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Carbon emission intensity and its impact on stock returns:

Revisiting the existence of a carbon premium in the American stock market.

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Preface and Acknowledgements

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Abstract

This thesis investigates the existence of a carbon premium in the American stock market over the period 2010-2023 using a sample size of 497 companies. I find weak evidence that emission intensity has a significant positive predictive power on stock excess returns. Precisely, it suggests that one standard deviation increase in the logarithmic emission intensity will increase stock excess returns by 0.51 percentage points. Next, a long-short portfolio based on emissions yields a positive return of 3.41% per year. However, these excess returns are explained by the Fama-French five-factor model, yielding no abnormal returns.

Keywords: Carbon Premium, Carbon Risk, Climate Change Risk, Carbon Emissions

JEL Classification: G11, G12, Q54

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1 Introduction

In recent years, there has been growing concern regarding climate change, including in the field of finance. In financial economics, there has been growing interest in the implications of carbon emissions for the financial system. This thesis aims to study the relationship between corporate carbon emissions and the effect they have on stock prices. The implementation of policies by governments around the world to reduce carbon emissions, exemplified by the Paris Agreement of 2015, presents a credible risk for investors. This raises the question of whether such risk is effectively reflected in the cross-section of stock returns and portfolio holdings (Bolton & Kacperczyk, 2021). Also, firms are increasingly subject to future regulations that can imply compliance costs, carbon taxes, fines, legal actions, and reputation damage, thus affecting their overall competitiveness and profitability. Consequently, these firms face a transition risk associated with a shift towards a low-carbon economy, which heavily depends on their particular greenhouse gas emissions, operational practices, business models, and R&D capabilities (Enders et al., 2023). Asset pricing theories, including the efficient market hypothesis, the capital asset pricing model (CAPM) by Sharpe (1964) and Lintner (1965), and its extensions, suggest that stock prices should reflect the investor's expectations of future payoffs, which are affected by new information and perceived risks. Theoretically, it can be expected that carbon risk exposure should be reflected in financial markets, as private actors (firms) and their value chains may be impacted by the transition to a carbon-free economy (Venturini, 2022). In this thesis, I investigate the concept of transition risk from carbon emissions at both the firm and portfolio level, referring to the mentioned premium as carbon premium. In this study, I investigate the carbon premium in both time series and cross-section of stock returns to determine whether this premium is explained and priced by standard asset pricing theory.

The review paper by Venturini (2022) suggests that climate risks significantly influence stock prices, but this risk is not efficiently priced as investors underreact to it. However, there is contradictory evidence regarding the existence of a carbon premium in both Europe and the United States (U.S.). In Europe, Santi and Moretti (2021) employed a questionnaire to collect the level of concern from investors regarding climate risk, complementing their analysis with regression techniques. Their findings suggest a premium exists only when investors are concerned about climate risk, yet the stocks fail to deliver higher returns when investors ignore this risk, indicating potential mispricing of risk. Research from Bolton and Kacperczyk (2021) found a positive carbon premium even after controlling for traditional risk factors using the

Trucost and FactSet databases over the period 2005-2017. Their study associates the premium with various emission metrics, such as total emissions and annual emission changes, while finding no association with emission intensity. In a subsequent paper, Bolton and Kacperczyk (2023) employed the Trucost and MSCI databases over the period 2005-2018 and identified a positive carbon premium in direct and indirect emissions across countries and industries. Particularly, countries with lower economic development, larger energy sectors, and less inclusive political systems exhibit a higher premium, as do countries with stricter climate policies. Hsu et al. (2023) constructed a measure of emission intensity of pollutants at the firm-level in the U.S. employing the Toxic Release Inventory (TRI) and the Centre for Research in Security Prices (CRSP) databases over the period 1991-2016. Their research revealed a pollution premium on the cross-section of stock returns, unexplained by other risk factors when building a long-short portfolio sorted on emission intensity. The authors attribute this premium to behavioural explanations, corporate policies, and other risks.

Ongoing research in both the U.S. and Europe has failed to reach a consensus concerning the existence of a premium for carbon risk exposure. Research has mainly focused on employing current emissions (scope 1, 2, and 3) as one of the main indicators to assess transition risks (Venturini, 2022). While this approach has limitations, as highlighted by Venturini, it serves as a way to categorise stocks according to exposure. This approach is popular given the absence of a consensus on effective transition risk indicators and the complexity of accessing data, as many economic actors are required to disclose information. Researchers have examined portfolio and firm-level performance and have found inconclusive evidence of the existence of abnormal returns. Li and Zheng (2024) have found an underperformance of high-emission firms compared to low-emission firms using machine learning techniques over the period 2002-2021. This underperformance is even more pronounced after the Paris Agreement. Despite the findings, Li and Zheng anticipate this emission-return relationship will reverse in the future. Wang (2024) found results that hold at a firm-level and portfolio-level. Wang found that green portfolios (portfolios with lower carbon emissions) consistently outperformed brown portfolios over the period 2002-2021. These findings contradict the research conducted by Hsu et al. (2023) and other authors, suggesting the need for more convincing research. Consequently, the U.S. presents a favourable research environment due to the greater availability of studies and quality of data on yearly greenhouse gas emissions. The primary research question arises: *What impact, if any, does carbon risk (transition risk) exposure have on stock returns in the U.S. in the period 2010-2023?*

In line with previous studies, this study focuses on U.S. stocks over the period 2010-2023 to facilitate comparisons with results from previous research. I construct a proxy for emission intensity and follow a similar methodology as in Hsu et al. (2023). However, instead of employing an emissions-to-total assets ratio, I employ an emission-to-total revenue ratio proposed by Enders et al. (2023). I employ the DataStream database to retrieve yearly carbon emission data and monthly stock return data. I retrieve the Fama French five-factor coefficients from the Kenneth R. French website.

