Norwegian School of Economics
Bergen, Fall, 2021

The Impact of Carbon Emissions on US Stock Returns

An empirical study of how carbon intensity impacts financial performance

Thor-Bjørn Brunborg & Per Kristian Haldorsen

Supervisor: Gunnar Eskeland

Majors: Financial Economics (FIE) and Energy, Natural Resources and the Environment (ENE)

NORWEGIAN SCHOOL OF ECONOMICS

Acknowledgements

This thesis concludes our Master of Science in Economics and Business Administration at the Norwegian School of Economics (NHH), with majors in Financial Economics (FIE) and Energy, Natural Resources and Environment (ENE).

We would both like to express our most sincere gratitude towards our supervisor for this thesis, Gunnar Eskeland, and Jens Kværner for their valuable insight and feedback.

Norwegian School of Economics (NHH)

Bergen, 2021

Thor-Bjørn Andresen Brunborg

Per Kristian Haldorsen

Abstract

The aim of this thesis is to research what effect carbon emissions have on a company's financial performance in the stock market. We want to examine if investing in greener portfolios can yield returns equal to more carbon heavy portfolios with a larger environmental footprint. Historically such investing strategies have been linked with perceived increased risk and lower return, making it challenging to convince investors to invest more sustainably. In recent years there has been a growing interest amongst investors to incorporate different environmental and societal criteria into their investment strategy. Socially responsible investing is increasing, and ESG factors are becoming a benchmark for evaluating company performance as well as financial performance. This is mainly due to a change in society's values and their expectations of how large firms should operate. It is also a response to tackling the effects of climate change, where companies are a crucial part of mitigating these effects.

In order to conduct our research this thesis will use the observed companies' carbon intensity scores and examine whether there is a significant difference in low carbon and high carbon intensity portfolios in terms of risk adjusted return for shareholders. We focus on the US stock market from 2007 to 2018. We construct two portfolios that are composed of stocks with low and high carbon-intensity levels respectively. Moreover, we employ OLS regressions and are applying the CAPM and the Fama French five factor model to identify the different risk exposures and potential abnormal return that exists within the portfolios. We supplement the regressions by performing a mean-variance analysis of the portfolios and calculate the risk-adjusted returns.

Our results indicate no significant abnormal return for either the low carbon-intense portfolio, or the high carbon-intense portfolio, although we observe clear differences between the portfolios in terms of their risk exposure to the respective FF-factors. From the mean-variance portfolio analysis we observe that the optimal weighting of the FF-factors differ between the carbon-portfolios, and that the analysis yielded no significant difference between the risk-adjusted returns for the respective portfolio. This indicates that the implied shadow price on green capital - the price of green investing - is near zero.

Contents

1 Introduction

The ever growing effects of climate change is a leading factor for change in how we perceive and act on environmental sustainability in the corporate sector. Societal aspects are becoming increasingly important along with the fact that investors are incorporating more and more of these factors into their investment strategy. The rise of socially responsible investments and ESG factors are driving companies to reevaluate certain aspects of their business model as well as their carbon footprint. Investors are increasingly interested in societal benefits, as well as high risk-adjusted returns. This kind of investing is based on incorporating select environmental and societal criteria in their portfolio choice. Traditionally, societal and environmentally sustainable investments have been viewed as sub-optimal investments from a financial point of view, with such investments being perceived as bearing higher risk and lower return. Whether you have to pay a premium in order to invest sustainably is a matter of debate, and in this thesis we will present previous literature and research from different authors on how the aforementioned criterias affect financial performance.

The aim of the thesis is to research if, and to what extent, the financial performance of companies is linked with different carbon exposure. The data in this thesis encompasses the US stock market, examining historical data from 2007 to 2018. We examine how listed companies with different carbon footprints perform in the stock market, and how carbon intensity may affect shareholder value. By creating portfolios composed of low (and high) carbon intensity respectively, we assess and compare how the different compositions affect financial performance. Our results suggest that investing in low carbon portfolios does not provide lower risk adjusted returns than the alternative.
Our contribution to literature is to add to the field of research on carbon emissions and its effectson financial performance.

The structure of our thesis is as follows: Section 2 provides background information and a review of relevant literature, as well as presenting our research question and hypothesis. Section 3 describes our dataset and a variance-decomposition of sector-specific carbon emissions. Section 4 outlines the methodology employed, and section 5 presents the findings. We further discuss the implications of these results in section 6. Various limitations related to the thesis are presented in section 7, before concluding our thesis in section 8.

2 Literature review

This section of the thesis will provide background information on how companies and investors can contribute to mitigate the effects of climate change. The section also explores previous literature and research from different authors on how corporate responsibility and ESG considerations impact a company's performance and shareholder value. Additionally, we shed light on how ESG and Carbon Intensity is measured and scored. The research question and hypothesis for this thesis is also presented.

2.1 Climate change

The subject of climate change has been a topic of debate for decades. The challenges climate change imposes, as well as the commitments we have to make in order to mitigate the results of climate change is an ever increasing reality in modern society. According to the United Nations, global emissions are reaching record levels with no sign of peaking. We are currently not on track to meet the agreed environmental targets, and the global temperature is expected to increase by as much as 3-5°C by the end of the century due to carbon emissions (UN, 2020). The safe limit to global warming is to restrain the warming to 1,5°C. This is the scientific global consensus. Following this pathway the world's fossil fuel production will need to decrease by an approximate 6 percent per year in the next 10 years. In lieu of this, global production is on route to resulting in more than double the production consistent with the limit of 1,5°C. Upholding the Paris agreement goal of net zero emissions by 2050 is critical to achieve this (UN, 2020). In accordance with the Paris Agreement of 2015, the aim is to keep the global rise in temperature below 2°C. The agreement reflects a global goal to strengthen countries' abilities to combat the impacts of climate change through the appropriate financial flows and a new technology framework. The focus is on institutional and technological change to mitigate these effects and further the transition into a climate resilient economy. With the increasing focus on limiting emissions of greenhouse gasses, and reducing our carbon footprint, companies are being held increasingly accountable for their environmental impact. New legislations, global treaties and stakeholder pressure is a growing concern for a company's strategy going forward.

2.2 Corporate Social Responsibility

Corporate Social Responsibility (CSR) is businesses taking responsibility for their respective impact on people, the environment, and the societies and communities they operate in (Regjeringen 2016). CSR implies that businesses implement factors such as climate change, human rights and anti corruption into their overall strategy. It is a self regulating business model that lets the companies be held socially responsible to both the company itself and its shareholders, as well as to the public. Implementing CSR ensures a commitment to be conscious of the company's impact and contributing positively to society and the environment, rather than the other way around. Our traditional understanding of CSR is still built upon the approach that companies should comply with society's moral and legal standards. However, some companies have started to redefine these standards and assume a politically enlarged responsibility (Scherer & Palazzo 2009).

Governments usually expect businesses to exercise a degree of Corporate Social Responsibility. The larger and more successful a company is, the opportunities and responsibility to exercise CSR on a larger scale is higher. While some parts of CSR can be a liability to a company, as they must change certain aspects of how they operate, the company can experience several positive outcomes themselves. As well as contributing more to the community and the environment, the effects can be equally valuable for the company. CSR can contribute immensely to a company's brand and exposure, increasing overall public opinion of the firm. Employees can experience a higher degree of satisfaction with their employer and a raised morale in being part of a company with a positive societal impact. Today's society has certain expectations of corporate behavior and how companies should operate, and making sure the company complies with CSR factors is a way of pleasing stakeholders. Contemporary CSR research attempts to justify CSR from an empirical standpoint with the argument that social performance contributes to financial performance (Scherer & Palazzo, 2009). Albuquerque et al. (2019) found supporting evidence for their predictions that CSR decreases systematic risk and increases firm value.

2.3 Socially Responsible Investing (SRI)

With the growing interest and focus on corporate social responsibility, socially responsible investing developed alongside it (Sparkes, 2008). Socially responsible investing involves socially conscious investments in businesses and funds that meet certain criteria. Both the social impact and potential return may be valued in such investments, where sustainability is a key factor. The equity portfolio construction includes environmental and social issues as well as conventional investment theory of risk and return as determinants (Sparkes, 2008). Traditionally this has ment investing in assets that promote sustainable and future minded factors such as the environment, civil rights, health, and clean energy. Companies and funds linked with gambling and the production of addictive substances are often excluded in socially responsible investing. In recent years we have seen an increase in socially responsible investing. SRI has also matured, shifting from being a marginal investment philosophy to a more mainstream investment philosophy adopted by an increasing number of investment institutions (Sparkes & Cowton, 2004). This creates a growing shareholder pressure which corporate executives need to take into account.

Hong & Kacperczyk (2009) researched so-called “sin” stocks, where they observed publicly traded companies that were involved in the production of alcohol, tobacco and gambling. They found that these stocks were less held by the norm-constrained institutions and received less coverage from analysts than other comparable stocks. The “sin” stocks also provided higher expected returns, as they were being neglected by norm-constrained investors and that norms were affecting returns and stock prices.

