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The Impact of Carbon Emissions on Investment Performance

An empirical analysis of how carbon footprint affects risk-adjusted return for stocks listed on the Oslo Stock Exchange

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Acknowledgements

This thesis is written as a final part of our Master of Science in Economics and Business Administration at the Norwegian School of Economics (NHH), with specialization in Financial Economics.

Our main goal was to conduct a relevant and quantifiable analysis, which fills a gap in the existing literature. As two finance students, with a particular interest in sustainability, we were inspired to contribute to this field of research.

The process of completing this thesis has been both challenging and frustrating at times, yet highly rewarding. Throughout the process, we have focused on developing a broad knowledge of how carbon emission affects financial markets by applying financial theory and econometric analysis. Conducting the research has required experience in both Excel and R-studio, which has further developed our skills.

We want to express our gratitude for the valuable guidance and constructive feedback from our supervisor Jøril Mæland, who has graciously shared her expertise. We would also like to thank Gjensidige Forsikring for providing us with access to Carbon Delta Projects' confidential database.

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Abstract

Climate change have led to a rising interest in how climate risks affect investors portfolios. The purpose of this thesis is to increase investors understanding of how climate change can influence investment returns. Specifically, we examine whether low-carbon investments yield higher risk-adjusted returns than high-carbon investments. The study focuses on stocks listed at the Oslo Stock Exchange during the period 2010- 2018.

We obtain the risk-adjusted returns by computing alpha estimates for portfolios consisting of stocks with low carbon footprints (good portfolio) and high carbon footprints (bad portfolio).We also compute alpha estimates for the difference portfolios based on a zero investment strategy that goes long the good portfolio and shorts the bad portfolio. The portfolios are sorted both on their scope 1 and scope 2 emissions. We employ the Captial Asset Pricing Model and the Carhart four-factor model to control for potential variations in risk exposure between the portfolios.

Our results report significant positive abnormal returns in the difference portfolio for scope 1. We further detect negative abnormal returns in the bad portfolios for both scope 1 and scope 2. These results indicate that low-carbon portfolios outperform high-carbon portfolios and that stocks with high carbon emissions underperform in the market. The results further suggest that investors holding high-carbon stocks do not receive sufficient compensation for their level of risk. At a sector-level, stocks with high emissions in our dataset belong to the energy and industrial sector.

Keywords – Climate Change, Carbon Footprint, Investment Performance

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1 Introduction

Climate change is currently a global challenge threatening the future viability of our planet. The occurrence of climatic change and extreme weather has accelerated in recent years (Guterres, 2019). Despite its growing concern and awareness, it is uniquely challenging to predict the exact timing and severity of climate change. However, scientific evidence indicate that risks of climate change will continue to increase. According to the Secretary-General António Guterres (2019) of United Nations: "Climate-related natural disasters are becoming more frequent, more deadly, more destructive, with growing human and financial costs."

There is growing awareness amongst investors that the changing climate will impact the stability of the financial system (Carney, 2015). The broad consensus argues that investors' portfolios are exposed to two types of climate risk: physical risk and transition risk (Clapp et al., 2017). Physical risk refers to the physical damages from changes in the climatic conditions on the location of the financed project, e.g., more extreme weather, rising sea levels, and drought. Transition risks refer to the financial risk associated with the transition towards a low-carbon economy, e.g., the risk of regulations or emerging technological innovations resulting in stranded assets.

No investor can afford to disregard climate change, and there is an increasing pool of investors who pick stocks based climate measures (Ross, 2019). Carbon footprint is the most common approach, and it measures the greenhouse gas influence of a portfolio through its investee companies (Wiedmann and Minx, 2008). This measure assumes that carbon intensity can have a material impact on the value of securities and long-term investment performance (Andersson et al., 2016). Thus, by picking stocks with lower carbon footprints, investors expect that reducing climate risk exposure will increase risk-adjusted return. This concept, however, depends on whether financial markets properly account for climate risks in equity valuations (Rottmer et al., 2018).

We want to understand how climate change risk affects investment performance. Our thesis aims to study whether low-carbon investments yield higher risk-adjusted returns than high-carbon investments. We measure carbon level relatively by using investments' carbon footprint. Emissions can split into three scopes (UNEP, 2019), and we will focus on the first two. Scope 1 refers to emissions produced directly from sources that are controlled or owned by a firm. Scope 2 refers to indirect emissions that come from bought and consumed electricity, heat, and stream off-site.

To conduct this analysis, we match emission data from the Carbon Delta Project and stock prices from the Oslo Stock Exchange. This provides us with a dataset of 53 stocks in the period 2010-2018. We divide the equities into two mutually exclusive portfolios based on their carbon footprint, which we refer to as the "good" and the "bad" portfolio, using equally-weighted construction methods. These portfolios consist of the stocks with the 30% lowest and 30% highest carbon footprint in the sample each year, which involves annually rebalancing. For robustness, we conduct a supplementary analysis where we use portfolios without rebalancing and value-weighted portfolios. We examine risk-adjusted returns by computing alphas for the two portfolios individually, and for the difference portfolio that goes long in the good portfolio and short the bad portfolio[1]. We estimate the alphas by employing the Capital Asset Pricing Model and the Carhart four-factor model. This controls for potential variations in risk exposure between the portfolios.

Our results suggest that good portfolios perform better than the bad portfolios. From the alpha estimates using equally-weighting, the scope 1 difference portfolio reports a monthly average abnormal return of approximately 0.01%. This indicate that stocks with low scope 1 carbon emissions have statistically significant higher abnormal returns than stocks with high scope 1. However, we cannot draw the same conclusion for the difference portfolio in scope 2, as it does not report significant alpha estimates. Regarding the individual portfolios, the alpha estimates for the bad portfolio in both scopes come out as significantly negative. Thus, high-carbon stocks are underperforming in the financial market. Consistent alpha generation is impossible in efficient markets, as stock prices reflect all information (Fama, 1991). Our evidence of significant alpha estimates, therefore,

[1] The difference portfolio refers to a zero-investment portfolio; a collection of investments that has a net value of zero when the portfolio is constructed (Alexander, 2000)

indicate a violation of market efficiency. For instance, the significant negative alphas in our bad portfolios imply that low-carbon stocks are overpriced. Thus, investors who hold these stocks are potentially not fairly compensated for their level of risk. Investors might achieve abnormal returns from shorting these stocks.

Our study builds on previous literature, which also reports similar conclusions. Derwall et al. (2005) and In et al. (2018) investigated the alpha difference between climate-friendly portfolios and climate-unfriendly portfolios. They reported a performance difference of 6% and 3.5-5.4% per annum, respectively. Furthermore, Liesen et al. (2017) found that investors achieved abnormal returns of up to 13% annually by exploiting inefficiently pricing of stocks' GHG emissions disclosure. Bernardini et al. (2019) also found a positive correlation between low-carbon stocks and investment returns. As these studies focused on U.S., and global stocks, we contribute to this field of research by confirming similar performance amongst stocks listed on the Oslo Stock Exchange.

The remaining parts of this thesis are structured as follows: Section two outlines the background for this thesis and review the relevant literature. The third section presents the data sample and portfolio construction, while the fourth section provides the applied methodology to detect potential significant abnormal returns. The fifth section will present and discuss our findings, whereas the sixth section further discusses how relevant sectors are exposed to climate risk. Lastly, we provide a conclusion of our thesis.

2 Background and Literature Review

Does climate change affect portfolio performance? If so, are investment strategies that focus on climate-friendly stocks achieving increased risk-adjusted returns? As impacts of climate change are becoming more prominent, such questions are increasingly important for investors (Bioy, 2019). However, this field of research lacks consensus, making it hard to draw general conclusions.

In this section, we discuss how climate change may give rise to risk for investors. First, we introduce challenges related to climate change and climate risks that can potentially affect equities. Secondly, we present the importance of climate risks in investment decisions, followed by a review of existing literature. Next, we present Gjensidige Forsikring ASA, which we collaborated with during our study. Lastly, we outline our primary investigation focus - the research question.

2.1 The Climate Change Challenge

Climate change is currently the largest and most complex sustainability issue threatening the future livability of our planet (Guterres, 2019). The Intergovernmental Panel on Climate Change predicts an average increase of global warming from the present 1°C above pre-industrial level to 1.5°C between 2030 and 2052, given that carbon emissions continue at its current pace (IPCC, 2014). The expected future consequences are severe, including higher risks of droughts and flooding, species extinction and significant sea-level rise. Consequently, the need to stop climate disruption and reverse its impact are prominent. As former United Nations Secretary-General Ban Ki-Moon (2016) stresses, "There can be no Plan B because there is no Planet B."

Climate change mitigation has risen rapidly up the agendas of policymakers worldwide (Guterres, 2019). In particular, the Paris Agreement (2015) was a wake-up call for several countries regarding externalities of the current high-carbon economy (UNFCCC, 2015). Leaders from all over the world gathered and agreed to keep the rise in global average temperature under 2°C over pre-industrial levels, preferably limiting the temperature increase to only 1.5°C. The Paris Agreement showed a global commitment to mitigate climate change and 187 out of 197 countries have ratified since the convention.

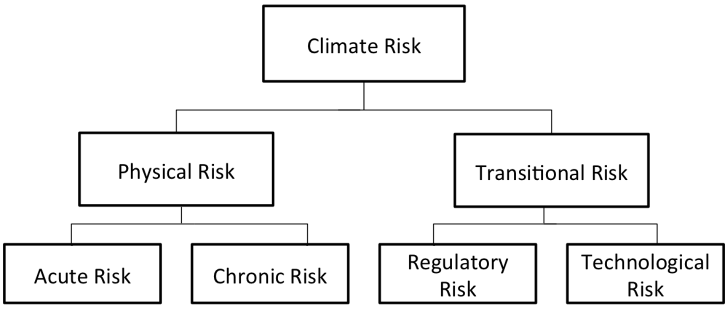
Climate change can negatively impact the value of investments and the stability of the financial system (Ross, 2019). Equity investors concern abundant and widespread consequences affecting their investment returns, both regarding short-term profits and long-term value creation. Climate-related risks on investors' portfolios derive from two primary sources: physical risk and transition risk (Clapp et al., 2017), see figure 0.1.

Physical risk describes costs related to physical damages to the location of the financed project and the quality of the adaptation plan (Fang et al., 2018). Physical risk classifies as acute or chronic (Mazzacurati et al., 2018). Acute risk includes extreme weather events, intensified by climate change, which cause physical damages on, e.g., buildings and other infrastructure. Chronic risk represents long-term, permanent changes in climate patterns, e.g. growing frequency of extreme weather, rising sea levels, floods, and wildfires.

Transition risks derive from the activity and sector that the project is going to finance. It refers to financial risk associated with the transition towards a low-carbon, and eventually de-carbonized, economy in line with the goals of the Paris Agreement (Fang et al., 2018). Transition risks can further split into regulatory and technological risks (Krueger et al., 2019). Regulatory risk evolves from extensive changes or expectations of changes in policy and regulations that aim to reduce emissions, e.g., carbon taxes, requirements of fuel-efficiency, and emission trading systems such as the ETS[2] (Bjartnes et al., 2018). Technological risk refers to the progress of development, investment, and use of emerging technologies, to support the transition towards the low-carbon economy.

[2]ETS refers to The EU emissions trading system, which aims to reduce greenhouse gas emissions in Europe (EU, 2019)

Figure 2.1: Categories of climate risk



Investors are increasingly concerned about transition risk when choosing equities, which will be the main focus of our thesis. The risk of assets becoming stranded are amongst the most prominent transition risks (Andersson et al., 2016). This risk is both a technological and regulatory risk, and refers to an unanticipated devaluation of assets due to a sudden shift in technology, regulations, social norms, or the environment. Future development of emerging technologies and regulations aiming to decrease emissions, can reduce demand for high-carbon products. Thus, generating stranded assets as investments are not able to meet a viable economic return, leaving resources unexploited.

The sum of new policies, regulations, and technologies can change market conditions and potentially influence investment returns (Bjartnes et al., 2018). An intriguing question is how investors can integrate climate risk throughout their investment process to achieve sustainable returns, which we will discuss in the following chapter.

2.2 Managing Sustainability Investing Issues

"I don't want you to be hopeful. I want you to panic." said climate change activist Greta Thunberg (2019) at the World Economic Forum in Davos. She emphasizes that hoping for the best is insufficient. Finance can support the transition towards lower emissions and climate-resilient development (UNFCCC, 2015). According to Thunberg (2019), one should take action by managing current, and future capital flows towards more sustainable investments.

Solutions supporting mitigation of climate change, such as cutting-edge technology, has recently experienced a new wave of funding from investors. This constitutes the increasingly popular environmental, social, and governance (ESG) strategy (Ross, 2019). According to Hortense Bioy (2019), the director of sustainability research at Morningstar, the climate aspect has become the most critical factor in ESG investing. She claims this is triggered by the Paris Agreement. Moreover, there is currently a shift in investment strategies from solely using negative screenings approaches, to actively investing in stocks with a positive impact on the climate. However, investing in financial markets is not philanthropy. For investors, the objective is to achieve the highest possible return with modest risk and few are willing to sacrifice financial return for impact (Hebb, 2013). Investors question the implications of transforming their portfolios, as climate-friendly investments must perform to capture the available capital.

Bioy (2019) states that investors should focus on avoiding stocks with return highly sensitive to climatic changes. Academic research has, during recent years, made progress in terms of measuring investment portfolios' exposure to greenhouse gases (GHG) emissions (Monasterolo et al., 2018). As equities with high emissions are more exposed to climate risks, especially transition risks, such measures are essential for investors to evaluate. A recognized approach is to measure the carbon footprints of investments', which refers to the total GHG emissions of a portfolio standardized by some proxy of size (Wiedmann and Minx, 2008). Emissions, and carbon footprint, can be measured through three different scopes (UNEP, 2019), see table 2.1. Scope 1 refers to emissions produced directly from sources that are controlled or owned by a firm. Scope 2 refers to indirect emissions that come from bought and consumed electricity, heat, and steam off-site. Scope 3 emissions include all indirect emissions that occur in the value chain of the firm, not counted in scope 2, including both upstream and downstream. By actively choosing investments with a lower carbon footprint, investors can reduce their risk exposure to climate changes (Ross, 2019).

Table 2.1: Examples of emission sources within scope 1, 2, and 3, retrieved from Greenhouse Gas Protocol.