I follow the approach by Hsu et al. (2023) and conduct a Fama-Macbeth regression to evaluate the emission- return relationship while controlling for firm-specific factors but also adding traditional risk factors. The results provide weak evidence that emission intensity has a significant and positive predictive power on stock returns. Specifically, results suggest that one standard deviation increase in the logarithmic emission intensity variable will increase excess returns by 0.51 percentage points. Additionally, I construct value-weighted quintile portfolios based on emission intensity within industries to examine the carbon premium while controlling for traditional risk factors going long (short) on high (low) pollutant firms, as in Hsu et al. The results show that the long-short portfolio does not yield abnormal returns after controlling for the Fama-French five-factor model. This thesis recognises the positive association between emission intensity and excess returns while finding no significant carbon premium in any direction.

The remainder of this thesis is structured in the following manner: Section 2 presents the theoretical framework and most relevant literature on the topic. Section 3 introduces the hypotheses. Section 4 describes the methodology used to conduct the research. Section 5 presents the main results. Section 6 discusses in detail the obtained results. Section 7 provides a summary of the key findings. Section 8 discusses the limitations of this thesis and proposes ideas for future research. Additional tables for preliminary test are exhibited in the Appendix.

2 Theoretical Framework

This chapter contains a concise literature review on the topic of carbon premium, primarily focusing on the latest literature from academic journals. Subsection 2.1 introduces the concept of carbon risk premium. Subsections 2.2 and 2.3 describe the Fama-MacBeth regression analysis and the relevant asset pricing theories, respectively. Sections 2.4 and 2.5 present contradicting evidence regarding the existence of a carbon risk premium in the stock markets around the world.

2.1 Introduction to the Carbon Risk Premium concept

The carbon premium concept is defined as a premium that firms face as a transition risk associated with a shift towards a low-carbon economy. This risk is heavily dependent on a firm's greenhouse gas emissions, operational practices, business models, and R&D capabilities (Enders et al., 2023). A second definition, provided by Zhang (2023), defines the carbon premium as the theoretical risk premium (higher returns) brown firms should earn in equilibrium according to their exposure to the transition towards a low-carbon economy compared to green firms. The existence of a carbon premium in the stock market is still an ongoing debate in the scientific community. This thesis presents contradictory empirical evidence from both sides of academia in the following sections. According to Bua et al. (2024), climate change risk affects asset price changes through changes in either physical or transition risk. In particular, Engle et al. (2020) help distinguish between these two types of risks, which serve as a base to categorise the risks used by Bua et al. in their paper. The approach by Engle et al. consisted of recognising specific vocabulary for each type of risk. For instance, Bua includes sea levels, ecosystems, and precipitation for physical risks. Meanwhile, transition risks include hydrofluorocarbons (HFC), bioenergy, and greenhouse gases (GHG). In this thesis, GHG is employed as an indicator of transition risk. Notably, different authors have constructed different methods to measure this transition risk. For example, some authors choose emission intensity scaled by either revenues or assets as a correct measure, while others choose the yearly change in total emissions.

2.2 The Fama-MacBeth regression analysis

The Fama-MacBeth regression (Fama & MacBeth, 1973) analysis is an important tool widely used in asset pricing that has contributed to the empirical finance research field. This procedure was developed and tested by Fama and MacBeth in their seminal paper. The Fama-MacBeth regression offers insights and improves the comprehension of the relationship between a factor of interest and asset returns while accounting for time and unique asset characteristics. This procedure consists of a two-step regression analysis. The first step consists of regressing all assets against a risk factor (i.e., size, value, macroeconomic variables) in time series data, yielding the respective exposure to a specific risk factor (Louraoui, 2022). The formula is simplified by Louraoui and expressed by Formula 1:

$$R_{i,t} = \alpha_i + \beta_i F_t + \varepsilon_{i,t} \; for \; t = 1, T \quad (1)$$

Where: $R_{i,t}$ denotes the return on asset *i* at time *t*. *F* denotes the risk factor. The period ranges from [*0*, *T*]. $\varepsilon_{i,t}$ denotes the error term. The model calculates the asset-specific coefficients for α_i, β_i.

The second step consists of a cross-sectional analysis of returns on a specific data point in time by their respective estimated betas in the previous step. This is explained by Louraoui (2022), and expressed by Formula 2:

$$R_{i,t} = \gamma_{t,0} + \gamma_{t,1}\hat{\beta}_i + \varepsilon_{i,t} \; for \; t = 1, T \quad (2)$$

Where: $\hat{\beta}_i$ denotes the estimated betas in the previous step. γ denotes the coefficients that will be used to calculate the respective risk premium. The rest of the terms are the same as in equation number 1 above. Then, the calculated coefficients are averaged out to derive the risk premium over the period for a unit exposure to each risk factor.

As stated by Louraoui (2022), this approach overcame the conditional heteroskedasticity of the beta computation of individual stocks and the stability of beta. The Fama-MacBeth regression is used to determine the risk premium associated with exposure to the chosen risk factors, offering great insights. Furthermore, Louraoui argues that the coefficients estimated in the time series regression step are sensitive to the market index chosen for the research, recognising it as a shortcoming.

