the markets, due to the myopic nature of investors. It could also be the case that investors place an intrinsic value on the sustainability of a company, leading to appreciation of the more sustainable ones. Since sustainable in many regards is related to resource efficiency, it could as well be the case that the more sustainable companies over time gain in competitive advantages against their less sustainable peers.

The purpose of this study is to investigate whether more environmentally sustainable companies are better investments, and to do this in a more robust way than what is done in previous research, which is based on ratings from agencies. Instead of using these ESG-ratings in this work, the definition of *sustainable* is based on hard data using several reported impact-metrics related to environmental sustainability. The sustainability is seen as a relative measure, which means that the most sustainable companies are those that have the lowest reported negative impact per sales and the least sustainable companies are those that have the highest reported negative impact per sales. In effort to answer the question whether sustainable companies are better investments, the risk-adjusted returns of pairwise portfolios are compared by their daily Sharpe ratios. The portfolios consist of top and bottom quantiles of companies ranked by each metric, both separately and in combination. For example, the top 25% of companies ranked by Greenhouse gas emissions per sales are compared to the bottom 25% of companies ranked this way. Since comparisons between companies in different sectors in some ways can be misleading, the focus is on tests performed within each sector, although tests are performed for all sectors jointly as well. The sample period is 2005 to 2019, and in total 2110 global companies from the index S&P Global 1200 are included in the test. All tests are done in Python through custom scripts, presented in Appendix 10.5.

This research is made in collaboration with Handelsbanken Asset Management, through continuous discussions with Simon Park, Sustainability Analyst, about the choice of topic based on previous research, about the scope of research, the methods, and the results. For Handelsbanken, the reason for this research is the relevance of the topic of impact investing, as well as the lack of previous research investigating returns from sustainable companies using hard data.

To the knowledge of the author and the contacts at Handelsbanken, no previous research has been done on whether more sustainable companies are better investments using hard data, although much research has been dedicated to investigating the question using ESG-ratings and the like. In addition to in some sense pioneering the field, the vast number of companies included in this study and the relatively long time series used, make this research a serious contribution to the present field.

The overall results of this study show support of the sustainable companies being better investments, although there are some constraints to the generalisation of these results.

The structure of the rest of this essay is as follows: Section 2 presents the basic theories that this study builds upon and that the results are tested against. Section 3 outlines the previous research in the field by a short literature study. Section 4 describes the data, what it consists of, how it is collected and how it is adjusted. Section 5 describes the methods used to test the hypothesis of the study, as well as the methods used to determine the scope of the results. Section 6 presents the result, which in Section 7 is discussed in relationship to the theories and previous research. Section 8 concludes the essay.

2 Theory

In this section, two major theories within financial economics are outlined, which in some sense pose contradicting views on what to expect of the results from this study. Thereafter, the theory behind the Sharpe ratio is presented together with formulas for how to calculate and compare this ratio.

2.1 Portfolio Theory

In Modern Portfolio Theory (MPT), introduced by Markowitz in 1952, an optimal portfolio can be obtained through calculations based on expected returns and the variance of returns, given that investors find expected returns desirable and variance undesirable. A main conclusion from this is the ability to reduce idiosyncratic risk through diversification between covaried assets (Markowitz, 1952). By reducing the investment universe based on factors other than the expected return, variance and covariance, investors are according to MPT not necessarily able to construct the most efficient portfolio and thus they lower their expected risk-adjusted returns.

2.2 Behavioural Economics

While standard economic theory relies on human behaviour governed by rational choice, behavioural economics focuses on the deviations from economic rationality and challenges the rational models with empirical evidence (eds. Zamir & Teichman, 2014). Baron (2014) describes the models of rationality as normative models, stating how to make optimal decisions under uncertainty, distinct from the descriptive models that explain how people actually make decisions and, in many ways, deviate from the optimum. This is deviation is explained through heuristics and biases, a heuristic being a rule of thumb, a simple and sometimes accurate way to efficiently approximate the optimal decision. The use of these heuristics leads to systematic biases where the approximations are faulty in a predictable way (Baron, 2014).

2.3 Sharpe Ratios

The Sharpe ratio is one of the most used metrics of risk-adjusted returns, measuring the expected excess return in relation to its standard deviation, using the standard deviation of excess returns as a proxy for risk (Sharpe, 1994). The expected excess return (d_i) is defined as the difference between the expected return (r_i) of the asset i, and the expected risk-free rate

(r_f). For this asset i, the ex-ante Sharpe ratio SR_i is the expected excess return d_i divided by the expected standard deviation (σ_{di}) of d_i (Sharpe, 1994).

$$d_i = r_i - r_f \tag{1}$$

$$SR_i = \frac{d_i}{\sigma_{di}} \tag{2}$$

The estimate of the ex-ante Sharpe ratio ($\widehat{SR}_i$) of asset i, is calculated using the sample average excess returns m_i as an estimate of d_i, and the standard deviation (s_i) of m_i as an estimate of σ_{di}.

$$\widehat{SR}_i = \frac{m_i}{s_i} \tag{3}$$

To perform significance tests of Sharpe ratios, Jobson and Korkie (1981) propose a test under the null hypothesis that the difference (SR_{ij}) between the Sharpe ratio of asset i (SR_i) and the Sharpe ratio of asset j (SR_j), is equal to zero. In a two-sided test, the alternative hypothesis is that the differences are not equal.

$$\begin{gathered} H_0 : SR_{ij} \equiv SR_i - SR_j = 0 \\ H_1 : SR_i \neq SR_j \end{gathered} \tag{4}$$

For statistical testing, this difference is transformed into, and estimated by:

$$\widehat{SR}_{ij} \equiv \widehat{SR}_i - \widehat{SR}_j = m_i s_j - m_j s_i \tag{5}$$

Where m_i and m_j is the estimate of the expected excess return for asset i and j, respectively, and s_i and s_j is the estimate of the expected standard deviation of m_i and m_j, respectively.

The asymptotic distribution of the transformed difference is normal with mean SR_{ij} and variance θ, and $\hat{\theta}$ is estimated as:

$$\hat{\theta} = \frac{1}{T}\left[2s_i^2 s_j^2 - s_i s_j s_{ij} + \frac{1}{2}m_i^2 s_j^2 + \frac{1}{2}m_j^2 s_i^2 - \frac{m_i m_j}{2s_i s_j}\left(s_{ij}^2 + s_i^2 s_j^2\right)\right] \tag{6}$$

Where T is the number of observations and s_{ij} is the covariance of m_i and m_j.
Due to the asymptotic normality, the test statistic is thus given as a z-test:

$$z_{SR_{ij}} = \frac{\widehat{SR}_{ij}}{\sqrt{\hat{\theta}}} \sim N(0, 1) \tag{7}$$

3 Previous Research

This section is divided into four parts. The first two parts present previous research on the topic of measuring sustainability and constitutes the foundation for metric-related choices in this essay, discussed further in Section 5.1. The third part presents some relevant findings in studies investigating the effect of sustainability-ratings on returns as well as on capital costs. The fourth part describes research in investor decisions that is of relevance in discussions about potential excess returns from investing in sustainable companies.

3.1 CISL & Sustainability Metrics

In the report “In Search of Impact”, the University of Cambridge Institute for Sustainability Leadership (CISL, 2019) presents a framework for describing and measuring the social and environmental impact of investments, both positive and negative. The report builds upon the previous work done by CISL, which has been publishing yearly reports on the subject discussing impact metrics based on the 17 SDGs, among other things (CISL, 2019). For six impact themes, (i) Resource Security, (ii) Healthy Ecosystems, (iii) Climate Stability, (iv) Basic Needs, (v) Wellbeing and (vi) Decent Work, CISL (2019) suggests an ideal way of measuring the impact of companies. The first three themes cover SDGs related to environmental sustainability and the last three cover SDGs related to social sustainability. Finding that the ideal measurements seldom are reported or in any other way available, CISL (2019) presents an alternative metric for each theme based on the currently available data. While these alternative metrics cannot capture the entire complexity of sustainability and which companies that have a positive impact on their surroundings, they allow for a rough estimate and for a quantitative comparison of companies. The three themes related to environmental sustainability are presented here in further detail.

3.1.1 Resource Security

The theme relates to the 12th SDG, “Responsible Consumption and Production”, and is meant to guide in assessing whether companies are using natural resources in a sustainable way (CISL, 2019). Linear production models are described as one example of unsustainable use of resources, with virgin materials used as an input for products that are consumed or used shortly to be dumped into the environment. The alternative is a circular and efficient use of resources, aimed to minimise waste and pollution, keeping products in use for as long as possible and giving natural systems time to regenerate (CISL, 2019).

As an ideal measure of this, CISL (2019) proposes a metric that considers among others: durability of products, usage of virgin materials adjusted for scarcity and disposed waste adjusted by toxicity. The closest alternative, with regards to alignment and data availability is a combination of two available metrics, (i) Total waste discarded by a company, both hazardous and non-hazardous, and (ii) Total waste recycled, both in units of thousands of metric tonnes (CISL, 2019). From these two, the suggested metric Net waste can be calculated as the difference between Total waste discarded and Total waste recycled.

3.1.2 Healthy Ecosystems

Based on the 14th and 15th SDG, "Life in Water" and "Life on Land", the theme aims to examine whether companies are acting in accordance to the preservation of sound landscapes and seas, for humans, animals and nature alike (CISL, 2019). Given the vast complexity of the relationship between economic activity and natural systems such as forests, oceans and the atmosphere, even the ideal metric is to be considered a simplified proxy. The proposed ideal metric is land degradation, which CISL states can be described as "a long-term loss of ecosystem function and productivity caused by disturbances from which the land cannot recover unaided" (CISL, 2019, page 31). Measuring this would take into account the status of land at a given location and the trend in degradation at that location. CISL (2019) concludes that little data of land degradation is available to investors, and suggests fresh water use as the best alternative, largely based on the great role fresh water plays in maintaining life and healthy ecosystems.

3.1.3 Climate Stability

The theme is based on the 9th and 13th SDG, "Industry, Innovation and Infrastructure" and "Climate Action", and the aim of the theme is to help determine whether companies are acting in accordance with Paris agreement, holding global temperature rise below 2°C above pre-industrial levels (CISL, 2019). The proposed ideal metric for this theme is a measurement that describes company alignment to future warming trajectories, and while CISL (2019) states that this is possible to apply today using the global carbon budget, the analysis is not provided. As an alternative and available metric, CISL (2019) suggests using the Total greenhouse gas emissions for Scope 1 and 2, in units of tonnes carbon dioxide equivalents.

3.2 Divergence in Ratings

Much of the previous research investigating whether sustainable companies are better investments rely on rankings and evaluations, such as ESG-rankings and CSR-scores (Corporate Social Responsibility), rather than hard data (see Section 3.3). This is problematic, since research shows that there is great divergence in the ratings between the different rating agencies, not only in the way they rate other companies, but also in what different agencies conclude about the same companies. In this section follows a presentation of said research, examining in which ways and how much the rating agencies disagree.

Semenova and Hassel (2015) investigate the convergent validity (agreement) of the environmental risk and environmental performance assessment conducted by three agencies, KLD (MSCI), Asset4 (Thomson Reuters) and GES (Global Engagement Services). The convergent validity is measured as pairwise correlations, with an emphasis on the separation of environmental performance and environmental risks as different theoretical constructs. Their conclusion is that, while there are common dimensions of the ratings with high agreement, the ratings does not converge on aggregate.

Chatterji et al. (2016) in many ways repeat the study of Semenova and Hassel (2015), but with a broader scope. For six rating agencies, KLD, Asset4, Innovest, DJSI (Dow Jones Sustainability Indices), FTSE4Good and Calvert, the convergent validity is tested by an estimation of pairwise correlations, first for the ratings as they are, and secondly after adjusting for explicit differences in what the rankings are attempting to measure. The rating agencies are said to follow similar processes, using both qualitative and quantitative data, and the comparison is made by analysing ratings from the period 2002-2010, with some variations for different raters (Chatterji et al. 2016). Their conclusion is that the overall convergent validity is low, with an average correlation of 0.3, and that the result does not change after adjusting for differences in measurement.

In an even more extensive study, Berg, Koelbel and Rigobon (2020) examine both the convergent validity and the different ways in which rating agencies diverge. Five rating agencies are used, KLD, Sustainalytics, Vigeo-Eiris, Asset4 and RobecoSAM. To analyse the convergent validity, Berg, Koelbel and Rigobon (2020) test not only the pairwise correlations, but also the heterogeneity at the firm level as well as common ranking in different quantiles. Their results are unanimous in that there is a high level of disagreement among the rating agencies, and in that there is heterogeneity, meaning that the agencies agree more on some firms and disagree more on others. No driver for this heterogeneity is found; the effect is present for firms of all different sectors and in all regions. From the quantile analysis, Berg, Koelbel and Rigobon (2020) find that the disagreement is higher near the top of the distribution of companies, that is, for the top-ranked companies. In their investigation of the ways in which rating agencies diverge, three divergences are outlined, divergence in (i) scope, which variables that are included in the ratings, (ii) measurement, how the variables are measured, and (iii) weights, how the variables are combined into a rating. To test these factors, Berg, Koelbel and Rigobon (2020) develop a bottom up taxonomy that unifies the different rating methods used in categories. An additional taxonomy, built top down from the Sustainability Accounting Standards Board (SASB) is used in comparison to test the robustness, showing little to no difference from the first results in any of the tests. In conclusion, the measurement divergence is the most contributing factor of rating divergence, meaning that the performance of a single company in a single category is measured differently by different rating agencies (Berg, Koelbel & Rigobon 2020). Second to most important is the divergence in scope, meaning differences in which categories that are being considered by the rating agencies. Divergence in weights is found to by the least important factor for the diverging ratings.

3.3 Sustainable Stocks

In this section, the results of a meta study is presented to show the overall state of the field, followed by some in-depth examples of how such studies are performed, with more detailed results.

In the meta study *From the Stockholder to the Stakeholder*, Clark, Feiner and Viehs (2015) review and summarise the literature on several large questions regarding sustainable finance. They show that 33 of 41 (80%) of reviewed studies conclude a positive relation between ESG-factors and stock prices, and that the more sustainable companies tend to outperform the less sustainable. Moreover, 45 of 51 (88%) of reviewed studies show that operational performance is positively correlated with ESG-factors and sustainability. This is further supported by the examination of nine previous meta studies, reaching the general conclusion of a positive relationship. Lastly, 26 of 29 (90%) of reviewed studies show that companies with high sustainability standards, measured by different ESG-factors, have lower costs of capital, considering both costs of debt and costs of equity (Clark, Feiner & Viehs 2015).

Although the meta study by Clark, Fiener and Viehs (2015) is extensive, so is the field. One of the studies not included in their review is that of Kempff and Osthoff (2007), that here serves as an example of research on the relationship between sustainability and stock prices. Kempf and Osthoff (2007) show that long-short portfolios created by screening, using SRI-ratings (Socially Responsible Investment) from KLD, delivers significantly higher returns for stocks included in S&P 500 and DS 400 in the years 1992 to 2004. The authors use the Carhart four-factor model (Carhart, 1997), testing value-weighted portfolios that are rebalanced yearly, for three different screening methods. The first screening method is positive screening, including the top 10% percent of companies as ranked by the several factors. The second screening method is negative screening, including bottom 10% rank of companies, and the third method is to include the “best-in-class” companies, those that rank best within their sector. The tests are performed for each factor (i) Community, (ii) Diversity, (iii) Employee Relations, (iv) Environment, (v) Human Rights and (vi) Product, as well as for two combinations of these factors. While the results show overall positive alphas for all tests (some significant), including tests for robustness using equally weighted portfolios and two sub periods of the data, the strongest results are for the combined ranks using the best-in-class screening. Note: alpha is the intercept in the four-factor model and is meant to represent the excess returns (Carhart, 1997).

The results presented by Kempf and Osthoff (2007) are replicated and supported by Statman and Glushkov (2009), extending the period to 1992-2007. While showing that the companies with higher ratings yield higher returns, Stutman and Glushkov (2009) also find that excluding so-called “sin-stocks”, companies associated with tobacco, alcohol, gambling, and weaponry, have a negative effect of returns. This strengthens the support of the best-in-class approach, not excluding any industries, although the authors raise the question whether such portfolios are to be considered “doing good” (Statman & Glushkov, 2009).

In contrast to the studies presented above, Halbritter and Dorfleitner (2015) show that the relationship between ESG ratings and future returns is not all that clear. By using ESG scores from Asset4, Bloomberg and KLD for the years 1991-2012, testing both an ESG portfolio approach in the spirit of Kempf and Osthoff (2007), as well as cross-sectional regressions, the authors find significant influence of ESG-variables on returns, but also that the results are highly dependent on the rating agency, company sample and subperiod. In their study, the portfolio approach is based on positive and negative screening, using the top and bottom 20% of companies. For robustness regarding the selection, cut-offs at 1, 5, 10, 25 and 50% are also tested, both value-weighted and equally weighted. The best-in-class selection method is also included, but as a means of further testing the robustness rather than as a main method of analysis. Testing available stocks from each rating provider, they find that portfolios based on the score from Asset4 exhibit positive four-factor alphas but are not significant. For the Bloomberg ESG-data, there are some positive significant results and some negative significant, but most insignificant. The same holds true for the portfolios based on KLD ratings. Restricting the investment universe to the stocks that are common for all rating agencies, does not change the results from Bloomberg or Asset4, but changes the KLD-portfolios to exhibit negative alphas. In the robustness tests, most results are insignificant with just a few exceptions, not forming any noticeable pattern (Halbritter & Dorfleitner, 2015). A pattern that do show, is the decline in alphas over time. Dividing the data into subperiods, 1991-2001, 2002-2006 and 2007-2012, show that the alphas for many portfolios based on all three ratings were positive in the first period, most insignificant in the middle period, and negative in the last period, some significant.

On the topic of operational performance, Guenster et al. (2011) examine the effect of eco-efficiency scores, derived by the rating agency Innovest Strategic Value Advisors. Through cross-sectional regressions on US companies between 1997 to 2004, the eco-efficiency scores, as well as dummies for low and high eco-efficiency, are used to explain operational performance and market valuation. The companies’ return on assets is used a proxy for operational performance, and Tobin’s q as a proxy for valuation. Note: return on assets (ROA) is the net income of a company, divided by total assets. Tobin’s q is ratio between the market value of a company and the replacement cost of total assets (Tobin and Brainard, 1977), and is meant to reflect the intangible value of a company. Guenster et al. (2011) show that the eco-efficiency is significantly and positively correlated with both operating performance and valuation.

Investigating the relationship between cost of capital and ESG-factors, Bauer and Hann (2010) show that companies associated with environmental concerns have significantly increased costs of debt financing and lower credit ratings, using pooled regressions for KLD-data on environmental performance for 582 US firms between 1995 and 2006. In contrast, the companies rated as having proactive environmental engagement have significantly reduced costs of dept, and higher credit ratings. These results are in large supported by Chava (2014), also using KLD-data, showing that companies with environmental concerns have significantly higher bank loan spreads, analysing 5 879 bank loans to nonfinancial US firms between 1992 and 2007.

3.4 Investor Decisions

Choosing what to invest in is a complex process if one does not follow theories such as the mean-variance framework suggested by Modern Portfolio Theory (see Section 2.1). Through the lens of Behavioural economics (see Section 2.2), one would expect investors to follow heuristics in their decision making – rather than solving the multidimensional optimisation necessary to assess what is the correct choice. This could potentially lead to systematic biases in portfolio selection, and for large systematic biases affect the market price and returns of certain stocks. Although there are some obstacles in the way of measuring what investor decisions are based on, such as the risk of investors not knowing it themselves even though they think they do, some studies investigate this through surveys. This section presents two such studies on investor decisions, as well as a report from the asset management BlackRock, discussing its view on the market's assessment of risks related to climate change.

Through a survey of 3 382 investors investing in SRI mutual funds, and 35 000 investors investing only in conventional funds, Riedl and Smeets (2017) show that the most important factors of the decision between SRI funds and conventional, is social preferences and social signalling. In addition, they show that the investors choosing SRI fund do so even though they expect to earn lower returns and pay higher management fees for these funds. The individual investor data comes from one of the largest mutual fund providers in the Netherlands and includes data in the period 2006 to 2012. For the survey, all 3382 investors that during the period held at least one SRI mutual fund were invited to participate, as well as 35 000 randomly selected investors from the remainder of the database. Riedl and Smeets (2017) also concludes that despite the lower expected returns, SRI investing likely is not a substitute for charity, since the SRI investors reportedly donate about 41% more to charity.

Krueger, Sautner and Starks (2020) examines institutional investor beliefs abouts and assessments of climate risks, through a survey with 439 respondents, one third of which hold executive positions in their institutions. Overall, they show that institutional investors believe that climate risks have financial implications for their portfolio firms, that the materialisation of the risks already has begun and that the current market valuations do not reflect risks posed by climate change. Although most respondents believe that the climate and environmental risks have an impact, they rank the importance of these risks lower than traditional financial risks. Krueger, Sautner and Starks (2020) reports that no single motivation outweighs the others for incorporation of climate risks in decision-making but notes that motivations ranked most important is agreement with regulations, moral considerations, and reputational concerns. Almost all respondents state that they have been trying to manage their climate risks in the five years before the survey. 38% have done this through the analysis of carbon footprints, and 29% have tried to reduce this footprint. 35% have done this through the assessing the risk of stranded assets, and 23% have tried to reduce this risk. While 84% of all respondents state that they have taken engagement actions in their portfolio firms, only 17% state that have divested the firms when they were dissatisfied with the firms responses to their engagement (Krueger, Sautner & Starks, 2020).

The research on risks and opportunities in sustainable finance does not come solely from academia, many of the large asset managers worldwide have their own research teams. BlackRock is one of the largest asset management firms worldwide, with $6.47 trillion assets under management as of March 31, 2020 (BlackRock, n.d.). In their report “Adapting Portfolios to Climate Change”, BlackRock (2016) state that they think climate factors and risks have been under-appreciated by the markets, and thus also under-priced. They describe four climate-risks as central for the investment world in the years to come: (i) physical risks from increased climate variability and extreme weather events, (ii) technological risks from advances in energy efficiency and energy storage, rendering some existing business models obsolete, (iii) regulatory risks from changing standards, restrictions and taxes, and (iv) social risks from changing preferences for stakeholders. BlackRock (2016) argues that these risks may be under-appreciated due to myopia of market participants, focusing on the risks that are visible and related to the near future, in contrast to climate change that is less visible and in many eyes perceived as distant.

4 Data

The selection of stocks included in this research are all the unique stocks that has been included in the S&P Global 1200 index the last of December any of the years between and including 2005 and 2019. The data on index constituents was received from Simon Park at Handelsbanken (mail correspondence, 26th of January 2020). The starting year of 2005 is chosen out of consideration of the share of companies that report the relevant sustainability metrics. All selected companies are used in the entirety of the period between 2005 and mid 2019 of which there is available data, including the dates for which the companies no longer are or not yet have been a part of the S&P Global 1200 index. This amounts to a total 2110 unique stocks, of which around 1600 to 1800 stocks are listed each year and thus included in the tests for that year (see Table 1, Section 4.1). The 2018 total market cap for unique companies in this study sums up to 44.14 trillion dollars, which constitutes 64.3% of the 68.65 trillion dollars that was the total market cap of listed companies worldwide at the end of 2018 (Worldbank, n.d.).

For each company the following data is downloaded from Bloomberg: (i) daily closing prices, (ii) yearly market cap in USD, (iii) yearly sales in USD, (iv) yearly Greenhouse gas emissions, (v) yearly Total waste, (vi) yearly Waste recycled, (vii) yearly Water use, (viii) country and (ix) sector. All data is reported data, in contrast to many other sources of sustainability data including estimations of values such as yearly Greenhouse gas emissions. See Appendix 10.1.1 for a detailed description of the variables and their associated Bloomberg field.

In addition to company specific data, US 1-year Treasury yield rate is downloaded from US Department of Treasury (US Treasury, n.d. A). The rate is used as the risk-free rate in calculation of daily Sharpe ratios, which is described in Section 5. The yields on the 1-year Treasury is based on actual day counts, and the rate is thus divided by 365 or 366 for the daily yield (US Treasury, n.d. B).