Socially responsible investing shares several similarities with ESG investing. Although lack of standardization in terminology might cause confusion, they do differ. ESG investing allows the investor to invest sustainably, but at the same time maintain the level of financial return as one would with a traditional investment approach (S&P Global, 2021). SRI considers both financial returns and moral values. The strategy emphasizes that financial returns are a secondary consideration, and that the investors' moral values being accounted for is the primary consideration (S&P Global, 2021).

2.4 ESG Scoring

ESG are a set of operational standards for a company used by socially conscious investors to screen and evaluate the potential investment. The criteria are *environmental, social* and *governance*. The environmental criteria measures the company's impact on environmental issues such as pollution and the carbon footprint. The social criteria considers the impact on the local community as well as how the company manages relationships with employees, customers and suppliers. Lastly, the governance criteria examines company leadership, accounting information and shareholder rights. The respective criteria is a measure on how the company contributes to sustainable development. The company's ESG score is calculated from publicly available data and a corporate sustainability assessment of the company (S&P Global, 2020).

ESG oriented investing has experienced a meteoric rise in recent years, with increased attention on the broader impacts of corporations (Henisz et al., 2019). The scale of investments indicates that ESG is not a passing fad. In their report "Everyones on the ESG Bandwagon", Natixis (2021) reported significant increases in ESG investments. In 2020 ESG strategies brought in flows of a record breaking 152 billion USD, and record asset levels of 1,6 trillion USD. Institutional investors that implement ESG strategies also rose by 18 percent from 2019 to 2021 (Natixis, 2021). Investors and executives are realizing that having a strong ESG proposition can safeguard long term success for the company. ESG is also correlated with higher equity returns and reduction in downside risk. Firms are increasingly taking a proactive approach to ESG investments aiming at improving both financial performance as well as shareholder value (Dennis, 2013). Employee satisfaction is positively correlated with shareholder returns as well (Henisz et al., 2019).

Investors mainly use ESG information in relevance to investment performance (Amel-Zadeh & Serafeim, 2018). A drawback and impediment for using ESG information is the lack of reporting standards for businesses. There are several styles of ESG investing. A style of full integration driven by the relevance to investor performance is considered to be the most beneficial (Amel-Zadeh & Serafeim, 2018). A negative screening driven by product range and ethical considerations is considered the least beneficial. A study by Friede et al., (2015) showed that a large majority of studies found positive findings in the relationship between ESG and corporate financial performance. There are however still a significant proportion of investors who do not adhere to incorporating ESG factors into their traditional investment process, assuming that such a strategy can provide sub-optimal results. The majority and most impactful of these investors are often institutional investors with an obligation to maximize profit (In et al., 2019).

A paper published by Pedersen et al. (2020) proposed a theory that each respective stock's ESG score provided information about the firm fundamentals, as well as affecting investor preferences. Pedersen et al. uses an ESG-efficient frontier (the highest attainable sharpe ratio for each ESG level) to solve investor's portfolio problems. In this way they were able to add to the academic literature by showing the costs and benefits of responsible investing. Responsible investing can thus be reduced to a tradeoff between sharpe ratio and the ESG score. The sharpe ratio represents the relationship between risk and return. The authors also found that the expected returns for ESG stocks depended heavily on which types of investors are most prominent in the economy, and whether the investors bid up the prices, or are more willing to accept a lower return for a higher ESG score.

2.5 Carbon Intensity

Companies are a vital part of dealing with the issue of carbon based dependence due to industrial production and the potential for technological innovation. Concerns about climate change are leading to increased pressure on firms to incorporate these issues into their strategy, and to report on these efforts. Carbon reporting has become mandatory in several countries, including North America and many EU member states.

Academic literature has not yet reached an overall consensus on whether sustainability and environmental performance leads to improved financial performance. The main issue of establishing a consensus is due to conflicting results in the relevant literature. These conflicting results can in turn be attributed to limited data availability (In et al., 2019). A company's carbon footprint can be measured by carbon performance. Physical carbon performance is often measured as carbon intensity. Carbon intensity can be used both for internal and external analysis, as well as for reporting and ranking purposes (Hoffman & Busch, 2008).

This thesis focuses primarily on the Environmental (E) aspect of ESG and uses S&P Trucost's indicators of carbon emissions and carbon intensity (CI) when studying companies. The metric denominates greenhouse gas emissions by annual consolidated revenues for the firm (S&P Global, 2020). The CI score is thus presented as tons of CO_2 emitted divided by USD 1 million revenue.

A company's greenhouse gas (GHG) emissions are traditionally classified according to the GHG Protocol Corporate Standard (2004), which classify emissions into three scopes:
Scope 1: The company's direct emissions from controlled or owned sources.
Scope 2: The company's indirect emissions from the generation of purchased energy.
Scope 3: All indirect emissions from the value chain of the company (excluding scope 2). The third scope includes both upstream and downstream emissions.

S&P Global Trucost uses direct and first-tier indirect emission scopes, which are slightly different from GHG Protocol scopes 1, 2 and 3. Direct emissions are defined as traditional scope 1 emissions plus other emissions from the company's wider range of relevant greenhouse gasses from company operations. S&P Global Trucost defines the first-tier indirect emissions as scope 2 emissions plus direct suppliers. The first tier upstream supply chain of the company. This is an enhanced way to use emission scopes, as it includes relevant upstream emissions from scope 3, and limits the extent of double counted emissions.

There are several studies indicating a positive relationship between capital market financial performance and environmental performance for a firm (Kumar & Firoz, 2018). In et al. (2019) argues that there is a scarcity of nuanced studies on the subject, but highlights findings from several authors which all found that environmentally sustainable firms tend to exhibit an increase in value. In Christopher Murphy's review of the research on the subject (2002), he concluded that there is a clear correlation between corporate profitability and environmental performance. The effects can also be seen on the return on equity (ROE) and return on assets (ROA), which improved alongside environmental performance improvement (Murphy, 2002).

Other studies argue against this positive relationship. Especially when it comes to the subject of how carbon emissions affect an investor's stock returns. In their 2020 paper, Bolton & Kasperczyk examined whether carbon emissions affected stock returns in the US. Their findings indicated that carbon heavy companies earned higher returns. Carbon emissions significantly and positively affected stock returns in their research, and they did not find any carbon premium associated with carbon emissions.

2.6 Shadow prices

From the impending results of this thesis we will attempt to identify the implied shadow price of green capital, defined here as the tradeoff that exists between maximizing the risk-adjusted return for a given level of carbon intensity. Shadow price is used conceptually in this thesis as part of the discussion and analysis of our results. If the implied shadow price is near zero, it means that you do not have to sacrifice any risk-adjusted return when investing in an alternative security or portfolio.

2.7 Research question and hypothesis

After reviewing the previous literature, we observe that existing research on the subject is somewhat divided. Previous findings vary based on the methodology applied, different datasets, and what societal or environmental criterias is the most prominent factor of interest. Other differentiating factors such as investor preferences, included emission scopes, and whether the portfolio construction is purely to maximize returns, contributes to varying findings as well. As we stated earlier, the focus of this thesis is on the E aspect of ESG, and measuring a company's environmental impact based on carbon emissions via Carbon Intensity. It has been clearly stated by the UN that if we are to reach the goals of the Paris Agreement, companies must be held increasingly accountable for environmental impact, and this must be reflected in the investors as well. Literature has presented findings that investors are increasingly more aware and interested in investing “greener”, but that traditionally some are hesitant to do so because of perceived increased risk and lower returns. Hence, in this thesis we want to examine whether investing in portfolios with low carbon intensity can yield equal or comparable returns to investing in a portfolio composed of more carbon heavy stocks. Thus the research questions for our thesis is:

How does carbon intensity affect financial performance in the US stock market?

In addressing financial performance, we are most interested in examining abnormal returns and risk-adjusted returns for shareholders. We will compare two portfolios, each composed of high and low carbon intensities respectively, and assess how the different compositions affect risk-adjusted returns. By doing so, we can compare how the financial performance of companies is linked with different carbon exposure.

To address this we have developed the following hypothesis:

H0: Portfolios with low Carbon Intensity have statistically significant lower risk-adjusted returns than portfolios with high Carbon Intensity.

HA: Portfolios with low Carbon Intensity do not have statistically significant lower risk-adjusted returns than portfolios with high Carbon Intensity.

In answering our research question we will address our hypothesis by testing the two sided null hypothesis against the alternative hypothesis. To further supplement our answer to the research question we will also be utilizing an expanding window in order to estimate the mean-variance optimal portfolio. In addition, we will be addressing the shadow price on investing in green portfolios.

3 Data

This section of the thesis presents the data used in assessing the different performances of low/high CI score portfolios. The investment opportunity set is constructed from the intersection of multiple data sets. The data in this study is from the New York Stock Exchange (NYSE) and the National Association of Securities Dealers Automated Quotations (NASDAQ). The sample period is from January 2007 to December 2018, with 130 observations. We are choosing to observe American stocks for two reasons; the companies featured in the datastream are mostly big companies, and we can more easily rely on accurate historic data for the respective companies.