2.3 Asset pricing theories

The Capital Asset Pricing Model (CAPM) was primarily developed by Sharpe (1964) and Lintner (1965) within the framework of the Modern Portfolio Theory introduced by Markowitz (1952). The CAPM suggests a linear relationship between the expected return of an asset or portfolio and its systematic risk, represented by Beta (β). According to the CAPM, firm-specific risk (idiosyncratic risk) is not priced because it can be diversified through portfolio construction. However, systematic risk cannot be eliminated through diversification, hence priced in the financial markets. The model is constructed based on the assumptions of efficient financial markets, characterised by investors having full access to all available information, no transaction costs, the absence of taxes, unrestricted trading, all investors being price takers, and the existence of a market portfolio that contains all assets (Markowitz, 1952). Despite these assumptions may not fully reflect reality, they served to create an initial framework in finance, which ultimately led to the development of other models built on it. Roll (1977) challenges the notion of a market portfolio, arguing it is impossible to capture all the asset classes (i.e., real estate, art pieces) and questions the testability of the model due to its assumptions. The CAPM considers market risk as the only risk factor impacting asset returns, expressed by Formula 3:

$$E[R_i] - R_f = \alpha + \frac{Cov[R_i, R_m]}{Var[R_m]} \times \ [E[R_m] - R_f] \tag{3}$$

Where: $E[R_i]$ is the expected return of an asset i, R_f is the risk-free rate of return, α denotes the constant or alpha, $Cov[R_i, R_m]$ is the covariance between the returns of an asset i and the market portfolio R_m, $Var[R_m]$ is the variance of the market portfolio, and the $[E[R_m]$ is the expected return of the market portfolio. Some of these terms can be further simplified by substituting $\frac{Cov[R_i, R_m]}{Var[R_m]}$ with just the beta (β). Beta denotes the asset's sensitivity to changes in market returns. The CAPM assumes only the market risk factor is priced in the financial markets, which was later proved not to be entirely true by empirical evidence. Fama and French (1993) conducted research on the cross-section of returns and found that there were significant risk factors that helped explain more variation in the empirical data in addition to the market factor from the CAPM.

The Fama-French three-factor model introduced in the seminal paper by Fama and French (1993) expands the CAPM by adding two risk factors. The added two factors are size (SMB) and value (HML), which aim to expand the explanation of variation in returns in addition to the traditional market risk factor. The work by Fama and French (1993) assumes that market efficiency exists and holds, but argues that the market factor does not explain all sources of risk. Fama and French justify the inclusion of these factors by demonstrating the outperformance of small capitalisation stocks compared to large capitalisation stocks and the outperformance of value stocks compared to growth stocks (the difference of returns between the portfolios of high-book-to-market stocks and low-book-to-market stocks). The model proved to outperform the traditional CAPM by explaining returns better using size and value factors. The more recent work by Fama and French (2015) led to the introduction of the profitability (RMW) and investment (CMA) factors into their 1993 model. This addition aimed to develop a more complete asset pricing model that properly captures the empirical returns in financial markets. These two additional factors significantly added to the asset pricing research field. The initial model is improved by accounting for the evidence that firms with higher profitability tend to yield higher returns and that firms with a conservative investment policy tend to yield higher returns compared to firms with aggressive investment policies. In sum, the model accounts for the market return from the traditional market factor, the size factor (small-minus-big, SMB), the value factor (high- minus-low, HML), the profitability factor (robust-minus-weak, RMW), and the investment factor (conservative-minus-aggressive, CMA). The Fama-French five-factor model is expressed by Formula 4:

$$E[R_i] - R_f = \alpha + \beta_{iMkt} \times \left[E[R_m] - R_f\right] + \beta_{iSMB} \times SMB + \beta_{iHML} \times HML + \beta_{iRMW} \times RMW + \beta_{iCMA} \times CMA \quad (4)$$

Where: β_{iMkt}, β_{iSMB}, β_{iHML}, β_{iRMW}, β_{iCMA}, represent the sensitivity of a stock *i* to each factor, SMB, HML, RMW, CMA, and represent the respective risk premiums. Despite its improved performance over the Fama-French three-factor model (1993), there is a limitation that the authors recognise in their work. The limitation is that the model fails to capture the low mean returns of small stocks that behave like firms that invest excessively given their low profitability.

2.4 Empirical evidence of the non-existence of a carbon premium

Li and Zheng (2024) investigated the underperformance of high-emission firms compared to low-emission U.S. firms over the period of 2002-2021. For this, the authors employed machine learning techniques, specifically XGBoost. During the period before the Paris Agreement, they found an insignificant risk premium, whereas in the post-Paris Agreement period, they found a significant negative risk premium. Their findings contradict important researchers in the field, such as Bolton and Kacperczyk (2021, 2023). Li and Zheng addressed the problem derived from vendor-estimated emissions data, which was a problem initially highlighted by Aswani et al. (2024). This problem states that 70% of standard U.S. emissions data is vendor-estimated rather than firms voluntarily disclosing their emissions.

Aswani et al. have found empirical evidence of systematic differences between estimated data and disclosed emissions data. To address this, Li and Zheng constructed an estimate of carbon emissions using machine learning, employing the Trucost dataset to compare it to the final data sample. They found the datasets to be comparable, especially after 2016. The authors later conducted a pooled OLS regression model, as in Bolton and Kacperczyk (2021). The authors controlled for several factors, including the CAPM, the Fama-French five-factor model, betting-against-beta (BAB), and a liquidity factor (Pástor & Stambaugh, 2003).