Scope 1	Scope 2	Scope 3
Fuel combustion	Purchased electricity, heat,	Investments
Company vehicles	and steam for own use	Use of sold products
Fugitive emissions		Purchased goods and services
		Waste disposial
		Employee commuting
		Leased assets and franchises
		Business travel

Whether low-carbon investment strategies translate into significantly higher risk-adjusted returns, depends on whether financial markets properly account for transition risks in equity valuations (Rottmer et al., 2018). According to the Efficient Market Hypothesis (EMH), stock prices reflect all available information, making it impossible for stocks to be over- or undervalued (Fama, 1991). As it is impossible to "beat the market," investors cannot achieve excess returns on a risk-adjusted basis i.e., precluding any abnormal returns[3]. Thus, financial theory states that investors neither gain nor sacrifice return on a risk-adjusted basis if they adapt a low-carbon investment strategy.

However, financial markets have proven not always to be efficient, and some equity investors aim to exploit these inefficiencies. In the following chapter, we explore existing research that studies whether equity valuation properly accounts for climate risk.

2.3 Literature Review

Ever since climate risk in financial markets became evident, the potential linkage to investment returns has been of increased interest amongst researchers. Several studies suggest that climate-friendly investments are less exposed to climate risk, resulting in higher risk-adjusted returns than climate-unfriendly investments. These studies are searching for abnormal returns, thus testing market-efficiency. Most of the literature

[3]Abnormal return describes the unusual profits generated by given securities or portfolios, different from the expected rate of return based on an asset pricing model (Jensen, 1969). We also refer to abnormal return as alpha.

reports positive results. Still, a few researchers provide inconclusive or contradicting empirical findings, making it hard to conclude on the link between stock returns and climate risk.

The literature employs three approaches when analyzing a relationship: portfolio studies, event studies, and regression studies (Wagner et al., 2001). In this chapter, we separately review relevant empirical findings for the effect of climate risk using these methods. They all use stock return as a financial performance measure.

2.3.1 Portfolio studies

Portfolio studies compose mutually exclusive portfolios sorted after stocks' climate measures and compare their differences in economic or financial performance (Hamada, 1969). White (1996) used the Capital Asset Pricing Model (1964) to compare the performance of three differently ranked portfolios in the period 1964-1989. He observed that the leading portfolio generated a significantly positive alpha, while the other inferior portfolios neither outperformed nor underperformed. Daniel and Blank (2002) applied the same approach for the period 1997- 2001. They detected a climate-friendly portfolio with both a positive abnormal return and a higher Sharpe Ratio than the market portfolio. These findings indicate abnormal returns of climate-friendly investing due to undervalued stocks.

More recent literature has enhanced White (1996) and Daniel and Blank (2002) findings by applying multi-factor models. Derwall et al. (2005) used the Carhart four-factor model to examine portfolio performance from 1995 to 2003. They discovered that the high-raked portfolios outperformed the low-ranked portfolios with a significant alpha of 6% per annum. Similar results were detected by In et al. (2018) using the Fama-French three-factor model from 2010 to 2015. They found that an investment strategy of buying high-ranked stocks and selling low-ranked stocks earned yearly abnormal returns of 3.5% to 5.4%. Their research further observed that high-ranked firms had significantly better financial performance than their low-ranked counterparts, which also indicates a positive correlation between climate-friendliness and financial performance. The results of Derwall et al. (2005) and Daniel and Blank (2002) remained significant even after controlling for industry fixed-effects. This implies that abnormal returns are not driven by different industry composition in the portfolios.

Cohen et al. (1997) detected ambiguous results when discovering neither a premium nor a penalty for investing in stocks with low emissions. They also controlled for industry effects in a multi-factor model like Derwall et al. (2005) and In et al. (2018), indicating these effects did not explain the dissimilar results. However, Cohen et al. (1997) conducted their research in 1997 and they anticipated a stronger relationship in the years following their study.

2.3.2 Event studies

Event studies typically analyze how the publication of equity-specific information affects stock prices (Wagner et al., 2001). If stock prices adjust accordingly with climate disclosures, investors should not gain abnormal returns over time by exploiting this information. Markets are assumed to be efficient (Fama, 1991) if climate risk is reflected in equity valuations. The question is whether this assumption holds.

The Carbon Tracker Initiative emphasizes that the financial market might hold a carbon bubble, because the valuation of equities depending on fossil-fuel in production does not account for the increasing cost of carbon (CarbonTracker, 2019). Thus, these equities are considered overvalued, and assets risk becoming stranded. McGlade and Ekins (2015) discovered that 80% of current coal resources, 50% of gas reserves, and 33% of our oil reserves must remain unused from 2010 to 2050 to reach the two-degree target in the Paris Agreement. It will potentially cost the fossil fuel industry 28 trillion dollars in revenues over the next two decades (Leggett, 2015). Thus, investors holding fossil energy stocks might experience a decline in future prices. Even though this knowledge is familiar for most investors, stock prices are not adjusting accordingly, suggesting market inefficiency.

The research of Liesen et al. (2017) studied stock performance amongst investors that exploited stocks' GHG emissions disclosure for the period 2005-2009. Investing in stocks that reported low GHG emissions resulted in yearly, abnormal returns of 13%. Their results confirm that stocks are not efficiently priced according to the publicly available information. Contrarily, Matsumura et al. (2014) showed that stock prices adjust to disclosed firms' carbon emission data. The study found an average decrease in equity value by $212,000 for every additional thousand metric tons of reported carbon emissions. Additionally, they discovered a higher equity value of approximately $2.3 billion for firms disclosing emission data compared to non-disclosing firms. Their results suggest that market valuation adjusts to firms' carbon disclosures. Nevertheless, Matsumura et al. (2014) did not analyze whether the price adjustments were adequately, i.e., confirming no abnormal returns, which Liesen et al. (2017) proved wrong.

2.3.3 Regression studies

Regression studies estimate the relationship between stock prices and climate measures by including the latter as an independent variable in time-series regressions (Wagner et al., 2001). Thomas (2001) added environmental policy variables in his regression model, controlling for size effects and market sensitivity. He discovered that environmental responsibility had significant positive explanatory power on excess return. The same study was conducted more recently by Ziegler et al. (2007), who confirmed the detected correlation in the research of Thomas (2001).

A few modern regression analysis have included carbon emission as a variable. Bernardini et al. (2019) showed a significant low-carbon premium during recent years in which decarbonization has increased. They found that investment strategies focusing on low-carbon stocks, rather than high-carbon stocks, yield higher returns without increasing the overall risk profile. In contrast, insignificant influence was detected by Kacperczyk and Bolton (2019), who included the different scopes of carbon emission as independent variables. After controlling for all known risk factors and characteristics, including industrial components, they found that carbon emissions did not affect stock returns.

For all three study methodologies, the existing literature is inconclusive on whether climate-friendly investments positively affect risk-adjusted returns. However, there are potential limitations to all approaches (Ziegler et al., 2007). Portfolio analysis is criticized for not separating the influence of the objective from other factors. In this case, it includes isolating the effect of climate measures from other influencing variables. Event studies generally study short-term reactions amongst investors and assumes that markets truly are efficient. However, this assumption has received its fair share of criticism. Lastly, regression analyzes are criticized due to the use of confounding variables, which can result in misinterpreted causal relations.

We base our analysis on a portfolio study similar to the research of Derwall et al. (2005) and In et al. (2018). We form hypotheses aligned with the belief that low-carbon investments outperform high-carbon investments, despite equivocal findings in these studies. Most recent research supports this belief, and because climate change is a fast-changing field of study, recent studies constitute a good benchmark. These sources are more current and reflect the newest discoveries, theories, and best practices (EY, 2016). Mentioned studies mainly focus on the market for global or U.S. stocks. We extend prior portfolio studies by analyzing stocks listed on the Oslo Stock Exchange (OSE), as there is little research on the impact of climate change in the Norwegian financial market.

2.4 Gjensidige Forsikring

Climate change poses a threat to the solidity of the financial system, especially for the insurance sector (Gjensidige, 2018). Gjensidige Forsikring ASA, hereafter Gjensidige, is a leading Nordic insurance group listed on the OSE. Gjensidige is one of many institutional investors that has recognized the value of incorporating climate change impacts in its investment decisions. Firstly, their ambition is to be the most customer-oriented insurance company in the Nordic and Baltic countries, and climate issues are becoming increasingly more critical for their stakeholders. Moreover, Gjensidige is concerned about how climate change poses a financial risk to capital markets and affecting the profitability of their investments. Gjensidige, therefore, wanted to know more about how climate change affects equity investments as this knowledge can improve their investment strategies, and help allocate capital more efficiently. We found Gjensidige's inquiry interesting, and they provided us with data to conduct the following analyzes.

Gjensidige's equity investments are both internally and externally managed. Gjensidige provided us with its internally managed portfolio, which is sorted according to the Global Industry Classification Standard (GICS), developed by MSCI and S&P Dow Jones Indices (MSCI, 2016). The portfolio's sector exposure is illustrated in table 2.2. This sector composition is sorted according to the first level, which consist of 11 sectors[4]. We we will further discuss Gjensidige's sector composition in section 6.

Table 2.2: Sector composition in Gjensidige's internally managed investment portfolio, ranked at GICS level 1

Sector	Share of investment
Financials	66.5%
Industrials	14.1%
Energy	12.1%
Information Technology	3.2%
Materials	2.6%
Communication Services	1.6%

[4]The GICS structure are detailed further under A1 in the Appendix

2.5 Research Question for the Thesis

We conduct a portfolio study that focuses specifically on portfolios' carbon footprint as a measure of climate impact. Given the limited research on the Norwegian stock market, we look at equities listed on the OSE. Our hypothesis is that high-carbon investments are more affected by climate risk, such as policy risk aimed at reducing emissions, and thus perform worse in the financial market. Previous research on investments' carbon emissions have mostly presented similar findings, e.g., Derwall et al. (2005). Specifically, we formulate the following research question:

Have low-carbon investments delivered significantly higher risk-adjusted returns than high-carbon investments?

1. **H0:** Portfolios with low scope 1 carbon footprint **do not** have statistically significant higher abnormal return than portfolios with high scope 1 carbon footprint
   H1: Portfolios with low scope 1 carbon footprint **have** statistically significant higher abnormal return than portfolios with high scope 1 carbon footprint

2. **H0:** Portfolios with low scope 2 carbon footprint **do not** have statistically significant higher abnormal return than portfolios with high scope 2 carbon footprint
   H1: Portfolios with low scope 2 carbon footprint **have** statistically significant higher abnormal return than portfolios with high scope 2 carbon footprint

We investigate this research question by testing the two-sided null hypotheses against the alternative hypotheses. The two following sections present the data material and methodology used to investigate the research question.

3 Data and Portfolio Descriptions

In this section, we present the data used to analyze performance differences between low- and high-carbon portfolios. We begin by presenting the data retrieved from Datastream, Carbon Disclosure Project, and Ødegaard data library. The last chapter describes how we constructed our portfolios based on this data.

3.1 Datastream

Thomson Reuters Datastream is a global financial and macroeconomic data platform (Reuters, 2008), which provided us with stock data regarding prices, industry categorization, and market value. We use time-series data as it contains more observations compared to only using one-period. This enables us to develop a dynamic model that will enhance our analysis (Wooldridge, 2012).

We chose to filter out stocks listed on the OSE. This focus can benefit investors with interest in the Norwegian financial market, specifically Gjensidige, as previous studies mainly focused on US and global stocks. After the screening process, our data sample contained 692 stocks listed on the OSE from 2010 to 2018[5]. We chose to study recent stock prices, as climate change has become increasingly influential during recent years.

Stocks return rates are essential to answer our research question. Since the monthly reported stock prices in Datastream adjusts for both dividends and corporate actions (Reuters, 2008), we did not need to correct this before calculating the rates. We converted the stock prices into returns by calculating the return series for all the stocks in the dataset:

$$r_t = \frac{P_t}{P_{t-1}} - 1 \tag{3.1}$$

Where,

[5]The time-period analyzed is from 01.01.2010 until 31.12.2018

$r_t = Return\ in\ month\ t$

$P_t = Stock\ price\ in\ month\ t$

Datastream also offers climate measures for stocks. However, we considered their metrics as insufficient. Most of the reliable measures in Datastream covers the full ESG criteria, or a broader focus on environmental performance, e.g., climate measures also accounting for water discharges. Furthermore, when we matched some of these figures with our return data, the sample decreased to 31 stocks. Such a small sample would reduce the power of the study and increase the margin of error, which can render the analysis meaningless (Wooldridge, 2012). Hence, we decided to retrieve emission data from the Carbon Disclosure Project (CDP) as it offers more relevant and superior material.

3.2 Carbon Disclosure Project

Assessing stocks' carbon emissions can increase investors understanding of their portfolios' exposure to climate risk (Frankel et al., 2015). Gjensidige expressed interest in an analysis of this issue, and provided us access to emission data from the CDP.

CDP is an organization that both owns and controls the world's largest database of primary corporate environmental data (CDP, 2019). The CDP academic data package provides modeled and reported emissions, covering over 5,500 equities. The database facilitates high-quality energy and emissions estimates for companies, also covering companies who do not disclose such information themselves. CDP reports scope 1 and scope 2 in tons of CO_2 emissions, which we collected for the period 2010-2018. CDP also provides scope 3 estimates for a few equities. However, companies are not obligated to report scope 3 emissions, making the available data for this measure too small to obtain meaningful results. As we do not consider the data for scope 3 reliable, we chose to solely focus on scope 1 and 2 emissions.

Matching our data from Datastream data with CDP data gave us a sample containing 53 stocks. A few of the stocks missed emission data for 2010 and 2011. As asset-pricing tests require many data points, we acknowledged that our dataset suffered from a small-sample problem, which could reduce the quality of our results (Wooldridge, 2012). However, we detected low variability within stocks' carbon emissions each year, i.e., the measure remained relatively constant throughout the years for each company. Hence, we extended the reported emission data from 2012 two years backward for the companies lacking data from 2011 and 2010[6].