4.1 Descriptive Data

The total number of daily price observations is 5.8 million, as can be seen in Table 1, together with the number of daily price observations for each year. For the first year, 2006, only observations in July through December are included, and for the last year, 2019, only observations in January through June are included. The reason for this is explained in further detail in Section 5.3 and Section 5.4. Table 1 also shows the number of companies per sector and year, as well as the total number of companies each year, and the average number of companies in each respective sector for all years. The number of companies per country and year is shown in Appendix 10.1.2.

TABLE 1 – NUMBER OF OBSERVATIONS PER YEAR

		COMPANIES PER SECTOR										
YEAR	TOTAL DAILY PRICE DATA	BASIC MATERIALS	COMMUNICATIONS	CONSUMER, CYCLICAL	CONSUMER, NON-CYCLICAL	DIVERSIFIED	ENERGY	FINANCIAL	INDUSTRIAL	TECHNOLOGY	UTILITIES	TOTAL COMPANIES
2006	234,600	154	147	249	318	7	107	335	247	149	93	1806
2007	468,039	151	143	251	315	7	109	339	247	151	92	1805
2008	463,176	145	139	251	307	7	111	334	243	152	88	1777
2009	455,541	143	141	248	303	7	111	323	238	151	91	1756
2010	452,556	139	137	248	304	6	110	317	237	153	90	1741
2011	450,286	140	138	251	304	6	108	318	234	149	89	1737
2012	450,009	141	139	251	302	6	109	315	237	145	87	1732
2013	446,554	140	134	250	304	6	109	314	234	143	83	1717
2014	443,361	135	130	251	302	6	108	315	233	137	84	1701
2015	441,316	135	134	247	299	6	108	319	234	134	84	1700
2016	433,036	136	132	240	291	5	107	316	233	136	83	1679
2017	423,343	134	127	239	288	5	101	312	229	126	81	1642
2018	423,457	130	126	235	282	5	97	310	228	123	82	1618
2019	199,234	125	127	238	281	5	93	307	230	125	82	1613
Total	5,784,508											
Average per year		139	135	246	300	6	106	320	236	141	86	1716

The table shows the number of daily price observations per year, as well as the number of companies per year, in total and in each sector.

4.2 Adjustments

The price data is manually checked and corrected for errors, by method of looking for three types of abnormal price changes: (i) large single day jumps, (ii) large single day drops and (iii) long stationary periods. Through this method of investigation, all stocks are checked that have at least one single day price increase of more than 100%. In addition, the 30 stocks with the largest single day price decreases and the 30 stocks with the most 0% daily changes are checked. Out of these, 32 adjustments are made by removal of the presumed erroneous period. In almost all these cases, the abnormal single day movements are caused by presumed erroneous data showing no change in price for a long period, followed by a jump or drop back to regular price movements. The data is presumed to be erroneous if the price is unchanged for a consistent period of more than six months, indicating that the data is in fact missing, and that the price shown for each day is the last available price. In each case of presumed erroneous data, the price data is removed from the affected portfolio year, July through June. For all adjustments made, see Appendix 10.1.3.

5 Method

This section is divided into three parts. Part one describes the choice of metrics and the calculation of new data from the downloaded data. Part two describes the method used for determining whether the companies that report the sustainability related metrics are representative of the entire group of companies, which is done both through aggregations of data and through portfolio tests. Part three describes the method used for testing whether investing in the more sustainable companies would have resulted in higher risk adjusted returns.

All data analysis in this research is done through custom scripts in Python, built from scratch for the purpose of this study. The code is presented in Appendix 10.5.

5.1 Metrics

The metrics used in this research to compare companies in terms of sustainability are based on the available metrics suggested by CISL (see Section 3.1) for the environmental themes: (i) Resource Security, (ii) Healthy Ecosystems and (iii) Climate Stability. This choice is made with consideration to the extensive research by CISL into the subject of measuring sustainability, and with consideration to the ability of quantitatively comparing companies in terms of sustainability. The choice of metrics related to each theme is as follows. With regards to the first themes, Resource Security, all three of the metrics suggested by CISL are used. Total waste and Net waste are used separately to rank companies in the portfolio tests, and Waste recycled is used in combination with Total waste in the calculation of Combined rank which is described in further detail later in this section. With regards to the second theme, Healthy Ecosystems, CISL (2019) suggests the use of data on fresh water use. In this research however, the amount of available data for fresh water use is considered insufficient, and the related metric used is instead the Total water used to support operational processes, in the unit of thousands of cubic metres. The criteria for determining whether a metric is reported in sufficient share to be deemed usable in the CISL report is that a metric is to be reported by at least 10% of the companies in MSCI World index (CISL, 2019). Three fresh water-related metrics pass that level, (i) Surface water withdrawal with 10.6% coverage, (ii) Municipal water use with 19.8% coverage and (iii) Groundwater withdrawal with 14.9% coverage. In contrast, Total water use has 42.1% coverage in MSCI World Index. While the first three metrics better reflect the theme, the coverage is much lower than that of the other

metrics used in this research, which is why the choice is made in favour of data quantity, potentially sacrificing some quality. With regards to the third theme, Climate Stability, the suggested metric of Total greenhouse gas emissions for scope 1 and 2 is used as it is.
For all companies, all of the five sustainability related metrics (i) Greenhouse gas emissions, (ii) Total waste, (iii) Waste recycled, (iv) Net waste and (v) Water use, are divided by sales to get the metrics used in the portfolio tests, (i) Greenhouse gas emissions/sales, (ii) Total waste/sales, (iii) Waste recycled/sales, (iv) Net waste/sales and (v) Water use/sales. Where data is missing for either the sustainability metric or for sales, the corresponding derived metric/sales is given no value. The sustainability metrics are all divided by sales for reasons of comparability, allowing for better comparisons between companies of different size in terms of revenue.

The Combined ranking is calculated by summation of the ranks within each metric Greenhouse gas emissions/sales, Total waste/sales, Waste recycled/sales and Water use/sales. Companies are ranked in ascending order for all metrics but Waste recycled/sales which is ranked in in descending order, and in the summation Total waste/sales and Waste recycled/sales contribute with only half the weight of the other metrics, so that the combined rank is equally weighted for the three types of metrics. The Combined ranking-metric is included as a way of capturing the joint impact for all the separate metrics.

In the main portfolio tests, the metrics used are always divided by sales, but for readability the metrics often referred to as the original metric, for example “Greenhouse gas emissions”.

5.2 Representability

5.2.1 Data Availability

As a first step to analyse representability, the share of companies that report each of the sustainability metrics is investigated for all metrics and all years 2005 to 2018. This analysis is made once for all companies and repeated for subsections of the data using various means of aggregation. The share of companies that report (i) Greenhouse gas emissions, (ii) Total waste, (iii) Net waste, (iv) Water use is analysed in relation to company size (market cap), sector, and country of domicile. These results are presented in Section 6.1.1.

5.2.2 Portfolio Test

To further investigate if there is any relevant difference between the companies that do and do not report each individual sustainability metric, a portfolio test is performed in a manner similar to the main tests of this research, and all the choices related to this method is described in further detail in Section 5.3 and Section 5.4. In this approach, an equally weighted portfolio of all stocks that have reported a given metric is compared to an equally weighted portfolio of all stocks that have not reported this metric. The portfolios are created and rebalanced the first day of July, using the reported data of the previous year. For example, this means that in the test between companies that do and do not report Greenhouse gas data, two portfolios are created the first day of July 2006. The first portfolio consists of the listed stocks that reported Greenhouse gas data for 2005, and the second portfolio consists of the listed stocks that did not report Greenhouse gas data for 2005. A company is in this instance considered listed if there is a closing price available for the date in question. The two portfolios are held for one year, until the last day of June 2007. The first day of July 2007 the two portfolios are rebalanced in the same way as they are created, by including and equally weighting all listed companies that did and did not report Greenhouse gas data for 2006. This process is repeated for all available data, which means that portfolios are rebalanced the last time the first day in July 2018, using the reported data from 2017, and the portfolios are closed the last day of June 2019. Through each rebalance, the end value of each portfolio is kept as the starting value of portfolio the following year.

For all of these portfolios, computed from mid-2006 to mid-2019, the daily Sharpe ratio (see Section 2.3) is calculated and through a two-sided z-test the Sharpe ratios of each pair of portfolios is compared under the null hypothesis that the daily Sharpe ratios are equal (see Section 2.3). A rejection of the null thus means that there is a significant difference in risk adjusted returns between the companies that have reported and those that have not reported the given metric. The results for these tests are presented in Section 6.1.2.

5.2.3 Sector Impact

To analyse which sectors that have the largest impact on the environment, the reported 2018 data is investigated in further detail. For each of the four metrics, (i) Greenhouse gas/sales, (ii) Total waste/sales, (iii) Net waste/sales and (iv) Water use/sales, the companies are ranked and grouped by deciles, and the sector representation in each decile is plotted (Section 6.1.3).

5.3 Main Portfolio Tests

The main question investigated in this research is whether sustainable stocks are better investments, and this is tested through a series of pairwise portfolio comparisons. As described in Section 5.2.2, in each test two portfolios are created and rebalanced the first day of July in the years 2006 to 2018, using the reported data of the previous year. For each pair of portfolios, the daily Sharpe ratios are compared in a two-sided z-test, testing the null hypothesis that the daily Sharpe ratios are equal (see Section 2.3). The main reported value in each test is the *P*-value. In contrast to the tests described in Section 5.2.2, the differentiating factor in the main tests is how the companies are ranked by the sustainability metrics. In each test, the portfolios consist of the top and bottom 10%, 25% or 50% respectively; for example, the portfolio consisting of the top 10% companies is compared to the portfolio consisting of the bottom 10% of companies. These tests are performed using the following five ranking metrics (i) Greenhouse gas emissions/sales, (ii) Total waste/sales, (iii) Net waste/sales, (iv) Water use/sales and (v) Combined rank. For each of these metrics, tests are performed both sector-dependent and over all sectors. A minimum required amount of companies for a portfolio is set to 10 companies, and this is controlled for during creation/rebalance. If the number of companies in a portfolio during a year is less than 10, no results are used for that year and the portfolio keeps the end value of the previous year if any. The breakpoint of 10 companies is chosen for there to be sufficient diversification of idiosyncratic risk within each portfolio. Although there is no mathematical reasoning behind the number 10, it is commonly regarded as sufficient.

5.4 Method Discussion

When conducting a historical analysis of portfolios based on accounting variables, such as reported sustainability metrics, it is of high relevance for the applicability of the results that the accounting variables are known before they are used. It is to account for this, that the portfolios that are created and rebalanced in July year *t* are using the fiscal year-end data for calendar year *t-1*. This creates a minimum 6-months gap between the fiscal year-end and the use of the data, in the spirit of Fama and French (1992).

Even though much of the previous research in returns from more sustainable companies investigate this question using regressions like the Carhart four-factor model (Kempf & Osthoff, 2007; Statman & Glushkov, 2009; Halbritter & Dorfleitner, 2015), in this research, the use of Sharpe ratios is preferred to the use of regressions for two reasons. The first reason in favour of Sharpe ratios is that it is arguably more widely used and understood by asset managers, which thus makes the results of this research is more easily applied in practise for those within the industry. The second reason is that, although there are many problems with the use of Sharpe ratios (see Section 7), the use of regression models add a layer of complexity that on one hand may solve some of the problems faced by Sharpe ratios, but on the other hand arguably makes some problems worse. A detailed comparison between these two methods is merited and a subject for further research, but beyond the scope of this essay.

The different testing methods, testing within sectors or over all sectors, and using 10%, 25% or 50% of the companies, each serve a different purpose as parts of the broad question investigated in this study. Testing within sectors compares companies that face similar opportunities and challenges, and thus in many aspects are more comparable. Results in these tests are of interest for, among others, institutional investors that by policy or choice spread their funds over all sectors. While tests performed over all sectors in some regards are comparing apples and oranges, the results could be of interest for investors that want to minimise their environmental impact from investing even if it means excluding some sectors entirely.

In testing whether there is a difference in returns from investing in more and less sustainable companies respectively, there is a trade-off to be made between the amount of companies included and the dissimilarities in sustainability related metrics. Comparing the top and bottom 10% of companies ranked by a specific metric excludes a large share of the available data but could potentially show stronger results due to the relatively high dissimilarity in the metric investigated. It is by no means obvious that a relationship between returns and sustainability, if there is any, should be linear in the sense that the difference is most visible at the end points and least visible in the middle; but since this in many aspects is a pioneering study in the field, such a linear relation is implicitly assumed due to its simplicity, and further studies of higher order effects and non-linearities can build on these results.

Based on this reasoning, the greatest emphasis in this thesis is placed on the tests comparing the top and bottom 10% and 25% of companies, as long as the number of companies and years of data allow for a valid statistical analysis. In the sector-dependent tests, the amount of companies is too low for the use of top-bottom 10%-tests, which is why 25% is used as the primary test. For those tests where 25%-portfolios contains less than 10 companies for all years, and thus no results can be obtained, the corresponding 50%-test is used instead. In these instances, the change is made visible and noted in the text. Since the tests over all sectors allow for 10%-tests, these are the main tests in this category, and the 25%-tests are considered as tests for robustness.

Given the multitude of tests performed, considering the sector-dependencies and different ranking metrics, a few sectors are highlighted. These are the sectors with the highest environmental impact, and the test to determine these sectors is described in Section 5.2.3. The sector Diversified is excluded in the sector-dependent tests, since no tests within the sector are available due to the low number of companies (see Table 1, Section 4.1).

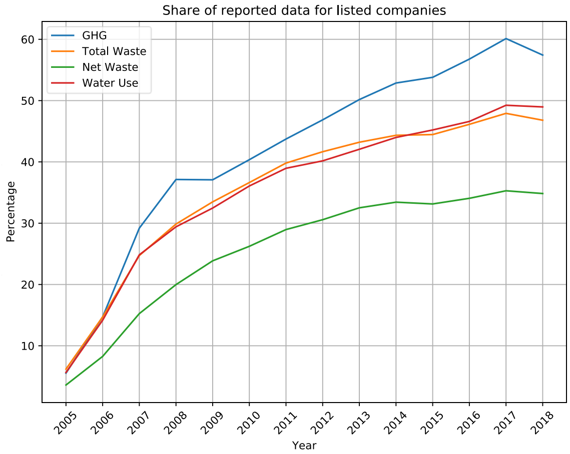
6 Results

This section is divided into two parts. Part one describes the result of the representability tests, and part two presents the results of the portfolio tests, the main results of this study.

6.1 Representability

6.1.1 Data Availability

As can be seen in Figure 2, each of the four metrics is reported by around 3-6% of companies in the beginning of the sample, and by around 35-60% of companies at the end of the sample. Overall, there is a yearly increase in the amount of companies reporting each metric, even though the pace shows a decline. This is more easily seen in Figure 1, showing the same results as Figure 2 but in a different form. There are clear differences in the share of companies reporting each metrics, Net waste being reported in the lowest share throughout the period, and Greenhouse gas emissions being reported in the greatest share throughout the period. Two notes are in place concerning these two figures. First, the share of companies reporting Net waste is the share of companies that report both Total waste and Waste recycled. Secondly, the data for 2018 may at the time of collection not yet have been reported, or not yet compiled by Bloomberg, giving the false appearance of a decreasing share of reporting companies.



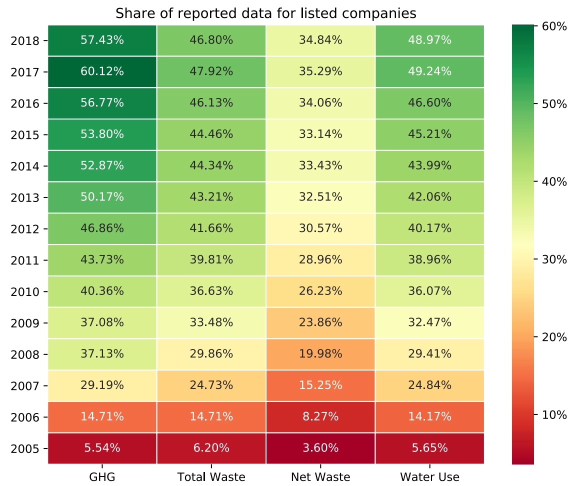


Figure 1 (to the left) and Figure 2 (to the right), both show the share of listed companies reporting each of the four metrics Greenhouse gas emissions (GHG), Total waste, Net waste, and Water use. Figure 1 shows the declining rate at which the share of reporting companies grows, and Figure 2 makes the relative differences year by year more apparent by presenting the values in a heatmap. The values in Figure 2 are coloured from dark red to dark green, following the colour bar presented in the right of the figure.

There is a trend of larger companies reporting in greater share than smaller companies, most visible for the share of companies that report Greenhouse gas emissions, shown in Figure 3, although the result holds for the other metrics as well (see Appendix 10.2). In the figure, the y-axis shows the yearly deciles of market cap, ranging from the smallest 10% of companies at the bottom to the largest 10% of companies at the top. The smallest companies in the first years of the data report sustainability metrics in the smallest share, and the largest companies in the most recent years report in the greatest share.

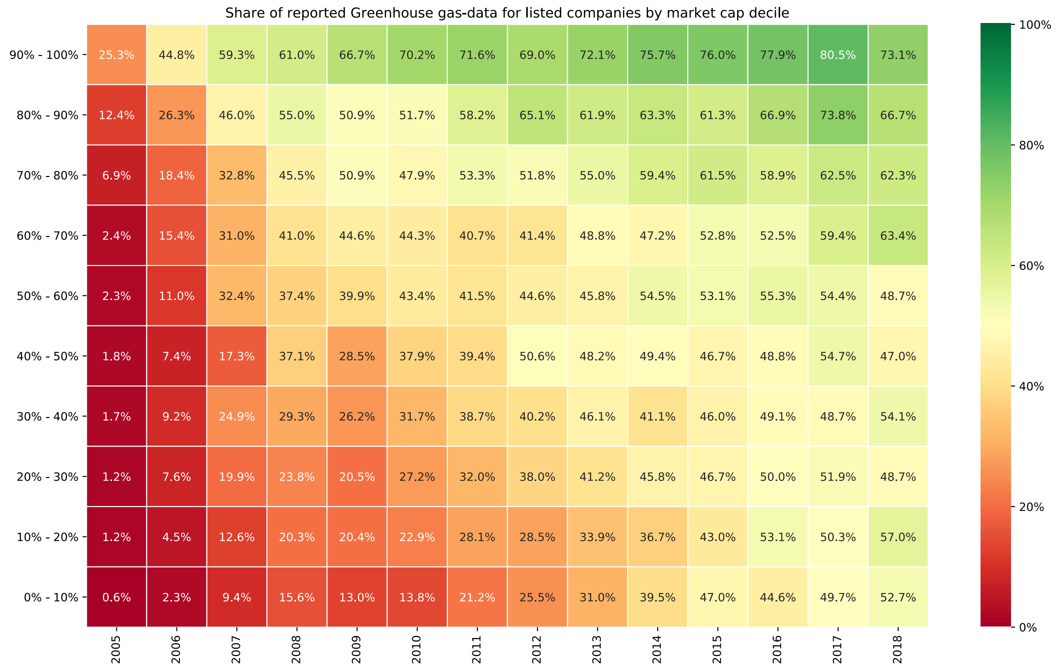


Figure 3, the figure shows the share of companies that report Greenhouse gas emissions for each year, grouped into market cap deciles with the 10% smallest companies at the bottom and the 10% largest companies at the top. The values are coloured from dark red to dark green, following the colour bar presented in the right of the figure.

There are clear differences in the share of reporting companies in different sectors, with companies within Basic Materials and Utilities generally reporting in the greatest share. This is shown for companies reporting Greenhouse gas emissions in Figure 4 (next page), but the trend holds for the other metrics as well (see Appendix 10.2). In the figures showing the share of reporting companies by sectors, the y-axis is sorted in descending order by the average number of companies in the sector (see Table 1, Section 4.1). This means that the sectors with the highest average number of companies are at the top, and the sectors with the lowest average number of companies are at the bottom. The size of the sector in the dataset does not seem to have a consistent relation to the share of reporting companies in the sector.

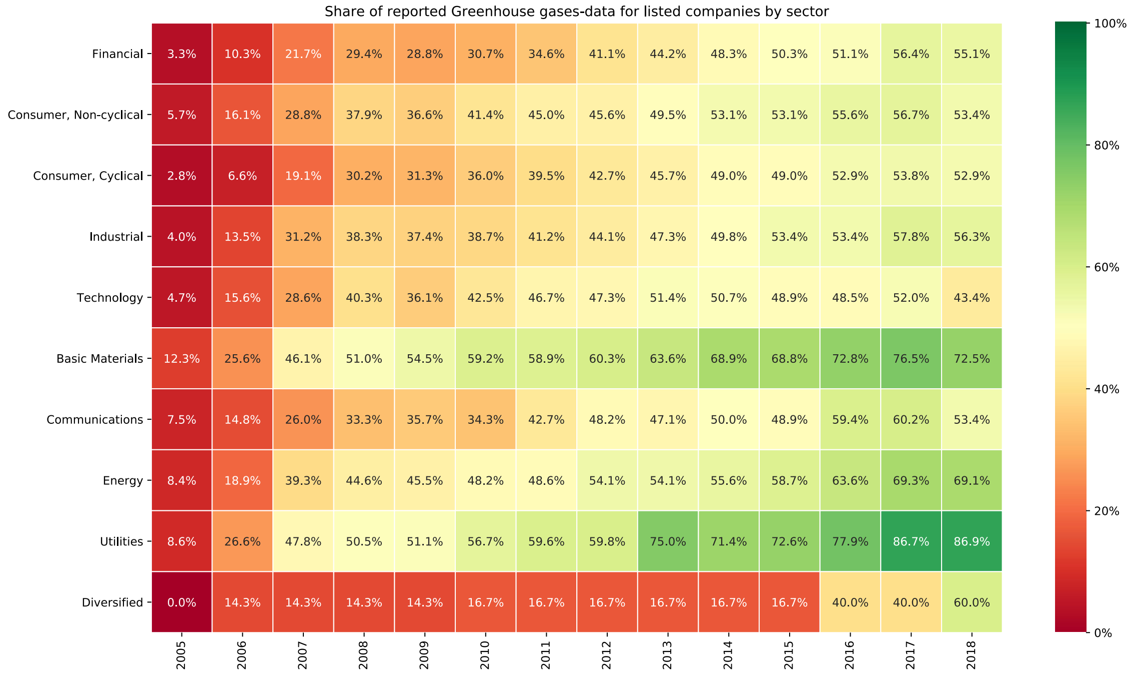
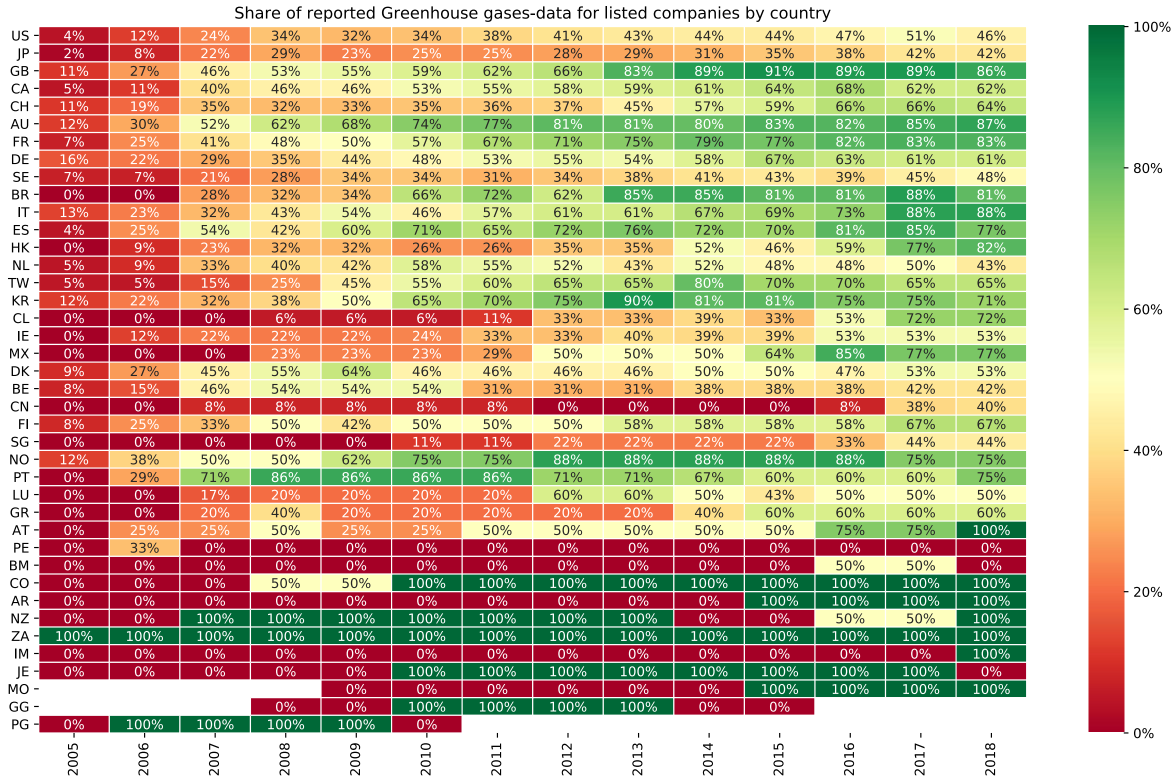


Figure 4, the figure shows the share of companies that report Greenhouse gas emissions for each year, grouped by sectors, with the largest sectors (in terms of companies in the data) at the top, and the smallest sectors at the bottom. The values are coloured from dark red to dark green, following the colour bar presented in the right of the figure.