Recent research conducted by Wang (2024) provides results that hold for firm-level and portfolio-level, demonstrating that green portfolios (portfolios with lower carbon emissions) consistently outperform brown portfolios (portfolios with higher carbon emissions) over the period 2002-2021 in an American context. The research by Wang accounts for different GHG emission data retrieved from the Trucost database. The author retrieves stock data from CRSP/Compustat. Wang constructed quintile portfolios for every industry based on carbon emissions to then create value-weighted portfolios within each industry. The results suggest that the green portfolio outperforms the brown portfolio by 1.45% monthly. Additionally, the GMB (green-minus-brown) portfolio constructed by taking long positions in green firms and short positions in brown firms (based on emissions) yields a significant positive monthly alpha of 1%. This alpha is unexplained by the most prevalent factors in asset pricing, such as market factor, size, value, and profitability. Wang emphasises that assessing the relationship between firm-level sustainability is equally as effective as ESG scores. An important finding from his research suggests that emission intensity does not yield significant results, which differs from Enders et al. (2023). Wang claims that the findings are a direct contradiction to classic asset pricing theory but demonstrate how expectations and beliefs about the risk-return relationship might shift due to unexpected climate change concerns and increasing awareness. This awareness may shift preferences in financial markets, driven by hedging motivation and compliance with green investing mandates, resulting in a high demand for green assets.

In a European context, Santi and Moretti (2021) employed a questionnaire to collect the level of concern among investors regarding climate risk and create a proxy to measure concern. They supplemented their analysis with regression techniques, controlling for different country-specific and firm characteristics while focusing on both clean and emission stocks. Their findings suggest the existence of a positive premium when investors are concerned about climate risk; however, the stocks fail to deliver higher returns when investors ignore this risk, indicating potential mispricing. Similarly, Enders et al. (2023) investigated the existence of a carbon premium in the U.S. and Europe employing emission intensity data. They extracted firm-level data and carbon emission data (scopes 1 and 2) from Refinitiv over the period 2009-2019. The authors constructed a carbon premium portfolio by taking a long position in high-intensity portfolios (brown) and a short position in low-intensity portfolios (green), constructing a BWG (brown-minus-green) factor in a multi-factor model. This model controlled for the Fama-French five-factor model (Fama & French, 2015) and the Carhart momentum model introduced by Carhart (1997). The findings suggest that there is a significantly negative carbon premium, implying that green stocks outperformed brown stocks in the particular period. The authors argue that this is likely to be the result of institutional investors choosing to decarbonise their portfolios to mitigate carbon risk exposure. However, they expect this decarbonisation process to end, which will lead to an observable brown premium in the future.

2.5 Empirical evidence of the existence of a carbon premium

Research from Bolton and Kacperczyk (2021) investigated the effect of carbon emissions on the cross-section of U.S. stocks, employing the Trucost and FactSet databases over the period 2005-2017. Their study reveals a significant carbon premium after controlling for risk factors, including CAPM, size, value, momentum, investment, betting-against-beta, liquidity, net issuance, and idiosyncratic volatility. The authors link the premium to various emission metrics, such as total emissions and annual emission changes, while finding no association with emission intensity (scaled by unit of sales). In a subsequent paper, Bolton and Kacperczyk (2023) extend their work to an international context by employing the Trucost and MSCI databases for the period 2005-2018. The authors identified a positive carbon premium related to direct and indirect emissions, as well as to the annual change in emissions across countries and industries. This premium exists in Asia, North America, and Europe, including all industries. Particularly, the study argues that countries with lower economic development, larger energy sectors, and less inclusive political systems exhibit a higher premium, as do countries with stricter climate policies. Besides, Bolton and Kacperczyk (2023) suggest that the carbon premium can vary in magnitude across industries. This is a finding that needs to be considered in the following research, as it is logical that more carbon-intensive industries will have higher premiums compared to firms that are not.

Bua et al. (2024) conducted research on climate risk, focusing on both physical risk and transition risks within the Euro Market. The authors retrieved data from Datastream for prices on the Eurostoxx 600 index and GHG emission level data from the Refinitiv database over the period 2005-2021. Bua et al. constructed a transition risk indicator to evaluate the relationship between stock returns and climate risk. Next, they followed a standard portfolio approach, sorting stocks by low transition risk against high transition risk, and found a higher required return for stocks that provided a bad hedge for climate risk. The results suggest that the climate risk premium has increased for both transition risk and physical risk since the Paris Agreement in 2015. In sum, the long-short transition risk portfolios generated an abnormal return of -3.01% before 2015 and a positive premium of 7.05% after 2015.

Hsu et al. (2023) investigated the existence of a pollution premium and its relation to stock returns. They accounted for a firm´s toxic releases by constructing a measure of the emission intensity of pollutants at a firm-level in the U.S. employing the TRI and CRSP databases over the period 1991-2016. The authors calculate different measures of emission intensity, scaling them by total assets, sales, property plant and equipment, and market equity. Their analysis included a Fama-MacBeth regression, controlling for several factors, including size, book-to-market, investment rate, return on equity, tangibility, leverage, WW index, and industry fixed effects. The authors decided to control for these firm characteristics because they can serve as an explanation for cross-section variation in the emission portfolio's returns. The explanations they provide are due to systematic risks, investor preferences, underreaction, governance, and political connection. The Fama-MacBeth regression found a statistically significant positive relationship between emission intensity and stock returns. Furthermore, their research revealed a pollution premium on the cross-section of stock returns, unexplained by other risk factors (traditional CAPM, the Fama-French five-factor model, and the HXZ q-factor model) when building a long-short portfolio based on emission intensity. The authors attribute this premium to behavioural explanations, corporate policies, and other risks.