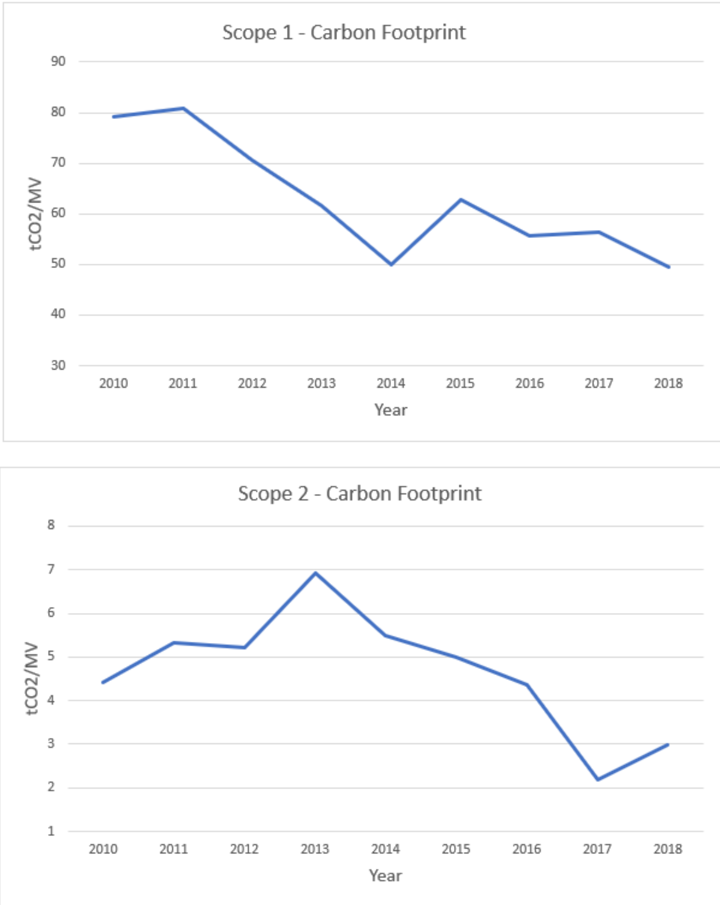
CDP reports absolute measures of scope 1 and scope 2 emissions, which makes it challenging to compare the relative level of carbon emissions between the stocks. To facilitate comparison independent of portfolio size, we calculated the carbon footprint[7] of the 53 stocks in our dataset. According to MSCI[8], market value and sales revenue are size proxies typically used when calculating carbon footprint (Frankel et al., 2015). MSCI's survey consider market value as the superior choice, an opinion which is supported by studies conducted by Aggarwal and Dow (2011), Balkissoon and Heaps (2014), Saka and Oshika (2014), and Kim et al. (2015). They emphasized that using market value as a proxy is beneficial when analyzing the result of investment choices, as it enables portfolio decomposition and attribution analysis (Hegerl et al., 1997). Thus, we used market value data from Datastream and calculated the carbon footprint as:

$$Carbon footprint = \frac{Total\, tCO_2\ Emissions}{Market\, Value} \tag{3.2}$$

Figure 3.1 below illustrates the historical trend of carbon footprints for both scopes. We observe that scope 1 emissions are, on average, higher than scope 2 emissions. Thus, scope 1 emissions are the most significant contributor to carbon emissions in our data set. The data further shows a downward trend for both scopes, which implies a reduction in stocks' carbon emissions from 2010 to 2018.

[6]We further discuss the sample size under limitations in chapter 5.5
[7]Carbon footprint is presented in section 2.2
[8]MSCI is a global provider of, amongst many, equity indexes and portfolio analysis tools (Frankel et al., 2015)

Figure 3.1: Historical trend showing average carbon footprint in our dataset from 2010-2018



The label tCO_2/MV refers to equation 3.2

3.3 Asset Pricing Data for the Oslo Stock Exchange

We collected asset pricing factors from Bernt Arne Ødegaard's online data library. These factors are similar to those developed by Eugene Fama and Ken French, but explicitly calculated for the OSE (Ødegaard, 2019). The following variables were retrieved:

- Market portfolio: Returns of two indices constructed from most stocks at the OSE where the least liquid and smallest stocks are filtered out. We collected both equally- and value-weighted portfolios
- Risk-free rate: Forward-looking interest rates, i.e. the rate for borrowing in the stated month
- Pricing factors: Fama French factors HML and SMB, and Carhart Momentum factor, calculated using Norwegian data

3.4 Portfolio Construction

We compose mutually exclusive portfolios by sorting stocks into portfolios according to their carbon footprint. One grouping is based on scope 1 emissions and one is based on scope 2 emissions. The good (bad) portfolios consist of the stocks with the 30% lowest (highest) carbon footprint in the sample. Because emission data in CDP is annually updated, we use the quantile function in a loop in RStudio to annually rebalance the portfolios. Thus, the portfolios contain the stocks with the lowest and highest carbon footprint at all times. For robustness, we conduct a supplementary analysis where the stocks with the highest frequency in the good and bad portfolio are applied, i.e., no rebalancing.

The yearly rebalancing of the portfolios differs considerably between scope 1 and scope 2 emissions. Our data reports a standard deviation of 165 tCO_2 for scope 1 and 12 tCO_2 /MV for scope 2. Thus, scope 1 portfolios have less turnover of stocks due to higher variation between the stocks measures. Consequently, some players dominate the portfolios. To illustrate, figure 3.2 depicts the carbon footprint range between top and bottom stocks in both scopes. The lowest and highest carbon footprint is 0.0017 tCO_2 /MV and 811.4 t CO_2 /MV in scope 1 and 0.0034 t CO_2 /MV and 64 t CO_2 /MVin scope 2.

Figure 3.2: Top and bottom five stocks based on average carbon footprint in 2010-2018, ranked from the lowest to the highest

Scope 1		Scope 2	
Company	**tCO2/MV**	**Company**	**tCO2/MV**
Nordea Bank	0.0017	Sbanken	0.0034
Norwegian Property	0.0052	Sparebank 1 SR-Bank	0.0040
EVRY	0.0079	Protector Forsikring	0.0142
DNB	0.0082	Norway Royal Salmon	0.0204
Gjensidige Forsikring	0.0101	AF Gruppen	0.0213
Norwegian Air Shuttle	356.6	Orkla	5.6
Aker Solutions	446.0	Aker Solutions	11.4
DOF	466.3	Wilh. Wilhelmsen Holding	29.5
Frontline	649.2	Norsk Hydro	57.1
SAS	811.4	Borregaard	64.0

The label tCO_2/MV refers to equation 3.2

We will use the following acronyms for the constructed portfolios throughout our analysis and discussion:

Table 3.1: Portfolio acronyms

Acronym	Portfolio Description
S1G	Scope 1 Good
S1B	Scope 1 Bad
S1GMB	Scope 1 Good Minus Bad
S2G	Scope 2 Good
S2B	Scope 2 Bad
S2GMB	Scope 2 Good Minus Bad

3.4.1 Calculating Portfolio Return

We calculate the portfolio returns for all our portfolios, see table 3.1. The S1GMB and S2GMB employs a zero-net investment strategy, taking a long position in the good portfolios and a short position in the bad portfolios. As we aim to analyze whether low-carbon stocks perform better than high-carbon stocks, examining the difference portfolios is more relevant than studying the individual portfolios.

We use equally-weighted portfolios for our primary analysis. Thus, we assign equal weights to each stocks by calculating the portfolio returns as follow:

$$R_t = \sum_{i=1}^{N} \frac{r_{it}}{Nfirms_t} \tag{3.3}$$

where,

$R_t = Portfolio\ return\ in\ month\ t$

$r_{i,t} = Stock\ return\ in\ month\ t$

$Nfirms_t = Number\ of\ stocks\ in\ portfolio\ in\ month\ t$

For robustness, we also value-weight our portfolios. We assign weights to each stock in the portfolio according to their market capitalization. The portfolio returns are calculated as follow:

$$R_t = \frac{\sum_{i=1}^{N}(w_{i,t} * r_{i,t})}{\sum_{i=1}^{N}(w_{i,t})} \tag{3.4}$$

where,

$w_{i,t} = market\ value\ of\ stock\ divided\ by\ total\ market\ value\ of\ portfolio\ in\ month\ t$

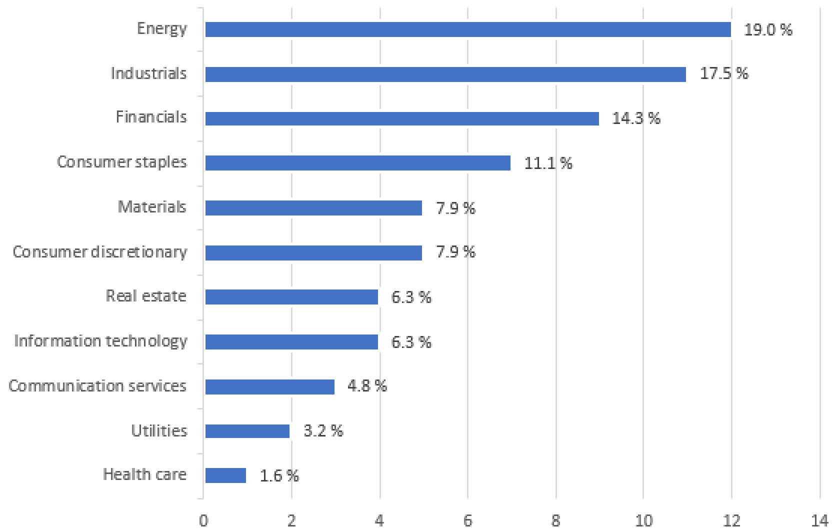
We argue that equally-weighted portfolios are more applicable when analyzing the Norwegian financial market, as a few large-cap firms dominate the OSE. Thus, the calculation of returns is evenly distributed on all stocks represented in the portfolio. This this allows for broader risk exposure and reduces the emphasis on risks related to value and size (Plyakha et al., 2012). However, we supplement with value-weighting to examine the sensitivity of our results are when giving large-cap stocks more influence on the portfolio return. Consequently, our robustness tests consist of both value-weighted and equally-weighted portfolios without rebalancing.

3.5 Data Reliability and Validity

We assess the reliability and validity of our data to estimate the quality of our research. Reliability describes the consistency of a measure, i.e., indicating to what extent similar research can confirm our findings (Saunders et al., 2016). Our sample contains an unbalanced distribution of sectors, see figure 3.3, as the energy, industrials, and financials sectors dominate our dataset[9]. This unbalanced structure is a well-known characteristic for the Norwegian financial market. The same three sectors dominate the OSBX-index (Ødegaard, 2019), as well as Gjensidige's portfolio presented in table 2.2. Hence, similar research examining at the OSE should obtain related findings. However, the sector bias raises the question of whether our results conform to studies examining other markets with a different sector composition.

[9]Sector structure in portfolios are presented in section 6.1

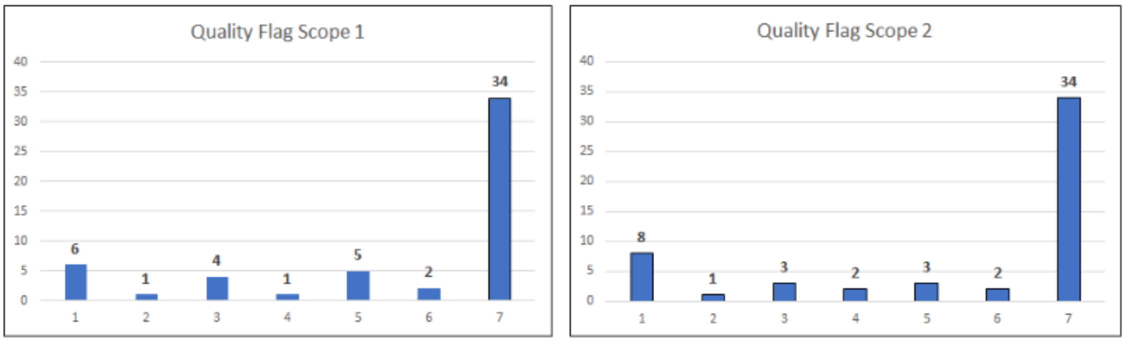
Figure 3.3: Sector composition in our dataset, sorted after GICS level 1



The x-axis indicates amount of companies represented in our dataset.
The graph labels indicate the percentage the sector makes of our sample

Validity refers to the accuracy of a measure (Stinchfield, 2003). Our concern was whether carbon emissions are precisely measured, as CDP relies on self-reported emissions that can lead to misreported data (CDP, 2019). CDP conduct internal consistency checks to verify that the data aligns with information companies have reported earlier. Furthermore, they conduct external consistency tests to reconcile the companies' CDP disclosed emissions compared to what they have reported in other data sources. After CDP has run several consistency checks, they report data reliability by assigning scores from 1 until 7 to the company's emission figures, referred to as quality flag. A score of 7 indicates that the self-reported data has passed both internal and external tests. As illustrated in figure 3.4, only a few of the emission measures in our dataset hold a score lower than 7, validating the reliability of our dataset.

Figure 3.4: CDP quality flag for scope 1 and 2



CDP ranks the quality of their data by assigning a quality flag for each measure.
The x-axis indicates the quality flag where 1 (7) represents the lowest (highest) score.
The y-axis denotes stock quantity

4 Methodology

In this section, we describe the methodology applied to detect potential abnormal returns. We conduct a portfolio study similar to the research of Derwall et al. (2005) and In et al. (2018). Portfolio studies aim to examine how a portfolio performs relative to other portfolios (Hamada, 1969). Consequently, this approach is well suited to analyze the performance differences between our constructed low- and high-carbon portfolios. In chapter 4.1, we present the risk-adjusted measures we use to evaluate portfolio performance. Chapter 4.2 introduces model specifications that we are employing in the regressions, while chapter 4.3 discusses the tests we have carried out to ensure our results are valid.

4.1 Risk-Adjusted Measures

We measure risk-adjusted returns primarily by Jensen's alpha and supplement with the Sharpe Ratio. The latter represents mean return earned in excess of the risk-free rate per unit total risk[10], thus giving a risk-adjusted performance measure at an absolute level (Sharpe, 1964). Jensen's alpha, hereafter referred to as alpha or abnormal return, reports the risk premium that exclusively accounts for systematic risk (Jensen, 1969). Most portfolio managers typically pick stocks that will be included in an existing portfolio, resulting in benefit from diversification by reducing exposure to unsystematic risk. As the alpha only account for systematic risk, we consider it as the most relevant measure to examine our research question.

The alpha is calculated by deducting the estimated expected rate of return in an asset-pricing model, from the actual rate of return of the portfolio (Jensen, 1969). If the portfolio is fairly priced, the actual return will match the expected return given by the asset-pricing model. Consequently, the alpha will be zero. However, the alpha will be positive (negative) if a stock is earning above (less than) its expected return. In the following chapter, we present the asset-pricing models we apply to calculate the predicted returns.

[10]Total risk consists of systematic risk and unsystematic risk. Systematic risk is the risk inherent to the entire market, making it unavoidable. Unsystematic risk is unique to a specific company or industry and can be eliminated through diversification (Aaker and Jacobson, 1987).