Aggregating companies by country shows that there are a lot of differences between and within countries, regarding the share of reporting companies (see Figures 5 and 6 on the next page). As can be expected, some metrics are reported in larger share in some countries and lesser in others, for example 42% of Japanese (JP) companies report Greenhouse gas emissions for 2017, compared to 89% of British (GB) companies (see Figure 5). Considering Total waste, the relationship between the reported share is reversed for the two countries, with 72% of Japanese and 44% of British companies reporting in 2017 (see Figure 6). In the figures showing the share of reporting companies grouped by countries, the countries on the y-axis is sorted in descending order by the average number of companies in the sector, the data for which is available in Table A1, Appendix 10.1.1. This means that the countries with the highest average number of companies in this sample are at the top of the figures, and that the countries with the lowest average number of companies are at the bottom. As can be seen in Figure 5 and 6, the share of US companies reporting Greenhouse gas emissions and Total waste is relatively low in comparison to many of the other countries with large financial markets, such as Australia (AU), France (FR) and Germany (DE). These results hold for the other metrics as well, although there are considerable variations in the share of reporting companies within and between countries.



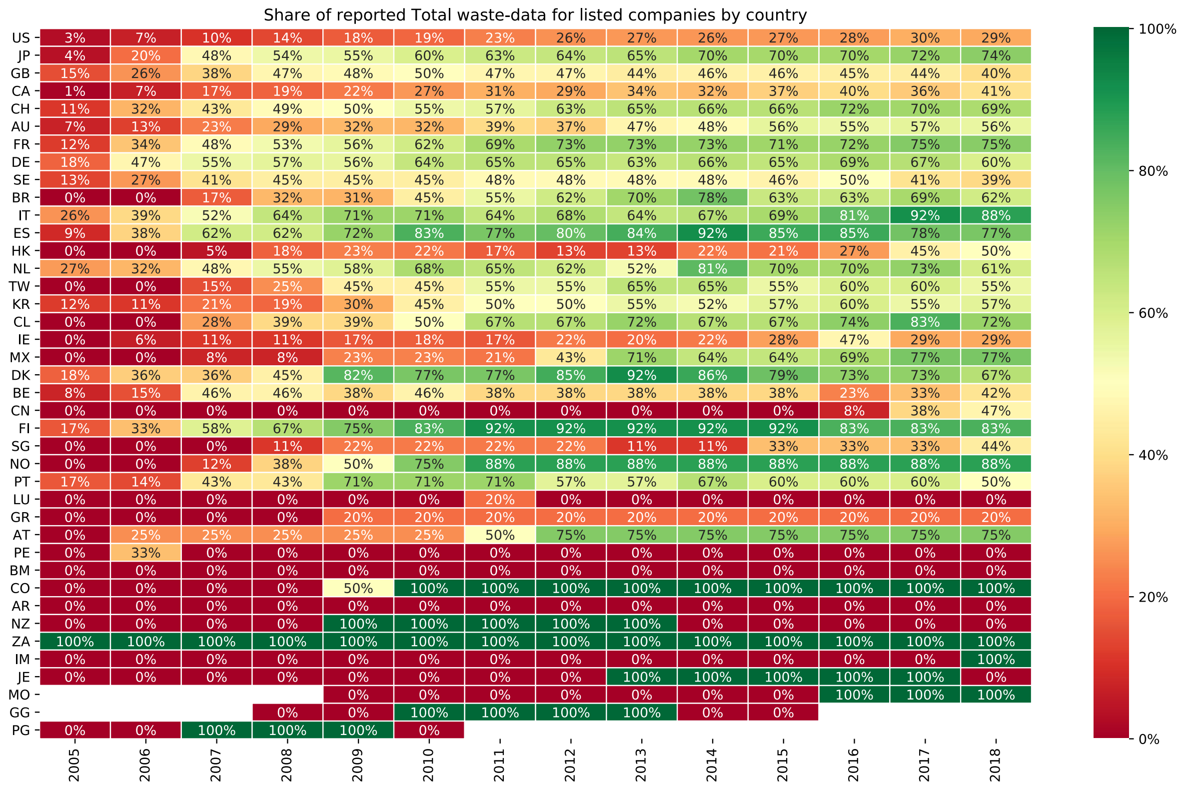


Figure 5 (at the top) and 6 (at the bottom), the figures show the share of reporting companies for each year, grouped by countries, with the largest countries (in terms of companies in the data) at the top, and the smallest countries at the bottom. Figure 5 shows the share of companies reporting Greenhouse gas emissions, and Figure 6 shows the share of companies reporting Total waste. Countries are denoted by their ISO-code. The values are coloured from dark red to dark green, following the colour bar presented in the right of the figure.

6.1.2 Portfolio Test

Table 2 shows the results from the portfolio tests of representability, where the risk adjusted returns of companies that do and do not report specific metrics are compared. These tests show that there is a difference in daily Sharpe ratios between the companies that do and do not report Greenhouse gas emissions; with a *P*-value of 0.014 the difference is significant at the 5%-level. For the companies that do and do not report water use, there is a large but not significant difference in daily Sharpe ratios (*P* = 0.16). The tests for total and net waste show no significant differences. As can be seen in Figure 7, the portfolio of companies that do not report Greenhouse gas emission exhibit consistent outperformance of the portfolio of companies that do report Greenhouse gas emissions, since around 2010. This suggests that the difference in risk-adjusted returns does not come solely from a single event or from a single short period of time.

TABLE 2 – PORTFOLIO TEST, REPORTED AND NOT

METRIC	PORTFOLIO	TOTAL GAIN	DAILY SHARPE	THETA	Z-STATISTIC	P-VALUE
GREENHOUSE GAS EMISSIONS	Reported	105.5%	0.02389	1.40E-13	-2.4650	0.014**
	Not	192.3%	0.03404			
TOTAL WASTE	Reported	113.5%	0.02566	4.63E-13	-0.7810	0.44
	Not	174.8%	0.03156			
NET WASTE	Reported	119.5%	0.02654	3.85E-13	-0.6120	0.54
	Not	164.4%	0.03083			
WATER USE	Reported	94.4%	0.02240	4.68E-13	-1.4014	0.16
	Not	186.9%	0.03294			

****: P < 0.01, **: P < 0.05, *: P < 0.10. The table shows the results from the portfolio tests described in Section 5.2.2, comparing the Sharpe ratios of the portfolio of companies that do and that do not report each metric, labelled "Reported" and "Not", respectively.*

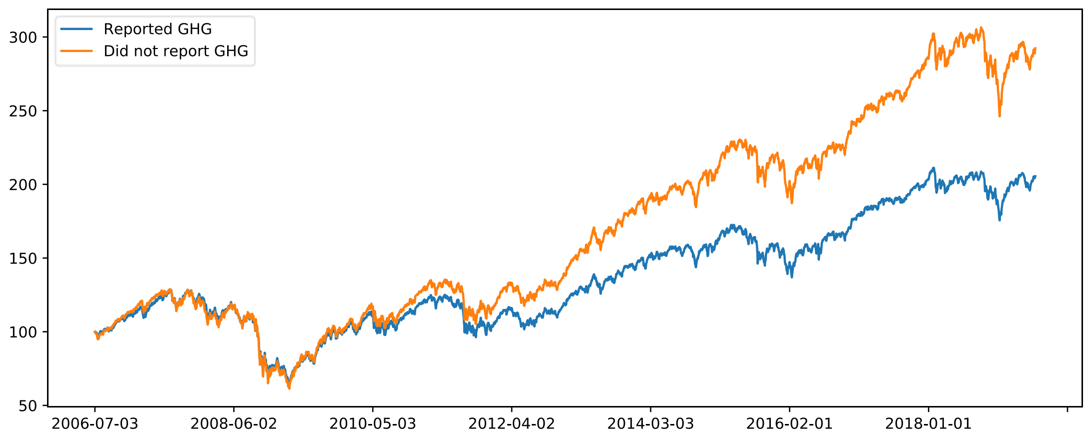


Figure 7, the figure shows the relative accumulated returns for the companies that do report and that do not report Greenhouse gas emissions. Both portfolios are indexed to 2006-07-03 start at 100.

6.1.3 Sector Impact

The sectors with the most impact per sales vary depending on which metric that is in focus, but overall, the companies within Basic Materials, Energy, Industrial and Utilities, are among those with the largest footprint (see Figure 8 and Appendix 10.3). Figure 8 shows this through the sector representation 2018 in each decile of Total waste/sales, the leftmost bar representing the 10% of companies that generate the highest amount of Total waste/sales, and the rightmost bar representing the 10% of companies that generate the lowest amount of Total waste/sales. The coloured area in each bar shows the share of companies from the corresponding sector. The figure can be viewed in two complementing ways. The first way is by focusing on a specific sector, such as for example Financial. By doing so, one can see the distribution of companies within that sector. Figure 8 shows that the great majority of companies within the Financial sector are in the bottom two deciles, which suggests that the companies in this sector have a relatively low impact in terms of Total waste/sales. The second way is by focusing on a specific decile, for example the top 10% of companies ranked by Total waste/sales. By doing so, one can see that companies within Basic Materials constitute more than half of this decile, which suggests that the companies within this sector have a relatively high impact in terms of Total waste/sales. See Appendix 10.3 for the figures showing sector representation ranked by the other three metrics.

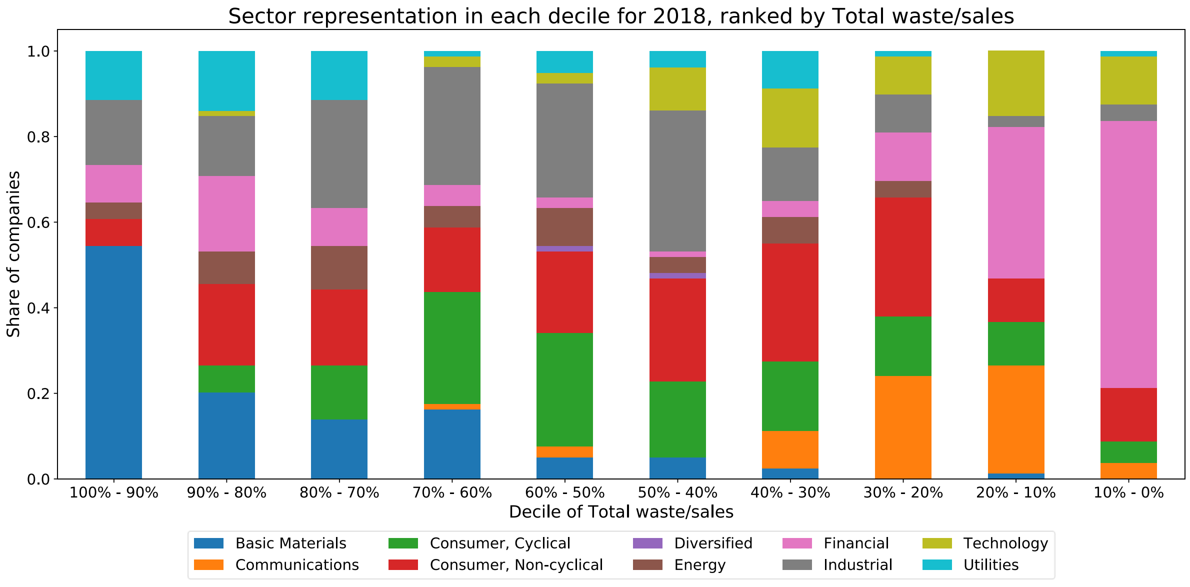


Figure 8, the figure shows the sector representation in each decile of Total waste/sales, for the fiscal year 2018. The deciles are displayed as bars, with the 10% highest Total waste/sales to the left, and the 10% lowest Total waste/sales to the right. In each bar, the coloured area shows the share of companies in that decile from the corresponding sector.

6.2 Main Portfolio Tests

In this section the main results of this study are presented, first in general and thereafter in more detail for the sectors with high environmental impact discussed in section 6.1.3.

6.2.1 Overall Results

In general, the more sustainable portfolios exhibit higher risk-adjusted returns than the less sustainable portfolios in the sector-dependent tests, some but not all differences being statistically significant. In the tests where all sectors are included (Table A3, Appendix 10.4), the less sustainable portfolios exhibit the higher risk-adjusted returns, but none of these results are statistically significant. As can be seen in Table 3, three of the sector-dependent tests show differences that are significant at the 5%-level, and six more at the 10%-level. The more sustainable portfolio exhibits the higher risk-adjusted return in all significant cases at the 5%-level, and in all but one case at the 10%-level (exception: Energy, Combined rank). Note that *P*-values in Table 3 are for the tests comparing top and bottom 25%-portfolios, except for values presented within parenthesis which are for the tests comparing top and bottom 50%-portfolios. Out of the ten significant results at the 10%-level shown in Table 3, six are in the four high impact sectors, two in Basic Materials, two in Energy and two in Industrial. No significant results are obtained for tests within the fourth high impact sector, Utilities. The portfolios made using a combined rank are the shortest time series, since this ranking requires available data for all four constituent metrics and thus leaves a smaller sample. Still, it is within the combined rank that five of the ten significant results are found.

TABLE 3 – *P*-VALUES FOR SECTOR-DEPENDENT TESTS

	COMBINED RANK	GREENHOUSE GAS EMISSIONS	TOTAL WASTE	NET WASTE	WATER USE
BASIC MATERIALS	0.046**	0.039**	0.13	0.26	0.20
COMMUNICATIONS	(0.088*)	0.54	0.73	(0.92)	0.92
CONSUMER, CYCLICAL	0.72	0.92	0.69	0.73	0.83
CONSUMER, NON-CYCLICAL	0.069*	0.91	0.19	0.059*	0.57
ENERGY	(0.062*)	0.34	0.068*	(0.68)	0.31
FINANCIAL	0.61	0.48	0.80	0.71	0.25
INDUSTRIAL	0.18	0.22	0.084*	0.49	0.015**
TECHNOLOGY	0.065*	0.86	0.18	0.45	0.35
UTILITIES	(0.61)	0.36	0.65	0.75	0.98

****: P < 0.01, **: P < 0.05, *: P < 0.10. The table shows the results from the portfolio tests, comparing top and bottom 25% portfolios, except for the values in parenthesis that show the results from top and bottom 50% portfolios. These values are presented when no results are available for the 25%-tests. The complete results of the tests are shown in Appendix 10.4.*

6.2.2 Basic Materials

Results from the portfolio tests are shown in Table A4, Appendix 10.4.1.

Even though Basic Materials is one of the mid-size sectors in the study (see Section 4.1), the high degree of reporting companies results in long testable time series (see Section 6.1.1 and Appendix 10.2 for data availability). The portfolios of companies ranked top and bottom 25% in Greenhouse gas emissions (GHG) are tested for twelve years of data and show a significant difference in risk-adjusted returns ($P = 0.039$). Figure 9 shows the accumulated return for these two portfolios, as well as for the portfolios of top-bottom 25% of the combined rank. The portfolios of the Combined rank are tested for seven years of data, also resulting in a significant difference in risk-adjusted returns ($P = 0.046$). While it is evident in Figure 9 that the portfolios diverge more in some periods, there is no apparent single incident or period that seem to explain the differences in risk-adjusted returns.

All portfolio tests within Basic Materials show that the more sustainable portfolios exhibit higher risk-adjusted returns than the less sustainable portfolios, and although the tests for Total waste, Net waste and Water use do not show significant differences, the results are strong with *P*-values 0.13, 0.26 and 0.20, respectively.

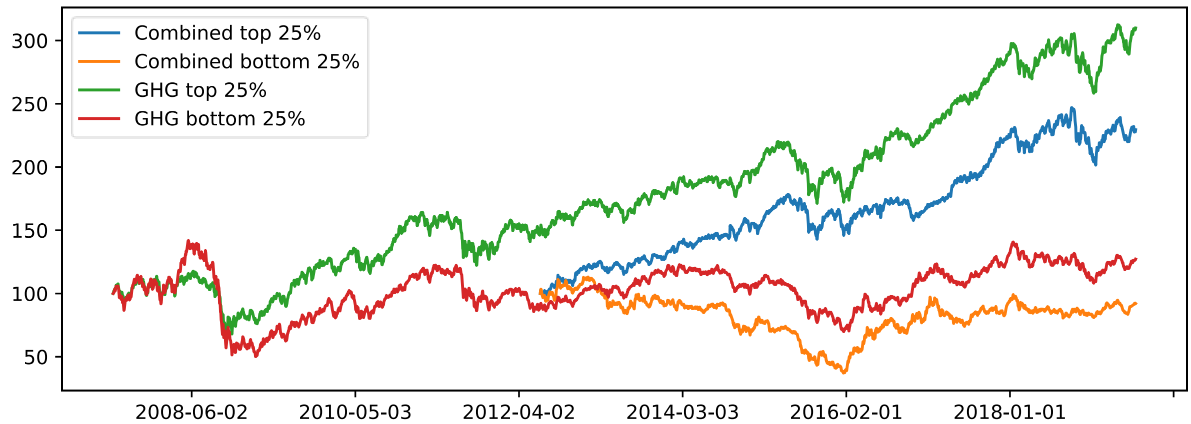


Figure 9, showing the accumulated returns over time from the portfolios tested within Basic Materials, comparing the top and bottom 25% of companies ranked by Greenhouse gas emissions (GHG) and Combined rank. Each pair of portfolios is indexed to start at value 100, shown on the y-axis. The portfolios by Combined rank are 100 at 2012-07-02, and the portfolios by Greenhouse gas emissions at 2007-07-02.

6.2.3 Energy

Results from the portfolio tests are shown in Table A8, Appendix 10.4.5.

Although the share of companies within the Energy sector reporting Greenhouse gas emissions data is relatively high, it is less so for the other metrics (see Section 6.1.1 and Appendix 10.2). In combination with Energy being one of the smallest sectors in this study (see Section 4.1), this results in a relatively small sample size and thus also short time series.

The portfolios ranked top and bottom 25% in Total waste are tested for four years, showing a significant difference in risk-adjusted returns at the 10%-level (P = 0.068) with the more sustainable portfolio being the higher. The portfolios ranked top and bottom 50% by Water use is tested for nine years, showing a significant difference at the 5%-level (P = 0.034), also with the more sustainable portfolio being the higher. For the top-bottom 50% portfolios in Combined rank, three years are tested, and the tests show a significant difference at the 10%-level (P = 0.062), the less sustainable portfolio exhibiting the higher Sharpe ratio. While there is a visible divergence in the accumulated returns between the top and bottom 50% portfolios ranked by Water use until around 2016, the effect thereafter is less distinct, as can be seen in Figure 10. The significant difference in risk-adjusted returns between the top and bottom 50% portfolios in the Combined rank seem to come from one single year of testing, 2017-07-01 to 2018-06-31, where the top portfolio lost 2.2% in value and the bottom portfolio gained 42.7% (see Table A8, Appendix 10.4.5). For the top and bottom 25% portfolios in Total waste, the difference seems to be gradual and consistent over time.

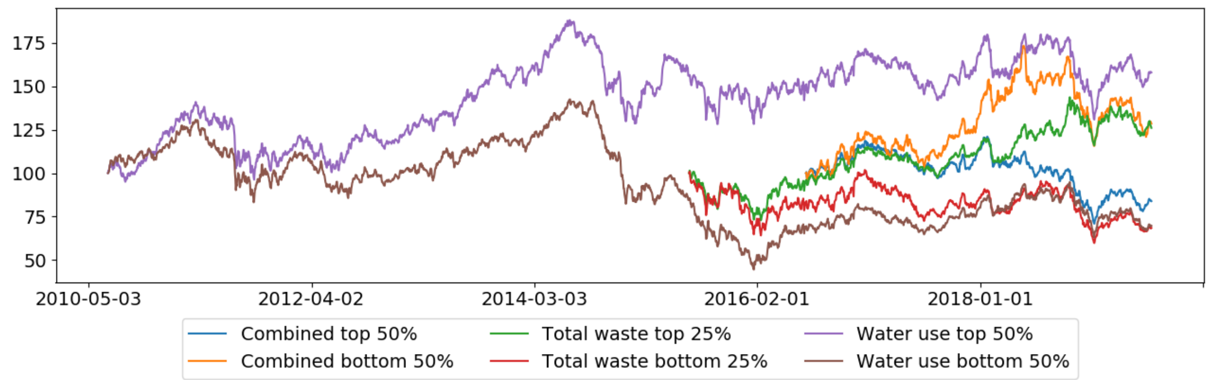


Figure 10, showing the accumulated returns over time from the portfolios tested within Energy, comparing the top and bottom 25% of companies ranked by Total waste, and the top-bottom 50% of companies ranked by Water use and the Combined rank, respectively. Each pair of portfolios is indexed to start at value 100, shown on the y-axis. The portfolios by Combined rank are 100 at 2016-07-01, the portfolios by Total waste at 2015-07-01, and the portfolios by Water use at 2010-07-01.

6.2.4 Industrial

Results from the portfolio tests are shown in Table A10, Appendix 10.4.7.

Industrial is one of the larger sectors in this study (see Section 4.1), and in combination with the above average share of reporting companies (see Section 6.1.1 and Appendix 10.2) this results in long testable time series. The exception is the tests for Combined rank, where relatively few data points are available, indicating that there is a high degree of variation in which companies that report which metrics (see Table A10, Appendix 10.4.7).

Two of the portfolio tests within Industrial, comparing top and bottom 25% portfolios, show significant differences in risk-adjusted returns, the portfolios ranked by Total waste and by Water use. The Total waste portfolios are tested for twelve years of data and show a *P*-value of 0.084, and the Water use portfolios are tested for eleven years, resulting in $P = 0.015$. In all but one highly insignificant test, the more sustainable portfolio exhibits the higher risk-adjusted returns. The two significant results are in some sense supported by the strong, but not significant results by the 50%-tests.

Figure 11 shows the accumulated returns over time from the two pairs of portfolios with significant differences, and in both cases, there is no evident single incident or period that seems to explain the results.