Aligned with previous research, Huij et al. (2021) identified a small but significant positive carbon risk premium of 1.15% annually for each standard deviation increase in carbon beta. The authors used a self-financing long-short portfolio strategy, consisting of a long position in the top 30% of stocks with the highest carbon emissions and a short position in the bottom 30% of stocks with the lowest emissions. This strategy controls for CAPM, the Fama-French three-factor model, and the Carhart momentum model. According to the authors, an important strength of this research paper is the inclusion of a rich cross-sectional dataset. Also, they added an index construction approach following Engle et al. (2020) to create an index for climate risk news using the Wall Street Journal. They also followed the approach proposed by Baker et al. (2016) to create an index for economic policy uncertainty. The employed dataset is based on the Trucost database for GHG emission data and the WRDS database for stock-level data. The authors sum the scope 1 and 2 emissions data and denote them as firm total emissions while calculating emission intensity by dividing emissions by revenues in U.S. dollars.

3 Hypothesis Development

As previously mentioned, the Fama-MacBeth regression is a tool that offers additional insights and improves the comprehension of the relationship between a factor of interest and the asset returns by accounting for time and unique asset characteristics. In this thesis, I am interested in the relationship between emission intensity (scaled by revenues) and stock returns. For example, Hsu et al. (2023) found a significant positive relationship between emission intensity and stock returns. Despite the ongoing debate, I expect a positive and significant relationship to persist despite the period differences with other authors due to the presence of transition risk. Consequently, the first hypothesis arises:

> $\mathbf{H_0}$: *There is no significant relationship between emission intensity (carbon risk) and stock returns in the U.S. over the period 2010-2023.*
>
> $\mathbf{H_1}$: *There is a positive and significant relationship between emission intensity (carbon risk) and stock returns in the U.S. over the period 2010-2023.*

Fundamental models estimate an asset's price based on highly dependent assumptions, which can potentially lead to mispricing. In contrast, arbitrage models compare asset prices across asset classes; however, they fail to be reliable in cases of global mispricing (Venturini, 2022). Therefore, Venturini concludes that the best models to assess and investigate further climate risk are fundamental models because they are based on estimated future flows and risks, which can integrate projected values under different climate scenarios. Also, it is popular that researchers employ fundamental models such as the CAPM and the Fama-French five-factor model, considered ideal for conducting research. Studies conducted by Hsu et al. (2023), Bolton and Kacperczyk (2021, 2023), and Bua et al. (2024) has found a significant risk premium associated with a transition risk derived from carbon or an emission intensity factor. These findings are supported by a theoretical framework and are a rational outcome if we account for asset pricing theories and risk exposure. Consequently, the second hypothesis arises:

> $\mathbf{H_0}$: *A long-short portfolio with high (low) emission intensity will not yield significant abnormal returns on the cross-section of stock returns in the U.S. over the period 2010-2023 after controlling for the Fama-French five-factor model.*
>
> $\mathbf{H_2}$: *A long-short portfolio with high (low) emission intensity will yield positive and significant abnormal returns on the cross-section of stock returns in the U.S. over the period 2010-2023 after controlling for the Fama-French five-factor model.*

The Fama-French model acts as a control variable, accounting for the risk factors in the regressions. The variable emission intensity serves as an independent variable when conducting the Fama-MacBeth test. I expect the Fama-MacBeth test to reveal a positive and significant relationship between the variable emission intensity and stock returns ($\mathbf{H_1}$).

Lastly, when building quintile portfolios based on emission intensity, there will be a positive premium when constructing the long-short emission intensity portfolio. Furthermore, it will yield abnormal returns after controlling for the Fama-French five-factor model ($\mathbf{H_2}$).

4 Research Design and Data

This chapter presents and describes both the methodology and the data employed to conduct this research. Subsection 4.1 describes the data source, its features, and the methodology followed for each hypothesis. Subsections 4.2, 4.3, and 4.4 describe in detail the dependent, independent, and control variables, respectively.

4.1 Data

The final dataset is the result of merging the retrieved Datastream/LSEG sample and the Kenneth R. French Website Fama-French factors. The studied period covers the period 2010-2023, with a monthly data frequency for both Fama-French factors and firm excess returns. For firm characteristics, I employ a yearly frequency. Returns are calculated using monthly stock prices retrieved from the Datastream/LSEG database. The studied period is motivated by the presence of both the period pre-Paris Agreement as well as the period after, plus extending the studied period to the year 2023 compared to previous studies. Earlier years are not considered due to limited data completeness; this is explained in the limitation section in Chapter 7.

The final dataset has a panel data structure and contains 77,532 observations, 49 distinct industries, and a sample of 497 companies after conducting data cleaning. I included all American companies with a valuation greater than ten million USD. For fundamental data, I employed Datastream/LSEG to retrieve firm-level data from U.S. public companies from all sectors, excluding the financial sector. Additionally, I retrieved the monthly Fama-French five-factor data (SMB, HML, RMW, CMA, market factor (MKT), and risk-free rate (RF)) for the U.S. from the Kenneth R. French website. All the results of this thesis are calculated employing the statistical software STATA.