4.2 Model Specification

First, we measure the abnormal returns by employing the Capital Asset Pricing Model (CAPM). This model dates back to the 1960s and is known as the traditional pricing model for valuing stocks (Sharpe, 1964). The model was separately developed by Treynor (1961), Sharpe (1964), Lintner (1965), and Mossin (1966), who argued that investors should only receive compensation for portfolios' exposure to market risk. As a result, the expected return of a portfolio equals the risk-free rate plus a risk-premium that adjust for the portfolios' market exposure. Thus, when applying the CAPM, Jensen's alpha represents the average abnormal return above the return suggested by CAPM (Jensen, 1969). For all portfolios, we use ordinary least-squares (OLS) regression to estimate the following:

$$R_{it} - R_{ft} = \alpha_i + \beta_i(R_{mt} - R_{ft}) + \epsilon_{it}, \tag{4.1}$$

where,

$R_{i,t} = return\ on\ portfolio\ i\ in\ month\ t$

$R_{f,t} = one\ month\ Norwegian\ risk\ free\ rate\ in\ month\ t$

$R_{m,t} = return\ a\ equally\ or\ value\ weighted\ market\ proxy\ in\ montht$

$\epsilon_{i,t} = error\ term\ in\ month\ t$

$\alpha_i = Jensen's\ alpha, i.e.\ intercept\ and\ abnormal\ return$

$\beta_i = Portfolio\ i's\ market\ risk\ exposure$

We further analyze the portfolio performance by employing the Carhart four-factor model. Fama and French (1991) noticed that stocks with the same market beta, but different market capitalization and book-to-market ratio, yielded highly differing returns. Hence, Fama (1991) developed the three-factor asset pricing model as a response to CAPM. This model includes two additional risk factors, size and book-to-market, which are proven to correlate with portfolio returns. Carhart (1997) further enhanced the three-factor model by including a momentum factor. Carhart (1997) 's momentum factor describe the tendency for the stock prices to continue rising (declining) if they recently have gone up (down).

Instead of adding the momentum factor to the classic 3-factor model, Fama and French (1998) suggested adding investment and profitability factors to the 3-factor model. However, adding more factors reduces the efficiency of the estimators. Given our somewhat small sample size, the number of independent variables should be held at a minimum to obtain meaningful results (Wooldridge, 2012). Moreover, these factors have less empirical observed robust effect on returns than the market capitalization, book-to-market, and momentum factors (Blitz et al., 2016).

When applying the Carhart four-factor model, Jensen's alpha represents the average, abnormal return above the predicted return calculated (Jensen, 1969). Formally, the approach to performance assessment entails implementing OLS regression to estimate the following model:

$$R_{it} - R_{ft} = \alpha_i + \beta_{0i}(R_{mt} - R_{ft}) + \beta_{1i}SMB_t + \beta_{2i}HML_t + \beta_{3i}MOM_t + \epsilon_{it}, \qquad (4.2)$$

where,

$\mathrm{SMB}_t = Return\ difference\ between\ a\ small-cap\ portfolio\ and\ a\ large-cap\ portfolio$
$in\ month\ t$

$HML_t = Return\ difference\ between\ a\ value\ (high\ BV/MV)\ portfolio\ and\ a\ growth$
$(low\ BV/MV)\ portfolio\ in\ month\ t$

$MOM_t = Return\ difference\ between\ a\ portfolio\ of\ past\ 12-month\ winners\ and\ a$
$portfolio\ of\ past\ 12-month\ losers\ in\ month\ t$

$\beta_{1,i},\ \beta_{2,i},\ \beta_{3,i} = Portfolio\ i's\ exposure\ to\ the\ SMB,\ HML,\ and\ MOM\ factors\ respectively$

Note that the "return differences" in the SMB, HML, and MOM factors bases on a long-short zero investment strategy.

Model Rationality

We chose to employ both the CAPM and Carhart four-factor model to increase the complexity of the analysis and the validity of the findings. We chose to first utilize the

CAPM as it measures the link between market risk and expected return by simplistic calculations (Sharpe, 1964). Moreover, controlling for only one risk factor does not require such a large sample to guarantee robust results, compared to adding more risk factors (Wooldridge, 2012). Secondly, we apply the Carhart four-factor model to control for additional risk factors. This model can predict increasingly accurate risk-returns, and potentially mitigate severe biases that could result from style tilts in stock portfolios (Derwall et al., 2005).

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4.3 Model Testing

We conduct relevant tests to verify our results from the CAPM and the Carhart. All tests results are given in the appendix A2.

Employing OLS regression requires the following five Gauss-Markow Assumptions to be fulfilled: i) Linear in parameters, ii) zero conditional mean, iii) no perfect collinearity, iv) homoscedasticity, and v) no serial-/autocorrelation (Wooldridge, 2012). If all assumptions are met, we can guarantee the validity of OLS for estimating regression coefficients. We will not test i) and iii), as these assumptions are more relevant for prediction purposes, i.e., adding independent variables to test their effect on the dependent variable. In addtion, we employ already established independent factors that previously have shown to significantly affect stock returns (Carhart, 1997), which indicates that the two assumptions already holds.

Autocorrelation is a common problem when using time-series data, as it leads to problems such as biased standard errors and invalidate inference (Wooldridge, 2012). Furthermore, the existence of heteroscedasticity can invalidate the standard errors and test statistics, which is essential when interpreting our findings. We test for autocorrelation by applying a Breush-Godfrey test, and we test for heteroscedasticity through a Breuch-Pagan test. The test statistics suggest that autocorrelation and heteroscedasticity are not a concern in the models. We further test for normality given our questionable sample size. Small samples often results in non-normal distributions, reducing the statistical power of the results. The applied histogram tests verify that the sample mean is centered around zero for both the scope 1 and scope 2 sample, although the former comes out as stronger. Altogether, the OLS assumptions hold, ensuring realistic model results.

In addition to the meeting the Gauss-Markow Assumptions, our time-series data have to be stationary (Wooldridge, 2012). Applying non-stationary time series in regression models can result in findings that indicate a significant relationship even when there is none. Thus, leading to spurious regressions. To test for stationarity, we conduct an augmented Dickey-Fuller test for unit root, where we apply the optimal lag length constructed by Ng and Perron (1995). The results indicate that the stationary assumption is satisfied.

5 Findings and Discussion

This section presents a performance evaluation of the portfolios constructed to investigate scope 1 and scope 2 emissions. We first provide descriptive statistics, and then present the findings from the regression models in the next chapter. We further present the robustness tests to analyze the strength of our results. Next, we discuss the significant abnormal returns and their implications, while the last chapter elaborates on the limitations of our results.

Prior to presenting the results, we find it expedient to recall the research question: *Have low-carbon investments delivered significantly higher risk-adjusted returns than high-carbon investments?*

1. **H0:** Portfolios with low scope 1 carbon footprint **do not** have statistically significant higher abnormal return than portfolios with high scope 1 carbon footprint
   H1: Portfolios with low scope 1 carbon footprint **have** statistically significant higher abnormal return than portfolios with high scope 1 carbon footprint
2. **H0:** Portfolios with low scope 2 carbon footprint **do not** have statistically significant higher abnormal return than portfolios with high scope 2 carbon footprint
   H1: Portfolios with low scope 2 carbon footprint **have** statistically significant higher abnormal return than portfolios with high scope 2 carbon footprint

We investigate this research question by testing the two-sided null hypotheses against the alternative hypotheses. By testing returns of both hypotheses, we can analyze return differences separately for scope 1 and scope 2 emissions. Rejecting our null hypotheses will suggest a positive relationship between stocks with low carbon emissions and risk-adjusted returns.

5.1 Descriptive Analysis

In this chapter, we provide descriptive statistics of the constructed portfolios for both scope 1 and scope 2. We begin by presenting portfolio characteristics before we analyze the cumulative returns for our chosen time period.

5.1.1 Portfolio Overview

Table 5.1 presents descriptive statistics of our monthly, equally-weighted constructed portfolios, as well as the market portfolio retrieved from Ødegaard's data library.

Table 5.1: Descriptive statistics for carbon footprint ranked portfolios, monthly average from 2010 to 2018

Statistic	Sharpe Ratio	Mean Return	St. Dev.	Min	Max
Panel A: Scope 1					
Good Portfolio	0.216	0.011	0.045	−0.136	0.160
Bad Portfolio	0.012	0.002	0.058	−0.191	0.159
Market Proxy	0.323	0.011	0.030	−0.071	0.080
Panel B: Scope 2					
Good Portfolio	0.226	0.012	0.047	−0.118	0.149
Bad Portfolio	0.119	0.007	0.048	−0.161	0.142
Market Proxy	0.323	0.011	0.030	−0.071	0.080

Note: Sharpe Ratio is the average monthly return earned in excess of the risk-free rate per unit of total risk. Mean Return is average monthly return. St.Dev. represents total risk. The Min and Max states the minimum and maximum monthly return in the portfolios. The good (bad) portfolio represents the 30% of the stocks with the lowest (highest) carbon footprint in our dataset. The Market Proxy consists of two indices constructed from most stocks at the OSE

Panel A suggests that the S1G portfolio performs better than the S1B portfolio, with a Sharpe Ratio of respectively 21.6% and 1.2%. Similar results, but with less performance difference between the portfolios, can be detected in Panel B. The Sharpe Ratio for the S2G portfolio is 22.6% and 11.9% for the S2B portfolio. We find it essential to mention that the Sharpe Ratio measure risk-adjusted return that considers both unsystematic and systematic risks[11]. Even though the good portfolios have a higher Sharpe Ratio than the bad portfolios, we must isolate the effect of systematic risk before concluding on any

[11]Performance measures are detailed in section 4.1

differences in risk-adjusted return. In chapter 5.2, we examine alphas between the good and the bad portfolios, where we control for systematic risk factors.

The bad portfolios have a higher standard deviation than the good portfolios for both scopes. This seems reasonable, as we expect stocks with a high carbon footprint to have higher risk exposure, a feature we further discuss in section 6. However, we observe that despite higher volatility, the bad portfolios do not achieve a higher mean return. This finding indicate high exposure to unsystematic risk, which investors do not receive compensation for.

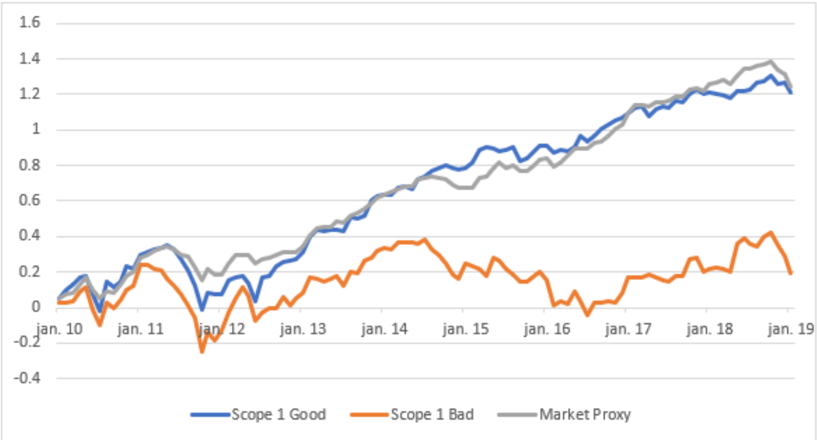
The market portfolio is superior to all our portfolios, with a Sharpe Ratio of 32.3%. This finding is in line with financial theory that considers the market portfolio to be the optimal choice. Our findings contradict the portfolio study of Daniel and Blank (2002), who found a higher Sharpe Ratio in their good portfolio. However, they covered a broader climate focus than our study, including both companies' waste and pollution. Our results suggest that investors should be critical of whether they can expect higher risk-adjusted returns than the market proxy when solely focusing on carbon emissions.

5.1.2 Cumulative Returns

Figure 5.1 and 5.2 depicts the cumulative returns of the equally-weighed good (blue) and bad (orange) portfolios for both scopes. It also show the cumulative return of the equally weighted market proxy (grey) across all examined years.

Figure 5.1 charts scope 1 emissions. The S1G portfolio, together with the market portfolio, show a positive trend during this period. However, from mid-2014 to 2017, the S1G portfolio generated a higher cumulative return than the market portfolio. The S1B portfolio remains relatively constant across all years, with a cumulative return of 0%. This observation shows that the S1B portfolio underperforms, similarly to the results from table 5.1. In sum, the figure indicates a rejection of our first null hypothesis, confirming that portfolios with lower scope 1 emissions outperform their low-ranked counterparts. Our findings in section 5.1.1 where we adjusted the mean return for total risks strengthen this argument. However, we still have to analyze the statistical significance when controlling for systematic risk factors to confirm this inferential, which we do in the next chapter.

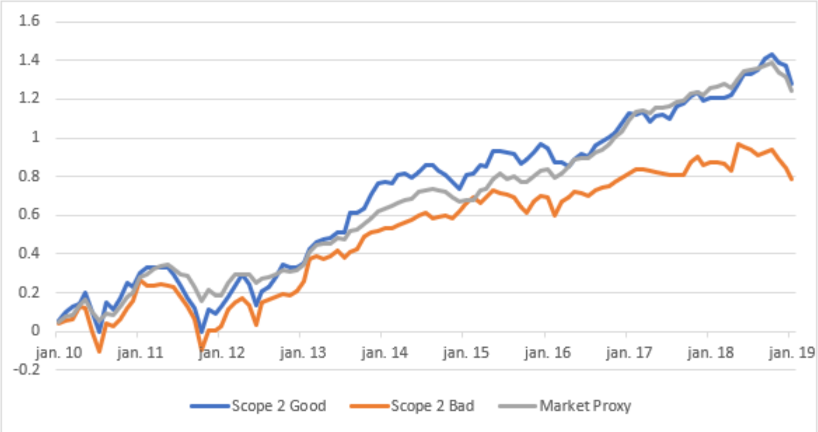
Figure 5.1: Cumulative returns for portfolios regarding scope 1, 2010-2018



Y-axis represents cumulative return

We observe similar results for scope 2 in figure 5.2, where the S2G portfolio has a higher cumulative return than the S2B. However, the difference in return is not as prominent as between the S1 portfolios. As of January 1th 2019, the S2G portfolio shows a cumulative return of 120%, while the S2B portfolio reports 80%. For scope 1, the returns were respectively 120% and 20%. Linking this observation with the findings in section 5.1.1, we anticipate that the regression results for the GMB portfolios will exhibit a higher significance for scope 1 than for scope 2.