3.1 Data source

The data is predominantly derived from the CRSP database, Compustat, SP-Trucost and MSCI-KLD. The CRSP (Center for Research in Security Prices) is a provider of historic stock market data. The data on market capitalization and returns for all equity listed companies in the US is obtained from CRSP. The data on accounting information is obtained from the Compustat, a comprehensive database of fundamental financial and market information. Carbon footprint and carbon intensity at firm level data is collected from SP-Trucost (as described in section 2.5). Data on ESG ratings are obtained from MSCI-KLD 400 Social Index, a Socially Responsible Investing (SRI) Index of 400 US securities providing exposure to companies with outstanding ESG ratings.

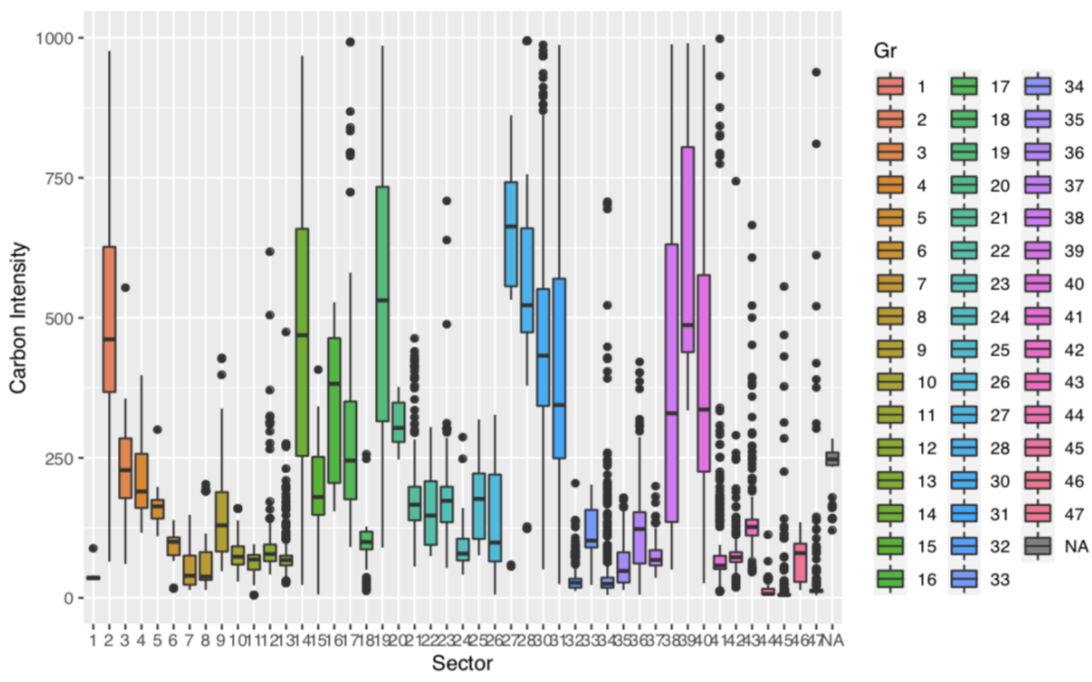
3.2 Reliability and validity of the data

In order to check the validity of our data and ensure research quality we pursue by checking the data and assessing the reliability of our findings. Concerns about how the carbon footprint is documented may jeopardize the validity of the final findings. Carbon footprint is in this thesis mainly covered by The Trucost CI score at the firm level, presented as tons of CO2 emitted divided by USD 1 million revenue. A standalone greenhouse gas (GHG) emission measure could give a misguided representation of a company's carbon intensity, as

GHG emissions are generated throughout the value chain and in both direct and indirect operations. As company revenue can reasonably be correlated with scale of operations, it serves as a suitable market-standard normalizing factor (S&P Global, 2020). To calculate the CI score Trucost uses a variety of public sources, environmental data sources, and data published by the respective company. Through a continuous research process companies may be subject to revisions, quality checks and data verification. Issues concerning potential company “Greenwashing” are addressed in section 7.4 in the thesis' limitations.

The data sample is composed of companies in the US, with a broad range of sectors. Figure 3.2 shows a variance-decomposition of sector-specific carbon emissions. As one can read from the figure, the carbon intensity variance observed is large within sector (35%), and between sector (65%).

Figure 3.2



3.3 Portfolio construction for the analysis

In order for us to understand the differences in risk exposure, as well as the return-composition, for stocks with low carbon intensity and stocks with high carbon intensity, we opt to utilize the Fama French five factor model. In order to perform these OLS regressions we construct two portfolios: one containing all stocks belonging to the bottom 20-percentile of carbon intensity, and the other portfolio containing all stocks belonging to the upper 20-percentile. This partitioning will allow us to determine whether there actually exists any reasonable differences in risk exposure and return composition for the stocks with the most and the least carbon emissions, within our entire time-period.

After the regression we extend our research by performing a mean-variance analysis for two portfolios respectively reflecting stocks with high and low carbon intensity for the entirety of our sample time period. The portfolios are constructed by grouping stocks based on each respective year's median level of carbon emission. Consequently, the *Low CI-portfolio* will be composed of stocks below the median level of carbon emissions for each respective year. Similarly, the *High CI-portfolio* contains the stocks that score above the respective year's median level of carbon emission. Each year's stocks are then compiled and added into two portfolios. We utilize value-weighted returns in order to enhance the robustness of our analysis.

4 Methodology

This section of the paper will present the different methodologies utilized in order to complete our analysis, derive our results, and answer the stated hypothesis. Firstly, we begin describing the methodology to detect abnormal return and the composition of risk-and-return factors within the portfolios. Moreover, the rationale behind the specified model will be explained. Secondly, the section will discuss the methodology and process performed to derive the optimal weights, variance and return, and subsequently, the risk-adjusted return (Sharpe Ratio) for both portfolios. Lastly, we expand on what assumptions need to be upheld in order to implement our analysis, and cover weaknesses within our models.

4.1 Risk-Adjusted Measures, Jensen's Alpha

In order to detect abnormal return and the composition of returns within the respective portfolios, we primarily use Jensen's Alpha (henceforth referred to as alpha or abnormal return). The measurement is calculated by subtracting a portfolio's expected return from the actual return achieved. Thus the alpha represents a risk premium derived from the risk-adjusted return of the portfolio, accounting for systematic risk (Jensen, 1969). Consequently if the portfolio is priced fairly, the alpha will be zero. Moreover, if the portfolio's performance is above (below) its expected return, the alpha will be positive (negative).

4.2 Sharpe Ratio

The analysis is further supplemented by analyzing each portfolio's Sharpe Ratio; a risk-adjusted evaluation tool that directly measures a portfolio's performance. Sharpe Ratio is the portfolio's mean return less the prevailing risk free rate, divided by the total risk of the portfolio (referred to as the standard deviation) (Sharpe, 1964). The Sharpe Ratio output is the mean excess return per unit of risk, and is widely used by financial investors and institutions in evaluating the performance of a given portfolio.

4.3 Model Choice

In order to investigate the potential existence of abnormal return, and to understand the underlying characteristics of the portfolio's risk exposure in relation to its return, we choose to employ the Capital Asset Pricing Model (CAPM) and the Fama French Five-Factor model (FF5). The rationality behind choosing both models is that it increases both the analytical complexity of our paper, as well as the explanatory power and validity of our findings. CAPM contributes to the analysis by creating a simplistic link between the return for each portfolio, and the systematic risk the portfolio undertakes. The FF5 builds onto the CAPM by adding several additional risk factors the portfolios can be exposed to. Thus, the rationale behind utilizing the CAPM in conjunction with the FF5 is that it strengthens both our analytical framework and further validates our findings. All models to be estimated will use ordinary least-squares regressions (OLS).

The CAPM was independently developed by Treynor (1961), Sharpe (1964), Lintner (1965), and Mossin (1966), and is commonly used in pricing securities for a given level of risk and cost of capital. The model postulates that an investor is expected to be compensated for the time value of money and the systematic risk it is exposed to. This compensation is manifested through the risk-free rate, and the *β,* representing the market risk exposure. The model we estimate is constructed as follows:

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

Where:

R_{it} = *The return on investment at time t*

R_{ft} = *The prevailing risk-free rate at time t*

R_{mt} = *The return on equally weighted market proxy in time t*

ε_{it} = *The error term in month t*

α_i = *Jensen’s alpha, the abnormal return (/intercept)*

β_i = *The portfolios market exposure*

As previously stated, the FF5 contributes to the analysis by further evaluating a portfolio's performance, and is shown by Fama and French (1991) to more accurately explain a portfolio's return than its previous ancestor, the three-factor model, by adding additional two risk factors. The goal of Fama and French's model was to inherently capture all variations in stock prices by adding several risk-factors that the portfolio might be exposed to. The rationale behind this is that if the portfolio achieved an intercept of zero, meaning an alpha of zero, the model would accurately explain the portfolio's return.