The final dataset is checked for outliers using the three-standard deviation rule. After identifying outliers, I removed them to enhance the accuracy and reliability of the model's results. I follow the methodology proposed by Hsu et al. (2023), where the independent and control variables are standardised for interpretation purposes and all independent and control variables are transformed into a logarithmic form, except for ROE, which is only standardised. The control variables are inspired by the research from Hsu et al, as their explanations for including that set of controls seem value-adding. However, I decided to exclude some control variables presented in the work by Hsu et al. for simplicity purposes and because of limited data availability in the Datastream/LSEG database. Furthermore, the final dataset is checked for multicollinearity while autocorrelation of returns, non-normality of data, and the presence of heteroskedasticity are assumed. The results of these tests are discussed thoroughly in the preliminary test subsection 5.2 in Section 5. The Fama-French coefficients are employed in their original form. Further details on the variables are discussed in the next subsection. It is necessary to mention that the emission intensity variable is calculated following the suggested methodology by Enders et al. (2023). Notably, my methodology is primarily based on the work by Hsu et al. (2023).

The methodology to test **H1** consists of several Fama-MacBeth regressions including different controls. The Fama-MacBeth regressions have the variable excess return as a dependent variable, emission intensity as an independent, and the rest of the variables as control variables. The first regression only includes the independent variable emission intensity, while the second regression incorporates industry fixed effects to the model. The corresponding industries are included as dummy variables to account for industry fixed effects on the Fama-MacBeth regression. The third regression includes emission intensity, controlling for industry fixed effects, and the CAPM. The fourth regression includes the independent variable controlling for the Fama-French three-factor model and industry fixed effects. The fifth regression controls for the Fama-French five-factor model and industry fixed effects. The last regression includes all control variables as well as firm characteristics. The Fama-MacBeth regressions are corrected by two lags using the Newey and West (1987) robustness of standard errors approach by adjusting the number of lags expressed by Formula 5:

$$n = FLOOR[4(T/100)^{\frac{2}{9}}] \tag{5}$$

The methodology to test **H2** consists of assigning stocks into quintile portfolios based on emission intensity within the same industry for each year to separate high emitters from low emitters. Portfolio rebalancing occurs at a yearly frequency. After assigning stocks into quintiles, I calculate the value-weighted return for each quintile over the period 2010-2023. In addition to the five portfolios, I construct a long-short portfolio consisting of subtracting the excess returns of every year from the low-emitter portfolio from the high-emitter one. The univariate portfolio sorting accounts for the average return of each quintile over the whole period, serving for further analysis. The asset pricing factor tests are achieved by performing a time series regression of each quintile's monthly excess returns over the period 2010-2023 against the monthly CAPM, and Fama-French three- and five-factor coefficients employing a Newey-West correction with four lags (as proposed by Formula 5). This approach aims to assess to what extent the excess returns of the portfolios are explained by traditional risk factors or if there are abnormal returns that can be recognised as a carbon premium in the long-short portfolio.

4.2 Dependent Variable

Excess return: this variable is constructed by first calculating the returns from the adjusted closing price of the stock data retrieved from Datastream/LSEG to later subtract the risk-free rate provided by the Kenneth R. French website.

4.3 Independent Variable

Emission Intensity: this variable is constructed employing the *Estimated CO2 Equivalents Emission Total* (the estimate of total CO2 and equivalents in tonnes) and dividing it by revenues. This emission-to-total revenue ratio variable is proposed by Enders et al. (2023). The method to calculate the estimated CO2 equivalents emission total is composed of four models, each giving one value. The models are based on: reported emissions, CO2 model, energy model, and a median model. Both revenues and estimated emissions are retrieved from the Datastream/LSEG database.

4.4 Control Variables

Market Capitalisation (MV): this variable measures the market capitalization of a stock, calculated as the stock price multiplied by the number of shares. This variable is retrieved from the Datastream/LSEG database.

Revenues from Business Activities (REVENUES): this variable measures the total consolidated revenues of a firm. This variable is retrieved from the Datastream/LSEG database.

Book-to-Market (BM): this variable is calculated as total book capital divided by the market capitalisation. This variable is retrieved from the Datastream/LSEG database.

Return on equity (ROE): this variable is calculated as EBIT divided by total assets. This variable is retrieved from the Datastream/LSEG database.

TRBC Industry Group Name (INDUSTRY): this variable classifies companies into 61 industry groups according to the reference data business classification operated by Datastream/LSEG. This variable is retrieved from the Datastream/LSEG database.

MKT, *RF*, *SMB*, *HML*, *RMW*, and *CMA:* These control variables account for the coefficients of the Fama-French five-factor model for developed economies. *MKT* represents the market premium; *SMB*, HML, RMW, and CMA represent the size, value, profitability, and investment risk factors, respectively. The variables are all retrieved from the Kenneth R. French website.

Table 1. **Variables employed for all the regression analyses.**

	Variable	**Acronym**	**Definition**
Dependent variable	Excess Return	Excess Return	Returns – risk-free rate
Independent variable	Emission Intensity	Emission Int	Estimated CO2 equivalents emission total/ Revenues from business activities
Control variables	Market Capitalisation	MV	Market value of a firm
	Book-to-Market ratio	BM	Total book capital/ Market capitalisation
	Return on Equity	ROE	EBIT/ Total assets
	Industry Group Name	INDUSTRY	Dummy variable of each industry given TRBC
	Market Risk Factor	MKT	Market risk premium
	Size Risk Factor	SMB	Small-minus-Big
	Value Risk Factor	HML	High-minus-Low
	Investment Risk Factor	CMA	Conservative-minus-Aggressive
	Profitability Risk Factor	RMW	Robust-minus-Weak

Note: All control variables and the independent variable are standardised and employed in their logarithmic transformation, except ROE, which is only standardised. The Fama-French factors are used in their original form.