Figure 5.2: Cumulative returns for portfolios regarding scope 2, 2010-2018



Y-axis represents cumulative return

5.2 Regression Results

This chapter presents the results from our regression analysis. We present the results for scope 1 and scope 2 separately. We focus on clarifying the reported estimates from the output, and discuss the following implications in section 5.4. Note that our object is not to analyze whether the CAPM or the Carhart model are best suited, but if one or both the models present significant abnormal returns.

Table 5.2 and 5.3 presents regression results obtained from the equally-weighted portfolios, constructed for both scopes. Given that our primary focus is the performance differential between the good and bad portfolios, we find the most relevant observations from the output under the difference portfolios. These estimates depict the results of the long-short portfolios from the CAPM and the Carhart model. Because we are studying differences, both the variable estimates and the R-square must be interpreted differently compared to the long portfolios represented under "Good Portfolio" and "Bad Portfolio". An insignificant estimate indicates that there is no difference in exposure to a factor. The R-square measures how much of the return difference that can be explained by differences in risk exposure, thus being of less importance compared to the long-portfolios.

5.2.1 Scope 1 Portfolios

The following table present our empirical results for scope 1 analysis.

Table 5.2: Scope 1 empirical results of the CAPM and Carhart regressions, monthly data for the period 2010-2018

	Dependent variable:					
	Good Portfolio (S1G)		Bad Portfolio (S1B)		Difference portfolio (S1GMB)	
	(CAPM)	(Carhart)	(CAPM)	(Carhart)	(CAPM)	(Carhart)
Rm - Rf	1.1499***	1.1371***	1.5519***	1.3963***	-0.4020***	-0.2592**
	(0.0938)	(0.0862)	(0.1129)	(0.1067)	(0.1302)	(0.1227)
SMB		-0.3675***		-0.4554***		0.0880
		(0.0815)		(0.1008)		(0.1159)
HML		0.1331*		-0.2473***		0.3805***
		(0.0759)		(0.0939)		(0.1080)
MOM		0.2042***		-0.2168**		0.4210***
		(0.0755)		(0.0934)		(0.1075)
Constant (α)	-0.0018	-0.0030	-0.0152***	-0.0110***	0.0134***	0.0080*
	(0.0030)	(0.0029)	(0.0036)	(0.0035)	(0.0041)	(0.0041)
Observations	109	109	109	109	109	109
R^2	0.5842	0.6927	0.6385	0.7176	0.0819	0.2860
Adjusted R^2	0.5804	0.6808	0.6351	0.7067	0.0733	0.2586
Note:	*p<0.1; **p<0.05; ***p<0.01				Standard Errors in parentheses	

We estimate the models for scope 1 portfolios, formally defined by equations 4.1 and 4.2. The table reports monthly estimates for the period 2010-2018. The dependent variables represent the return achieved above the risk-free rate for rebalanced equally-weighted portfolios. The good (bad) portfolio represents 30% of the stocks with the lowest (highest) carbon footprint in our dataset. The difference portfolio represents the results from the good portfolio minus the bad portfolio, i.e., a zero investment. The variable Rm-Rf is the equally-weighted market return minus the risk-free rate, where the coefficient is a measure of the portfolios' volatility to the market. SMB stands for "Small Minus Big (market capitalization)" and capture the historic abnormal returns of small caps over big caps. HML stands for "High Minus Low (book-to-market ratio)" and capture the historic abnormal returns of value stocks over growth stocks. MOM refers to the rate of recent price movements in the portfolios. Sample alphas, the Constant, are monthly percentage abnormal returns.

Table 5.2 reports the regression results related to scope 1 emissions. The alpha estimates for the S1GMB portfolio indicates an average monthly risk-adjusted return of 0.0134% in the CAPM and is significant at a 1% level. The alpha estimate in the Carhart model indicates an average risk-adjusted return of 0.0080% per month, but is only significant at a 10% level. According to these results, we can reject our null hypothesis, at least at a 10% level. The rejection suggests that portfolios with low scope 1 emission significantly outperform portfolios with high scope 1 emission. This observation aligns with the sizeable cumulative performance gap between these two portfolios, as illustrated in figure 5.1.

Further analysis of the S1GMB portfolio illustrates a significant negative exposure to the market proxy. The S1G portfolio is 0.402 less exposed than the S1B portfolio in the CAPM and 0.259 less exposed in the Carhart model. The Carhart Model further shows a positive difference in exposure to the other risk factors, however only HML and MOM are significant.

The S1G portfolio in the CAPM and Carhart exhibit negative, but insignificant alphas, whereas the S1B portfolios in CAPM and Carhart report negative and significant alphas. The latter result implies unfavourable results of investing in high-carbon stocks. Moreover, the market beta is significantly above 1 for both the individual portfolios, which indicates that our dataset includes stocks of high volatility in comparison to the stock market. The other risk factors in the Carhart model are significant for both the S1G and S1B portfolios. The coefficient on SMB is negative for both portfolios, which indicates a bias toward large-cap companies in our portfolios. The factor loadings on HML imply a value-stock orientated S1G portfolio and a growth-stock orientated S1B portfolio.

In et al. (2018)[12] identified better financial performance and, thus, higher stock prices amongst low-carbon stocks. Based on his observation, we assumed the low-carbon portfolio to have positive exposure to the momentum factor as it describes stocks' recent price trend. The results from scope 1 emissions confirm our theory, as the coefficient for the momentum factor is significantly positive for S1G portfolios and significantly negative for S1B portfolios.

The increase in R-square and adjusted R-square from the CAPM to the Carhart model indicates that the risk factors in the Carhart model explain a higher percentage of variation in the portfolio returns. For instance, in the CAPM for S1B 63.85% of the variation in the abnormal return is explained by the market factor. The market, SMB, HML, and MOM

[12] The study of In et al. (2018) are presented in section 2.3.1

variables explain 71.76% in the Carhart model. As the applied models do not explain all variations in portfolio returns, missing relevant risk factors might justify the existence of abnormal returns. Our significant alphas make us suspect that stocks' carbon footprint can explain some of the variation in their achieved return above risk-free return.

5.2.2 Scope 2 Portfolios

In the following table, we present the empirical results for our scope 2 analysis.

Table 5.3: Scope 2 empirical results of the CAPM and Carhart Regressions, monthly data for the period 2010-2018

	Dependent variable:					
	Good Portfolio (S2G)		Bad Portfolio (S2B)		Difference Portfolio (S2GMB)	
	(CAPM)	(Carhart)	(CAPM)	(Carhart)	(CAPM)	(Carhart)
Rm - Rf	1.2739***	1.2117***	1.2192***	1.1283***	0.0547	0.0833
	(0.0909)	(0.0899)	(0.0983)	(0.0914)	(0.1048)	(0.1111)
SMB		-0.3495***		-0.4949***		0.1454
		(0.0849)		(0.0863)		(0.1049)
HML		-0.0063		-0.0454		0.0390
		(0.0791)		(0.0804)		(0.0978)
MOM		0.0247		0.0280		-0.0033
		(0.0787)		(0.0800)		(0.0973)
Constant (α)	-0.0024	-0.0015	-0.0064**	-0.0051*	0.0040	0.0036
	(0.0029)	(0.0030)	(0.0031)	(0.0030)	(0.0033)	(0.0037)
Observations	109	109	109	109	109	109
R^2	0.6472	0.6984	0.5899	0.6898	0.0025	0.0210
Adjusted R^2	0.6439	0.6868	0.5861	0.6779	-0.0068	-0.0166

Note: *p<0.1; **p<0.05; ***p<0.01 Standard Errors in parentheses

We estimate the models for scope 2 portfolios, formally defined by equations 4.1 and 4.2. The table reports monthly estimates for the period 2010-2018. The dependent variables represent the return achieved above the risk-free rate for rebalanced equally-weighted portfolios. The good (bad) portfolio represents 30% of the stocks with the lowest (highest) carbon footprint in our dataset. The difference portfolio represents the results from the good portfolio minus the bad portfolio, i.e., a zero investment. The variable Rm-Rf is the equally-weighted market return minus the risk-free rate, where the coefficient is a measure of the portfolios' volatility to the market. SMB stands for "Small Minus Big (market capitalization)" and capture the historic abnormal returns of small caps over big caps. HML stands for "High Minus Low (book-to-market ratio)" and capture the historic abnormal returns of value stocks over growth stocks. MOM refers to the rate of recent price movements in the portfolios. Sample alphas, the Constant, are monthly percentage abnormal returns.

Table 5.3 shows the regression results for the S2 portfolios, and there are several prominent differences from the S1 results in table 5.2. The difference portfolios report a positive alpha, but it is not statistically significant. Hence, we cannot reject our null hypothesis and confirm a higher risk-adjusted return amongst low-carbon portfolios compared to high-carbon portfolios. This finding aligns with our expectations of higher significance for scope 1 compared to scope 2, as expressed in section 5.1.2. Furthermore, there are no significant differences in exposure to applied risk factors between the S2G and the S2B portfolio. In sum, the results of the difference portfolio for scope 2 clearly differ from the results of scope 1.

The alpha estimates for scope 2 in the S2B portfolio report a monthly abnormal return of -0.0064% in the CAPM and -0.0051% in the Carhart model. The coefficients are significant at a 5% and 10% level, respectively. This finding aligns with the results of scope 1, and strengthen our conception that high-carbon stocks yield negatively abnormal returns. The alpha estimates in the S2G portfolio are not statistically significant, similarly to the results from scope 1. The market beta is still significantly above one in both the S2G and S2B portfolios. However, the S2B portfolio holds a significantly lower market beta than the S1B portfolio, thus consisting of less volatile stocks.

The coefficients on SMB in the S2G and S2B are significantly negative for the Carhart model, similar to what we observed in scope 1. Consequently, these portfolios also consist of more large-cap companies. In contrast to the S1 portfolios, the HML and MOM factors do not have a statistically significant effect on portfolio return. Moreover, the R-square increases when including additional factors, but is lower compared to the R-square in the S1 portfolios.

5.3 Robustness Test: Results under Alternative Methodologies

As mentioned in section 4, we test the robustness of our findings by applying OLS regression to both the value-weighted portfolios and the portfolios without rebalancing. By combining these robustness analysis with our main analysis, we aim to gain a more thorough understanding of how the portfolios with low and high carbon footprint perform. This chapter focus on analyzing the estimated abnormal returns in the alternative methods as this is the objective of our thesis. We have attached complete regression outputs in the Appendix A3.

Value-Weighted Portfolios

The value-weighting approach assigns weights to the different stocks according to their market value relative to the total market value in their assigned portfolio. The following table presents the results:

Table 5.4: Reported abnormal returns using value-weighted portfolios, monthly data for the period 2010-2018

	Dependent variable:					
	Good Portfolio		Bad Portfolio		Difference portfolio	
	(CAPM)	(Carhart)	(CAPM)	(Carhart)	(CAPM)	(Carhart)
α (*Scope* 1)	-0.0039	-0.0056	-0.0098***	-0.0060*	0.0058	0.0004
	(0.0035)	(0.0040)	(0.0032)	(0.0035)	(0.0047)	(0.0052)
α (*Scope* 2)	-0.0050	-0.0074**	-0.0061*	-0.0060	0.0011	-0.0014
	(0.0031)	(0.0033)	(0.0033)	(0.0037)	(0.0040)	(0.0043)

Note: *p<0.1; **p<0.05; ***p<0.01 Standard Errors in parentheses

The table reports monthly estimates for the period 2010-2018. The dependent variables represent the return achieved above the risk-free rate for rebalanced value-weighted portfolios. The good (bad) portfolio represents 30% of the stocks with the lowest (highest) carbon footprint in our dataset. The difference portfolio represents the results from the good portfolio minus the bad portfolio, i.e., a zero investment. Sample alphas are monthly percentage abnormal returns.

Table 5.4 illustrates that our results, to an extent, change when we give larger companies more influence. This indicates that our findings are sensitive to adjustments in the portfolio formation. This sensitivity is reasonable as our sample is quite small, and regression results tend to converge to a stable frequency when the sample size grows (Wooldridge, 2012). We further discuss the implication of the sample size in section 5.5.

We observe that the estimated alphas decrease for the difference portfolio scope 1 when value-weighting, compared to the results from the equally-weighting approach. In CAPM the estimated alphas decrease from 0.0134% to 0.0058%, and from 0.008% to 0.0004% in the Carhart model. Although the estimates still come out as positive, they are no longer statistically significant, which weakens our confidence of rejecting the first null hypothesis. This finding also suggests that the alpha to a greater extent depends on small-cap companies than large-cap companies. The S1B portfolios still holds a significant negative alpha, at least at a 10% level, thus confirming negative abnormal return amongst high-carbon stocks. The alphas for the S1G portfolios are still insignificant.

The alphas for the S2GMB remains insignificant in the value-weighted method. A notable difference from equally-weighting is that we now observe significant negative alpha for the S1G portfolio when using the Carhart model. Hence, we believe that low-carbon stocks with larger capitalization averagely yield negative risk-adjusted returns. The negative alphas for high-carbon stocks are now only significant in the CAPM, whereas they were both negative in our main analysis.

Portfolios Without Rebalancing

Holding the portfolios constant involves no yearly rebalancing. The portfolios are sorted after the stocks with the lowest and the highest average carbon footprint during the entire time-period investigated. In this approach we use equally-weighted portfolios. The following table presents the estimated abnormal returns:

Table 5.5: Reported abnormal returns using portfolios without rebalancing, monthly data for the period 2010-2018

	Dependent variable:					
	Good Portfolio		Bad Portfolio		Difference portfolio	
	(CAPM)	(Carhart)	(CAPM)	(Carhart)	(CAPM)	(Carhart)
α (*Scope* 1)	-0.0029	-0.0035	-0.0136***	-0.0103***	0.0107***	0.0068*
	(0.0030)	(0.0028)	(0.0034)	(0.0035)	(0.0039)	(0.0039)
α (*Scope* 2)	-0.0038	-0.0018	-0.0072**	-0.0063**	0.0034	0.0045
	(0.0032)	(0.0033)	(0.0031)	(0.0030)	(0.0036)	(0.0040)

Note: *p<0.1; **p<0.05; ***p<0.01 Standard Errors in parentheses

The table reports monthly estimates for the period 2010-2018. The dependent variables represent the return achieved above the risk-free rate for constant equally-weighted portfolios. The good (bad) portfolio represents 30% of the stocks with the lowest (highest) carbon footprint in our dataset. The difference portfolio represent the results from the good portfolio minus the bad portfolio, i.e. a zero investment. Sample alphas are monthly percentage abnormal returns.