An advantage of using the model is due to its intuitive interpretation in that it attempts to capture risk that has empirically impacted asset returns. As they found this to be the case, expanding on the CAPM, Fama and French (1991) has identified four additional factors that historically impacts and correlates with returns. The additional risk-factors are size, book-to-market, profitability, and investment. Size, "Small Minus Big", is a size premium that measures difference in return when a portfolio is long in small cap stocks, and short in large cap stocks. Book-to-market, or "High Minus Low" (HML) is the portfolio's exposure to stocks with high book-to-market ratio, called value stocks, or its exposure to low book-to-market stocks, called growth stocks. This exposure is reflected through a value premium. Profitability, "Robust Minus Weak" (RMW), and investment, "Conservative Minus Aggressive" (CMA) were incorporated in the FF5-model (Fama, 2014). RMW represents a portfolio's difference in return when being composed of companies with robust profitability, or when composed of companies with weak profitability, while both portfolios were diversified. Likewise, the CMA factor reflects the return difference for a portfolio consisting of firms with a conservative investment strategy, or a portfolio consisting of firms with an aggressive investment strategy. Both portfolios are diversified. The factor-differences are all based on a long-short zero investment strategy. When estimating the model on our time series data, we utilize ordinary least-squares (OLS). The estimated model will be as follows:

$R_{it} - R_{ft} = \alpha_i + \beta_{0i}(R_{mt} - R_{ft}) + \beta_{1i}SMB_t + \beta_{2i}HML_t + \beta_{3i}RMW_t + \beta_{4i}CMA_t + \varepsilon_{it}$,

where,

SMB_t = the return difference in a portfolio exposed to small cap stocks and a portfolio exposed to large cap stocks, in month t.

HML_t = the return difference in a portfolio exposed to value stocks (high B/M), and a portfolio exposed to growth stocks (low B/M), in month t.

RMW_t = the return difference in a portfolio exposed to firms with robust profitability, and a portfolio exposed to firms with weak profitability, in month t.

CMA_t = the return difference in a portfolio exposed to companies with a conservative investment strategy, and a portfolio exposed to companies with an aggressive investment strategy, in month t.

β_{1i}, β_{2i}, β_{3i}, β_{4i} = represents the exposure to the risk-factors respectively.

4.4 Mean-Variance Analysis

After establishing the potential existence of abnormal return within the two portfolios, and investigating what distinguishes the one portfolio from the other in terms of risk exposure, we seek to understand whether the risk-adjusted return, the Sharpe Ratio, differ between a portfolio consisting of high carbon-intense stocks, and a portfolio of low carbon-intense stocks. By adopting the analytical framework of a mean-variance efficient portfolio, established by Harry Markowitz (1952), we can seek to finalize our analysis of the risk-adjusted return of each portfolio.

To fulfill the requirements above it is necessary to create two new portfolios. The first portfolio will be constructed by adding all stocks with above median carbon intensity score, from 2007 to 2018, as monthly data. For the second portfolio we add all companies with below median carbon intensity score, from 2007 to 2018, also as monthly data. For both portfolios, based on each stocks' characteristics', we form the previously stated FF-factors, and the result is two portfolios, respectively exhibiting monthly returns and their exposure to each of the five FF-factors. In order for us to correctly combine the FF-factors attained, it is important that the stocks with carbon intensity scores are similar to the stocks gathered from Fama and French. A correlation matrix (A3) is presented in the appendix.

The mean-variance analysis is a risk-weighting process that attempts to minimize variance for a given level of return, and is a strategy widely used in investment decision making as it pinpoints how much risk one is willing to take for a given level of return. Assumptions essential to the analysis is that investors are rational in their decision making, given the available information, and that they seek to: (1) maximize return, and (2) minimize risk (Markowitz, 1987). The mean-variance analysis specifies a particular portfolio weight function for each stock at each time based on a function of each stock's market value and characteristics. The weights are restricted so they sum up to one, which implies that the investor will hold the market if the portfolio is mean-variance efficient (Markowitz, 1987).

Seeking to understand the implications of risk-adjusted returns when investing in low versus high carbon-intense companies, we incorporate carbon-intensity scoring to our portfolios. Depending on whether the portfolio is composed of high, or low, carbon-intense stocks, we can learn what the mean-variance efficient level of risk is for a given level of return and carbon intensity-score, for each portfolio. The analysis will thus provide us with five weights, each representing the optimal share of the portfolio to invest in each of the respective FF-factors, in order to mitigate risk for a given level of return. Subsequently, we can calculate the optimal risk-adjusted return, Sharpe Ratio, for each portfolio. As a consequence, decreasing a portfolio's carbon intensity score, i.e. reducing its carbon emissions beyond the prevailing score of the market, will require financial investors to accept a lower expected return per unit of risk (Sharpe Ratio). Implicitly, the tradeoff between a lower Sharpe Ratio and a lower carbon intensity score can therefore be seen as the implied shadow price of green capital, which relies on the relationship between expected return, variance, and carbon intensity.

When accurately estimating the portfolio weights required for the mean-variance framework, it is important to opt for a suitable estimation-window. In our analysis we will be utilizing an expanding window as our estimation anchor; with a fixed starting point, starting in month 36 (January 2011) and ending in month 132 (December 2018). The mean-variance analysis, sample and accuracy will increase as the window expands, in conjunction with the validity of our findings.

4.5 Model Testing

In order to employ our regressions, validate and justify findings, our data is required to meet certain assumptions and pass statistical tests to prove significance. All test results can be found in the appendix.

To be able to employ OLS regressions to our time series data, the data is required to meet the five Gauss-Markow set of assumptions; (1) Linear in Parameters, (2) No Perfect Collinearity, (3) Zero Conditional Mean, (4), Homoscedasticity, and (5) No Serial Correlation (Wooldridge, 2012). If these requirements are not met, we cannot validify our OLS coefficient-estimates.

Gauss-Markow assumptions (1) and (2) will not be tested as they are primarily focused towards forecasting. The parameters for the CAPM and FF5 are linear, and Fama and French (2014) already established that the factors added are independent and shown to affect stock returns, which indicates that the assumptions are fulfilled.

A critical assumption to meet in order to validify our regressions is no autocorrelation, which occurs when the error terms are correlated across time, the implications of which can invalidate our statistical inference (Wooldridge, 2012). Performing a Breusch-Godfrey test we are able to determine whether autocorrelation exists within our data. The test statistic suggests that there does not exist autocorrelation within our data. Another vital assumption to uphold is no heteroskedasticity. Maintaining a constant variance over time, i.e. homoscedasticity, is important as skewness and heteroskedasticity may lead to wrongful interpretation of test result due to invalidated error terms. In order to test for heteroskedasticity, we perform a Breusch-Pagan test. After performing the test, there is no indication of heteroskedasticity present. Given our large sample size there is little concern for non-normal distribution and consequently reduced statistical power of our test results. Nevertheless it is an important underlying assumption.

Lastly, we need to test for stationarity in our time-series data to ensure stable probability distributions over time. Non-stationary data cannot be used in an linear regression as it can potentially indicate significant relationships within the regression even when there is none existent. If data are non-stationary, they must be transformed. We can check for nonstationarity by performing an augmented Dickey-Fuller test for unit root. In order to derive the optimal lag-length to be selected, we opt to apply the lag-length constructed by Ng & Perron (1995).

5 Findings

In this section of the thesis we present the results of our analysis. We cover the regression results and show the different risk-exposures from implementing the CAPM-model and the FF5-model to our constructed portfolios. Furthermore we will present our findings when applying the mean-variance portfolio optimization and disclose the resulting risk-adjusted return for each respective portfolio. In addition we have performed an initial regression without attributing CI-scores to the sample. The result can be found in table A1, in the appendix.

5.1 Regression Results

This chapter showcases the regression result achieved from the separate portfolios. The section will attempt to highlight important estimates and outputs, and will proceed to interpret the results in the following section. Additionally, the purpose of the results are to underline key differences between the Low CI-score and High CI-score portfolios, and investigate whether one or both portfolios return significant abnormal returns under each of the specific models.

Table 5.1

Regression Results

	Dependent variable:			
	Excess Return			
	Low CI Score		High CI Score	
	(1)	(2)	(3)	(4)
Mkt	0.820***	0.976***	1.065***	0.855***
	(0.037)	(0.041)	(0.069)	(0.059)
SMB		0.582***		0.872***
		(0.099)		(0.090)
HML		-0.238***		-0.024
		(0.051)		(0.092)
RMW		-0.133		0.079
		(0.086)		(0.109)
CMA		-0.126		0.223***
		(0.078)		(0.085)
Abnormal Return	-0.0001	-0.002	-0.0003	-0.002
	(0.002)	(0.002)	(0.003)	(0.002)
Observations	130	130	130	130
R^2	0.790	0.863	0.652	0.824
Adjusted R^2	0.788	0.858	0.649	0.817
Residual Std. Error	0.026 (df = 128)	0.021 (df = 124)	0.033 (df = 128)	0.024 (df = 124)
F Statistic	480.461*** (df = 1; 128)	156.426*** (df = 5; 124)	239.862*** (df = 1; 128)	115.945*** (df = 5; 124)

Note: *p<0.1; **p<0.05; ***p<0.01

Table 5.1 showcases the regression results from the CAPM and Fama-French Five factor model, (1) and (3), and (2) and (4), respectively. The table investigates two portfolios, categorized as *Low CI Score* and *High CI Score*, where both portfolios utilize monthly excess return as the dependent variable. Both portfolios are value-weighted. The initial market factor, “Mkt”, is the value-weighted monthly market return less the risk-free rate. The SMB factor, “Small Minus Big” (market capitalization), indicates to which degree the portfolios are exposed to small caps over big caps, while the HML factor, “High Minus Low” (book-to-market ratio) captures the portfolios’ spread in return between value stocks and growth stocks. The portfolios’ exposure to stocks with robust profitability is encompassed within the RMW factor, while the CMA factor captures the exposure to stocks that utilizes a conservative investment strategy, over an aggressive one. Lastly, the intercept/constant shows the monthly abnormal return generated.