5 Results

This chapter presents the results obtained from the regressions and tests. Subsection 5.1 presents the descriptive statistics from the data and discusses its main characteristics. Subsection 5.2 discusses the preliminary tests to ensure the validity of the methodology and the correlation matrices between the relevant variables. Subsection 5.3 presents the regression results from the Fama-MacBeth analysis. Subsection 5.4 discusses the portfolio returns from the univariate portfolio sorting strategy. At last, subsection 5.5 presents and discusses the asset pricing test results for the portfolios.

5.1 Descriptive statistics

Table 2 exhibits the descriptive statistics of the entire sample. The final sample after data cleaning consists of 497 distinct American companies and 49 industries for the period 2010-2023. The sample only contains 49 distinct industries while the TRBC Industry Group Name classifies companies into a total of 61 industries. This means that the sample exhibits a lower number of represented industries, which can lead to a generalisation of the results.

Table 2. Descriptive statistics of the companies included in the sample.

Identifier	**Count**
TRBC Industry Group Name	49
Company	497

Note: The abbreviation TRBC refers to the reference data business classification from Datastream/LSEG.

Table 3 exhibits the descriptive statistics of the variables employed to conduct the tests. The mean excess return of the firms included in the sample is 1.06% and displays a standard deviation of around 11.24%, providing evidence of the variation of stock returns throughout the sample. The emission intensity ratio has a mean close to zero and a maximum emission intensity of 0.06. It is expected that emission intensity will be a small number because it is a scaled variable. Additionally, the range of emission intensity companies reveals that there are high emitters and low emitters present in the sample. The sample includes all types of companies, for instance, growth/value, small/big, and profitable/unprofitable companies, as revealed by the wide range of values regarding market capitalisation, book-to-market, and return on equity. The descriptive statistics are displayed for untransformed variables; however, transformed variables are used in the statistical tests.

Table 3. Descriptive Statistics of variables used in regressions.

Variable	N	Mean	Std. Dev.	Min	Max
Excess Return	77532	1.06	11.24	-55.31	56.65
Emission Intensity	6461	0.0005	0.0011	0	0.0643
MV	6461	37.5B	124B	0.04B	2,990B
BM	6461	1.25	6.48	.00	251.45
ROE	6461	.10	.079	-0.61	1.522
MKT	77532	1.02	4.34	-13.39	13.65
SMB	77532	-0.09	2.66	-8.28	7.33
HML	77532	-0.09	3.34	-13.87	12.75
CMA	77532	0.03	2.15	-7.22	7.73
RMW	77532	0.31	2.02	-4.75	7.20

Note: BM, ROE, and emission intensity are variables expressed as a ratio. The excess return is expressed as a percentage. Market capitalisation (MV) is expressed in billions of U.S. dollars.

5.2 Preliminary Tests

To provide reliable and valid results for the regression analyses, it is necessary not to violate its underlying assumptions. Thus, it is indispensable to account for autocorrelation, heteroskedasticity, and normality in the data, as it is assumed to present these features. I conduct test for correlation and multicollinearity in my models. The results of the preliminary tests are shown in Appendix A.

The first test that is conducted is for multicollinearity in the model. Therefore, I calculate the variance inflation factor (VIF) and find no problematic presence of multicollinearity. Results are exhibited in Table A1 in Appendix A.

After identifying the potential problems with the sample, it is essential to mitigate them with data manipulation techniques. Autocorrelation and heteroskedasticity will be tackled by employing robust standard errors, specifically Newey-West corrected standard errors, which help mitigate both problems. For this, I use lags according to the seminal paper of Newey and West (1987). I decided to standardise my variables for easier interpretation following the methodology by Hsu et al. (2023). Lastly, to tackle the normality problem, I decided to use the logarithm of the variables to mitigate this problem. To further tackle normality problems, I also investigated and eliminated the outliers in the sample according to the three-sigma rule, which states that 99.7% of all observations lie within three standard deviations away from the mean. The observations (companies) classified as outliers are eliminated to improve normality and have more reliable results.

At last, I further investigate the employed variables and construct two correlation matrices to add information on the relationship between them. The first correlation matrix is constructed considering variables with a monthly frequency. The first correlation matrix is exhibited in Table A2 in Appendix A. The variable excess return exhibits a weak positive correlation of 0.43 with the market factor and a very weak correlation with the remaining risk factors. These observations suggest that the excess returns in the sample are weakly positively correlated with the market factor, aligning with the CAPM theory. The size factor (SMB) exhibits a weak positive correlation with the market factor of 0.35 and a weak negative correlation of -0.43 with the profitability factor (RMW). A possible explanation for this negative correlation might be due to small stocks having lower profitability compared to firms with higher market capitalization, partially explaining the correlation. Notably, the value risk factor (HML) and the investment risk factor (CMA) exhibit a moderately positive correlation of 0.65, suggesting that these two factors tend to perform similarly under the same conditions. A possible explanation might be that value stocks do not grow as quickly as growth stocks, therefore, having more conservative investment policies. On the contrary, growth stocks pursue rapid expansion and thus require aggressive investment policies.