Compared to the value-weighted robust test, the results from the no rebalancing test are more similar to the initial result. The abnormal return for S1 portfolios are remains positively significant for the difference portfolios, and negatively significant for the S1B portfolios. The difference portfolio for scope 2 is also positively insignificant, and the S2B portfolios now exhibit an even more significant negative abnormal return than in the initial analysis.

The fact that both portfolios with rebalancing and no-rebalancing provide similar results indicate a low turnover rate in the portfolios, i.e., the good and bad portfolio rarely rebalance stocks. This observation confirms the low variability of stocks carbon footprint over the years, which we detected in section 3. As a result, typical trading costs occurring from rebalancing portfolios should not absorb profits and dilute the benefits of abnormal returns, as investors can generate alpha with low trading activity.

To summarize the most relevant results from the robustness tests, we cannot reject our null hypotheses when using value-weighted portfolios because the alpha is not statistically different from zero. Comparing these insignificant results with the significant results from our main analysis, indicates that stocks of larger value are less affected by climate exposure than smaller equities. By holding the stocks represented in our portfolios constant each year, we can reject the first null hypothesis and thus presume that S1G portfolios outperform the S1B portfolios.

5.4 Discussion of Abnormal Returns

So far, this analysis has described the performance of stocks with different carbon footprints. In this chapter, we will analyze the implications of our most relevant results and how these relate to existing studies. Even though we suggest profitable investment strategies, note that our analysis aims to detect performance differences, not to give concrete trading suggestions.

The following table summarizes the alpha estimates for scope 1 and scope 2:

Table 5.6: Summary of abnormal returns from main analysis and robustness tests

	Dependent variable:					
	Good Portfolio		Bad Portfolio		Difference Portfolio	
	(CAPM)	(Carhart)	(CAPM)	(Carhart)	(CAPM)	(Carhart)
Panel A: Scope 1						
α (*EW with reb.*)	-0.0018	-0.0030	-0.0152***	-0.0110***	0.0134***	0.0080*
α (*VW with reb.*)	-0.0039	-0.0056	-0.0098***	-0.0060*	0.0058	0.0004
α (*EW no reb.*)	-0.0029	-0.0035	-0.0136***	-0.0103***	0.0107***	0.0068*
Panel B: Scope 2						
α (*EW with reb.*)	-0.0024	-0.0015	-0.0064**	-0.0051*	0.0040	0.0036
α (*VW with reb.*)	-0.0050	-0.0074**	-0.0061*	-0.0060	0.0011	-0.0014
α (*EW no reb.*)	-0.0038	-0.0018	-0.0072**	-0.0063**	0.0034	0.0045

Note: *p<0.1; **p<0.05; ***p<0.01
The dependent variables equals the returns achieved above the risk-free rate of monthly portfolios for the period 2010-2018. The good (bad) portfolio represents 30% of the stocks with the lowest (highest) carbon footprint in our dataset. The difference portfolio represents the results from the good portfolio minus the bad portfolio, i.e., a zero investment. Sample alphas are monthly percentage abnormal returns.

The alpha estimates of our equally-weighted portfolios for scope 1 show a significant monthly, average difference between the S1G and S1B portfolios of approximately 0.01%. This is significant at least at a 10% level, leading to a rejection of our first null hypothesis: *Portfolios with low scope 1 carbon footprint* ***do not*** *have statistically significant higher* *abnormal return than portfolios with high scope 1 carbon footprint.* The rejection indicates that investment strategies buying stocks with low scope 1 carbon footprint and selling stocks with high carbon footprint are preferable. However, we cannot reject the hypothesis when using value-weighting. This suggests that the significant alpha generation are somewhat dependent on investing in small-cap stocks.

There are no significant reported alpha estimates on the S2GMB, i.e., we cannot reject our second null hypothesis:*Portfolios with low scope 2 carbon footprint* ***do not*** *have statistically significant higher abnormal return than portfolios with high scope 2 carbon footprint.* However, the results from the S2G and S2B portfolios suggest weaker investment performance when betting on S2B stocks. This conclusion is based on the fact that the S2G and S2B portfolio show significant negative abnormal return in respectively, one out of six and five out of six cases. These outputs indicate better performance amongst S2G stocks than S2B stocks.

Our findings match the results of Derwall et al. Derwall et al. (2005) and Young In et al. In et al. (2018), who also found significant abnormal return when going long in high-carbon stocks and short low-carbon stocks. As they analyzed the U.S. stock market, our study contributes by confirming similar results for the Norwegian stock market, with particularly strong results for scope 1 emissions.

The individual portfolios for both scopes mostly report insignificant abnormal returns for the good portfolios. However, the portfolios report significant negative abnormal returns for the bad portfolios, indicating that stocks defined as bad have performed worse than the market. This outcome was surprising as White (1996) found contradicting result; good portfolios with significantly positive alpha, and insignificant alphas in the bad portfolios. However, White (1996) studied stocks in 1964-1989, while our analysis studies stocks from 2010 to 2018. The different results can also be explained by our analysis examining stocks listed at the OSE.

The fact that our analysis confirms significant alphas contradicts the theory of market efficiency, similar to the event study of Liesen et al. (2017). Our analysis, as well as Liesen et al. (2017), use available carbon emission data and prove it is not adequately reflected in the valuation of stocks. Thus, investors can achieve abnormal returns if stocks are mispriced. For instance, we detect significant negative alphas in high-carbon stocks for both scopes in all methods, except value-weighted Carhart. This suggests that high-carbon stocks are overpriced and that investors do not get adequately compensated for their level of risk. However, we cannot guarantee that our results are due to inefficient financial markets, and not inadequate use of asset pricing models.

The significant negative results for stocks with high emissions can also indicate a low-carbon premium, as detected in the regression study by Bernardini et al. (2019). However, as risk premiums are usually associated with higher risks, an intriguing discussion is whether it should be reversed, i.e., carbon premium for holding stocks with higher carbon emissions. This premium would thus require lower prices for stocks with a higher carbon footprint, as they are currently overpriced. However, from an ethical perspective, one might suggests these stocks to remain overpriced because offering a risk premium will reduce stock prices and thus increase the level of investments. This is not a good solution to mitigate global warming.

5.5 Limitations

In this chapter, we discuss the most relevant limitations of our research: the sample size, sector composition, and model specification.

Sample Size

Intending to analyze the relationship between carbon emissions and stock market return at the OSE, we ended up with a sample size of 53 stocks. It is questionable whether this sample size is large enough to conduct statistical analysis. In section 3, we explained that a small sample would imply additional statistical error, which increases the ambiguity of our findings (Wooldridge, 2012). There are several rule-of-thumb proposals regarding sample sizes. Roscoe (1975) states that any sample size over 30 is acceptable for statistical analysis. Nevertheless, when testing multiple correlations, the recommended sample size is 50 + 8 x number of independent variables (Greenacre, 1984). The latter indicates that our sample size should be larger in both the CAPM and the Carhart model. However, we tested the quality of our sample size in section 4.3[13]. We verified that the sample size is not a big concern and, thus, increasing the validity of our results.

Sector Composition

Figure 3.3 depicts the uneven sector structure in our data. If sector exposure has a larger effect on portfolio performance than carbon footprints, it might dilute the true impact of carbon emissions. For instance, the decrease in the oil price can potentially explain some of our negative abnormal returns, especially since the energy sector makes up 19% of our sample. Thus, we should eliminate performance differences due to sector classification. A potential solution is to examine the difference in carbon emissions within sectors. However, our largest sector consisting of 12 stocks is too low alone to obtain representative results. Another technique is including industry-fixed variables in the models, but our sample size restricts us from doing this as well. Moreover, adding more independent variables increases the dependency of a larger sample.

Alternately, we rely on the portfolio studies of Derwall et al. (2005) and In et al. (2018), which controlled for sector characteristics. They discovered that sector-effects could not explain the significant performance difference between their good and bad portfolios. These studies increase the robustness of our results. In section 6, we further discuss the implication of the sector structure regarding our findings.

Model Specification

It is challenging to determine whether we obtain abnormal returns due to market inefficiency or inadequate asset pricing models. A typical concern in regression analysis is whether the model includes all necessary variables, as missing variables can result in omitted variable bias[14](Wooldridge, 2012). We should be confident that no other essential

[13]Output from model testing is provided in A.2

[14]Omitted variable bias occur when the effect missing variables have on the dependent variable (portfolio return) are attributed to the included variables (Wooldridge, 2012)

factors determine the portfolio return. If our sample size was larger, we could control for more effects. As discussed, our small sample size limits the number of independent variables we can include. To minimize potential misspecifications, we base our results on both the CAPM and Carhart model, as well as both the primary and alternative analysis.

Despite these mentioned weaknesses, our findings concur with the majority of relevant existing literature. These studies increase the robustness of our results and reduce the impact of our limitations.

This section has presented and discussed our findings. The following section will further discuss how climate risks affect the sectors relevant to our findings.

6 Further Discussion of Sector Implications

We consider the skewness in our dataset's sector structure[15] to be an interesting feature and the same skewness applies to Gjensidige's portfolio. This section aims to examine how the prominent sectors can be affected by climate risk. We combine our historical performance results from section 5 with research regarding future transition risk. The first chapter discuss the sector composition in our portfolios. The next chapter elaborates on how transition risk predicts to affect these sectors. The last chapter presents the following implications for Gjensidige's portfolio.

6.1 Sector Composition

Figures 6.1 and 6.2 provide an overview of the average sector exposure in both the good and bad portfolios in the period 2010- 2018. The average stock representation in sectors are ranked from highest to lowest. The dominating sectors in our sample, energy, industrials and financials, also make up the most substantial portion of our portfolios. To specify the average stock representation within each sector, we add percentage of sector share in the portfolios:

$$Sector\ share = \frac{Average\ amount\ of\ stocks\ in\ the\ sector\ in\ the\ portfolio}{Total\ amount\ of\ stocks\ in\ the\ sector\ in\ our\ dataset} \tag{6.1}$$

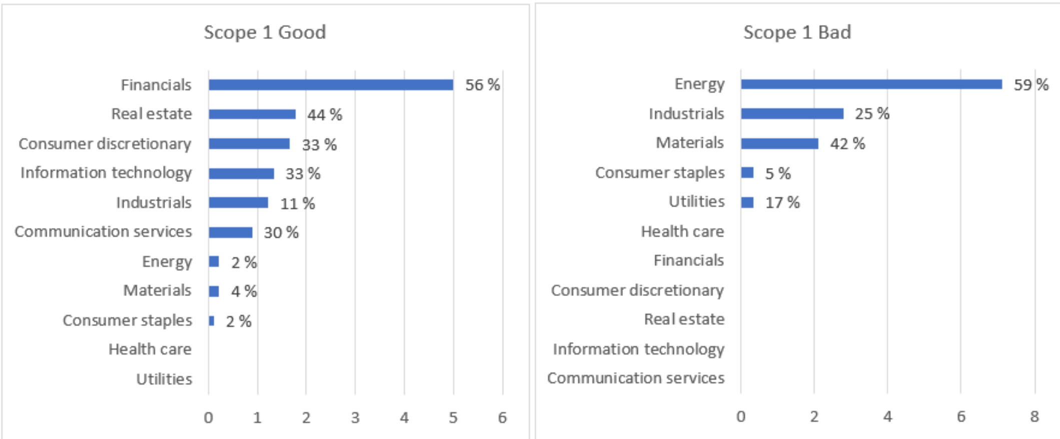
For example, the energy sector averagely has 7.1 out of 12 representative stocks in the S1B portfolio, which gives a sector share of 59 %.

Figure 6.1 presents the constructed portfolios to examine scope 1. Stocks in the financial sector are dominating the S1G portfolio and have a sector share of 56%. Real estate, consumer discretionary, and information technology also holds a high sector share above 30%. Hence, these sectors have low direct carbon emissions, resulting in low carbon footprints. High carbon sectors like energy and materials constitute a large portion of the S1B portfolio, in addition to having a high sector share. The industrial sector ranks as number two in this average portfolio. However, it has a low sector share of 25%, in contrast

[15] Sector structure is discussed in sections 3.5 and 5.5

to energy and materials with shares of respectively 59% and 42%. Its low sector share indicates that most industrial stocks in our sample are not represented in the S1B portfolio.

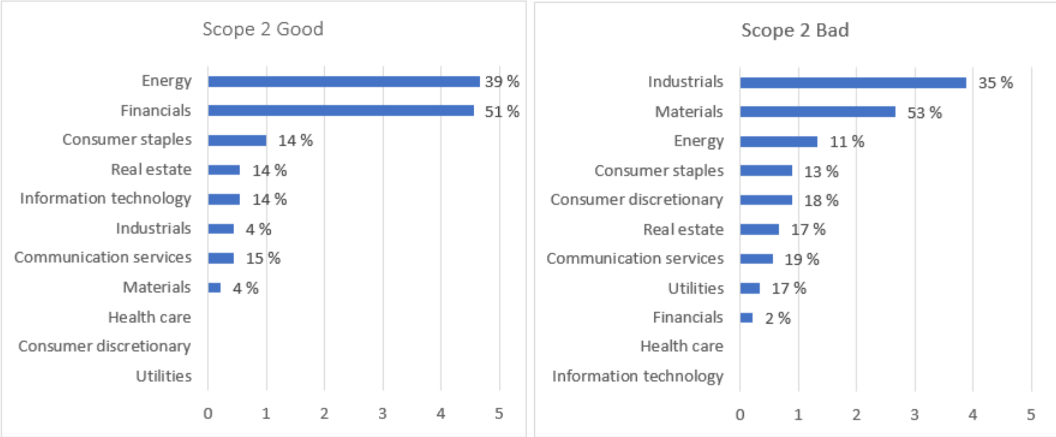
Figure 6.1: Sector composition in scope 1 portfolios, sorted after GICS level 1



The x-axis represent average amount of stocks
The graph labels represents sector shares, calculated as in equation 6.1

Figure 6.2 presents the sector composition in the S2 portfolios and exhibits a somewhat different structure than the S1 portfolios. Similarly to scope 1 results, the financial sector shows low emissions. However, the energy sector now dominates the good portfolio, which indicates a substantial difference between scope 1 and scope 2 emissions. The energy sector covers firms that primarily either produce or supply energy to other sectors (Naimoli and Ladislaw, 2019), making scope 2 emissions negligible compared to scope 1. The industrials and materials sector are the greatest sinners of scope 2 emissions. These sectors are energy-intensive and require large amounts of purchased or acquired energy, which translates into vast scope 2 emissions.