The regression results in Table 5.1 provides evidence that both portfolios exhibit negative, but insignificant abnormal returns, through the CAPM or the Fama-French Five Factor model. The constants not being significant signifies that the respective returns of the portfolios are captured through the other factors employed. Furthermore, it also implies that it’s not favorable one way or the other, strictly in terms of abnormal return, to invest in portfolios with low or high carbon intensity.

The portfolios’ exposure to the market proxy for systematic risk, is significant at 1% level across both models. We observe from Table 5.1 that the Low CI-score portfolio is 0.245 less exposed to market factors in CAPM, than the High CI-score portfolio, but 0.121 more exposed in the FF5-model. From the FF5-model we further observe that the market beta for Low CI-portfolio is higher than the High CI-portfolio, indicating that both portfolios consist of stocks tending to be less volatile than the market.

The SMB factor in the regression output is positive and significant at the 1% level for both portfolios. The High Ci-portfolio has an unambiguously larger exposure to small cap stocks compared to the Low Ci-portfolio, evident from the coefficient of 0.872 to 0.592. The HML coefficient is negative for both portfolios, but is only significant at the 1% level for the portfolio comprising low carbon emitting stocks. This observation indicates a higher risk exposure to, and out-performance of, low book-to-market growth stocks. For the High CI-portfolio, an insignificant p-value can be interpreted as the portfolio not being exposed more or less to either one.

We observe from Table 5.1 that the Low CI-portfolio exhibits a negative coefficient for the RMW factor, while the High CI-portfolio exhibits a positive one. The factor being insignificant at all levels for both portfolios implies that neither portfolio has a particular exposure to either robust firms with high profitability, or weak firms with lower profitability.

For the Low CI-portfolio, the CMA factor exhibits a negative coefficient and is insignificant. On the other hand, the High CI-portfolio exhibits a positive coefficient and is significant at the 1% level, indicating that the latter portfolio is more exposed towards companies with a conservative investment strategy rather than aggressive, whilst the low carbon intensity portfolio has a more balanced exposure.

We observe from table 5.1 that the R-squared and adjusted R-squared are increasing when moving from the CAPM, to the FF5 for both portfolios respectively. The increase is indicative of a higher explanatory power of the variance occurring in the portfolio return. In other words, the market factor in the CAPM for the Low CI portfolio explains 79% of the variation, while the market, SMB, HML, RMW and CMA factors in the FF5-model explains 86,3% of the portfolio return. For the High CI portfolio we see that the amount of variation explained by the different variables is lower for both models.

5.2 Mean-variance portfolio optimization

5.2.1 Summary Statistics

Table 5.2.1

Summary Statistics

	Low CI Portfolio	Mkt	SMB	HML	RMW	CMA
Average Returns	0,001	0,008	0,001	-0,004	0,002	0,000
Standard Deviation	0,031	0,047	0,018	0,037	0,021	0,019
Sharpe Ratios	0,043	0,177	0,048	-0,122	0,078	0,007
	High CI Portfolio	**Mkt**	**SMB**	**HML**	**RMW**	**CMA**
Average Returns	0,002	0,006	0,003	-0,002	0,002	0,002
Standard Deviation	0,029	0,042	0,029	0,026	0,02	0,023
Sharpe Ratios	0,077	0,136	0,108	-0,06	0,085	0,094

After establishing what characteristics distinguish the low CI-portfolio from the high CI portfolio in terms of the Fama French Five-Factor Model, we further seek to investigate if there exists any substantial differences in each portfolio's risk-adjusted return. In order to disclose this we opt to analyze the mean-variance optimal Sharpe ratio of the different portfolios, and for each FF-factor respectively.

Before presenting the results of the mean-variance approach we investigate how the portfolios perform as is. Table 5.2.1 exhibits the low CI-score and high CI-score portfolios respective average monthly return, standard deviation and Sharpe ratio, in total and for each individual FF-factor, for the entire sample period. The table indicates that the High CI portfolio outperforms the Low CI portfolio in terms of average return. As we can see, this is mainly due to the higher return achieved from the High CI-portfolio’s exposure to small cap-stocks, as well as the return achieved from their exposure to firms with an conservative investment strategy. From this summary statistic we also see that the total risk, manifested in standard deviation, is higher for the low carbon-intensity portfolio, mainly due to their market exposure of 4,7 and exposure to growth stocks of 3,7. Consequently, the Sharpe ratio for the High CI-portfolio is somewhat higher than that of the Low CI-portfolio.

5.2.2 Mean-variance Portfolio Results: Expanding Window

Table 5.2.2

Expanding Window: January 2011 - December 2018		
Mean-Variance Opt.	**Low CI**	**High CI**
Average Portfolio Expected Return	0,110183900	0,223233000
Average Opt. Standard Deviation	0,703487600	0,798712100
Portfolio Sharpe Ratio	0,156625220	0,279491196

The table exhibits the average monthly return (expected), standard deviation and Sharpe ratios, derived from the mean-variance analysis of the respective portfolios. The results are attained by implementing an expanding window where one month of data is added at the time from, January of 2011 to December 2018, to find the optimal weight-composition and standard deviation, for a given level of return.

Table 5.2.3

Optimal Factor Weights					
	Low Carbon Intensity				
Factor	**Market**	**SMB**	**HML**	**RMW**	**CMA**
Weight	0,07	0,27	0,16	0,39	0,12
	High Carbon Intensity				
Weight	0,03	0,12	0,22	0,44	0,19

Table 5.2.3 presents the optimal weight-composition when attempting to maximize the risk-adjusted return, given the level of carbon intensity within the portfolio. As Table 5.2.2 shows, the High CI portfolio has a higher risk-adjusted return than the Low CI-portfolio, as a consequence of its higher return, and slightly higher total risk. In order to investigate whether the risk-adjusted return, and thereby the respective portfolios, are significantly different we undertook a T-test on the portfolio's Sharpe ratios. The P-value of the test was 0.348779.

5.2.3 Findings: Can we reject the null hypothesis?

Previously in our thesis we presented the following hypothesis:

H0: Portfolios with low Carbon Intensity have statistically significant lower risk-adjusted returns than portfolios with high Carbon Intensity.

HA: Portfolios with low Carbon Intensity do not have statistically significant lower risk-adjusted returns than portfolios with high Carbon Intensity.

The test concludes that there is not enough statistical evidence to suggest that the respective portfolio's risk-adjusted returns are significantly different (p-value: 0.348779). By extension, this means that the risk adjusted returns from the low Carbon Intensity were not significantly lower than the risk adjusted returns of the high Carbon Intensity portfolio. We therefore reject the null-hypothesis (H0).

6 Discussion

In this section we will be discussing the implications the findings have on our research question: *How does carbon intensity affect financial performance in the US stock market?* We will also be comparing our findings to the results showcased in previous literature.

6.1 Findings from previous literature

From the literature review section of this paper we find that the previous research is somewhat divided on the subject, depending on the main focus of the study and the variables utilized. Conflicting results make it challenging to establish a literary consensus. Some previous studies indicate that this may be partly due to the fact that historically there has been a lack of industry standards of reporting, as well as limited availability of the data of interest (In et al., 2019).

There are several previous findings linking social performance and Corporate Social Responsibility to financial performance (Scherer & Palazzo, 2009) as well as decreased systematic risk and increasing firm value (Albuquerque et al., 2019). This is further substantiated by a large majority of studies having positive findings in the relationship between ESG and corporate financial performance (Friede et al., 2015). Other studies found that contrary to traditional approaches, responsible investing can be reduced to a tradeoff between sharpe ratio and the ESG score (Pedersen et al., 2020).

There are several papers arguing against these findings, however. While all the studies mentioned above incorporate some environmental element, it is important to distinguish between these considerations' effect on corporate performance versus investors' respective returns when incorporating these concerns into their investment strategy. While these effects may often be linked, the fact that companies tend to perform better when incorporating CSR and ESG, does not necessarily mean that investors experience increased returns when investing in greener companies. Some authors, perhaps especially those who focus solely on carbon emissions, have raised the argument that ESG considerations necessarily lower expected returns (Hong & Kacperczyk, 2009). Bolton & Kacperczyk (2020) found that carbon emissions had a significantly positive effect on stock returns. When they examined whether carbon emissions affected stock returns or not, their findings indicated that the carbon heavy companies earned higher returns. Another study investigating the risk-return relationship of low carbon investment found positive returns, but only from 2010 (In et al., 2019). This further illustrates the divide in the findings of previous literature.