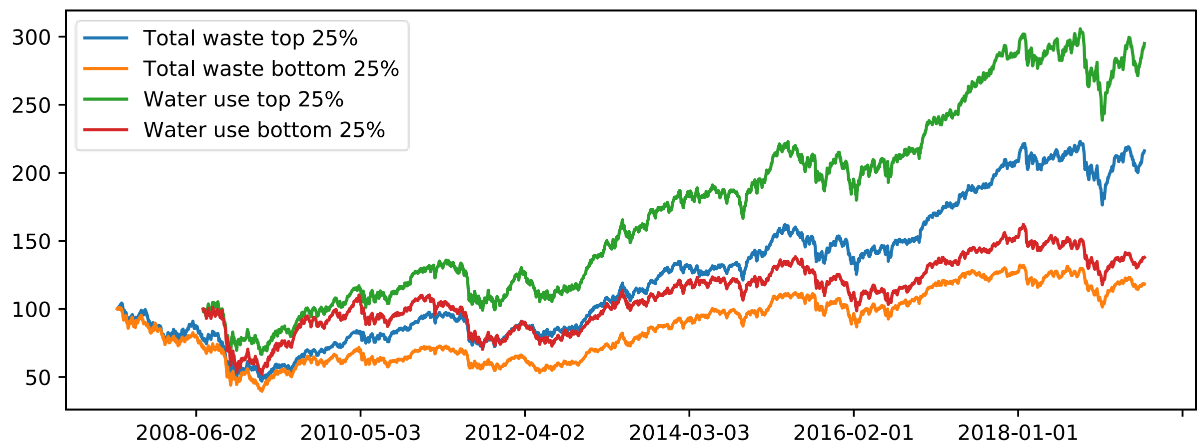


Figure 11, showing the accumulated returns over time from the portfolios tested within Industrial, comparing the top and bottom 25% of companies ranked by Total waste and Water use. Each pair of portfolios is indexed to start at value 100, shown on the y-axis. The portfolios by Total waste are 100 at 2007-07-02, and the portfolios by Greenhouse gas emissions at 2008-07-01.

6.2.5 Utilities

Results from the portfolio tests are shown in Table A12, Appendix 10.4.9.

Utilities is the smallest sector in this study (see Section 4.1), but with the greatest share of companies reporting Greenhouse gas emissions and above average share of companies reporting the other metrics (see Section 6.1.1 and Appendix 10.2). The result is that only short testable time series are available for many of the portfolio tests comparing top and bottom 25% of companies. None of the portfolio tests within Utilities show significant results, although the 50%-test ranking by Net waste and Water use are strong, with *P*-values 0.15 and 0.19, respectively (Table A12, Appendix 10.4.9). In terms of which portfolios that exhibit the higher risk-adjusted returns, no trend is visible. In some of the tests the more sustainable portfolio shows the higher returns, and in some others vice versa.

7 Discussion

The results show some support in favour of environmentally sustainable companies being better investments, although there are some caveats concerning the generalisation of the results. The differences in the share of companies reporting each metric indicates that the results best describe larger companies in countries with large financial markets (see Section 6.1.1). While these differences on their own do not pose a large threat to the interpretation of the findings in this study, the fact that there is a significant difference in risk-adjusted returns between the companies that do and do not report Greenhouse gas emissions, does limit the scope of generalisation to the companies that do report. This is an issue, but a fading one, since there is an evident increase in the share of companies that report Greenhouse gas emissions, and since around 60% of companies reported this metric at the end of the sample period.

Although the sectors that show the greatest share of reporting companies are among the smallest sectors, this may be entirely explained by the fact that the sectors have regulatory demands on reporting – considering that these are the sectors with the largest environmental impact, as is discussed further in Section 6.1.3.

Given the number of tests performed, one could argue that the significant results shown in this research are to be expected out of pure variation and thus may be spurious. For a series of multiple random significance tests at the 10%-level, one can expect around 10% to be significant by chance alone, and this should serve as a threshold when performing and examining multiple tests. Nine sectors tested independently for five ranking metrics means that 45 significance tests are performed in this set, which indicates that by pure randomness, 2.25 tests are expected to be significant at the 5%-level and 4.5 tests are expected to be significant at the 10%-level. As shown in Table 3, Section 6.2.1, three of the tests are significant at the 5%-level, barely exceeding the threshold, and ten of the tests are significant at the 10%-level, more than double the threshold value. In the tests performed over all sectors jointly, five significance tests are performed, none being significant. Calculating the threshold values for all main tests, sector-dependent and over all sectors, sums up to 50 tests in total which raises the threshold values of expected significant results from 2.25 to 2.5 for 5%-level and from 4.5 to 5 for the 10%-level. The summation does not change the conclusion that the shown number of significant results exceeds the expected number.

An additional strength of the results is that most of the significant results are found within the high impact sectors such as Basic Materials, Energy and Industrial, within which sectors it is reasonable to assume a higher degree of awareness from the investors and a higher degree of outside pressure on the companies. It shall also be noted that the tests are performed on daily resolution data for 13 years and for over 2100 companies, as well as that the statistical significance test used is two-sided as opposed to a one-sided test. A one-sided test would in this instance generate p-values half of those presented, and thus show a much higher degree of significance. Considering these factors, the presented results are relatively strong in support of the more sustainable companies being better investments.

In this research Sharpe ratios as used to measure the risk-adjusted returns of the portfolios. While the choice of metric may be motivated by its widespread use and the absence of better alternatives, the use of Sharpe ratios can be criticised from multiple standpoints. The main problem with Sharpe ratios is that the expected excess returns are assumed to be normally distributed, which means that the Sharpe ratios underestimate the risk if the returns for example have fatter tails than what is assumed. Fatter tails mean that extreme price changes, that is, changes far from the mean, are more likely to occur. It is reasonable to assume that stock price changes indeed have fatter tails than the normal distribution suggests, motivated by such price changes as the "Black Monday", 19th October 1987 when the US index Dow Jones Industrial Average fell 22,6% (Brady, 1988), which would be improbable to the extent of almost impossible for a normal distribution. For some fat-tailed distributions a metric such as Sharpe ratio cannot be defined, but if it is assumed that it is possible to define a Sharpe ratio for a fat-tailed distribution, a major problem using data with fat tails is the amount of observations needed for the convergence to the asymptotic distribution. This problem is solvable by larger samples, which means that the use of Sharpe ratios in this research in this sense may be justified due to the large amount of data used. Additional critique against Sharpe ratios include the use of standard deviation as a measure of risk, and the fact that negative Sharpe ratios are hard to interpret as they increase for higher standard deviations, keeping the expected return constant. This is contrary to how one interprets positive Sharpe ratios and how the ratio is reasonably meant to be interpreted, as the risk-adjusted returns should decrease if the risk is increased. As mentioned in the beginning of this paragraph, the used of Sharpe ratios may be motivated since it is one of the most used metrics, but for future research the field is in demand of better alternatives.

The outperformance by the more sustainable companies shown in this study is not easily explained through Modern Portfolio Theory (MPT), which suggest that sustainability considerations and reductions in investment universe would lead to worse performance. The results in this study may not be strong enough to refute the said theory, but they do provide reasons to continue looking for explanations elsewhere. The fact that these results are in line with the majority of the previous research on the topic, supports the abandonment of the MPT in regard to sustainability considerations. The point is further strengthened as this study remedies some of the weaknesses seen in previous research, using a data-driven definition of sustainability in contrast to the ESG-ratings which are shown to be inconclusive.

While the question of why sustainable companies might be better investments is not the focus of this essay, it is of importance and deserves a discussion. As has been shown in previous research, companies with better sustainability performance seem to have higher operational performance and lower costs of capital. These factors are undoubtedly major drivers for the long-term financial performance of a company and could thus help explain the excess returns from more sustainable companies. Even though the previous research in this topic do not use the same metrics as is used in this essay, it is reasonable to assume a high degree of correlation. The metrics used here are in many regards related to resource efficiency and constitute a clear link to the potential gain in operational performance seen for more sustainable companies in previous research. These factors, lower costs of capital and higher operational performance, in and of themselves might be sufficient to explain the relative outperformance by sustainable companies; but the factors are also likely to help these companies strengthen their competitive advantages, which in turn might earn them higher valuations and further increase the relative outperformance. While the link is not there stated, the increase in valuation is shown for more sustainable companies by Guenster et al. (2011) through increases in Tobin’s q, which is meant to represent the intangible value of a company.

The relative outperformance by sustainable companies might also be driven by market psychology. As shown by Riedl and Smeets (2017), investors are willing to pay higher performance fees for responsible mutual funds, even though they reportedly expect lower returns from these funds. The most import factors for investing responsibly is in their study are shown to be social preferences and social signalling. If this is the case, the stock prices of more sustainable companies may be increasing due to an unjustified inflow of capital from investors that in some sense are following a herd mentality. However, the studies such as the survey of institutional investors by Krueger, Sautner and Starks (2020) and the statements of BlackRock (2016), suggest that environmental factors and especially environmental risks are under-appreciated rather than exaggerated. If instead this is the case, the overperformance of sustainable companies might just be starting to show, and a justified increase in stock prices might be what is to come for the more sustainable companies. Of course, these two scenarios could coexist and be intertwined, affecting subsections of stocks in different ways at different times. This is one of many reasons why financial analysis may be so hard, the driving forces are never observed and constantly in change. What the driving forces are, how they affect each other, how we as market participants affect them back, and what the result of this interplay is – that is a question that might not ever be answered. In this setting it is hard to determine what is rational, and it is likely that investor biases have a heavy influence on pricing, perhaps leading to over-appreciation and perhaps leading to under-appreciation. In the light of this it is important to step back and discuss what can be observed and what can be measured.

CISL (2019) describes the complexity of measuring sustainability, but the suggested metrics are observable and undoubtedly in some way related to sustainability as commonly known. ESG-rating agencies fail to converge in their assessments of which companies that are sustainable, according to Berg, Koelbel and Rigobon (2020) most importantly due to different ways of measuring the companies' performance, even when the category is the same. While some data is available now, initiatives such as the EU Taxonomy will likely make the analysis easier for ESG-rating agencies as well as for researchers wanting hard data.

At present, this research contributes to the field by showing that more sustainable companies exhibit higher risk-adjusted returns, using a hard data definition of sustainability. The results are significant mainly in the sectors with high environmental impact, as can be expected. The validity of these findings is supported by the long time series and the large amount of companies included, which at the end of 2018 constitute 64% of total global market capitalisations.

The results presented in this study have several implications for investors, private and institutional investors alike. On the one hand the results of this research show support of a quantitative approach to investing sustainable. This suggests not only that sustainable investing may be achieved on a data-driven basis, but also that it may be done so with significant returns. On the other hand, one may criticize a data-driven definition of what is sustainable, given that there are some significant differences between companies that do report and the companies that do not report sustainability metrics. The second case is further supported by the fact that the reported metrics are far from ideal in capturing the complex nature of what actually is sustainable.

8 Conclusion

In this research, the question of whether environmentally sustainable companies are better investments is investigated through tests of pairwise portfolios, selected using the top and bottom quantile of companies ranked by several sustainability metrics. The results show support of the sustainable companies being better investments, although there are some limitations the generalisation of the results, due to differences between the companies that do and that do not report the given sustainability metrics. There are several reasons as to why sustainable stocks might overperform. First, research shows that such stocks generally enjoy some financial benefits and strengths such as higher operational performance. Secondly, the financial markets may under-appreciate the environmental risks facing companies, and the excess return from sustainable stocks may come from the materialisation of these risks. In conclusion, there may be many reasons to invest in sustainable companies – and the topic will definitely remain relevant for the foreseeable future.

9 References

Baron, J. (2014). The Oxford Handbook of Behavioral Economics and the Law. Chapter: Heuristics and Biases. Oxford University Press (Oxford Handbooks in Economics).

Bauer, R. & Hann, D. (2010). Corporate Environmental Management and Credit Risk. Working paper. European Centre for Corporate Engagement, Maastricht University. Available at SSRN: https://ssrn.com/abstract=1660470 [Accessed 2020-05-14]

Berg, F., Koelbel, J. & Rigobon, R. (2020). Aggregate Confusion: The Divergence of ESG Ratings. Available at SSRN: https://ssrn.com/abstract=3438533 [Accessed 2020-05-26]

BlackRock (2016). Adapting Portfolios to Climate Change: Implications and Strategies for All Investors. BlackRock Investment Institute, Global Insights. Available at: https://www.blackrock.com/corporate/literature/whitepaper/bii-climate-change-2016-us.pdf [Accessed 2020-03-31]

Brady, Nicholas F. (1988). Report of the Presidential Task Force on Market Mechanisms. United States Presidential Task Force on Market Mechanisms (Technical report). United States Government Publishing Office.

Carhart, M. (1997). On Persistence in Mutual Fund Performance. *The Journal of Finance*, vol. 52, no. 1, pp. 57 - 82.

Chatterji, A., Durand, R., Levine, D. & Touboul S. (2016). Do Ratings of Firms Converge? Implications for Managers, Investors and Strategy Researchers. *Strategic Management Journal*, vol. 37, no. 8, pp. 1597 - 1614.

Chava, S. (2014). Environmental Externalities and Cost of Capital. *Management Science*, vol. 60, no. 9, pp. 2223 - 2247.

CISL, University of Cambridge Institute for Sustainability Leadership (2019). In search of impact: Measuring the full value of capital. Available at: https://www.cisl.cam.ac.uk/resources/publications [Accessed 2020-03-31]

Clark, G., Feiner, A. & Viehs, M. (2015). From the Stockholder to the Stakeholder: How Sustainability Can Drive Financial Outperformance. Available at SSRN: https://ssrn.com/abstract=2508281 [Accessed 2020-03-31]

European Parliament (2020). Green finance: Parliament adopts criteria for sustainable investments. Press release. Available at: https://www.europarl.europa.eu/news/en/press-room/20200615IPR81229/green-finance-parliament-adopts-criteria-for-sustainable-investments [Accessed 2020-08-13]

EU TEG, Technical Expert Group on Sustainable Finance (2020). TEG final report on the EU taxonomy. Available at: https://ec.europa.eu/knowledge4policy/publication/sustainable-finance-teg-final-report-eu-taxonomy_en [Accessed 2020-08-13]

Fama, E. & French, K. (1992). The Cross-Section of Expected Stock Returns. *The Journal of Finance*, vol. 47, no. 2, pp. 427 - 465.

Guenster, N., Bauer, R., Derwall, J. & Koedijk, K. (2011). The Economic Value of Corporate Eco-Efficiency. *European Financial Management*, vol. 17, no. 4, pp. 679 - 704.

Halbritter, G. & Dorfleitner, G. (2015). The Wages of Social Responsibility - Where Are They? A Critical Review of ESG Investing. *Review of Financial Economics*, vol. 26, pp. 25-35.

Jobson, J. D. och Korkie B. M. (1981). Performance Hypothesis Testing with the Sharpe and Treynor Measures. *The Journal of Finance*, vol. 26, no. 4, pp. 889 - 908.

Kempf, A. & Osthoff, P. (2007). The Effect of Socially Responsible Investing on Portfolio Performance. *European Financial Management*, vol. 13, no. 5, pp. 908 - 922.

Krueger, P., Sautner, Z. & Starks, L. (2020). The Importance of Climate Risks for Institutional Investors. *Review of Financial Studies*, vol. 33, no. 3, pp. 1067 - 1111.

Markowitz, H. (1952). Portfolio Selection. *The Journal of Finance*, vol. 7, no. 1, pp. 77 -91.

NOAA National Centers for Environmental Information, State of the Climate: Global Climate Report for Annual 2019, published online January 2020. Available at: https://www.ncdc.noaa.gov/sotc/global/201913 [Accessed 2020-08-05]

Riedl, A. & Smeets, P. (2017). Why Do Investors Hold Socially Responsible Mutual Funds? *Journal of Finance*, vol 72, no. 6, pp. 2505 - 2549.

Semenova, N. & Hassel, L. (2015). On the Validity of Environmental Performance Metrics. *Journal of Business Ethics*, vol. 132, no. 2, pp. 249 - 258.

Statman, M. & Glushkov, D. (2009). The Wages of Social Responsibility. *Financial Analysts Journal*, vol. 65, no. 4, pp. 33 - 46.

Sharpe, W. F. (1994). The Sharpe Ratio. *The Journal of Portfolio Management*, vol. 21, no. 1, pp. 49 - 58.

Tobin, J. & Brainard W.C. (1977). Asset Markets and the Cost of Capital. Cowles Foundation for Research in Economics, Yale University. Discussion paper number 427. Available at: https://cowles.yale.edu/sites/default/files/files/pub/d04/d0427.pdf [Accessed 2020-08-13]

Zamir, E. & Teichman, D. (editors, 2014). The Oxford Handbook of Behavioral Economics and the Law. Chapter: Introducion. Oxford University Press (Oxford Handbooks in Economics).

Websites

BlackRock (n.d). Available at: https://blackrock.com/sg/en/about-us [Accessed 2020-08-13]

US Treasury (n.d. A). Available at: https://www.treasury.gov/resource-center/data-chart-center/interest-rates/pages/TextView.aspx?data=yieldAll [Accessed 2020-05-15]

US Treasury (n.d. B). Available at: https://home.treasury.gov/policy-issues/financing-the-government/interest-rate-statistics/interest-rates-frequently-asked-questions [Accessed 2020-05-15]

Worldbank (n.d.). Available at: https://data.worldbank.org/indicator/CM.MKT.LCAP.CD?end=2019&start=1975&view=chart [Accessed 2020-07-30]

10 Appendix

10.1 Data

10.1.1 Variables

Closing prices
Resolution: Daily
Bloomberg field: PX_LAST
Adjusted for spin-offs, stock splits/consolidations, stock dividend/bonus, rights offerings/entitlement. Not adjusted for normal cash dividends.

Market cap
Resolution: Fiscal yearly
Bloomberg field: HISTORICAL_MARKET_CAP
Calculated as Shares Outstanding * Last Closing Price, converted to USD by the current exchange rate at that time.

Sales
Resolution: Fiscal yearly
Bloomberg field: SALES_REV_TURN
Converted to USD by the current exchange rate at that time.

Sector
Bloomberg field: INDUSTRY_SECTOR
Legacy BICS (Bloomberg Industry Classification System) level 1 classification of the security based on its business or economic function and characteristics.

Country
Bloomberg field: CTRY_OF_DOMICILE
The ISO code of the country where the company's senior management is located.

Greenhouse gas emissions
Resolution: Fiscal yearly
Bloomberg field: TOTAL_GHG_EMISSIONS
Total greenhouse gas emissions from scope 1 & 2, in the unit thousands of metric tonnes CO2 equivalents.

Total waste
Resolution: Fiscal yearly
Bloomberg field: TOTAL_WASTE
Unit: Thousands of metric tonnes waste discarded.

Waste recycled
Resolution: Fiscal yearly
Bloomberg field: WASTE_RECYCLED
Unit: Thousands of metric tonnes waste recycled.

Water use
Resolution: Fiscal yearly
Bloomberg field: TOTAL_WATER_USE
Unit: Thousands of cubic meters water used to support operational processes.

10.1.2 Countries

TABLE A1 – NUMBER OF COMPANIES PER COUNTRY AND YEAR

Country	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	Average
US	786	782	754	742	737	729	725	720	714	710	694	668	650	656	719
JP	193	194	194	193	194	193	190	189	184	185	185	185	184	184	189
GB	161	156	151	145	141	141	142	139	138	138	138	133	130	124	141
CA	86	83	81	79	78	78	78	76	73	71	72	72	70	71	76
CH	72	73	74	74	75	75	75	75	74	74	71	71	70	69	73
AU	68	69	68	65	64	65	63	62	62	63	62	60	60	60	64
FR	58	61	63	64	64	64	63	63	62	62	61	60	59	57	62
DE	49	51	51	50	49	49	49	49	52	53	54	54	57	56	52
SE	30	29	29	29	29	29	29	29	29	28	28	28	29	31	29
BR	27	27	29	31	29	29	29	27	27	27	27	25	25	25	27
IT	31	28	28	28	27	28	28	27	27	26	24	24	24	23	27
ES	23	24	26	25	23	24	25	25	25	25	27	27	26	25	25
HK	22	22	22	22	22	23	23	23	23	23	22	22	22	22	22
NL	22	21	20	18	19	19	20	21	19	21	23	22	22	23	21
TW	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20
KR	17	18	19	20	20	20	20	20	20	21	20	20	20	20	20
CL	18	18	18	18	18	18	18	18	18	18	18	18	18	16	18
IE	15	16	18	18	17	17	18	18	18	18	17	17	17	17	17
MX	13	13	13	13	13	13	14	13	14	14	13	13	13	13	13
BE	13	13	13	13	13	13	13	13	13	13	13	12	12	12	13
DK	11	11	11	11	11	13	13	13	13	14	14	15	15	14	13
CN	8	12	12	13	13	13	13	13	13	13	13	13	13	15	13
FI	12	12	12	12	12	12	12	12	12	12	12	12	12	12	12
SG	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9
NO	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8
PT	6	7	7	7	7	7	7	7	6	5	5	5	4	4	6
LU	6	6	5	5	5	5	5	5	5	6	6	6	6	6	6
GR	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5
AT	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4
PE	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3
BM	2	2	2	2	2	2	2	2	2	2	2	2	2	1	2
CO	1	1	1	2	2	2	2	2	2	2	2	2	2	2	2
AR	2	2	2	2	1	1	1	1	1	1	1	1	1	1	1
NZ	1	1	1	1	1	1	1	1	1	1	2	2	2	2	1
IM	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
ZA	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
JE	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1
MO	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1
GG	0	0	0	0	1	1	1	1	1	1	0	0	0	0	0
PG	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0

The table shows the number of companies in the data per country and year, as well as the average number of companies for each country over all years. Countries are denoted by their ISO code.

10.1.3 Adjustments

TABLE A2 – DATA ADJUSTMENTS

NR	BLOOMBERG TICKER	PERIOD REMOVED	CAUSE
1	1166879D CT Equity	2009-07-01 – End	Jump
2	CHK UN Equity	2018-07-01 – End	Jump
3	NBR UN Equity	2018-07-01 – End	Jump
4	GGP UN Equity	2009-07-01 – 2010-06-30	Jump
5	MU UN Equity	2009-07-01 – 2018-06-30	Jump
6	ETFC UN Equity	Entire	Jump
7	TFCFA UN Equity	2008-07-01 – 2018-06-30	Jump
8	ADP UN Equity	2008-07-01 – 2018-06-30	Jump
9	UAL UW Equity	2010-07-01 – End	Jump
10	AMD UN Equity	2015-07-01 – 2018-06-30	Jump
11	EBR UN Equity	2016-07-01 – 2017-06-30	Jump
12	TXN UN Equity	2011-07-01 – 2018-06-30	Jump
13	MAR UN Equity	2014-07-01 – 2018-06-30	Jump
14	CME UN Equity	2008-07-01 – 2018-06-30	Jump
15	WDC UN Equity	2012-07-01 – 2018-06-30	Jump
16	MYL UN Equity	2008-07-01 – 2018-06-30	Jump
17	SLM UN Equity	2012-07-01 – 2018-06-30	Jump
18	JOY UN Equity	Start – 2012-06-30	Jump
19	ADI UN Equity	2012-07-01 – 2018-06-30	Jump
20	WINMQ UN Equity	2009-07-01 – 2018-06-30	Drop
21	FTR UN Equity	2012-07-01 – 2018-06-30	Drop
22	MRO LN Equity	Entire	Drop
23	MAT UN Equity	2009-07-01 – 2018-06-30	Stationary
24	HAS UN Equity	2011-07-01 – 2018-06-30	Stationary
25	RRD UN Equity	2009-07-01 – 2016-06-30	Stationary
26	VIAB UN Equity	2011-07-01 – 2018-06-30	Stationary
27	MDLZ UN Equity	2012-07-01 – 2018-06-30	Stationary
28	CMVT UQ Equity	2007-07-01 – 2012-06-30	Stationary
29	SCHW UN Equity	Start – 2010-06-30	Stationary
30	ODP UN Equity	2014-07-01 – 2018-06-30	Stationary
31	WBA UN Equity	2015-07-01 – 2018-06-30	Stationary
32	TMUS UN Equity	2015-07-01 – 2018-06-30	Stationary

The table shows the adjustments made, as described in Section 4.2.