Figure 6.2: Sector composition in scope 2 portfolios, sorted after GICS level 1



The x-axis represent average amount of stocks
The graph labels represents sector shares, calculated as in equation 6.1

We find it appropriate to recall Gjensidige's investment portfolio, which we will use in the following analysis. The following table presents the structure:

Table 6.1: Sector composition in Gjensidige's internally managed investment portfolio, sorted after GICS level 1

Sector	Share of investment
Financials	66.5%
Industrials	14.1%
Energy	12.1%
Information Technology	3.2%
Materials	2.6%
Communication Services	1.6%

Note: The sectors are presented in A1

6.2 Sector Exposure to Climate Risk

Stocks in the financial, industrial, and energy sector dominate both Gjensidige's investments and our constructed portfolios. As previously mentioned, this is also a distinct feature of the Norwegian financial market. Hence, we find it interesting to increase knowledge of how transition risk is likely to affect these sectors. We relate the following analysis to our most significant results in section 5.2; positive abnormal return in the S1GMB portfolio[16], and negative abnormal return in both the S1B and S2B portfolios.

[16]S1GMB involves holding the S1G portfolio and shorting the S1B portfolio

The Financial Sector

The financial sector dominates our S1G portfolio, and holding this portfolio showed significant positive alpha if combined with a short position in the S1B portfolio. Thus, this sector appears carbon-friendly in our analysis regarding scope 1 and 2 emissions. The financial sector also clearly dominates Gjensidiges portfolio, representing 66.5% of its investments. The financial sector is itself not very exposed to climate risks (Bjartnes et al., 2018). However, the financial sector is an important provider of capital to high-carbon sectors, resulting in high scope 3 emissions (Collins, 2012). As high-carbon sectors are highly exposed to transition risk, the financial sector is also exposed through its investments, lending, and insurance portfolios. Consequently, future transition risk in the financial sector depends on other sectors' ability to compete in a carbon-constrained economy.

The Energy Sector

The energy sector dominates the S1B portfolio, which reported significant negative abnormal returns. The sector is considered to be particularly high-carbon and is held accountable for a large proportion of global carbon emissions (Naimoli and Ladislaw, 2019). Regulations and policies that aim to limit GHG emissions predict to increase in the future, which suggests a shift away from fossil fuel energy, e.g., cap-and-trade programs and carbon taxes (Bjartnes et al., 2018). The energy sector also faces increase competition due to disruptive technologies, e.g., cheaper solar and wind power and the evolution of battery technology and hydrogen (Fang et al., 2018). Rapidly decreasing costs, along with increased demand for clean and energy-efficient technologies, can have notable implications for the energy sector.

According to (McGlade and Ekins, 2015)[17], fossil energy assets highly risk becoming stranded, as almost all energy reserves must remain unused to reach the Paris Agreement. This can potentially cost the fossil fuel industry 28 trillion dollars in revenues over the next two decades (Leggett, 2015). Current stock prices might

[17]The study of McGlade and Ekins (2015) are presented in section 2.3.2

not reflect this risk, suggesting negative abnormal return also in the future for the energy sector. In addition, both environmental focused and mainstream investors are increasingly restricting investments in specific categories of fossil fuels, e.g., coal and oil. Furthermore, the energy sector is highly dependent on the crude oil price. The downward trend in the S1B return from the mid-2014, exhibited in figure 5.1, coincides with the severe drop in oil price during the summer of 2014. The future evolution of the oil price is expected to have a significant impact on future stock return in the energy sector.

The Industrial Sector

The industrial sector dominates the S2B portfolio, which showed significant negative abnormal returns. The industrial sector requires a large amount of purchased or acquired energy for production purposes, resulting in substantial scope 2 emissions (Fang et al., 2018). The sector also has, on average, 25% representative stocks in the poorly performing S1B portfolio. In sum, this indicates both large direct and indirect emissions. There is extensive pressure to cut emissions, emerging from various regulations, which introduces considerable costs for firms in the industrial sector (Clapp et al., 2017). Especially the industry group transportation is under high pressure to lower emissions, where the increasingly stringent policies have tilted demand towards less carbon-intensive transportation types (Bjartnes et al., 2018).

6.2.1 The Limitation of Sector Classification

It is important to bear in mind that firms will have distinct risk exposure, which can be independent of their sector. E.g., there are considerable differences in firms' distinct business risk, research and development expertise, and management capabilities. Thus, our analysis is a generalization of a more complex matter. Nevertheless, firms often are exposed to the same type of risk, regulations, emission types, and often perform similar activities. Thus, we link carbon risk to sectors as this classification facilitates comparison. Moreover, this classification controls for the underlying fundamentals in the different industries.

6.3 Implications for Gjensidige

Although the expected transition towards a low-carbon economy affects most sectors, our findings show that some have higher exposure. We believe Gjensidige should actively examine both stocks' climate risk mitigation and adaptation to strengthen climate resilience in their portfolio. This is justified by our detection of significant abnormal returns.

Gjensidige has major investments in the financial sector. We reported beneficial gains of holding financial stocks, if combined with shorting energy and industrial stocks. In other words, the positive alpha generation regarding our scope 1 findings requires investors to actively make up a long-short portfolio. Gjensidige does not employ this strategy as they are not selling the required stocks. Hence, Gjensidige's portfolio do not fulfill the conditions to acquire our reported positive significant abnormal return. We further question the climate-friendliness of the financial sector due to its predicted high scope 3 emissions.

Gjensidige has substantial investments in the energy and industry sector, which reports high emission in our dataset and dominate our bad portfolios. Our findings suggest that investing in these sectors can result in negative abnormal returns. Moreover, we identified substantial transition risks that can profoundly affect these sectors. In sum, our results imply beneficial gains from tilting the portfolio away from the energy and industrials sector.

It is highly challenging to predict the future climate exposure of sectors. However, we discuss how climate change imposes risks for sectors given the current state. Future climatic conditions might change, leading to alteration in transition risk exposure. Nevertheless, we believe our assessment provide economic actors with useful insight of how climate risk can affects these sectors.

7 Conclusion

The primary purpose of this thesis is to investigate the effect of stocks' carbon emissions on investment performance. We explicitly intend to answer the following research question: Have low-carbon investments delivered significantly higher risk-adjusted returns than high-carbon investments? As existing literature report inconsistent results, we consider this an interesting topic for further exploration. We construct mutually exclusive portfolios, sorted both on scope 1 and scope 2 carbon footprint. This enables us to study performance differences between the portfolios with different emissions. We focus on stocks listed on the Oslo Stock Exchange from 2010 throughout 2018. As there exist limited prior research on this specific topic, our analysis benefits Gjensidige and other economic actors with interest in the Norwegian financial market.

Our results for scope 1 emission show that stocks with a low carbon footprint generate higher abnormal returns than stocks with a high carbon footprint. This abnormal return can be achieved if investors actively make up a long-short portfolio. We further detect negative performance for stocks with a high carbon footprint in both scopes. These findings indicate investment benefits when betting on low-carbon stocks and against high-carbon stocks. This observation validates our hypothesis, as well as the majority of previous studies.

Our results are intriguing as it is difficult to reconcile the detection of significant abnormal returns with conventional asset pricing models. The fact that well-established risk variables fail to account fully for our findings raises the potential for a mispricing story. It may further indicate that carbon footprint represents an unaccounted risk factor that should belong in future asset pricing models. We leave our results open for interpretation and encourage future studies to investigate if "low-carbon" can represent a systematic risk factor in equity valuation.

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Appendix

A1 Global Industry Classification Standard (GICS)

The Global Industry Classification Standard (GICS) was created in 1999 by MSCI and S&P Dow Jones Indices (MSCI, 2016). The categorization provide the global financial community an accurate, complete, and standard industry classification (MSCI, 2016). It is based on a four-tiered, hierarchical system, as represented in figure A1.1

Figure A1.1: GICS four-tiered, hierarchical system for industry classification

Gjensidige's investment portfolio, and our constructed portfolios, sort industry exposure based on level one GICS. This level consist of 11 sectors were each sector consist of the industry groups presented in figure A1.2

Figure A1.2: GICS two-level classification overview

GICS Sector	Industry Group
10 Energy	1010 Energy
15 Materials	1510 Materials
20 Industrials	2010 Capital Goods
	2020 Commercial & Professional Services
	2030 Transportation
25 Consumer Discretionary	2510 Automobiles & Components
	2520 Consumer Durables & Apparel
	2530 Consumer Services
	2540 Media
	2550 Retailing
30 Consumer Staples	3010 Food & Staples Retailing
	3020 Food, Beverage & Tobacco
	3030 Household & Personal Products
35 Health Care	3510 Health Care Equipment & Services
	3520 Pharmaceuticals, Biotechnology & Life Sciences
40 Financials	4010 Banks
	4020 Diversified Financials
	4030 Insurance
	4040 Real Estate
45 Information Technology	4510 Software & Services
	4520 Technology Hardware & Equipment
	4530 Semiconductors & Semiconductor Equipment
50 Telecommunication Services	5010 Telecommunication Services
55 Utilities	5510 Utilities
60 Real Estate	6010 Real Estate

A2 Model Testing

We conduct relevant tests to check if there are problems related to our regressions and, thus, our results.

A2.1 Breusch-Pagan Test for Homoscedasticity

We test our data for homoscedasticity, which is an essential assumption to verify statistical power (Wooldridge, 2012) The regression analysis cannot be used if this assumption is violated. The results are reported in the following table:

Table A2.1: Breusch-Pagan test for homoscedasticity

	Scope 1		Scope 2	
	(BP)	(P-value)	(BP)	(P-value)
CAPM				
Good Portfolio	0.1711	0.6791	0.2686	0.6043
Bad Portfolio	0.2098	0.6469	0.4480	0.5033
Difference Portfolio	1.2776	0.2583	1.6883	0.1938
Carhart				
Good Portfolio	10.304	0.0356	7.3440	0.1188
Bad Portfolio	2.2974	0.6812	1.5050	0.8258
Difference Portfolio	4.155	0.3854	1.7513	0.7814

This table shows the results of the Breusch-Pagan test for homoscedasticity. BP represents the test statistics, which follows a chi-squared distribution. The null hypothesis for this test is that the error variances are all equal, i.e., homoscedasticity. Hence, a high P-value means we do not have a problem. According to the results, we cannot reject the null hypothesis. Consequently, it is safe to state that our regression models do not have a problem.

A2.2 Breusch-Godfrey Test for Autocorrelation

We further test for autocorrelation. This is a common problem in time-series regressions occurring if the error term follows a pattern. The following table provides results from conducting a Breuch-Godfrey:

Table A2.2: Breusch-Godfrey test for autocorrelation

	Scope 1		Scope 2	
	(LM test)	(P-value)	(LM test)	(P-value)
CAPM				
Good Portfolio	0.7853	0.3755	1.4153	0.2342
Bad Portfolio	0.5117	0.4744	1.0601	0.3032
Difference Portfolio	0.1798	0.6715	0.3358	0.5622
Carhart				
Good Portfolio	3.1589	0.1212	3.6738	0.0710
Bad Portfolio	0.8396	0.3595	1.3433	0.2465
Difference Portfolio	0.7363	0.3909	0.3071	0.5795

This table shows the Breusch–Godfrey serial correlation LM test for autocorrelation in the errors. The null hypothesis is that there is no autocorrelation in our portfolios. If we obtain a large LM test-value and a low P-value, we have a problem since we have to reject the null hypothesis. As shown in the table, we cannot reject the null hypothesis for any of our portfolios, at least at a 5% significance level. Thus, we do not consider our regressions to have issues regarding autocorrelation.

A2.3 Augmented Dickey-Fuller Test for Unit Root

To avoid spurious regressions, we test our time-series data for stationary. The existence of non-stationariy would require us to transform the data. We use the Augmented Dickey-Fuller test, where results are presented in the following table:

Table A2.3: Augmented Dickey-Fuller test for stationarity

	Scope 1		Scope 2	
Dependent Variables	(DF)	(P-value)	(DF)	(P-value)
Good Portfolio	-4.5508	0.01	-4.8680	0.01
Bad Portfolio	-4.4218	0.01	-4.5719	0.01
Difference Portfolio	-4.5508	0.01	-5.3538	0.01
Pricing Factors	(DF)	(P-value)		
Rm-Rf	-4.4278	0.01		
SMB	-5.1577	0.01		
HML	-4.5362	0.01		
MOM	-3.9539	0.014		

The table reports output from an Augmented Dickey-Fuller (ADF) test for Stationarity, conducted for all the dependent and independent variables used in our thesis. The "DF" is the test statistics and should be lower than a critical value. The ADF tests the null hypothesis that a unit root is present in our time series sample, i.e., nonstationarity. Thus, a high p-value means we have a problem since we want to reject the null hypothesis. As shown in the table, there is a clear rejection of H0, indicating that all the variables are stationary and can apply in OLS regression.

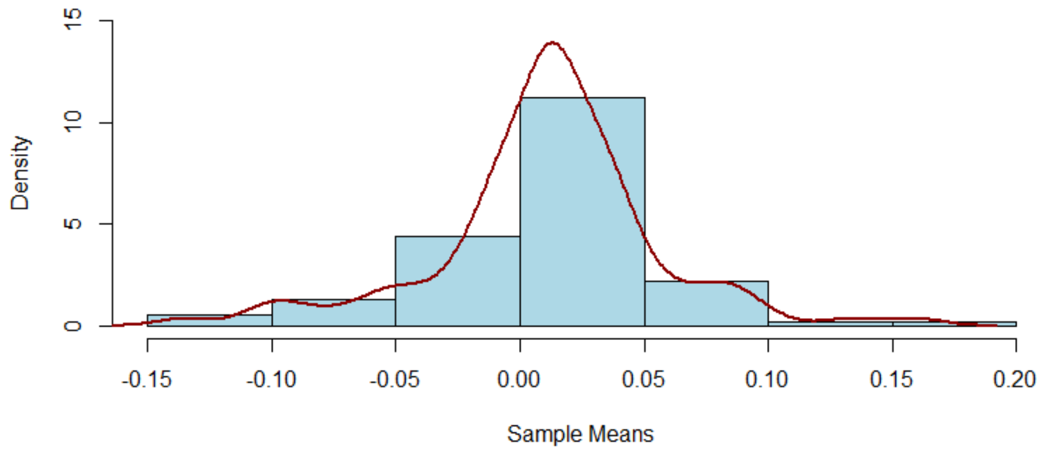
A2.4 Portfolio Distribution

Given the ambiguity whether our sample size are small, we impose stricter assumptions on the portfolios to ensure statistical validity to our test procedure. A common assumption is that the population from which our sample is taken from, has a normal probability distribution to start with. Normal distribution ensure statistical power of our results and ensure no additional statistical error.