6.2.1 Discussion of results

In the attempt to answer the aforementioned research question, the relevance of discussing the implications of our findings in regards to the analysis of our portfolios cannot be understated. By applying the FF5-framework to our analysis we seek to gain a deeper understanding of what the core drivers of return are for each respective portfolio. The portfolios are purposely constructed based on the outer percentiles of the carbon scores. By doing so we are able to clearly differentiate, and thus underline what separates the composition of risk exposure and return in our dataset. Looking at the outer percentiles is relevant as we are further able to establish differences in terms of return when wanting to control for the amount of CO2 being emitted by the stocks in the portfolio. This helps us further address how carbon emission affects financial performance.

From section **5.1** we observe that neither portfolio exhibited significant abnormal return. This indicates that neither portfolio is able to generate abnormal return and as such are similar in this aspect. For our thesis this implies that in the pursuit of abnormal returns it will not make an important difference when choosing whether to invest in high carbon emitting stocks or in low carbon emitting stocks.

Observing the SMB factor - like previously stated - we see that the factor is significant for both portfolios, at 1%. Both of the coefficients are positive indicating a risk exposure towards small cap stocks. We further observe that for the portfolio consisting of high carbon emitting stocks, the exposure towards small cap stocks is larger than for the low carbon-intense portfolio. This implies that when investing in the carbon heavy portfolio, the stocks comprising the portfolio are more exposed towards small caps stocks than when investing in the low carbon emitting portfolio.

Concerning the HML factor we observe that both portfolios exhibit negative coefficients in figure 5.2.2. The low carbon-intensity portfolio is the only one statistically significant at 1% level. This is an indication of a larger exposure towards growth stocks rather than value stocks, whilst the high carbon emitting portfolio can not be interpreted similarly. This result underlines an important implication in our findings, that companies with a low carbon-intensity score have a statistically larger tendency to be growth stocks; stocks aiming to outperform the market in terms of sales and revenue. Concerning the RMW factor, neither of the portfolios are significant at any level. This implies that there can not be drawn any conclusion as to how the carbon portfolios are exposed to this risk.

As one can read from figure 5.2.2, the portfolio consisting of low carbon-intense stocks exhibits a negative coefficient for the CMA factor, and is insignificant. Contrary to this finding, we observe that the stocks that constitute the carbon-intense portfolio exhibit a positive coefficient and are significant at the 1% level. These findings are relevant in addressing our research question as it underlines differences between the investment strategies utilized in high carbon-intense companies, and in low carbon-intense companies. The findings imply that portfolios consisting of high carbon-intense companies tend to be more exposed to conservative investment strategies, rather than aggressive ones. For companies of low carbon-intensity scoring - where the factor was insignificant - the findings do not suggest that the portfolio was more or less exposed to companies with an aggressive, or an conservative investment strategy. The take-away from this analysis is that carbon-intense companies tend to invest less, whilst less carbon-intensive companies seem to have a more balanced and regular investment strategy.

As the population samples utilized in the Fama-French five factor model differ from the much broader samples utilized in the performance of the mean-variance portfolio optimization, we cannot draw any straight line conclusion from parallels or similarities we may observe. However, utilizing our observations from the FF5-model where the sample was narrower, in combination with the observation from our findings in the mean-variance analysis, we can help provide insight into what our dataset indicates in terms of risk exposure and return in relation to carbon intensity.

6.2.2 Shadow price implications

To underline the utility of our findings we opt to further investigate the implications of a significant non-difference in risk-adjusted return between the two portfolios. As mentioned in section 4.4, in the spirit of Markowitz, the mean-variance analysis allows us to combine the desire for an investor to maximize the return and minimize the risk of the portfolio by attributing value-weights to the different components (Markowitz, 1987). By constructing two portfolios composed of stocks with value-weighted carbon intensity scores - one portfolio consisting of above-median scores, and one portfolio consisting of below-median scores - we are able to maximize the portfolio's return for a given level of risk and carbon intensity score, similarly to what Pedersen et al. (2020) did. The result of statistically non-different Sharpe Ratios suggest that an investor in the US stock market can achieve statistically similar risk-adjusted return when investing in either carbon heavy portfolio, or in an low carbon portfolio. For an investor wanting to maximize risk-adjusted return, the results of our findings have the following implications: There is no financial disadvantage or specific amount of risk-adjusted return you have to forfeit when investing in low carbon portfolios. Furthermore this allows us to identify that, for all intents and purposes of this thesis, the implied shadow price on green capital - the price of green investing - is near zero.

6.2.3 Implications and further discussion of results

By rejecting the null-hypothesis we are stating that: Given our data sample, low carbon intensity portfolios do not have significantly lower risk adjusted returns than portfolios with high carbon intensity. This statement has a number of implications. Historically it has been challenging to successfully convince mainstream and institutional investors to invest more sustainably (In et al., 2019). This has generally been due to perceived increased risk of reduced returns when doing so. The results of this thesis states that investors are not necessarily worse off when investing "green". This thesis therefore contributes to the existing literature of legitimizing environmentally sustainable investments, and showcasing that such investments may not be inferior to more carbon heavy investments in terms of risk adjusted return.

The second implication of such results can contribute to the discussion of responsible investing. If investing more sustainably can yield equal returns to the alternative, this should provide an added incentive to investors to incorporate more sustainable investments in their investment portfolio. Traditional approaches to sustainable investing can be perceived as a choice between “hearts” and “minds”, indicating that if you wish to invest in a way more aligned with moral values, then you may have to do so with a loss on your returns. At the very least it can be perceived as a tradeoff between ESG scores and sharpe ratio. Whilst this thesis is only concerned with carbon intensity (E), it adds to the literature showing that this tradeoff (and the gap between hearts and minds) may be smaller than traditionally perceived.

Whilst the results of the thesis indicates that “green” investments may be equal to the alternative in terms of risk adjusted returns, it does not indicate that one alternative is superior to the other. The results are somewhat ambiguous and inconclusive. This is therefore consistent with the previous research in the challenges of establishing a consensus. Especially in regards to recognizing a superior alternative based on financial performance and returns. The findings of our survey does not indicate that an investor that has traditionally invested in carbon heavy portfolios would be any worse off in terms of risk adjusted returns by continuing to do so. It can be argued that the biggest takeaway from the results of this thesis is this; the main argument for investing more environmentally sustainable is a moral one, but this choice may not affect your risk-adjusted returns.

7. Limitations

This section of the thesis addresses the identified limitations in our research. The main limitations in focus are related to data selection, time period, and limitations with the model itself.

7.1 Data selection

A possible challenge in our thesis is the selection of companies. In order to satisfy the criteria of multiple factors and historic data in our dataset, several companies had to be excluded from examination in this thesis. The companies omitted may have been excluded due to bankruptcy during the respective time period, failing to provide certain factors, or simply not having the registered historic data. If the companies omitted were on the ends of our scales, i.e displaying excessively high carbon intensity, this may impact the results of our thesis. The location specific nature of our data could also impact the results, as we only utilize data from the US stock market. The global consensus appears to be that ESG investing is more prominent in Europe than in the US, and that the US is lagging behind in the ESG market (Ralston 2017, Marsh 2020). This potential geographical difference in ESG investing implies that if we examined data from another region entirely, our findings might differ.

7.1.2 Scopes

As described in section 2.5, S&P Trucost uses slightly different emission scopes in their data. Their model only includes some of the most relevant upstream scope 3 emissions in order to limit double counted emissions. If this thesis was based on emissions data encompassing all of the traditional scope 3 emissions, or used a narrower approach to emission scopes, then the results might have differed from the results presented.

7.1.3 Greenwashing

Rising investments in ESG focused companies, as well as sustainable bonds issuance has in recent years raised concern amongst investors that the sustainability claims of the issuers might be overstated. Unreliable or untrue claims regarding a company's sustainability is known as greenwashing (S&P Global, 2021). A lack of consistency in instrument labeling, universal reporting standards, and post issuance disclosure further contributes to these concerns.

If there are irregularities or unreliable reports in our dataset regarding this topic, it can be a possible limitation for this thesis' results. In this thesis we assume that the evaluations of the respective companies' emissions are accurate. S&P Global aims to mitigate the risks of greenwashing by highlighting transparency and consistency. They also state that despite increasing concerns, there is little evidence that such misleading practices are becoming widespread.

7.2 Time period

The data in this thesis is composed of observations from a sample period from January 2007 to December 2018. We would argue that this is a sufficient time period to examine for our thesis. We are however aware that in recent years the focus on ESG have only been increasing. Consequently, having been able to expand our time period as far as 2020, would arguably have increased the present-day relevance of our findings.