10.2 Data Availability Plots

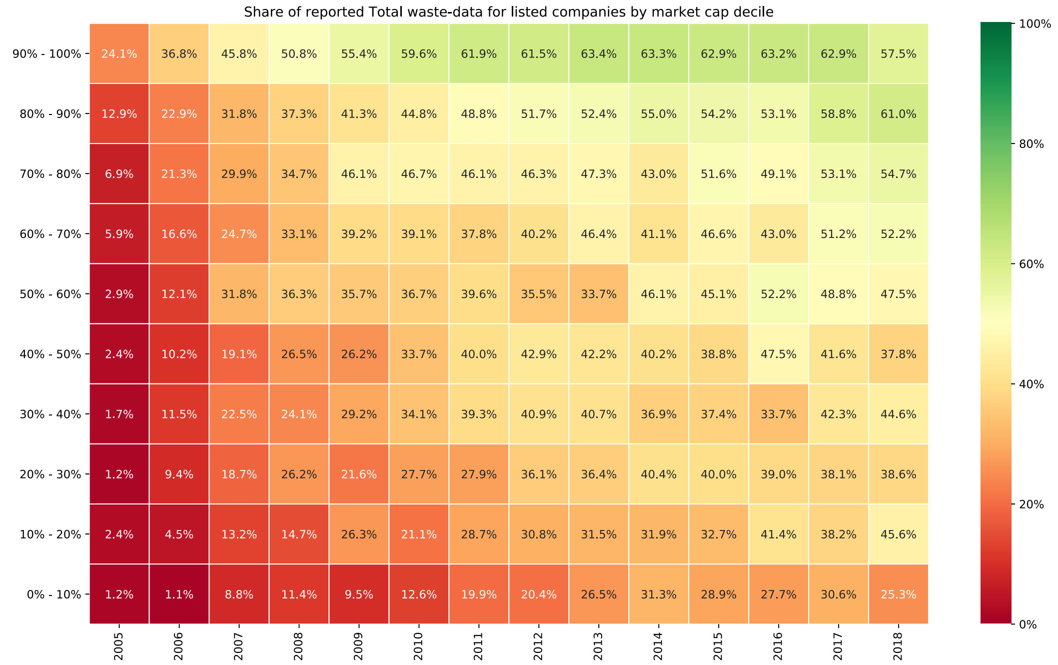


Figure A1, the figure shows the share of companies that report Total waste for each year, grouped into market cap deciles with the 10% smallest companies at the bottom and the 10% largest companies at the top. The values are coloured from dark red to dark green, following the colour bar presented in the right of the figure.

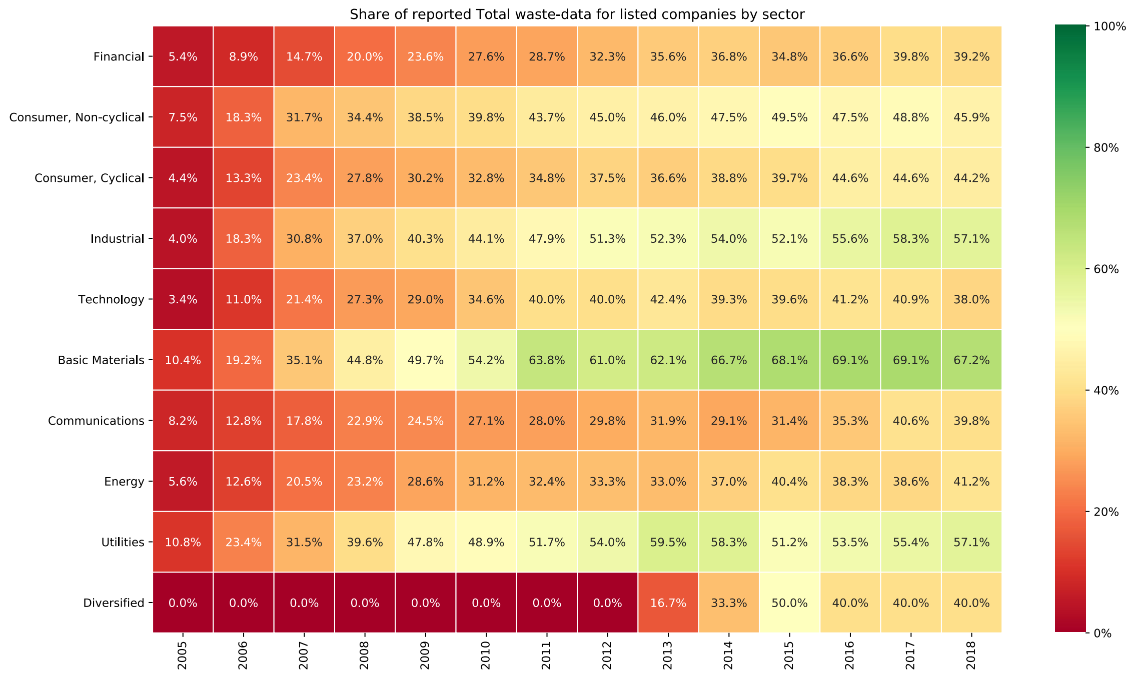


Figure A2, the figure shows the share of companies that report Total waste for each year, grouped by sectors, with the largest sectors (in terms of companies in the data) at the top, and the smallest sectors at the bottom. The values are coloured from dark red to dark green, following the colour bar presented in the right of the figure.

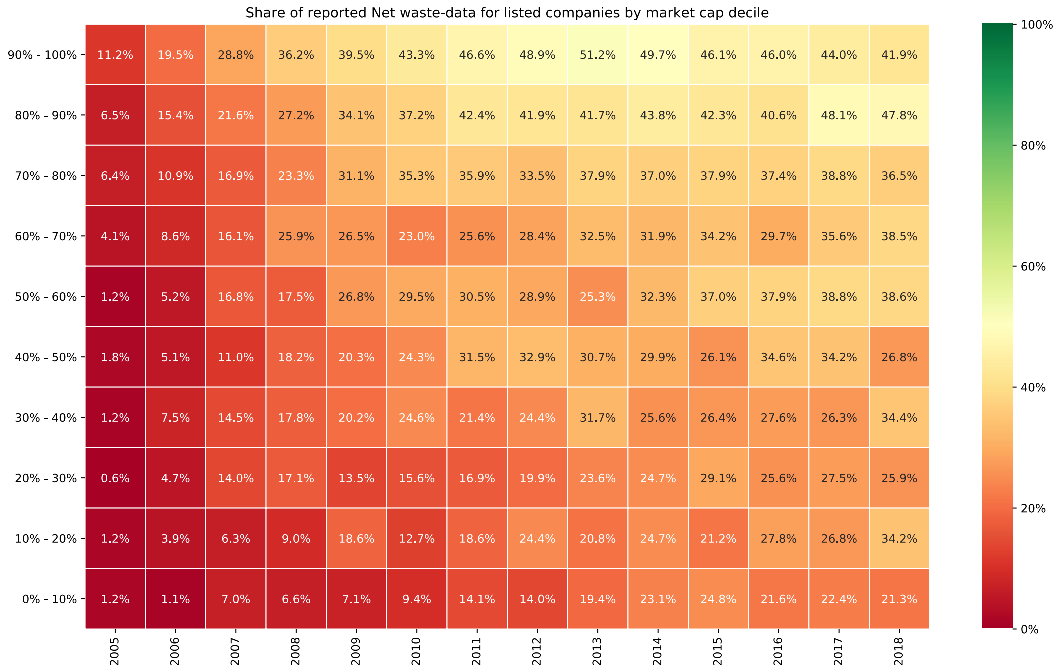


Figure A3, the figure shows the share of companies that report Net waste for each year, grouped into market cap deciles with the 10% smallest companies at the bottom and the 10% largest companies at the top. The values are coloured from dark red to dark green, following the colour bar presented in the right of the figure.

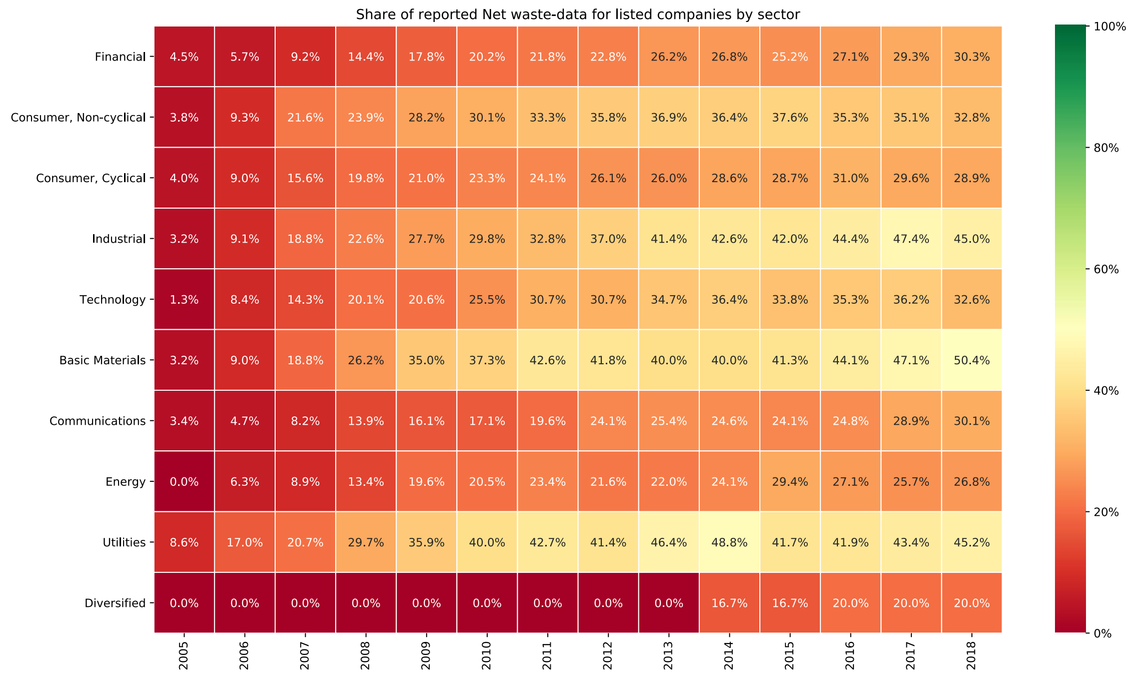


Figure A4, the figure shows the share of companies that report Net waste for each year, grouped by sectors, with the largest sectors (in terms of companies in the data) at the top, and the smallest sectors at the bottom. The values are coloured from dark red to dark green, following the colour bar presented in the right of the figure.

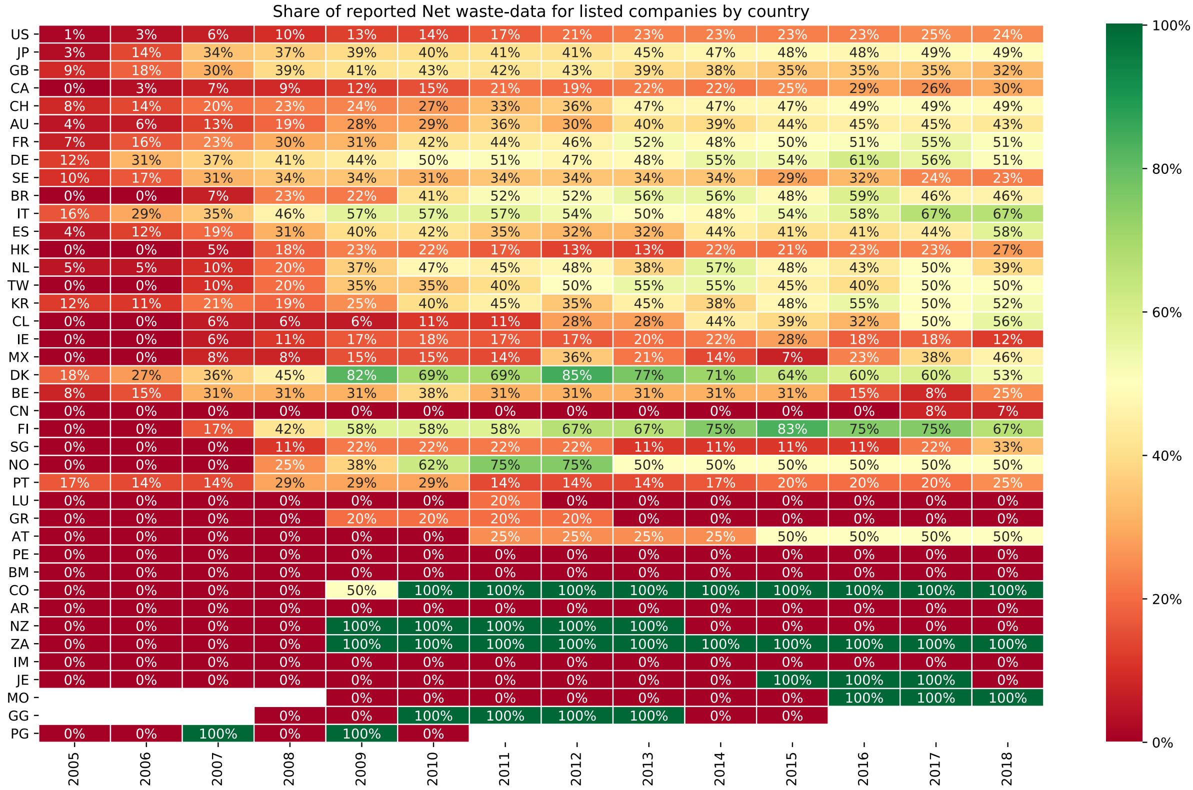


Figure A5, the figure shows the share of companies reporting Net waste for each year, grouped by countries, with the largest countries (in terms of companies in the data) at the top, and the smallest countries at the bottom. The values are coloured from dark red to dark green, following the colour bar presented in the right of the figure. Countries are denoted by their ISO-code.

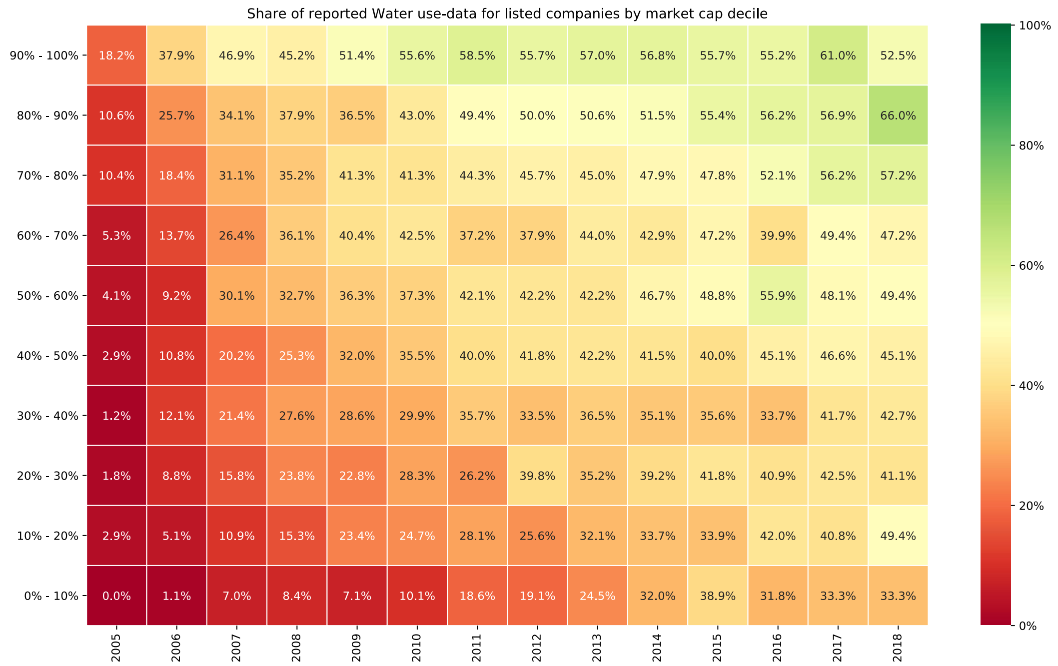


Figure A6, the figure shows the share of companies that report Water use for each year, grouped into market cap deciles with the 10% smallest companies at the bottom and the 10% largest companies at the top. The values are coloured from dark red to dark green, following the colour bar presented in the right of the figure.

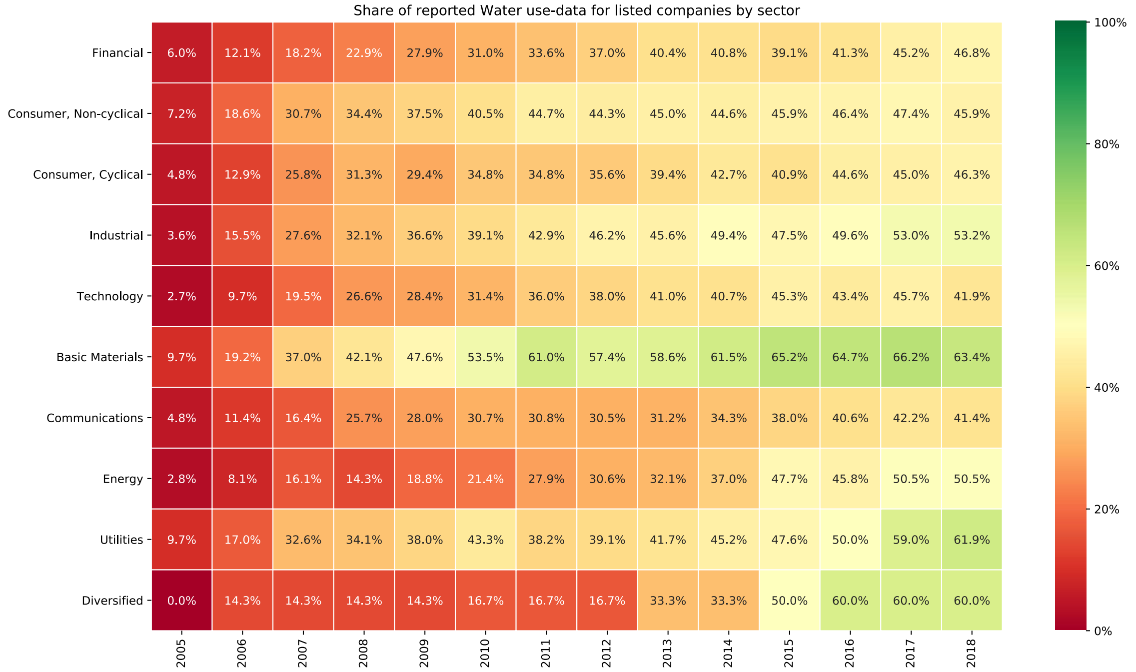


Figure A7, the figure shows the share of companies that report Water use for each year, grouped by sectors, with the largest sectors (in terms of companies in the data) at the top, and the smallest sectors at the bottom. The values are coloured from dark red to dark green, following the colour bar presented in the right of the figure.

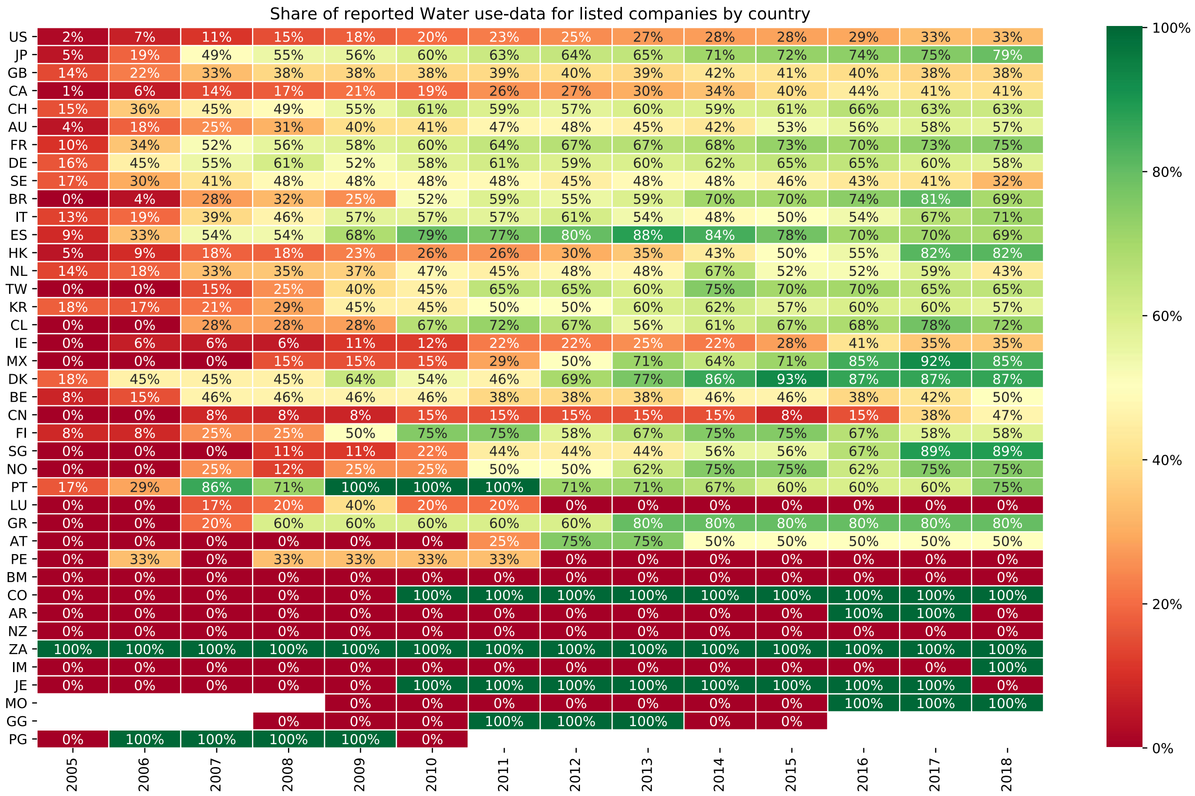


Figure A8, the figure shows the share of companies reporting Water use for each year, grouped by countries, with the largest countries (in terms of companies in the data) at the top, and the smallest countries at the bottom. The values are coloured from dark red to dark green, following the colour bar presented in the right of the figure. Countries are denoted by their ISO-code.

10.3 Sector Representation

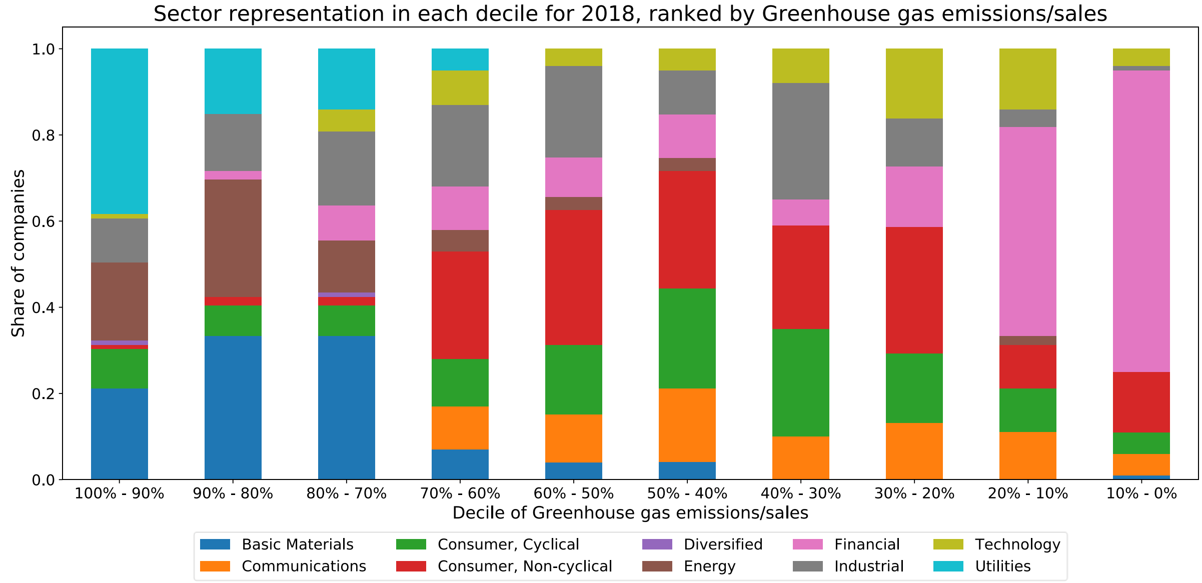


Figure A10, the figure shows the sector representation in each decile of Greenhouse gas emissions/sales, for the fiscal year 2018. The deciles are displayed as bars, with the 10% highest Greenhouse gas emissions/sales to the left, and the 10% lowest Greenhouse gas emissions/sales to the right. In each bar, the coloured area shows the share of companies in that decile from the corresponding sector.