We examine the normal distribution by comparing the frequency histogram and the density line for the portfolios. The figures A2.1, A2.2, A2.3 and A2.4 indicates a normal distribution. The density is centered around a sample mean of zero and we see limited skewness in the figures. Scope 1, see A2.1 and A2.2 comes out stronger than scope 2, see A2.3 and A2.4.

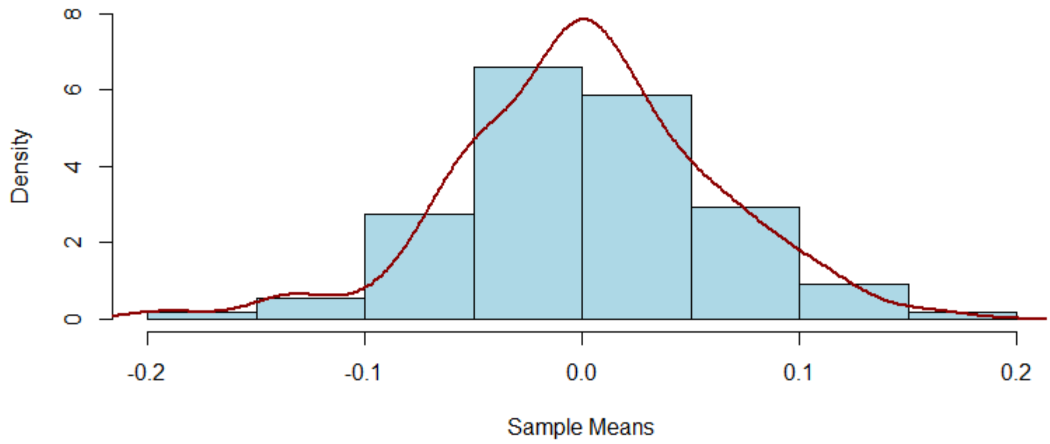
Scope 1 Good Portfolio

Figure A2.1: Distribution of S1G portfolio



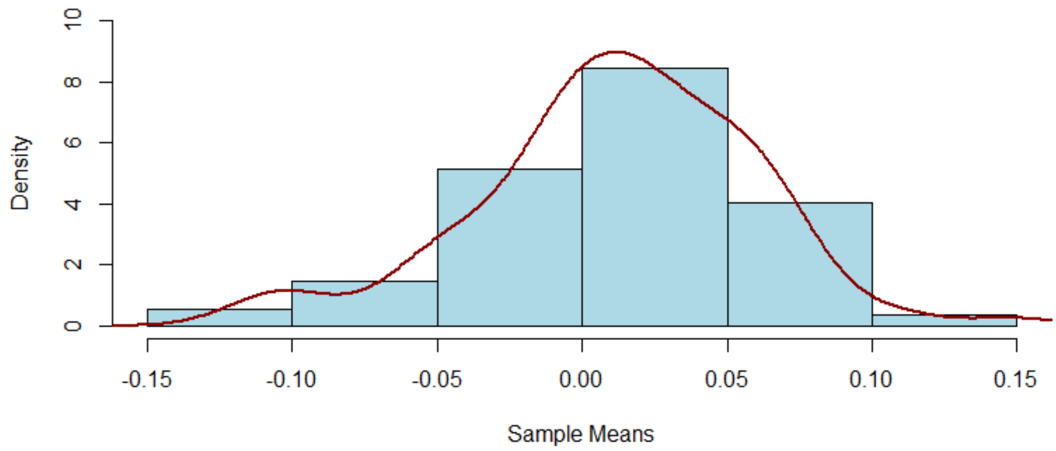
Scope 1 Bad Portfolio

Figure A2.2: Distribution of S1B portfolio



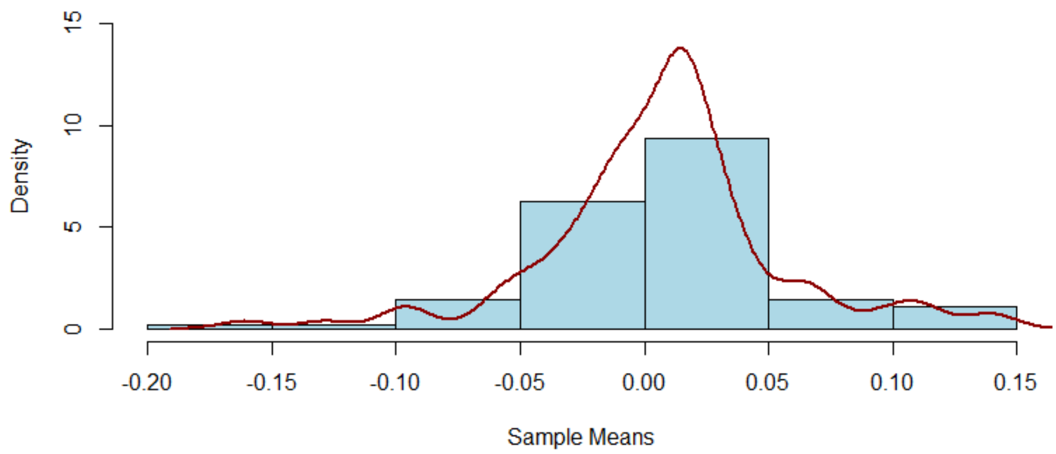
Scope 2 Good Portfolio

Figure A2.3: Distribution of S2G portfolio



Scope 2 Bad Portfolio

Figure A2.4: Distribution of S2B portfolio



A3 Output Tables

This section presents full output tables from our robustness tests.

A3.1 Value-Weighted Portfolios

Scope 1

Table A3.1: Scope 1 empirical results of value-weighted method, monthly data for the period 2010-2018

	Dependent variable:					
	High-ranked companies		Low-ranked companies		Difference portfolio	
	(1)	(2)	(3)	(4)	(5)	(6)
Rm - Rf	0.7863***	0.8027***	1.1243***	1.1048***	-0.3380***	-0.3021**
	(0.0892)	(0.1109)	(0.0798)	(0.0956)	(0.1185)	(0.1430)
SMB		0.0004		0.0355		-0.0351
		(0.1347)		(0.1161)		(0.1737)
HML		0.0455		0.1625*		-0.1170
		(0.1048)		(0.0904)		(0.1352)
MOM		0.1341		-0.2409***		0.3750***
		(0.1027)		(0.0885)		(0.1324)
Constant	-0.0039	-0.0056	-0.0098***	-0.0060*	0.0058	0.0004
	(0.0035)	(0.0040)	(0.0032)	(0.0035)	(0.0047)	(0.0052)
Observations	109	109	109	109	109	109
R^2	0.4209	0.4320	0.6500	0.6811	0.0707	0.1422
Adjusted R^2	0.4155	0.4102	0.6467	0.6689	0.0620	0.1092
Note:		*p<0.1; **p<0.05; ***p<0.01			Standard Errors in parentheses	

We estimate the models for scope 1 portfolios, formally defined by equations 4.1 and 4.2. The table reports monthly estimates for the period 2010-2018. The dependent variables represent the return achieved above the risk-free rate for rebalanced value-weighted portfolios. The good (bad) portfolio represents 30% of the stocks with the lowest (highest) carbon footprint in our dataset. The difference portfolio represents the results from the good portfolio minus the bad portfolio, i.e., a zero investment. The variable Rm-Rf is the value-weighted market return minus the risk-free rate, where the coefficient is a measure of the portfolios' volatility to the market. SMB stands for "Small Minus Big (market capitalization)" and capture the historic abnormal returns of small caps over big caps. HML stands for "High Minus Low (book-to-market ratio)" and capture the historic abnormal returns of value stocks over growth stocks. MOM refers to the rate of recent price movements in the portfolios. Sample alphas, the Constant, are monthly percentage abnormal returns.

Scope 2

Table A3.2: Scope 2 empirical results of value-weighted method, monthly data for the period 2010-2018

	Dependent variable:					
	High-ranked companies		Low-ranked companies		Difference portfolio	
	(1)	(2)	(3)	(4)	(5)	(6)
Rm - Rf	1.0682***	1.1531***	0.8339***	0.7572***	0.2343**	0.3959***
	(0.0773)	(0.0923)	(0.0840)	(0.1035)	(0.1016)	(0.1196)
SMB		0.1512		-0.1868		0.3380**
		(0.1121)		(0.1257)		(0.1452)
HML		0.2236**		-0.1367		0.3603***
		(0.0872)		(0.0978)		(0.1131)
MOM		0.1570*		0.0516		0.1054
		(0.0854)		(0.0958)		(0.1107)
Constant	-0.0050	-0.0074**	-0.0061*	-0.0060	0.0011	-0.0014
	(0.0031)	(0.0033)	(0.0033)	(0.0037)	(0.0040)	(0.0043)
Observations	109	109	109	109	109	109
R^2	0.6409	0.6756	0.4796	0.4988	0.0473	0.1636
Adjusted R^2	0.6376	0.6631	0.4748	0.4795	0.0384	0.1314
Note:		*p<0.1; **p<0.05; ***p<0.01			Standard Errors in parentheses	

We estimate the models for scope 2 portfolios, formally defined by equations 4.1 and 4.2. The table reports monthly estimates for the period 2010-2018. The dependent variables represent the return achieved above the risk-free rate for rebalanced value-weighted portfolios. The good (bad) portfolio represents 30% of the stocks with the lowest (highest) carbon footprint in our dataset. The difference portfolio represents the results from the good portfolio minus the bad portfolio, i.e., a zero investment. The variable Rm-Rf is the value-weighted market return minus the risk-free rate, where the coefficient is a measure of the portfolios' volatility to the market. SMB stands for "Small Minus Big (market capitalization)" and capture the historic abnormal returns of small caps over big caps. HML stands for "High Minus Low (book-to-market ratio)" and capture the historic abnormal returns of value stocks over growth stocks. MOM refers to the rate of recent price movements in the portfolios. Sample alphas, the Constant, are monthly percentage abnormal returns.

A3.2 Portfolios Without Rebalancing

Scope 1

Table A3.3: Scope 1 empirical results of portfolios without rebalancing, monthly data for the period 2010-2018

	Dependent variable:					
	High-ranked companies		Low-ranked companies		Difference portfolio	
	(1)	(2)	(3)	(4)	(5)	(6)
Rm - Rf	1.1533***	1.1354***	1.3929***	1.2696***	-0.2395*	-0.1342
	(0.0940)	(0.0838)	(0.1086)	(0.1070)	(0.1241)	(0.1170)
SMB		-0.3835***		-0.3699***		-0.0136
		(0.0791)		(0.1011)		(0.1105)
HML		0.1985***		-0.1981**		0.3965***
		(0.0737)		(0.0942)		(0.1030)
MOM		0.1918**		-0.1653*		0.3571***
		(0.0734)		(0.0937)		(0.1024)
Constant	-0.0029	-0.0035	-0.0136***	-0.0103***	0.0107***	0.0068*
	(0.0030)	(0.0028)	(0.0034)	(0.0035)	(0.0039)	(0.0039)
Observations	109	109	109	109	109	109
R^2	0.5844	0.7116	0.6057	0.6655	0.0336	0.2496
Adjusted R^2	0.5805	0.7005	0.6020	0.6526	0.0246	0.2207

Note: *p<0.1; **p<0.05; ***p<0.01 Standard Errors in parentheses

We estimate the models for scope 1 portfolios, formally defined by equations 4.1 and 4.2. The table reports monthly estimates for the period 2010-2018. The dependent variables represent the return achieved above the risk-free rate for constant equally-weighted portfolios. The good (bad) portfolio represents 30% of the stocks with the lowest (highest) carbon footprint in our dataset. The difference portfolio represents the results from the good portfolio minus the bad portfolio, i.e., a zero investment. The variable Rm-Rf is the equally-weighted market return minus the risk-free rate, where the coefficient is a measure of the portfolios' volatility to the market. SMB stands for "Small Minus Big (market capitalization)" and capture the historic abnormal returns of small caps over big caps. HML stands for "High Minus Low (book-to-market ratio)" and capture the historic abnormal returns of value stocks over growth stocks. MOM refers to the rate of recent price movements in the portfolios. Sample alphas, the Constant, are monthly percentage abnormal returns.

Scope 2

Table A3.4: Scope 2 empirical results of portfolios without rebalancing, monthly data for the period 2010-2018

	Dependent variable:					
	High-ranked companies		Low-ranked companies		Difference portfolio	
	(1)	(2)	(3)	(4)	(5)	(6)
Rm - Rf	1.3351***	1.2499***	1.1891***	1.1027***	0.1460	0.1472
	(0.1020)	(0.1008)	(0.0994)	(0.0914)	(0.1150)	(0.1218)
SMB		-0.3940***		-0.5126***		0.1186
		(0.0952)		(0.0864)		(0.1150)
HML		0.0128		-0.0592		0.0719
		(0.0887)		(0.0805)		(0.1072)
MOM		-0.0280		0.0579		-0.0859
		(0.0883)		(0.0801)		(0.1066)
Constant	-0.0038	-0.0018	-0.0072**	-0.0063**	0.0034	0.0045
	(0.0032)	(0.0033)	(0.0031)	(0.0030)	(0.0036)	(0.0040)
Observations	109	109	109	109	109	109
R^2	0.6155	0.6716	0.5724	0.6834	0.0149	0.0336
Adjusted R^2	0.6120	0.6590	0.5684	0.6713	0.0056	-0.0036
Note:		*p<0.1; **p<0.05; ***p<0.01		Standard Errors in parentheses		

We estimate the models for scope 2 portfolios, formally defined by equations 4.1 and 4.2. The table reports monthly estimates for the period 2010-2018. The dependent variables represent the return achieved above the risk-free rate for constant equally-weighted portfolios. The good (bad) portfolio represents 30% of the stocks with the lowest (highest) carbon footprint in our dataset. The difference portfolio represents the results from the good portfolio minus the bad portfolio, i.e., a zero investment. The variable Rm-Rf is the equally-weighted market return minus the risk-free rate, where the coefficient is a measure of the portfolios' volatility to the market. SMB stands for "Small Minus Big (market capitalization)" and capture the historic abnormal returns of small caps over big caps. HML stands for "High Minus Low (book-to-market ratio)" and capture the historic abnormal returns of value stocks over growth stocks. MOM refers to the rate of recent price movements in the portfolios. Sample alphas, the Constant, are monthly percentage abnormal returns.