7.3 Model limitations

A regular concern when performing regression analysis is whether the market is inefficient, or the asset pricing model utilized is inefficient. Despite the fact that our analysis showed no abnormal return generated, there are concerns linked to the use of CAPM and the FF5 model as they rest on assumptions such as rational investors and efficient markets. According to Fama and French (2014), the FF5 outperforms the three-factor model. However, when adding the profitability variable RMW and investment variable CMA, the HML risk-factor becomes redundant in many instances. In particular if parsimony is an issue. The main reason for this limitation is that average stock return is captured by the other factors present. Fama and French stated also that the model's main problem is its difficulty in capturing the low average return for small stocks that invest a lot despite them showing weak profitability (Fama, 2014). In order to mitigate the limitations arising from using the individual models respectively, we utilize both models to increase the robustness of our analysis.

7.4 Suggestions for further research

There is room for extension of the time period, as it is limited to 2018. It would be interesting to view the results of incorporating future data into our model. Future research could also employ a different provider of carbon emissions and intensity rating to see if this has implications for the findings. Lastly, further research could build upon this thesis and compare how carbon intensity may affect return depending on geographic regions and countries.

8 Conclusion

The main purpose of this study has been to explore how carbon intensity can affect financial performance, and compare how this performance is linked with varying levels of carbon exposure. Throughout this thesis we have studied whether investing in portfolios with low carbon intensity can yield equal returns to investing in carbon heavy portfolios. Our results indicate that investing in low carbon intensity portfolios does not have significantly lower risk adjusted return than high carbon intensity portfolios. We cannot establish that one alternative is superior to the other. At least not in terms of financial performance, when considering an investor wanting to maximize returns. This implies that the shadow price on green capital is near zero.

The results imply that the traditional perception that responsible investing carries increased risk and lower return is somewhat challenged. The same goes for the notion that portfolios composed of environmentally sustainable stocks negatively impacts sharpe ratio. Our findings suggest that this tradeoff seems to be less prominent than previously perceived. We argue that this further indicates that investors may not be as bound to settle for either “hearts” or “minds” when investing. Consequently, you may be able to maximize sharpe ratios as well as investing green. The somewhat ambiguous nature of our findings is consistent with the lack of consensus in existing literature. The findings in this thesis contribute to the previous research of legitimizing environmentally sustainable investments as a viable investment option, on par with more carbon heavy investments in terms of risk adjusted return.

References:

Albuquerque, R., Koskinen, Y. & Zhang, C. (2019). Corporate Social Responsibility and Firm Risk: Theory and Empirical Evidence. *Management Science, 65*(10), 4451-4469.

Amel-Zadeh, A,. & Serafeim, G. (2018). Why and How Investors Use ESG Information: Evidence from a Global Survey. *Financial Analysts Journal, 74(3),* 87-103.

Bolton, P. & Kacperczyk, M, T. (2020). Do Investors Care about Carbon Risk? *Journal of Financial Economics, Available at SSRN: https://ssrn.com/abstract=3398441*

Dennis, A. (2013). Enhancing Shareholder Value by Improving Sustainability Performance. *Corporate Finance Review, 17*(6), 11-15.

Fama, E. French, K. (1991). A three-factor asset pricing model. *Journal of Financial Economics.*

Fama, E. French, K. (2015). A five-factor asset pricing model. *Journal of Financial Economics, 116*(1)*, 1-22.*

Friede, G., Busch, T. & Bassen, A. (2015). ESG and financial performance: aggregated evidence from more than 2000 empirical studies. *Journal of Sustainable Finance and Investment, 5*(4), 210-233.

Greenhouse Gas Protocol. (2004). A Corporate Accounting and Reporting Standard. *Retrieved from: https://ghgprotocol.org/sites/default/files/standards/ghg-protocol-revised.pdf*

Henisz, W., Koller, T. & Nuttall, R. (2019). Five ways that ESG creates value. *McKinsey Quarterly. Retrieved from: https://www.mckinsey.com/~/media/McKinsey/Business%20Functions/Strategy%20and%20Corporate%20Finance/Our%20Insights/Five%20ways%20that%20ESG%20creates%20value/Five-ways-that-ESG-creates-value.ashx*

Hoffman, V. H. & Busch, T. (2008). Corporate Carbon Performance Indicators: Carbon Intensity, Dependency, Exposure, and Risk. *Journal of Industrial Ecology,* 12(4), 505-520.

Hong, H. & Kacperczyk, M, T. (2009). The price of sin: The effects of social norms on markets. *Journal of Financial Economics, 93,* 15-36.

In, S. Y., Park, K. Y. & Monk, A. (2019). Is 'Being Green' Rewarded in the Market?: An Empirical Investigation of Decarbonization and Stock Returns. *Stanford Global Project Center Working Paper,* Available at SSRN: https://ssrn.com/abstract=3020304

Jensen, M. C. (1969). Risk, the pricing of capital assets, and the evaluation of investment portfolios. *Journal of business,* 42(2), 167–247.

Kumar, P., & Firoz, M. (2018). Corporate Carbon Intensity Matter: Predicting Firms' Financial Performance. *SCMS Journal of Indian Management.*

Marsh, A. (2020). U.S. Falls Further Behind Europe in Fast-Growing ESG Market.

Bloomberg Green. Retrieved from: https://www.bloomberg.com/news/articles/2020-12-21/u-s-falls-further-behind-europe-in-fast-growing-esg-market

Murphy, C, J. (2002). The Profitable Correlation Between Environmental and Financial Performance: A Review of the Research. *Light Green Advisors.*

Natixis. (2021). Everyone’s on the ESG investing bandwagon. *ESG Investor Insights Report Executive Overview. Retrieved from: https://www.im.natixis.com/us/resources/2021-esg-investor-insights-report-executive-overview*

Ng, S. & Perron, P. (1995 and 2003). Lag Length Selection and the Construction of Unit Root Tests with Good Size and Power. *Journal of American Statistical Association, 90(429):268-281*

Pedersen, L. H., Fitzgibbons, S. & Pomorski, L. (2020). Responsible investing: The ESG-efficient frontier. *Journal of Financial Economics, 142(2),* 572-59.

Ralston, G. (2017). Global Investor Study 2016 – Plan Sponsors: A global study of pension fund investors, with a focus on investment outcomes and environmental, social and governance issues. *Schroders. Retrieved from: https://www.schroders.com/en/sysglobalassets/digital/insights/2016/pdfs/global-investors-study-pension-funds.pdf*

S&P Global. (2020). What is the difference between ESG investing and socially responsible investing? *Retrieved from: https://www.spglobal.com/en/research-insights/articles/what-is-the-difference-between-esg-investing-and-socially-responsible-investing*

S&P Global. (2021). To mitigate greenwashing concerns, transparency and consistency are key. *Retrieved from: https://www.spglobal.com/ratings/en/research/articles/210823-the-fear-of-greenwashing-may-be-greater-than-the-reality-across-the-global-financial-markets-12074863*

Scherer, A. G., & Palazzo, G. (2009). The New Political Role of Business in a Globalized World: A Paradigm Shift in CSR and its Implications for the Firm, Governance and Democracy. *Retrieved from: https://www.researchgate.net/publication/228533084_The_New_Political_Role_of_Business_in_a_Globalized_World-A_Paradigm_Shift_in_CSR_and_its_Implications_for_the_Firm_Governance_and_Democracy*

Sharpe, W. F. (1964). Capital asset prices: A theory of market equilibrium under conditions of risk. *The journal of finance*, 19(3), 425–442.

Sparkes, R. (2008). Socially Responsible Investment. *Investment Management and Finance Management*, (2).

Sparkes, R., & Cowton, C, J. (2004). The Maturing of Socially Responsible Investment: A

Review of the Developing Link with Corporate Social Responsibility. *Journal of Business Ethics*, 52, 45-57.

United Nations. (2020). Climate action fast facts. *Retrieved from: https://www.un.org/en/climatechange/science/key-findings#collapseTwo*

United Nations. (2020). Sustainable development goals. Goal 13: Take urgent action to combat climate change and its impacts. Retrieved from: https://www.un.org/sustainabledevelopment/climate-change/

Wooldridge, J. M. (2012). Introductory Econometrics- a Modern Approach. *Cengage Learning, (5), 268-380.*

Appendix

A1 Benchmark regressions

Table A1

	Benchmark Reg				
	Dependent variable:				
	Excess Return				
	(1)	(2)	(3)	(4)	(5)
MyMkt	1.035***	0.986***	0.944***	0.930***	0.911***
	(0.037)	(0.035)	(0.034)	(0.034)	(0.031)
MySMB	0.882***	0.838***	0.796***	0.797***	0.777***
	(0.078)	(0.072)	(0.067)	(0.067)	(0.061)
MyHML		0.270***	0.131**	0.189***	0.049
		(0.052)	(0.058)	(0.064)	(0.065)
MyRMW			-0.425***	-0.408***	-0.432***
			(0.095)	(0.094)	(0.087)
MyCMA				-0.164*	-0.083
				(0.084)	(0.078)
MyUMD					-0.149***
					(0.030)
Constant	-0.004***	-0.003*	-0.002	-0.002	-0.002*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	130	130	130	130	130
R^2	0.918	0.932	0.941	0.943	0.953
Adjusted R^2	0.916	0.931	0.940	0.941	0.951
Residual Std. Error	0.016 (df = 127)	0.015 (df = 126)	0.014 (df = 125)	0.014 (df = 124)	0.012 (df = 123)
F Statistic	706.590*** (df = 2; 127)	576.738*** (df = 3; 126)	502.534*** (df = 4; 125)	411.921*** (df = 5; 124)	414.554*** (df = 6; 123)
Note:					*p<0.1; **p<0.05; ***p<0.01

Table A1 showcases the regression results from the CAPM to Fama-French Five factor model. The table investigates our dataset categorized without attributing carbon intensity scoring to the portfolios. The initial factor, MyMkt, is the value-weighted monthly market return less the risk-free rate. The SMB factor, “Small Minus Big” (market capitalization), indicates to which degree the portfolios are exposed to small caps over big caps, while the HML factor, “High Minus Low” (book-to-market ratio) captures the portfolios’ spread in return between value stocks and growth stocks. The portfolios’ exposure to stocks with robust profitability is encompassed within the RMW factor, while the CMA factor captures the exposure to stocks that utilizes a conservative investment strategy, over an aggressive one. Lastly, the intercept/constant shows the monthly abnormal return generated.