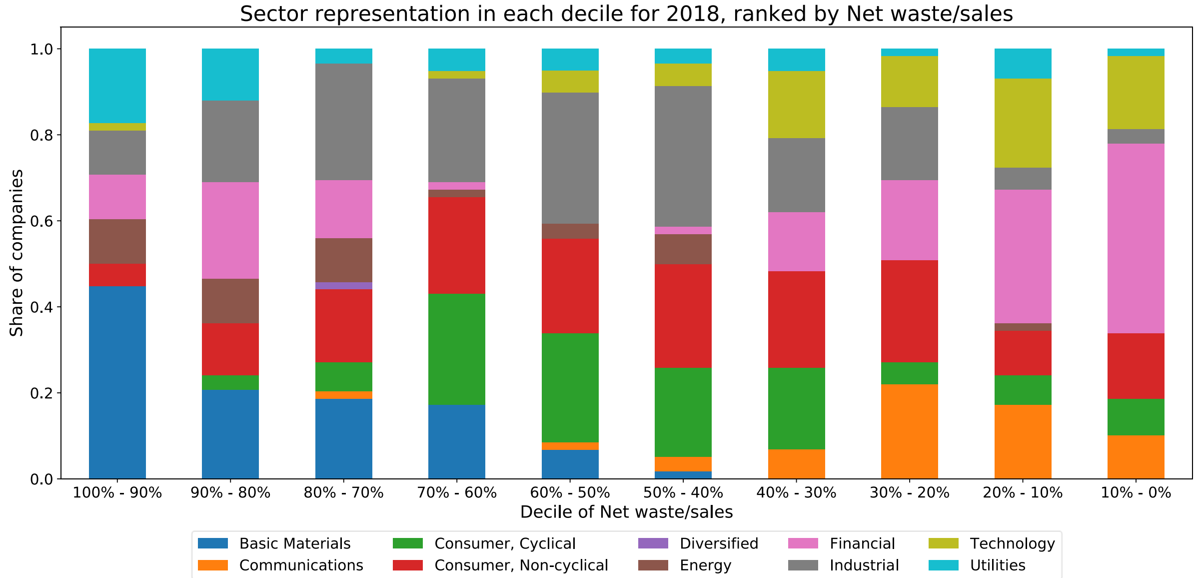


Figure A10, the figure shows the sector representation in each decile of the Net waste / sales, for the fiscal year 2018. The deciles are displayed as bars, with the 10% highest impact companies to the left, and the 10% lowest to the right. In each bar, the coloured area shows the share of companies in that decile from the corresponding sector.

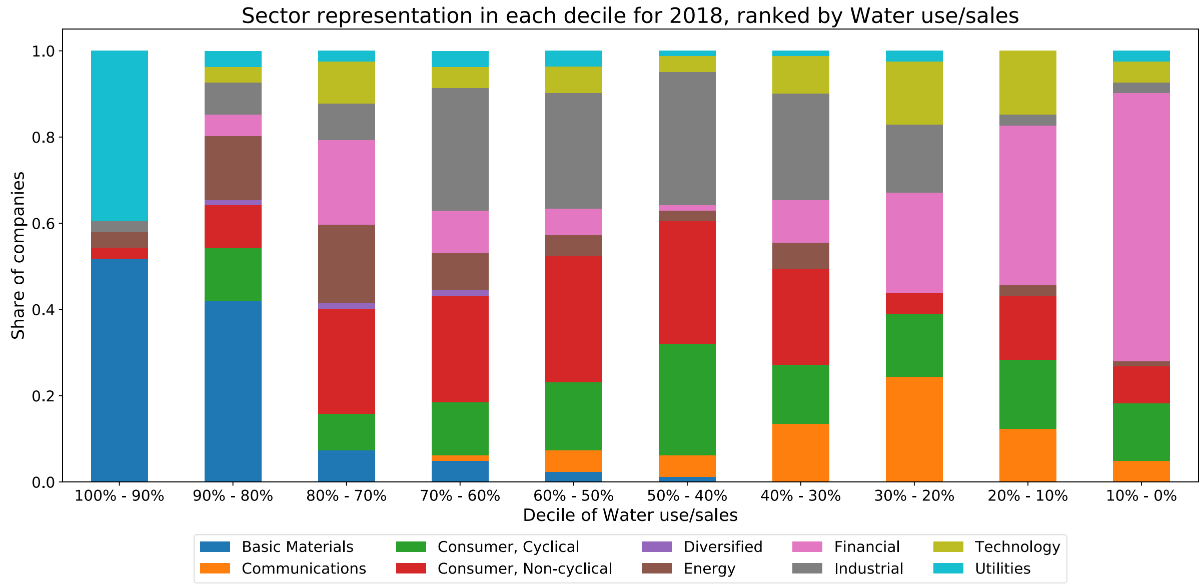


Figure A11, the figure shows the sector representation in each decile of the Water use / sales, for the fiscal year 2018. The deciles are displayed as bars, with the 10% highest impact companies to the left, and the 10% lowest to the right. In each bar, the coloured area shows the share of companies in that decile from the corresponding sector.

10.4 Portfolio Test Results

The tables in this section presents the results of the main portfolio tests described in Section 5.3, in which the top ranked portfolio is compared to the bottom ranked portfolio in a pairwise test. In each portfolio-pair shown in the tables, the results from the top ranked portfolio is shown as the top-most results and is formatted in italics. The tables show the yearly returns for each portfolio. These are the returns for the portfolio starting that year, which means that it covers the period from the first day of July in the shown year to the last day of June in the following year. Theta ($\hat{\theta}$) is the estimated variance of the transformed difference, as described in Section 2.3, equation 6. The z-statistic is the test statistic from the test described in Section 2.3, equation 7. The *P*-value is the corresponding probability of rejecting a false null hypothesis in a two-sided test. Significant *P*-values are marked with stars for the following significance levels, ****: $P < 0.01$, **: $P < 0.05$, *: $P < 0.10$.*

TABLE A3 – PORTFOLIO TESTS, ALL SECTORS

Greenhouse gas emissions	%	Total gain	Daily Sharpe	Theta	Z-statistic	P-value	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
	10	*22.6%*	*0.00846*	1.78E-12	-1.4198	0.16	*23.0%*	*-28.3%*	*-27.3%*	*14.5%*	*15.3%*	*-18.4%*	*20.4%*	*24.4%*	*7.5%*	*-17.3%*	*29.2%*	*-0.8%*	*4.0%*
		108.8%	0.02385				31.3%	19.2%	-33.3%	22.1%	26.2%	-16.0%	12.2%	26.6%	-8.7%	-1.3%	12.7%	8.1%	-0.9%
						Stocks:	10	26	51	64	63	68	74	78	83	88	89	92	96
	25	*76.3%*	*0.01764*	1.07E-12	-0.3485	0.73	*26.6%*	*-28.1%*	*-24.4%*	*14.7%*	*21.4%*	*-13.4%*	*24.0%*	*22.7%*	*11.5%*	*-12.0%*	*29.7%*	*6.4%*	*3.0%*
		92.5%	0.02083				26.6%	10.0%	-34.4%	23.6%	28.8%	-16.0%	8.8%	22.2%	-6.7%	-2.6%	16.7%	11.7%	0.1%
						Stocks:	24	65	128	160	157	171	184	196	208	219	222	230	240

Total waste	%	Total gain	Daily Sharpe	Theta	Z-statistic	P-value	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
	10	*47.2%*	*0.01275*	2.11E-12	-0.6070	0.54	*15.9%*	*-25.4%*	*-24.5%*	*9.9%*	*19.1%*	*-10.4%*	*18.6%*	*26.9%*	*8.7%*	*-17.9%*	*31.3%*	*2.9%*	*6.1%*
		87.4%	0.02009				28.3%	-2.7%	-25.0%	14.3%	23.6%	-15.5%	4.2%	18.5%	-1.4%	5.1%	17.2%	9.9%	1.8%
						Stocks:	11	26	44	52	58	63	68	70	72	74	74	75	77
	25	*50.9%*	*0.01377*	5.42E-13	-0.8828	0.38	*16.4%*	*-24.0%*	*-24.2%*	*9.3%*	*13.5%*	*-12.8%*	*22.6%*	*24.9%*	*9.2%*	*-11.6%*	*31.1%*	*3.2%*	*4.0%*
		86.1%	0.02053				27.9%	-6.3%	-22.5%	13.8%	21.6%	-15.3%	19.4%	18.3%	1.8%	-2.2%	16.4%	5.7%	-1.3%
						Stocks:	26	65	110	130	144	156	169	176	180	184	184	188	192

Net waste	%	Total gain	Daily Sharpe	Theta	Z-statistic	P-value	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
	10	*16.8%*	*0.00807*	2.06E-12	-0.3441	0.73		*-32.0%*	*-27.1%*	*14.0%*	*6.9%*	*-9.0%*	*28.1%*	*26.7%*	*15.4%*	*-18.7%*	*32.0%*	*0.6%*	*5.1%*
		35.0%	0.01206					-6.2%	-18.1%	20.5%	22.8%	-16.8%	7.5%	20.0%	-7.6%	-2.1%	13.5%	9.9%	-2.0%
						Stocks:	6	15	27	35	41	45	49	52	54	56	55	55	57
	25	*63.5%*	*0.01603*	7.41E-13	-1.0961	0.27	*17.4%*	*-24.5%*	*-25.1%*	*8.2%*	*18.9%*	*-12.5%*	*29.7%*	*22.8%*	*14.7%*	*-16.1%*	*29.8%*	*5.1%*	*4.5%*
		120.0%	0.02562				39.9%	1.0%	-21.5%	17.4%	26.4%	-14.5%	12.7%	19.0%	-0.7%	-1.4%	16.1%	5.3%	-2.5%
						Stocks:	15	37	68	87	103	112	123	129	135	139	137	138	142

Water use	%	Total gain	Daily Sharpe	Theta	Z-statistic	P-value	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
	10	*35.2%*	*0.01060*	2.20E-12	-0.8101	0.42	*44.1%*	*-22.5%*	*-29.0%*	*4.6%*	*7.7%*	*-15.5%*	*20.0%*	*22.1%*	*8.4%*	*-20.3%*	*32.6%*	*2.3%*	*4.2%*
		91.7%	0.02054				18.0%	18.3%	-25.4%	14.6%	22.8%	-17.5%	0.5%	19.1%	-5.0%	3.5%	19.6%	8.2%	4.2%
						Stocks:	10	25	44	51	56	61	66	68	70	73	74	75	79
	25	*64.0%*	*0.01582*	8.62E-13	-0.8327	0.41	*30.4%*	*-26.5%*	*-21.8%*	*7.7%*	*11.7%*	*-17.8%*	*24.1%*	*21.8%*	*9.2%*	*-10.9%*	*34.4%*	*4.8%*	*6.8%*
		103.5%	0.02330				31.4%	1.5%	-24.0%	17.5%	18.3%	-15.2%	13.1%	18.6%	-0.4%	-1.0%	18.9%	8.7%	-0.4%
						Stocks:	25	63	110	127	139	153	165	170	174	182	186	188	196

Combined rank	%	Total gain	Daily Sharpe	Theta	Z-statistic	P-value	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
	10	*46.1%*	*0.01509*	6.71E-12	0.5212	0.60			*-23.5%*	*10.2%*	*16.0%*	*-8.9%*	*19.8%*	*21.1%*	*9.8%*	*-22.8%*	*32.1%*	*-2.7%*	*3.7%*
		8.7%	0.00687						-33.4%	20.4%	24.1%	-21.5%	-1.2%	20.8%	-21.1%	5.8%	16.4%	18.1%	1.6%
						Stocks:	2	7	14	19	23	26	30	31	33	35	36	36	39
	25	*25.3%*	*0.00996*	1.56E-12	-0.2170	0.83		*-33.7%*	*-27.3%*	*14.6%*	*21.1%*	*-15.1%*	*27.3%*	*20.7%*	*13.7%*	*-12.8%*	*31.8%*	*4.5%*	*5.2%*
		35.3%	0.01221					3.8%	-28.5%	24.1%	20.9%	-18.9%	7.7%	16.8%	-8.5%	-1.7%	20.5%	10.6%	-0.6%
						Stocks:	5	17	36	48	57	66	74	78	82	88	90	90	98

TABLE A4 – PORTFOLIO TESTS, BASIC MATERIALS

	%	TOTAL GAIN	DAILY SHARPE	THETA	Z-STATISTIC	P-VALUE	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
GREENHOUSE GAS EMISSIONS	25	*209.9%*	*0.03417*	3.54E-12	2.0689	0.039**		*12.7%*	*-13.4%*	*20.3%*	*34.9%*	*-5.5%*	*6.4%*	*19.4%*	*7.7%*	*4.1%*	*18.3%*	*15.3%*	*6.5%*
		27.2%	0.01071					38.7%	-51.4%	19.2%	48.8%	-24.1%	8.3%	18.2%	-14.2%	-12.5%	24.9%	13.0%	3.2%
						STOCKS:	5	10	18	18	19	20	20	21	22	23	23	24	25
	50	*152.8%*	*0.02628*	1.50E-12	0.7409	0.46	*32.0%*	*5.4%*	*-22.8%*	*28.2%*	*38.6%*	*-12.4%*	*1.3%*	*13.5%*	*0.2%*	*-0.8%*	*18.8%*	*11.6%*	*-0.2%*
		105.9%	0.02037				32.3%	31.8%	-45.8%	28.3%	38.3%	-22.7%	4.3%	16.7%	-9.1%	-2.9%	28.6%	17.1%	-1.8%
						STOCKS:	10	20	36	36	38	41	40	42	44	46	46	48	50
TOTAL WASTE	%	TOTAL GAIN	DAILY SHARPE	THETA	Z-STATISTIC	P-VALUE	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
	25	*122.1%*	*0.02990*	8.91E-12	1.5353	0.13			*-22.4%*	*23.9%*	*50.5%*	*-4.1%*	*-2.3%*	*14.0%*	*7.9%*	*-4.9%*	*22.2%*	*13.4%*	*1.2%*
		-12.0%	0.00516						-35.3%	21.3%	35.2%	-31.8%	-22.7%	10.7%	-21.3%	23.3%	16.8%	17.4%	7.0%
						STOCKS:	4	7	13	16	17	19	22	21	22	22	23	23	22
	50	*110.1%*	*0.02447*	2.93E-12	0.7730	0.44		*13.6%*	*-29.0%*	*22.8%*	*42.8%*	*-10.3%*	*12.5%*	*12.2%*	*7.0%*	*-8.1%*	*27.4%*	*10.2%*	*-5.1%*
		59.4%	0.01594					22.0%	-31.8%	30.1%	34.9%	-26.4%	-0.2%	13.0%	-10.0%	-0.9%	24.2%	17.6%	0.7%
						STOCKS:	8	14	26	31	34	38	44	42	43	44	46	46	44
NET WASTE	%	TOTAL GAIN	DAILY SHARPE	THETA	Z-STATISTIC	P-VALUE	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
	25	*76.7%*	*0.03051*	9.13E-12	1.1316	0.26					*31.3%*	*-13.4%*	*12.0%*	*6.1%*	*6.7%*	*-13.0%*	*22.2%*	*13.6%*	*1.4%*
		-6.5%	0.00466								26.9%	-32.4%	-21.3%	10.2%	-28.2%	16.4%	26.7%	15.8%	2.5%
						STOCKS:	1	3	7	9	12	13	15	14	14	13	14	15	16
	50	*44.9%*	*0.01549*	3.64E-12	0.3833	0.70			*-31.6%*	*19.5%*	*29.3%*	*-11.9%*	*12.2%*	*9.9%*	*4.1%*	*-10.1%*	*30.2%*	*8.5%*	*-4.5%*
		22.7%	0.01067						-34.6%	41.6%	27.2%	-27.4%	2.2%	13.2%	-9.3%	-1.1%	25.8%	15.4%	-4.9%
						STOCKS:	2	6	14	18	24	26	30	29	28	26	28	30	31
WATER USE	%	TOTAL GAIN	DAILY SHARPE	THETA	Z-STATISTIC	P-VALUE	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
	25	*95.0%*	*0.02536*	3.34E-12	1.2903	0.20			*-24.1%*	*14.3%*	*26.7%*	*-7.4%*	*19.1%*	*18.2%*	*5.5%*	*-3.1%*	*21.7%*	*15.0%*	*-5.0%*
		12.9%	0.00821						-36.4%	31.6%	19.3%	-23.4%	4.8%	10.1%	7.0%	-4.4%	26.9%	8.0%	-8.7%
						STOCKS:	4	8	14	15	16	19	21	20	20	20	22	22	22
	50	*92.1%*	*0.02147*	2.00E-12	0.8260	0.41		*15.1%*	*-29.2%*	*21.6%*	*23.0%*	*-17.0%*	*13.0%*	*14.8%*	*4.9%*	*-4.4%*	*25.5%*	*15.4%*	*0.8%*
		46.4%	0.01398					29.5%	-33.3%	25.7%	31.0%	-22.1%	-3.0%	11.3%	-6.0%	-3.6%	28.8%	13.2%	-7.4%
						STOCKS:	8	15	28	30	33	38	42	40	40	41	44	43	43
COMBINED RANK	%	TOTAL GAIN	DAILY SHARPE	THETA	Z-STATISTIC	P-VALUE	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
	25	*129.4%*	*0.05659*	1.06E-11	1.9926	0.046**							*17.2%*	*23.5%*	*17.8%*	*-0.8%*	*12.0%*	*20.8%*	*0.4%*
		-8.0%	0.00248										-13.3%	4.4%	-24.5%	7.4%	5.2%	11.2%	7.2%
						STOCKS:	0	2	5	5	7	7	10	10	10	10	10	10	12
	50	*72.4%*	*0.02011*	7.97E-12	0.9956	0.32			*-24.0%*	*39.3%*	*26.7%*	*-21.7%*	*8.3%*	*15.4%*	*4.7%*	*-7.7%*	*23.1%*	*13.0%*	*-2.4%*
		-5.5%	0.00523						-44.2%	33.2%	30.0%	-23.4%	-4.1%	8.9%	-16.6%	2.6%	21.2%	15.4%	2.2%
						STOCKS:	0	4	10	10	14	14	20	20	20	19	20	20	24

TABLE A5 – PORTFOLIO TESTS, COMMUNICATIONS

	%	TOTAL GAIN	DAILY SHARPE	THETA	Z-STATISTIC	P-VALUE	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
GREENHOUSE GAS EMISSIONS	25	*50.4%*	*0.01953*	1.98E-12	-0.6210	0.54				*17.4%*	*12.6%*	*-11.9%*	*10.6%*	*21.5%*	*6.1%*	*-11.4%*	*-2.5%*	*5.4%*	*-0.4%*
		89.7%	0.03016							8.2%	14.9%	-8.4%	31.0%	25.3%	9.5%	0.3%	-4.0%	-7.0%	3.4%
						STOCKS:	2	5	8	11	12	12	14	16	16	16	16	18	18
	50	*-13.2%*	*-0.00122*	1.32E-12	-0.7645	0.45		*-31.7%*	*-15.2%*	*17.2%*	*11.2%*	*-13.5%*	*9.6%*	*14.2%*	*4.0%*	*-12.4%*	*6.2%*	*5.1%*	*4.5%*
		15.8%	0.00717					-23.5%	-20.2%	3.3%	20.1%	-14.4%	28.4%	27.4%	6.0%	-1.0%	9.2%	-6.0%	1.1%
						STOCKS:	5	10	16	22	24	23	28	32	31	32	32	36	36
TOTAL WASTE	%	TOTAL GAIN	DAILY SHARPE	THETA	Z-STATISTIC	P-VALUE	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
	25	*72.8%*	*0.04397*	2.06E-12	-0.3513	0.73							*17.2%*	*22.9%*	*3.9%*		*13.6%*	*-1.9%*	*3.6%*
		112.5%	0.05328										49.3%	38.6%	9.5%		0.3%	-3.7%	-2.8%
						STOCKS:	3	5	6	8	8	9	10	10	10	9	10	11	12
	50	*29.7%*	*0.01088*	1.52E-12	0.0465	0.96		*-16.6%*	*-14.9%*	*16.3%*	*12.0%*	*-6.8%*	*18.4%*	*20.4%*	*8.1%*	*-12.0%*	*7.4%*	*-0.4%*	*3.8%*
		27.5%	0.01031					-22.2%	-21.4%	8.7%	18.2%	-14.9%	32.2%	36.1%	4.8%	-0.7%	3.6%	-2.8%	1.1%
						STOCKS:	6	10	12	16	17	18	19	20	20	18	20	22	24
NET WASTE	%	TOTAL GAIN	DAILY SHARPE	THETA	Z-STATISTIC	P-VALUE	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
	25																		
							1	2	3	5	6	6	7	8	8	8	8	8	8
	50	*120.6%*	*0.03487*	1.55E-12	0.0723	0.94				*18.4%*	*4.1%*	*-15.3%*	*48.4%*	*32.8%*	*12.3%*	*-16.8%*	*8.5%*	*-1.1%*	*7.0%*
		98.9%	0.03373							18.1%	23.5%	-14.1%	16.9%	27.8%	-1.3%	2.8%	0.8%	0.2%	3.7%
						STOCKS:	2	4	6	10	11	12	13	16	16	16	15	15	16
WATER USE	%	TOTAL GAIN	DAILY SHARPE	THETA	Z-STATISTIC	P-VALUE	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
	25	*12.5%*	*0.00788*	1.94E-12	0.1031	0.92					*3.0%*	*-14.3%*	*-9.9%*	*16.6%*	*16.4%*	*-9.0%*	*9.7%*	*-2.7%*	*7.3%*
		8.0%	0.00573								19.3%	-3.4%	5.2%	5.2%	-2.3%	1.1%	1.7%	-12.0%	-4.3%
						STOCKS:	2	4	6	9	10	10	10	10	10	11	12	12	12
	50	*49.8%*	*0.01727*	1.36E-12	0.5360	0.59			*-15.7%*	*12.4%*	*10.4%*	*-18.4%*	*17.8%*	*16.1%*	*13.9%*	*-4.5%*	*9.1%*	*-1.2%*	*9.5%*
		24.8%	0.01082						-20.5%	7.5%	19.4%	-9.8%	20.1%	17.2%	1.1%	-3.9%	5.6%	-4.3%	-1.8%
						STOCKS:	4	8	12	18	20	21	21	20	20	22	24	25	24
COMBINED RANK	%	TOTAL GAIN	DAILY SHARPE	THETA	Z-STATISTIC	P-VALUE	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
	25																		
						STOCKS:	0	1	1	3	3	3	3	4	5	5	6	6	6
	50	*25.8%*	*0.02232*	2.39E-12	1.7048	0.088*									*8.1%*	*-6.8%*	*4.7%*	*4.1%*	*14.6%*
		-18.8%	-0.02134												-5.1%	-0.6%	6.5%	-15.5%	-4.3%
						STOCKS:	0	2	2	6	6	6	6	8	10	10	12	12	12