A 2 Model testing

A 2.1 Breusch-Pagan Test

In order to test our regressions for homoscedasticity we employ the Breusch-Pagan Test. This is an important assumption to address in order to verify statistical power in our dataset (Wooldridge, 2012). If the assumption does not hold, corrective measures should be taken. Table A2.1 reports the results from the BP-test:

Table A2.1

Breusch-Pagan Test for Homoskedasticity

	BP	P-Value
CAPM		
Low CI	0.08539	0.7701
High CI	0.20534	0.6504
FF5		
Low CI	4.554	0.4727
High CI	5.6914	0.3374

The results of the Breusch-Pagan Test for Homoscedasticity are reported in the table above. The test is applied to both the CAPM and the FF5-model, for each respective portfolio. BP is the test statistic and is distributed approximately as chi-squared. The null hypothesis of the test is that there exists homoskedasticity within the dataset, i.e all the error variances are equal. The p-values reported above are higher than the benchmark of 5%, meaning we can not reject the null hypothesis and no corrective measures must be taken.

A 2.2 Breusch-Godfrey Test

We utilize the Breusch-Godfrey Test in order to make sure autocorrelation is not prominent in our dataset. Time-series datasets are often troubled with autocorrelation, which occurs if the error terms are correlated and move in a pattern (Wooldridge, 2012). The test results are presented in table A2.2:

Table A2.2

Breusch-Godfrey Test for autocorrelation

	LM-stat	P-Value
CAPM		
Low CI	2.5986	0.6271
High CI	4.00074	0.405
FF5		
Low CI	8.5665	0.0729
High CI	8.3962	0.0781

Table A2.2 reports the LM-stat and P-value for the Breusch-Godfrey Test for autocorrelation. The test is undertaken for both models, and for each portfolio respectively. The null hypothesis for the test is that there exists no autocorrelation in the dataset. Thus, if the test statistic is high enough, and subsequently the P-value low enough, we have autocorrelation and need to take corrective measures. As one can read from the table, the null hypothesis is not rejected at 5% significance level in any instances, and consequently we do not have autocorrelation.

A 2.3 Augmented Dickey-Fuller Test for Unit Root

In order to test for spurious regressions we opt to use the Augmented Dickey-Fuller Test for Unit Root to test whether our time-series data are stationary or not. If the data is deemed non-stationary, it will need to be transformed in order for us to apply it to the OLS regressions. The results from the test is presented in table A2.3:

Table A2.3

Augmented Dickey-Fuller Test for Unit Root

	Low CI		**High CI**	
Dependant variable	**DF**	**P-value**	**DF**	**P-value**
Excess return	-9.21	0.01	-9.26	0.01
Pricing factors	**DF**	**P-value**	**DF**	**P-value**
Rm-rf (Mkt)	-9.73	0.01	-10.39	0.01
SMB	-9.91	0.01	-12.13	0.01
HML	-10.11	0.01	-9.65	0.01
RMW	-10.81	0.01	-10.63	0.01
CMA	-10.30	0.01	-13.14	0.01

Table A2.3 above presents the results from the Augmented Dickey-Fuller (ADF) test for stationarity. The null hypothesis of the test is that the data is non-stationary, meaning that if we achieve a low DF-statistic and a high P-value, our data is in need of transformation. As one can read from the table, the test statistics are high and the p-value is below the 5% significance level for the dependent variable and all pricing factors, allowing us to reject the null hypothesis and confirm that our data is stationary. We can apply the OLS regressions with our data.

A3 Factor correlations

Table A3

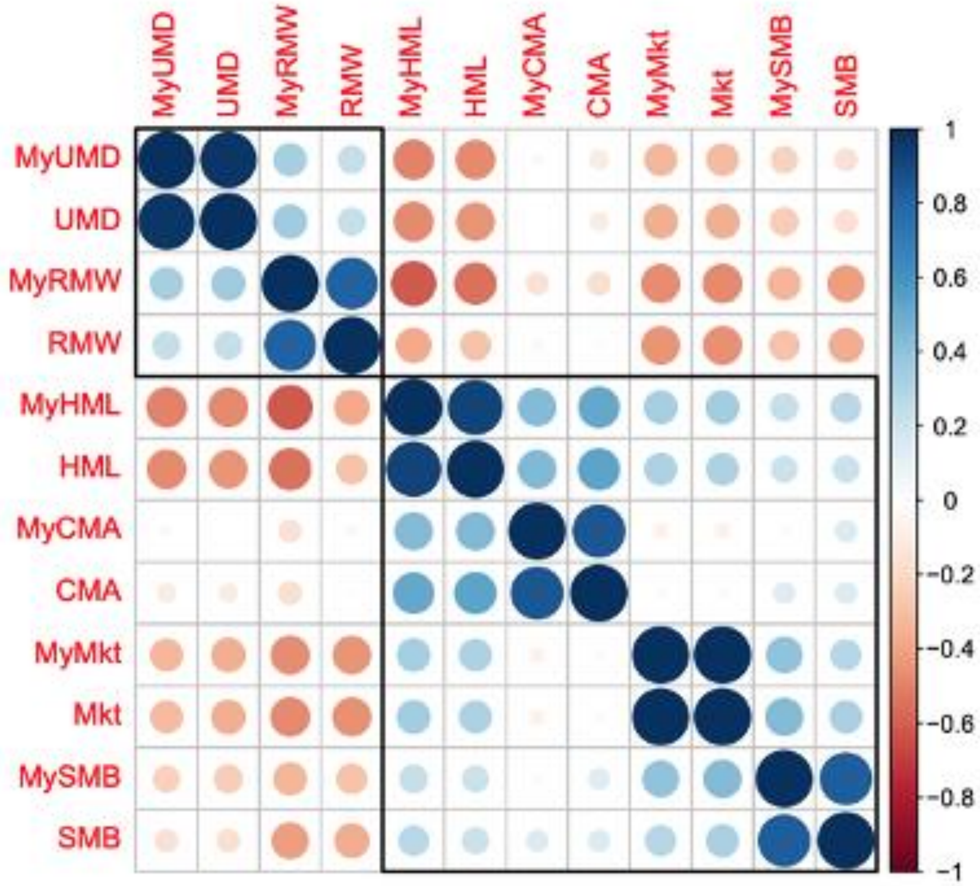


Figure 2 Factor Correlations

xis shows..

The figure above is a correlation matrix between the factors we constructed from the stocks attributed with carbon emission scores and the stocks from Fama-French. The figure indicates that there is a high correlation amongst the factors, from 85% and above. This is important as it verifies how representative our carbon-intensity dataset is, as we are able to generate factors similarly to Fama and French. In other words, the difference between the factors generated are almost indistinguishable.

A4 Summary statistics

Table A4

	year	nobs	nsec	r.value	sc.mean	sc.sd	sc.med
1	2007	1	1	0	71.79	NA	71.79
2	2008	750	48	0.76	174.74	212.01	86.48
3	2009	797	48	0.8	162.11	194.88	82.45
4	2010	820	48	0.81	159.35	196.45	78.49
5	2011	841	48	0.82	151.99	185.81	76.51
6	2012	843	48	0.82	159.85	196.99	77.24
7	2013	850	48	0.82	155.12	194.78	76.67
8	2014	856	48	0.81	152.37	193.14	73.34
9	2015	850	48	0.81	152.28	195.66	71.93
10	2016	891	48	0.8	146.9	188.4	69.29
11	2017	901	48	0.81	145.45	188.36	71.23
12	2018	884	48	0.81	152.02	199.06	69.46

Table A4 provides a summary statistic for the entire sample period, from 2007 to 2018. Column 3 (nobs) is the number of stocks with trucost data while column 4 provides the sector coverage (nsec). The “r.value” is the percentage of the market covered, followed by the mean, standard deviation, and median for the population sample. As the summary indicates, the dataset covers a large proportion of the market and consequently will yield large variations in scores.