TABLE A6 – PORTFOLIO TESTS, CONSUMER CYCLICAL

GREENHOUSE GAS EMISSIONS	%	TOTAL GAIN	DAILY SHARPE	THETA	Z-STATISTIC	P-VALUE	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
	25	*241.4%*	*0.03969*	5.30E-12	0.1009	0.92			*-9.6%*	*36.9%*	*32.8%*	*-2.0%*	*30.3%*	*14.6%*	*14.8%*	*-10.5%*	*27.9%*	*12.4%*	*-4.0%*
		266.7%	0.03831						-19.2%	66.1%	22.3%	-11.2%	31.6%	33.3%	20.4%	-14.0%	41.3%	-1.6%	-0.5%
						STOCKS:	2	4	12	18	18	21	23	25	27	30	29	30	32
	50	*169.1%*	*0.03530*	1.89E-12	0.6749	0.50			*-12.1%*	*29.9%*	*30.2%*	*-3.4%*	*33.6%*	*12.3%*	*15.2%*	*-15.6%*	*21.0%*	*10.4%*	*-3.9%*
		125.6%	0.02819						-25.3%	38.5%	21.8%	-12.5%	30.4%	23.8%	15.0%	-14.9%	33.5%	0.1%	-3.1%
						STOCKS:	3	8	23	35	36	42	46	50	54	60	58	60	63

TOTAL WASTE	%	TOTAL GAIN	DAILY SHARPE	THETA	Z-STATISTIC	P-VALUE	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
	25	*205.2%*	*0.03901*	3.71E-12	0.3948	0.69			*-20.9%*	*44.4%*	*9.6%*	*-9.7%*	*28.6%*	*13.8%*	*15.7%*	*-4.9%*	*51.2%*	*9.3%*	*1.7%*
		198.0%	0.03385						-8.8%	19.4%	33.0%	-8.9%	45.6%	25.4%	27.5%	-17.4%	26.1%	-1.8%	-5.2%
						STOCKS:	2	8	15	17	18	20	21	23	22	24	23	25	26
	50	*130.6%*	*0.02734*	2.42E-12	0.6389	0.52		*-19.8%*	*-18.2%*	*32.7%*	*15.3%*	*-8.1%*	*36.2%*	*13.0%*	*20.6%*	*-13.2%*	*43.7%*	*11.1%*	*-2.7%*
		86.5%	0.02021					-25.0%	-10.4%	23.7%	38.0%	-12.5%	33.5%	23.3%	18.0%	-19.3%	24.9%	2.3%	-7.2%
						STOCKS:	5	16	30	34	36	39	42	46	44	48	46	50	52

NET WASTE	%	TOTAL GAIN	DAILY SHARPE	THETA	Z-STATISTIC	P-VALUE	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
	25	*126.1%*	*0.02732*	1.04E-11	-0.3446	0.73			*-24.5%*	*25.9%*	*26.1%*	*-6.2%*	*31.0%*	*19.5%*	*23.9%*	*-22.7%*	*25.8%*	*14.5%*	*-7.0%*
		220.7%	0.03315						11.6%	13.4%	48.7%	-6.2%	33.7%	12.4%	17.3%	-15.8%	25.1%	2.2%	-4.2%
						STOCKS:	2	6	10	12	12	14	15	16	16	18	16	17	17
	50	*129.8%*	*0.02604*	4.51E-12	0.1323	0.90		*-21.2%*	*-24.7%*	*50.1%*	*21.1%*	*-9.8%*	*34.3%*	*25.6%*	*21.6%*	*-16.2%*	*32.4%*	*8.9%*	*-4.6%*
		124.2%	0.02428					-27.6%	0.9%	23.3%	35.8%	-11.1%	34.7%	16.1%	21.2%	-15.4%	26.4%	7.1%	-4.9%
						STOCKS:	5	12	20	24	25	28	30	32	32	35	33	34	34

WATER USE	%	TOTAL GAIN	DAILY SHARPE	THETA	Z-STATISTIC	P-VALUE	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
	25	*94.9%*	*0.02465*	2.79E-12	0.2142	0.83			*-13.6%*	*11.6%*	*19.2%*	*-13.6%*	*18.1%*	*11.7%*	*8.1%*	*-11.2%*	*47.8%*	*4.7%*	*0.2%*
		83.0%	0.02199						-37.7%	25.3%	17.3%	-12.9%	34.7%	23.4%	26.0%	-16.9%	37.4%	2.5%	-6.4%
						STOCKS:	3	8	16	19	18	21	21	22	24	26	24	25	26
	50	*64.3%*	*0.01749*	2.27E-12	0.2628	0.79		*-28.7%*	*-8.4%*	*13.4%*	*28.3%*	*-15.5%*	*29.9%*	*18.1%*	*14.0%*	*-15.9%*	*34.8%*	*7.4%*	*-3.9%*
		48.7%	0.01456					-22.1%	-33.6%	28.6%	24.0%	-11.4%	36.1%	17.6%	16.9%	-17.1%	39.2%	2.1%	-7.8%
						STOCKS:	6	16	32	38	35	42	42	43	47	52	48	50	52

COMBINED RANK	%	TOTAL GAIN	DAILY SHARPE	THETA	Z-STATISTIC	P-VALUE	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
	25	*66.2%*	*0.03469*	2.80E-12	0.3534	0.72								*11.5%*	*25.5%*	*-27.0%*	*40.1%*	*16.8%*	*-0.6%*
		36.5%	0.02687											12.6%	13.8%	-8.9%	20.9%	-0.4%	-3.0%
						STOCKS:	1	3	6	6	7	8	9	10	11	12	10	10	11
	50	*129.2%*	*0.02714*	3.60E-12	0.8468	0.40			*-19.2%*	*29.0%*	*36.1%*	*-13.7%*	*25.4%*	*20.7%*	*19.5%*	*-23.3%*	*32.4%*	*5.0%*	*-3.1%*
		53.4%	0.01689						-30.6%	31.0%	17.8%	-22.5%	26.6%	21.2%	9.5%	-12.4%	34.0%	0.0%	-6.2%
						STOCKS:	2	6	11	13	14	17	18	19	22	24	20	20	22

TABLE A7 – PORTFOLIO TESTS, CONSUMER, NON-CYCLICAL

	%	TOTAL GAIN	DAILY SHARPE	THETA	Z-STATISTIC	P-VALUE	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
GREENHOUSE GAS EMISSIONS	25	*170.3%*	*0.03706*	5.91E-13	-0.1181	0.91		*-17.3%*	*-10.2%*	*16.8%*	*26.0%*	*-1.5%*	*29.3%*	*26.7%*	*23.2%*	*-5.3%*	*11.6%*	*7.9%*	*9.0%*
		143.6%	0.03840					-15.2%	-8.2%	17.9%	13.4%	3.2%	23.2%	8.8%	13.9%	15.2%	6.2%	11.3%	9.3%
						STOCKS:	4	12	22	29	28	32	33	34	38	39	39	40	41
	50	*176.4%*	*0.04010*	2.46E-13	0.7502	0.45		*-13.3%*	*-9.3%*	*14.8%*	*26.1%*	*3.2%*	*28.4%*	*25.8%*	*15.1%*	*2.8%*	*10.0%*	*3.1%*	*8.6%*
		114.5%	0.03395					-12.6%	-10.1%	15.7%	14.8%	1.9%	23.2%	9.1%	12.2%	8.7%	8.1%	6.7%	6.6%
						STOCKS:	9	25	44	58	56	63	66	68	75	78	78	80	82

	%	TOTAL GAIN	DAILY SHARPE	THETA	Z-STATISTIC	P-VALUE	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
TOTAL WASTE	25	*199.8%*	*0.04425*	5.44E-13	1.2978	0.19		*-14.3%*	*-15.0%*	*10.7%*	*20.8%*	*2.5%*	*32.5%*	*29.4%*	*30.5%*	*1.1%*	*11.6%*	*14.1%*	*4.4%*
		102.1%	0.02934					-4.8%	-15.6%	8.9%	9.2%	3.3%	28.4%	10.9%	16.2%	6.1%	9.7%	-0.9%	7.2%
						STOCKS:	6	15	25	27	30	30	32	34	35	36	36	34	35
	50	*271.0%*	*0.05160*	2.08E-13	1.6981	0.089*	*21.5%*	*-10.5%*	*-9.0%*	*13.3%*	*16.1%*	*5.9%*	*27.3%*	*26.0%*	*22.9%*	*4.7%*	*11.3%*	*10.4%*	*6.3%*
		152.8%	0.03704				25.7%	-8.9%	-13.5%	12.3%	13.6%	5.0%	27.7%	12.4%	10.8%	8.3%	6.2%	-0.5%	4.6%
						STOCKS:	12	30	50	54	60	61	65	68	70	71	72	68	70

	%	TOTAL GAIN	DAILY SHARPE	THETA	Z-STATISTIC	P-VALUE	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
NET WASTE	25	*261.3%*	*0.05756*	7.25E-13	1.8881	0.059*			*-13.9%*	*11.8%*	*27.8%*	*3.7%*	*35.4%*	*28.7%*	*29.8%*	*-2.0%*	*8.3%*	*14.0%*	*3.5%*
		102.4%	0.03243						-12.1%	12.0%	15.0%	4.0%	27.8%	12.5%	7.4%	6.9%	0.7%	-2.5%	6.1%
						STOCKS:	3	8	17	19	22	23	25	27	28	27	28	26	26
	50	*193.0%*	*0.04507*	3.80E-13	1.0765	0.28		*-8.7%*	*-8.2%*	*9.9%*	*15.8%*	*5.0%*	*30.3%*	*24.2%*	*25.6%*	*3.1%*	*11.3%*	*7.0%*	*4.9%*
		119.1%	0.03374					-12.5%	-9.4%	16.4%	17.4%	6.3%	23.9%	16.0%	8.3%	7.7%	5.0%	0.9%	7.3%
						STOCKS:	6	15	34	38	44	46	50	54	56	54	55	52	51

	%	TOTAL GAIN	DAILY SHARPE	THETA	Z-STATISTIC	P-VALUE	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
WATER USE	25	*148.7%*	*0.03529*	5.86E-13	0.5684	0.57		*-14.0%*	*-13.4%*	*18.1%*	*17.3%*	*-3.3%*	*27.3%*	*27.7%*	*15.5%*	*0.5%*	*15.0%*	*7.0%*	*7.3%*
		92.6%	0.02853					-16.8%	-13.4%	14.6%	12.6%	1.8%	25.0%	9.6%	18.2%	13.5%	3.1%	1.5%	5.8%
						STOCKS:	6	15	24	26	29	31	33	33	34	33	34	33	34
	50	*225.2%*	*0.04524*	2.54E-13	0.6548	0.51	*24.3%*	*-11.4%*	*-12.8%*	*15.6%*	*17.3%*	*2.4%*	*29.5%*	*27.4%*	*15.3%*	*3.4%*	*9.9%*	*7.9%*	*4.7%*
		162.2%	0.03910				20.2%	-10.8%	-14.4%	12.1%	12.7%	6.3%	25.9%	11.0%	20.8%	9.3%	5.6%	2.8%	6.1%
						STOCKS:	12	30	48	53	58	62	66	66	68	66	68	66	68

	%	TOTAL GAIN	DAILY SHARPE	THETA	Z-STATISTIC	P-VALUE	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
COMBINED RANK	25	*338.1%*	*0.07340*	7.33E-13	1.8192	0.069*				*11.7%*	*37.8%*	*0.6%*	*34.6%*	*36.5%*	*23.5%*	*2.4%*	*8.7%*	*13.1%*	*-0.8%*
		113.1%	0.04401							12.8%	15.1%	0.6%	20.5%	10.8%	5.6%	13.9%	4.3%	-8.6%	6.6%
						STOCKS:	2	4	8	12	14	16	17	18	19	18	18	17	17
	50	*257.1%*	*0.05528*	3.95E-13	1.4735	0.14			*-8.9%*	*9.4%*	*27.7%*	*5.1%*	*35.3%*	*28.4%*	*17.8%*	*6.3%*	*9.3%*	*7.0%*	*5.0%*
		127.6%	0.04015						-11.6%	13.5%	14.8%	4.4%	22.3%	11.5%	11.0%	10.9%	6.2%	-1.1%	7.3%
						STOCKS:	3	7	17	24	27	31	34	37	38	36	37	34	34

Table A8 – Portfolio tests, Energy

	%	Total gain	Daily Sharpe	Theta	Z-statistic	P-value	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
Greenhouse gas emissions	25	*0.0%* -41.9%	*0.00568* -0.00571	6.81E-12	0.9540	0.34			*-39.4%* -34.6%	*12.4%* 11.2%	*43.4%* 38.8%	*-20.3%* -18.4%	*21.8%* 10.0%	*43.0%* 30.5%	*-6.6%* -30.0%	*-5.0%* -13.9%	*-7.6%* -13.4%	*8.1%* 35.6%	*-16.8%* -30.6%
						Stocks:	2	5	11	12	12	13	13	14	14	14	16	16	17
	50	*8.7%* -23.1%	*0.00706* 0.00096	3.46E-12	0.7103	0.48		*-1.4%* 41.1%	*-37.6%* -35.5%	*8.9%* 1.6%	*43.2%* 31.8%	*-15.9%* -20.5%	*24.9%* 7.1%	*31.7%* 30.3%	*-12.9%* -31.2%	*-6.6%* -13.2%	*-4.7%* -6.6%	*21.2%* 31.4%	*-12.8%* -22.5%
						Stocks:	4	10	22	25	24	26	26	28	28	29	31	33	34
	%	Total gain	Daily Sharpe	Theta	Z-statistic	P-value	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
Total waste	25	*26.1%* -31.6%	*0.02202* -0.01918	1.50E-11	1.8242	0.068*										*-4.4%* -16.7%	*8.3%* -10.0%	*18.3%* 21.2%	*3.0%* -24.7%
						Stocks:	2	4	6	6	8	8	9	9	9	10	10	10	10
	50	*-8.0%* -10.4%	*0.00311* 0.00349	3.85E-12	-0.0378	0.97			*-37.2%* -32.2%	*-10.0%* 8.7%	*20.6%* 32.4%	*-22.2%* -19.6%	*11.3%* 29.4%	*20.8%* 47.4%	*-4.4%* -30.1%	*-3.9%* -13.8%	*6.2%* 2.2%	*27.2%* 24.9%	*4.0%* -22.1%
						Stocks:	3	7	12	13	15	17	18	18	18	20	21	20	19
	%	Total gain	Daily Sharpe	Theta	Z-statistic	P-value	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
Net waste	25																		
							0	2	3	4	5	6	6	6	6	6	8	7	6
	50	*39.8%* 19.2%	*0.01652* 0.01076	4.23E-12	0.4105	0.68					*20.3%* 23.2%	*-24.6%* -15.9%	*11.6%* 21.6%	*24.1%* 42.9%	*-7.8%* -15.2%	*-11.2%* -18.8%	*8.1%* 3.8%	*24.2%* 20.9%	*1.2%* -23.4%
						Stocks:	0	4	5	8	10	11	12	12	12	12	15	14	12
	%	Total gain	Daily Sharpe	Theta	Z-statistic	P-value	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
Water use	25	*-18.4%* -1.7%	*-0.01717* 0.00421	1.17E-11	-1.0106	0.31										*-5.5%* -19.5%	*1.4%* 4.0%	*-2.5%* 47.5%	*-12.7%* -20.4%
						Stocks:	1	2	4	4	5	6	7	8	8	10	12	12	12
	50	*58.0%* -30.3%	*0.02119* -0.00545	3.96E-12	2.1225	0.034*					*32.4%* 14.5%	*-18.1%* -19.4%	*21.3%* 15.0%	*42.1%* 33.0%	*-16.5%* -40.1%	*-3.4%* -17.9%	*0.0%* -3.1%	*14.9%* 31.0%	*-8.9%* -20.8%
						Stocks:	2	4	9	8	10	12	14	16	16	19	24	23	24
	%	Total gain	Daily Sharpe	Theta	Z-statistic	P-value	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
Combined rank	25																		
							0	1	2	2	3	3	4	4	4	4	6	5	5
	50	*-16.1%* 28.5%	*-0.02193* 0.02838	1.17E-11	-1.8689	0.062*											*2.3%* 7.5%	*-2.2%* 42.7%	*-16.2%* -16.2%
						Stocks:	0	2	3	4	5	6	8	8	8	8	12	10	10

TABLE A9 – PORTFOLIO TESTS, FINANCIAL

	%	TOTAL GAIN	DAILY SHARPE	THETA	Z-STATISTIC	P-VALUE	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
GREENHOUSE GAS EMISSIONS	25	*10.7%*	*0.00902*	7.36E-12	-0.6997	0.48			*-34.8%*	*15.4%*	*17.7%*	*-26.1%*	*23.4%*	*20.4%*	*8.7%*	*-24.5%*	*37.9%*	*-5.3%*	*6.1%*
		63.7%	0.01849						-34.6%	16.9%	24.7%	-6.1%	22.2%	14.6%	7.7%	6.3%	6.4%	1.5%	5.6%
						STOCKS:	2	9	18	24	23	25	28	32	34	37	40	40	43
	50	*-26.5%*	*-0.00143*	2.17E-12	-0.0949	0.92		*-32.4%*	*-29.8%*	*9.8%*	*11.5%*	*-26.6%*	*23.9%*	*22.0%*	*5.6%*	*-18.4%*	*33.0%*	*-1.7%*	*1.5%*
		-16.7%	-0.00063					-41.6%	-33.7%	15.5%	17.1%	-11.6%	26.4%	17.8%	8.9%	-11.6%	25.2%	0.5%	-0.3%
						STOCKS:	5	18	36	48	46	50	55	63	68	74	80	80	86
TOTAL WASTE	%	TOTAL GAIN	DAILY SHARPE	THETA	Z-STATISTIC	P-VALUE	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
	25	*3.9%*	*0.00708*	4.94E-12	-0.2541	0.80			*-33.8%*	*4.6%*	*9.8%*	*-16.5%*	*20.0%*	*33.4%*	*7.9%*	*-28.2%*	*32.8%*	*-3.4%*	*2.9%*
		23.3%	0.01042						-39.2%	13.0%	15.9%	-5.9%	29.6%	16.1%	6.4%	2.8%	2.1%	-2.3%	0.3%
						STOCKS:	4	8	12	16	19	22	22	25	28	29	28	28	30
	50	*-29.2%*	*-0.00187*	1.82E-12	0.6470	0.52		*-34.0%*	*-28.2%*	*3.6%*	*10.3%*	*-23.6%*	*27.1%*	*30.0%*	*7.1%*	*-25.0%*	*35.9%*	*-4.8%*	*-0.5%*
		-33.8%	-0.00674					-35.1%	-33.3%	7.4%	5.0%	-16.4%	30.2%	16.2%	4.8%	-12.3%	21.8%	-3.2%	-1.3%
						STOCKS:	8	15	24	32	38	44	45	50	56	58	56	56	60
NET WASTE	%	TOTAL GAIN	DAILY SHARPE	THETA	Z-STATISTIC	P-VALUE	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
	25	*72.2%*	*0.02334*	2.08E-12	-0.3709	0.71				*15.2%*	*8.8%*	*-15.3%*	*22.7%*	*29.9%*	*14.3%*	*-28.2%*	*36.0%*	*-7.9%*	*-1.0%*
		79.6%	0.02961							11.3%	18.1%	-8.1%	21.7%	12.7%	6.5%	12.1%	-8.3%	-2.9%	2.0%
						STOCKS:	4	5	8	12	14	16	17	18	20	21	20	21	22
	50	*-39.0%*	*-0.00389*	2.84E-12	0.1450	0.89		*-40.1%*	*-34.2%*	*9.3%*	*9.5%*	*-20.9%*	*29.6%*	*22.9%*	*10.0%*	*-23.3%*	*34.8%*	*-6.1%*	*-3.8%*
		-29.7%	-0.00517					-34.0%	-37.0%	5.4%	11.0%	-14.3%	28.5%	12.2%	6.9%	-6.8%	15.1%	-1.1%	3.3%
						STOCKS:	7	10	16	24	28	32	34	35	40	42	40	42	44
WATER USE	%	TOTAL GAIN	DAILY SHARPE	THETA	Z-STATISTIC	P-VALUE	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
	25	*-27.3%*	*-0.00089*	3.72E-12	1.1415	0.25		*-42.1%*	*-29.7%*	*6.4%*	*9.9%*	*-21.1%*	*28.4%*	*24.1%*	*11.0%*	*-22.7%*	*35.6%*	*-2.7%*	*7.2%*
		-48.0%	-0.01269					-47.2%	-36.4%	10.7%	7.5%	-13.0%	22.3%	18.2%	3.8%	-3.1%	1.8%	-0.2%	1.3%
						STOCKS:	5	10	15	18	22	24	26	29	32	32	31	32	35
	50	*-17.7%*	*0.00016*	1.28E-12	1.1231	0.26	*19.9%*	*-27.2%*	*-30.4%*	*1.8%*	*7.5%*	*-22.5%*	*27.9%*	*18.0%*	*8.0%*	*-27.6%*	*35.2%*	*-1.8%*	*2.0%*
		-36.7%	-0.00733				14.8%	-40.7%	-34.6%	0.4%	2.8%	-21.2%	26.9%	23.3%	6.0%	-14.9%	24.5%	-0.7%	0.4%
						STOCKS:	10	20	30	37	45	48	53	58	63	64	62	64	70
COMBINED RANK	%	TOTAL GAIN	DAILY SHARPE	THETA	Z-STATISTIC	P-VALUE	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
	25	*58.1%*	*0.02353*	3.32E-12	0.5088	0.61						*-19.9%*	*26.2%*	*23.2%*	*9.3%*	*-20.1%*	*41.5%*	*-5.6%*	*8.8%*
		21.4%	0.01304									-4.8%	13.7%	13.5%	4.0%	9.0%	-9.3%	-5.8%	2.1%
						STOCKS:	1	2	4	6	8	10	11	10	13	14	14	15	17
	50	*55.7%*	*0.01939*	1.21E-12	-0.7056	0.48				*10.0%*	*14.1%*	*-20.6%*	*29.7%*	*12.9%*	*8.9%*	*-23.2%*	*34.5%*	*-4.4%*	*-0.9%*
		79.3%	0.02726							12.6%	14.2%	-14.8%	24.4%	14.1%	8.9%	-8.7%	16.4%	-3.5%	3.4%
						STOCKS:	2	4	8	13	16	19	22	21	26	29	28	30	34

TABLE A10 – PORTFOLIO TESTS, INDUSTRIAL

	%	TOTAL GAIN	DAILY SHARPE	THETA	Z-STATISTIC	P-VALUE	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
GREENHOUSE GAS EMISSIONS	25	*149.9%*	*0.03255*	1.23E-12	1.2400	0.22			*-21.4%*	*22.9%*	*32.2%*	*-20.8%*	*29.9%*	*22.3%*	*2.2%*	*4.3%*	*24.0%*	*16.1%*	*1.2%*
		71.1%	0.02104						-28.6%	24.3%	19.8%	-15.3%	17.6%	25.3%	2.8%	-11.1%	36.0%	-1.4%	5.3%
						STOCKS:	2	8	18	22	22	22	23	25	26	28	30	30	32
	50	*84.2%*	*0.02073*	6.86E-13	1.0776	0.28		*-27.9%*	*-24.2%*	*29.4%*	*30.7%*	*-15.8%*	*28.1%*	*22.6%*	*4.0%*	*-0.7%*	*27.1%*	*11.4%*	*3.1%*
		41.2%	0.01336					-27.2%	-27.5%	24.0%	23.3%	-18.4%	26.7%	25.0%	7.7%	-8.2%	29.0%	0.9%	5.3%
						STOCKS:	4	16	37	44	43	44	46	50	51	56	60	60	64
	%	TOTAL GAIN	DAILY SHARPE	THETA	Z-STATISTIC	P-VALUE	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
TOTAL WASTE	25	*116.1%*	*0.02614*	1.67E-12	1.7294	0.084*		*-21.5%*	*-26.4%*	*30.7%*	*27.0%*	*-12.7%*	*30.1%*	*19.5%*	*15.2%*	*-5.8%*	*31.6%*	*13.4%*	*2.5%*
		18.4%	0.00839					-27.1%	-25.6%	9.7%	18.6%	-17.4%	29.6%	29.8%	9.9%	-9.9%	29.5%	-1.7%	-4.3%
						STOCKS:	2	11	18	22	23	26	28	29	29	30	30	32	33
	50	*98.5%*	*0.02339*	7.07E-13	1.3824	0.17		*-19.6%*	*-24.1%*	*24.0%*	*27.0%*	*-15.3%*	*28.9%*	*18.0%*	*17.4%*	*-4.8%*	*28.5%*	*7.9%*	*3.4%*
		44.1%	0.01383					-27.3%	-23.8%	18.4%	20.0%	-12.8%	31.9%	25.9%	6.1%	-10.2%	34.0%	-0.1%	-1.0%
						STOCKS:	4	22	37	44	46	51	55	58	58	60	59	63	66
	%	TOTAL GAIN	DAILY SHARPE	THETA	Z-STATISTIC	P-VALUE	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
NET WASTE	25	*163.6%*	*0.03291*	2.41E-12	0.6920	0.49			*-20.9%*	*20.6%*	*26.2%*	*-16.5%*	*36.9%*	*15.8%*	*18.8%*	*-9.5%*	*35.8%*	*13.2%*	*0.0%*
		97.8%	0.02493						-25.0%	14.3%	24.5%	-16.7%	25.9%	31.8%	7.4%	-8.9%	31.1%	1.6%	2.7%
						STOCKS:	2	6	12	14	16	18	19	21	23	24	24	25	26
	50	*88.3%*	*0.02048*	1.20E-12	0.3546	0.72		*-19.5%*	*-26.8%*	*28.4%*	*27.9%*	*-17.7%*	*31.5%*	*20.4%*	*14.9%*	*-9.3%*	*31.7%*	*10.8%*	*-1.9%*
		62.3%	0.01756					-19.7%	-21.4%	14.8%	20.3%	-11.9%	28.6%	23.0%	9.9%	-9.0%	31.9%	0.3%	1.0%
						STOCKS:	4	11	23	27	32	35	38	42	46	48	48	50	53
	%	TOTAL GAIN	DAILY SHARPE	THETA	Z-STATISTIC	P-VALUE	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
WATER USE	25	*195.0%*	*0.03805*	1.68E-12	2.4242	0.015**			*-15.3%*	*24.2%*	*26.2%*	*-15.5%*	*36.3%*	*21.2%*	*11.3%*	*-1.8%*	*30.2%*	*7.6%*	*3.9%*
		37.9%	0.01378						-24.0%	17.1%	13.8%	-23.4%	31.7%	18.2%	8.2%	-18.2%	33.9%	2.0%	-5.6%
						STOCKS:	2	9	16	19	21	22	24	26	25	28	27	28	29
	50	*91.2%*	*0.02186*	1.06E-12	1.1080	0.27		*-25.0%*	*-20.1%*	*23.9%*	*25.3%*	*-14.9%*	*34.1%*	*22.9%*	*10.3%*	*-4.0%*	*28.5%*	*4.6%*	*2.9%*
		39.4%	0.01287					-26.7%	-24.7%	21.5%	20.2%	-18.6%	32.5%	22.6%	10.9%	-13.8%	34.6%	1.6%	0.0%
						STOCKS:	4	18	33	38	42	44	48	52	50	55	54	55	58
	%	TOTAL GAIN	DAILY SHARPE	THETA	Z-STATISTIC	P-VALUE	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
COMBINED RANK	25	*55.9%*	*0.04902*	5.09E-12	1.3567	0.18										*6.2%*	*29.8%*	*15.2%*	*-1.8%*
		12.0%	0.01226													-26.8%	42.8%	8.8%	-1.5%
						STOCKS:	0	2	4	6	6	7	7	8	8	10	11	12	14
	50	*167.8%*	*0.04120*	1.66E-12	-0.1072	0.92				*23.6%*	*22.9%*	*-22.1%*	*36.3%*	*22.6%*	*4.8%*	*-6.4%*	*30.8%*	*5.0%*	*0.7%*
		168.4%	0.04266							17.4%	22.2%	-19.5%	45.4%	16.9%	9.3%	-18.6%	36.9%	7.5%	4.4%
						STOCKS:	1	3	9	11	12	14	14	17	16	20	22	24	28

TABLE A11 – PORTFOLIO TESTS, TECHNOLOGY

	%	TOTAL GAIN	DAILY SHARPE	THETA	Z-STATISTIC	P-VALUE	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
GREENHOUSE GAS EMISSIONS	25	*190.6%*	*0.03206*	6.65E-12	0.1725	0.86			*-24.1%*	*-1.8%*	*43.4%*	*-1.5%*	*-0.5%*	*19.3%*	*18.5%*	*-2.4%*	*30.3%*	*23.3%*	*25.1%*
		142.4%	0.02953						-21.7%	27.4%	13.2%	-3.1%	22.2%	23.4%	-7.5%	-4.1%	49.8%	19.5%	-7.6%
						STOCKS:	2	5	10	14	12	14	16	16	16	16	16	15	16
	50	*220.6%*	*0.03374*	2.64E-12	1.3242	0.19		*-19.5%*	*-24.9%*	*7.8%*	*34.4%*	*0.6%*	*6.1%*	*25.6%*	*13.1%*	*10.3%*	*44.4%*	*21.6%*	*24.7%*
		75.5%	0.01918					-24.1%	-24.6%	24.2%	10.9%	-9.3%	20.9%	25.6%	-5.6%	0.1%	46.8%	16.4%	0.0%
						STOCKS:	3	10	19	28	25	29	32	33	33	33	32	30	32
TOTAL WASTE	%	TOTAL GAIN	DAILY SHARPE	THETA	Z-STATISTIC	P-VALUE	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
	25	*568.9%*	*0.06491*	6.55E-12	1.3454	0.18				*21.3%*	*46.0%*	*9.5%*	*-0.7%*	*28.6%*	*20.1%*	*-2.0%*	*29.0%*	*28.2%*	*39.0%*
		163.0%	0.03834							9.4%	2.2%	-4.2%	26.3%	22.4%	1.4%	-8.4%	56.3%	17.7%	-7.1%
						STOCKS:	1	4	7	10	10	12	14	14	14	13	13	13	12
	50	*360.1%*	*0.04813*	2.99E-12	1.5644	0.12			*-25.9%*	*13.9%*	*28.3%*	*0.0%*	*6.3%*	*29.6%*	*11.3%*	*13.8%*	*57.9%*	*22.9%*	*25.4%*
		124.1%	0.02874						-21.8%	16.9%	9.9%	-9.2%	26.6%	25.3%	0.4%	-7.9%	43.5%	16.9%	-0.1%
						STOCKS:	2	7	14	19	20	24	28	28	27	26	26	26	25
NET WASTE	%	TOTAL GAIN	DAILY SHARPE	THETA	Z-STATISTIC	P-VALUE	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
	25	*257.9%*	*0.06579*	7.14E-12	0.7543	0.45							*4.1%*	*28.6%*	*18.2%*	*-10.6%*	*54.1%*	*17.9%*	*39.3%*
		143.3%	0.04901										27.7%	29.1%	-13.3%	-6.0%	51.2%	24.9%	-4.1%
						STOCKS:	0	2	4	7	7	9	11	11	11	12	11	11	11
	50	*308.7%*	*0.05458*	2.42E-12	0.0691	0.95				*-3.3%*	*30.0%*	*-5.9%*	*5.4%*	*25.9%*	*15.3%*	*2.7%*	*49.0%*	*18.1%*	*24.9%*
		288.6%	0.05361							32.5%	8.0%	-6.5%	22.4%	25.5%	-6.3%	5.3%	58.8%	19.6%	1.0%
						STOCKS:	1	5	9	14	14	18	22	22	22	24	22	22	22
WATER USE	%	TOTAL GAIN	DAILY SHARPE	THETA	Z-STATISTIC	P-VALUE	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
	25	*442.7%*	*0.06479*	6.38E-12	0.9289	0.35					*31.7%*	*8.8%*	*0.4%*	*25.9%*	*8.2%*	*11.4%*	*43.2%*	*35.6%*	*28.1%*
		187.2%	0.04619								6.0%	-9.6%	31.1%	24.8%	4.4%	-1.1%	50.2%	25.7%	-5.9%
						STOCKS:	1	3	6	9	10	11	12	13	13	13	14	14	14
	50	*306.8%*	*0.04419*	3.39E-12	0.7096	0.48			*-30.3%*	*21.9%*	*26.4%*	*-1.4%*	*8.8%*	*19.9%*	*6.0%*	*18.2%*	*45.2%*	*28.7%*	*25.9%*
		174.1%	0.03493						-18.6%	13.0%	5.7%	-8.1%	30.0%	27.8%	7.5%	-6.6%	48.6%	20.9%	2.2%
						STOCKS:	2	6	13	18	20	22	25	26	26	26	29	28	28
COMBINED RANK	%	TOTAL GAIN	DAILY SHARPE	THETA	Z-STATISTIC	P-VALUE	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
	25	*66.5%*	*0.04238*	1.24E-11	1.8476	0.065*										*17.7%*			*41.5%*
		-12.2%	-0.01267													-3.1%			-9.4%
						STOCKS:	0	2	3	5	6	7	8	8	8	10	9	9	10
	50	*521.3%*	*0.06410*	3.86E-12	1.0712	0.28				*15.1%*	*37.4%*	*-3.9%*	*3.5%*	*25.1%*	*8.8%*	*22.6%*	*61.7%*	*14.8%*	*27.4%*
		212.6%	0.04643							30.1%	9.5%	-4.3%	19.1%	27.9%	-4.7%	-8.7%	44.7%	19.9%	-0.2%
						STOCKS:	0	4	6	10	12	14	16	17	16	20	18	18	19

Table A12 – Portfolio tests, Utilities

	%	Total gain	Daily Sharpe	Theta	Z-statistic	P-value	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
Greenhouse gas emissions	25	*18.0%*	*0.00877*	1.26E-12	-0.9095	0.36			*-19.9%*	*10.4%*	*16.6%*	*-4.5%*	*-3.8%*	*14.8%*	*-5.8%*	*11.1%*	*-1.1%*	*-9.4%*	*15.9%*
		65.4%	0.02246						-21.2%	9.9%	15.2%	2.8%	5.9%	18.6%	-8.1%	19.9%	0.6%	2.4%	13.1%
						Stocks:	2	6	10	11	11	12	13	13	15	14	14	16	18
	50	*13.0%*	*0.00607*	7.00E-13	-0.5438	0.59		*-4.7%*	*-27.1%*	*9.7%*	*16.4%*	*-10.5%*	*-2.8%*	*23.6%*	*-6.3%*	*5.7%*	*0.2%*	*-6.3%*	*27.6%*
		33.2%	0.01219					-4.0%	-24.3%	5.4%	11.4%	-9.4%	6.6%	23.0%	-5.3%	16.6%	6.3%	2.7%	8.8%
						Stocks:	4	12	21	22	22	25	26	26	30	29	29	32	35
Total waste	%	Total gain	Daily Sharpe	Theta	Z-statistic	P-value	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
	25	*78.1%*	*0.03490*	9.82E-13	0.4517	0.65					*22.8%*	*3.4%*	*9.0%*	*18.8%*	*-3.8%*	*16.0%*	*-2.0%*	*-3.8%*	*3.0%*
		73.6%	0.02818								10.3%	-16.8%	0.4%	37.6%	-6.3%	12.8%	10.6%	1.2%	15.9%
						Stocks:	2	5	7	9	11	11	11	11	12	12	10	11	12
	50	*28.2%*	*0.01071*	9.41E-13	0.8613	0.39		*-3.6%*	*-16.4%*	*4.9%*	*17.1%*	*-2.3%*	*-3.9%*	*12.2%*	*-1.7%*	*9.0%*	*3.2%*	*-1.7%*	*13.1%*
		-5.4%	0.00034					-13.8%	-20.6%	-3.7%	2.4%	-23.0%	16.5%	33.8%	-5.8%	1.3%	10.1%	-0.2%	11.4%
						Stocks:	4	10	14	18	22	22	22	22	24	24	21	22	23
Net waste	%	Total gain	Daily Sharpe	Theta	Z-statistic	P-value	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
	25	*-9.3%*	*-0.01715*	9.46E-13	0.3189	0.75										*-9.3%*			
		-13.5%	-0.02470													-13.5%			
						Stocks:	2	4	5	6	8	9	9	8	9	10	8	9	9
	50	*55.9%*	*0.01998*	1.48E-12	1.4388	0.15			*-18.1%*	*5.3%*	*11.4%*	*-5.5%*	*17.6%*	*7.1%*	*0.5%*	*7.3%*	*7.2%*	*-2.6%*	*21.0%*
		-9.2%	-0.00047						-24.6%	-4.9%	7.0%	-20.4%	-4.3%	32.0%	-9.9%	5.9%	8.7%	1.2%	12.0%
						Stocks:	4	8	10	13	16	18	18	17	18	20	17	18	18
Water use	%	Total gain	Daily Sharpe	Theta	Z-statistic	P-value	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
	25	*33.4%*	*0.04999*	4.17E-12	0.0254	0.98											*14.1%*	*-0.4%*	*17.5%*
		38.6%	0.04910														0.2%	2.9%	34.4%
						Stocks:	2	4	7	7	8	9	8	8	8	9	10	10	12
	50	*-6.2%*	*-0.00058*	1.48E-12	-1.3090	0.19			*-24.6%*	*5.6%*	*4.8%*	*-15.2%*	*-1.6%*	*9.9%*	*-3.1%*	*2.0%*	*9.5%*	*-2.1%*	*15.7%*
		52.7%	0.01767						-15.2%	-2.5%	12.1%	-14.9%	3.8%	34.6%	-5.0%	16.3%	1.9%	-2.1%	25.9%
						Stocks:	4	8	14	14	16	18	16	16	17	18	19	21	24
Combined Rank	%	Total gain	Daily Sharpe	Theta	Z-statistic	P-value	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
	25																		
						Stocks:	0	1	2	3	4	5	5	4	5	6	5	5	6
	50	*-2.6%*	*0.00030*	2.16E-12	-0.5178	0.61						*-13.6%*	*-14.5%*		*0.6%*	*-0.8%*	*8.2%*	*-3.4%*	*26.4%*
		15.5%	0.00984									-22.4%	16.2%		-13.0%	18.4%	6.9%	6.8%	8.9%
						Stocks:	1	2	4	6	8	10	10	8	10	12	10	10	12

10.5 Python Code

```python
import pandas as pd
import numpy as np
from datetime import datetime
import scipy.stats as st

#%%

def test_yearly_rebalance(df, n, metric, sector = None):

    years = [str(i) for i in range(2006, 2019)]

    portfolio1_constituents, portfolio2_constituents, portfolio1_value, portfolio2_value, portfolio1_yearly, portfolio2_yearly = ([], [], [], [], [], [])

    if sector is not None:
        df = df[df["Sector"] == sector]

    dates = df.index.get_level_values(1).unique().values
    dates = dates[(dates >= "2006-07-01") & (dates <= "2019-06-31")]

    for year in years:
        startdate = year + "-07-01"
        enddate = str(int(year) + 1) + "-06-31"

        if metric == "CombinedRank":
            period = get_combined_rank(df.xs(slice(startdate, enddate), level = "Date", drop_level = False).loc[:, ["Closing price", "GHGBySales", "TotWasteBySales", "RecWasteBySales", "WaterBySales"]])

        else:
            period = df.xs(slice(startdate, enddate), level = "Date", drop_level = False).loc[:, ["Closing price", metric]]

        if metric == "Closing price":
            firstDay = period.index.get_level_values(1)[0]
            n_pct = round(len(period.xs(firstDay, level = "Date").dropna()) * n  / 100)

            portfolio1_constituents.append(period.xs(firstDay, level = "Date").dropna().nsmallest(n_pct).index.get_level_values(0).values)
            portfolio2_constituents.append(period.xs(firstDay, level = "Date").dropna().nlargest(n_pct).index.get_level_values(0).values)

        else:
            n_pct = round(len(period.dropna()) * n  / 100)

            portfolio1_constituents.append(period.dropna().nsmallest(n_pct, metric).index.get_level_values(0).values)
            portfolio2_constituents.append(period.dropna().nlargest(n_pct, metric).index.get_level_values(0).values)

        startvalue1 = 100 if len(pd.Series(portfolio1_value, dtype = float).dropna()) == 0 else pd.Series(portfolio1_value).dropna().values[-1]
        startvalue2 = 100 if len(pd.Series(portfolio2_value, dtype = float).dropna()) == 0 else pd.Series(portfolio2_value).dropna().values[-1]

        if len(portfolio1_constituents[-1]) >= 10:
            portfolio1_value.extend(test_portfolio(period.loc[portfolio1_constituents[-1]], startvalue1))
            portfolio2_value.extend(test_portfolio(period.loc[portfolio2_constituents[-1]], startvalue2))

            portfolio1_yearly.extend([portfolio1_value[-1] / startvalue1 - 1])
```

```
            portfolio2_yearly.extend([portfolio2_value[-1] / startvalue2 - 1])

        else:
            portfolio1_value.extend([np.nan for i in range(len(dates[(dates >= startdate) & (dates <= enddate)]))])
            portfolio2_value.extend([np.nan for i in range(len(dates[(dates >= startdate) & (dates <= enddate)]))])

            portfolio1_yearly.extend([np.nan])
            portfolio2_yearly.extend([np.nan])

    return dates, portfolio1_constituents, portfolio2_constituents, portfolio1_value, portfolio2_value, portfolio1_yearly, portfolio2_yearly

def test_portfolio(df, startvalue):
    dates = df.index.get_level_values(1)

    length = len(df.index.get_level_values(0).unique())

    weights = (np.ones(length) * startvalue) / length

    portfolio_composition = weights / df.xs(dates[0], level = 1)["Closing price"].sort_index().values

    return [np.sum(portfolio_composition * prices) for prices in pd.DataFrame(df).reset_index().pivot(index = "Date", columns = "Name", values = "Closing price").fillna(method = "ffill").values]

def get_combined_rank(df):
    df_rank = df.dropna().sort_index()
    df_rank["GHGRank"] = df_rank.sort_values(by = "GHGBySales").reset_index().sort_values(by = "Name").index.values
    df_rank["TotWasteRank"] = df_rank.sort_values(by = "TotWasteBySales").reset_index().sort_values(by = "Name").index.values
    df_rank["RecWasteRank"] = df_rank.sort_values(by = "RecWasteBySales", ascending = False).reset_index().sort_values(by = "Name").index.values
    df_rank["WaterRank"] = df_rank.sort_values(by = "WaterBySales").reset_index().sort_values(by = "Name").index.values
    df_rank["CombinedRank"] = df_rank["GHGRank"] + (df_rank["TotWasteRank"] / 2) + (df_rank["RecWasteRank"] / 2) + df_rank["WaterRank"]
    return df.join(df_rank.loc[:, ["GHGRank", "TotWasteRank", "RecWasteRank", "WaterRank", "CombinedRank"]], how = "outer")

def print_results(results, riskfree):

    if len(pd.Series(results[3], dtype = float).dropna()) == 0:
        print("No results.")
        return pd.DataFrame()

    portfolio1_total = pd.Series(results[3]).dropna().values[-1] / 100 - 1
    portfolio2_total = pd.Series(results[4]).dropna().values[-1] / 100 - 1

    portfolio1_change = pd.Series(pd.Series(results[3]).pct_change().values - riskfree["1 Yr"].loc[results[0]].values)
    portfolio2_change = pd.Series(pd.Series(results[4]).pct_change().values - riskfree["1 Yr"].loc[results[0]].values)

    p1_m = portfolio1_change.mean()
    p2_m = portfolio2_change.mean()

    p1_v = portfolio1_change.var()
    p2_v = portfolio2_change.var()

    p1_s = portfolio1_change.std()
    p2_s = portfolio2_change.std()

```

```
    portfolio1_daily_sharpe = p1_m / p1_s
    portfolio2_daily_sharpe = p2_m / p2_s

    obs = len(portfolio1_change.dropna())

    covar = pd.DataFrame(np.array([portfolio1_change.astype(float), portfolio2_change.astype(float)]).T).cov().values[0,1]

    theta = (1 / obs) * ((2 * p1_v * p2_v) - (2 * p1_s * p2_s * covar) + ((1 / 2) * (p1_m ** 2) * p2_v) + ((1 / 2) * (p2_m ** 2) * p1_v) - (((p1_m * p2_m) / (2 * p1_s * p2_s)) * ((covar ** 2) + (p1_v * p2_v))))
    zstat = ((p1_m * p2_s) - (p2_m * p1_s)) / (theta ** (1/2))
    pval = st.norm.sf(abs(zstat)) * 2

    years = [str(i) for i in range(2006, 2019)]

    first = [portfolio1_total, p1_m, p1_s, portfolio1_daily_sharpe, np.nan]
    first.extend(results[5])
    first.extend(["Value"])
    first.extend(results[3])

    second = [portfolio2_total, p2_m, p2_s, portfolio2_daily_sharpe, np.nan]
    second.extend(results[6])
    second.extend(["Value"])
    second.extend(results[4])

    nr_stocks = [np.nan for i in range(5)]
    nr_stocks.extend([len(portf) for portf in results[1]])
    nr_stocks.extend([np.nan for i in range(len(results[3]) + 1)])

    Portf1Stocks = ["Theta", "z-stat", "p_value", np.nan, np.nan]
    Portf1Stocks.extend([portf for portf in results[1]])
    Portf1Stocks.extend(["Change"])
    Portf1Stocks.extend(portfolio1_change)

    Portf2Stocks = [theta, zstat, pval, np.nan, np.nan]
    Portf2Stocks.extend([portf for portf in results[2]])
    Portf2Stocks.extend(["Change"])
    Portf2Stocks.extend(portfolio2_change)

    df = pd.DataFrame(np.array([first, second, nr_stocks, Portf1Stocks, Portf2Stocks]).T, columns = ["Portfolio1", "Portfolio2", "NrStocks", "Portf1Stocks", "Portf2Stocks"])

    indx = ["Total gain (%)", "Daily change (%)", "Daily std (%)", "Daily sharpe", np.nan]
    indx.extend(years)
    indx.extend(["Daily"])
    indx.extend(results[0])

    df["indx"] = indx
    df.set_index("indx", inplace=True)

    pd.DataFrame(np.array([results[3], results[4]]).T, columns = ["Portfolio 1", "Portfolio 2"], index = results[0]).dropna().plot()

    return df

stocks = pd.read_pickle("SP1200_2006_2019_with_sustv2.gz")
riskfree = pd.read_csv("US1YrDaily.csv").set_index("Date")

start = datetime.now()

metrics = ["GHGBySales", "TotWasteBySales", "NetWasteBySales", "WaterBySales", "CombinedRank"]
sectors = [None]
```

```
sectors.extend(stocks["Sector"].unique())

collist = ["Metric", "Sector", "N", "Total gain", "Daily Sharpe", "Theta", "Z-statistic", "P-value"]
collist.extend(range(2006, 2019))
gathered = pd.DataFrame(columns = collist)

for metric in metrics:
    for sector in sectors:
        for n in [10, 25, 50]:
            print(f"\n{metric}, {sector}, {n}%")
            results = test_yearly_rebalance(stocks, n, metric, sector)
            df = print_results(results, riskfree)

            if len(df) > 0:
                df.to_csv(metric + "_" + (sector if sector is not None else "overall") + "_" + str(n) + ".csv", sep = ";", decimal = ",")

                first = [metric, (sector if sector is not None else "overall"), n, df["Portfolio1"]["Total gain (%)"], df["Portfolio1"]["Daily sharpe"], df.iloc[0, 4], df.iloc[1, 4], df.iloc[2, 4]]
                first.extend(df.iloc[range(5, 18), 0].values)

                second = [metric, (sector if sector is not None else "overall"), n, df["Portfolio2"]["Total gain (%)"], df["Portfolio2"]["Daily sharpe"], df.iloc[0, 4], df.iloc[1, 4], df.iloc[2, 4]]
                second.extend(df.iloc[range(5, 18), 1].values)

                third = [np.nan for i in range(7)]
                third.extend(["Stocks:"])
                third.extend(df.iloc[range(5, 18), 2].values)

                gathered = pd.concat([gathered, pd.DataFrame([first, second, third], columns = collist)])
                gathered.to_csv("Compiled_results.csv", sep =";")

            print(f"\nTime elapsed: {datetime.now()-start}")

print(f"\nTime elapsed: {datetime.now()-start}")
```