The second correlation matrix is constructed considering the variables with yearly frequency. The second correlation matrix is exhibited in Table A3 in Appendix A. For this, I manipulated the dependent variable by taking its mean monthly returns to be comparable to the set of control variables. The variable excess return exhibits a weak correlation with the control variables. This fact can be seen as an indication of a poor selection of control variables, as conducted in Hsu et al. (2023). This poor correlation can be due to the sample and frequency of data. Moreover, the control variables MV and BM exhibit a strong positive correlation between them. This observation can have implications for the regression analysis; however, the VIF exhibits nonproblematic multicollinearity. These high correlations may indicate the presence of a similar driver, such as the size of a firm, which ultimately can impact the two variables.

5.3 The Fama-MacBeth regressions

To test the first hypothesis, I conduct six different Fama-MacBeth regressions to check the robustness of the regressions. All regressions consider excess returns as a dependent variable. The regression results are exhibited in Table 4.

Hsu et al. (2023) conducted the Fama-MacBeth regression just considering firm characteristics and controlling for industry fixed effects. Therefore, I replicate their approach while also including the five-factor Fama-French as an additional to the firm characteristics. Adding extra relevant control variables allows me to ensure the relationship is not explained by other risk factors.

Model 1 only considers emission intensity as the independent variable, excluding industry fixed effects. The results exhibit a significant positive coefficient of 0.51 at the 1% level. However, Model 1 and 2 exhibit a very low R^2_{adj}. Model 2 replicates the first regression but adds industry fixed effects to ensure the relationship is not driven by industry differences. The results show that the significance of emission intensity is not driven by industry differences, as the coefficient remains positive and significant with a coefficient of 0.58 at the 1% level. To further investigate the significance of this relationship, it is necessary to include controlling variables.

Model 3 controls for the CAPM and industry fixed effects. The regression exhibits an R^2_{adj} of 0.21 indicating the high explanatory power of the market factor in the Fama-MacBeth regression. As expected, emission intensity remains significant at the 1% level with a coefficient of 0.44. Furthermore, the market factor exhibits a significant and positive coefficient of 1.09 at the 1% level.

Model 4 controls for the Fama-French three-factor coefficients and industry fixed effects. The results remain consistent, as emission intensity exhibits a significant positive coefficient of 0.38 at the 5% level. In addition, the market and size factors exhibit significant positive coefficients of 1.07 and 0.25 at the 1% level, respectively. The results suggest that the value risk factor does not significantly explain the stock return data in this sample, as it remains insignificant throughout the rest of the Fama-MacBeth regressions. The model's fit slightly improves, indicated by the higher R^2_{adj}.

Model 5 controls for the Fama-French five-factor coefficients and industry fixed effects. The emission intensity factor remains positive and significant, with a coefficient of 0.38 at the 5% level. The market factor remains positive and significant, with a coefficient of 1.09 at the 1% level. Consistent with the previous regression, the size factor remains positive and significant, with a coefficient of 0.21 at the 10% level. However, the investment and profitability factors exhibit insignificant coefficients, indicating their limited explanatory power. The explanatory power increased, as indicated by the slight improvement of the R^2_{adj} to 0.22.

Model 6 controls for the Fama-French five-factor coefficients, industry fixed effects, and firm characteristics. The emission intensity factor remains positive and significant, with a coefficient of 0.51 at the 10% level. The market factor remains positive and significant, with a coefficient of 1.09 at the 1% level. Notably, the significance of the size factor disappears when introducing firm characteristics. The firm characteristics exhibit insignificant coefficients, except for ROE, which shows a positive and significant coefficient of 0.15 at the 10% level. At last, the R^2_{adj} remains the same at 0.22 as in Model 5.

The Fama-MacBeth regressions suggest that one standard deviation increase in the logarithmic emission intensity variable will increase excess returns by 0.38 percentage points and Model 5 or 0.51 percentage points for Model 6. Results show that emission intensity positively predicts future stock returns considering the results of the Fama-MacBeth regressions, as the significance of the coefficients remain throughout the six models. Overall, the regression results suggest that there is a positive relationship between emission intensity and a stock's excess return. Plus, emission intensity has its own predictive power, as its significance does not disappear when adding relevant control variables.

Table 4. Fama-MacBeth regression analyses.

Variable	Model (1)	(2)	(3)	(4)	(5)	(6)
α	1.18***	1.53***	0.29	0.35	0.28	0.23
[t]	(6.23)	(4.9307)	(0.83)	(1.33)	(1.23)	(0.94)
Emission Int	0.51***	0.58***	0.44***	0.38**	0.38**	0.51*
[t]	(4.89)	(5.44)	(3.45)	(3.22)	(2.92)	(3.98)
MKT			1.09***	1.07***	1.09***	1.09***
[t]			(62.19)	(76.76)	(24.53)	(24.46)
SMB				0.25***	0.21*	0.21
[t]				(5.12)	(2.27)	(2.26)
HML				0.09	-0.06	-0.06
[t]				(1.16)	(-0.83)	(-0.82)
RMW					-0.07	-0.07
[t]					(-0.45)	(-0.45)
CMA					0.22	0.22
[t]					(1.36)	(1.36)
ROE						0.15*
[t]						(4.12)
BM						-0.36
[t]						(-2.42)
MV						-0.13
[t]						(-0.33)
IND. FIXED EFFECTS	NO	YES	YES	YES	YES	YES
R^2	0.00	0.00	0.21	0.21	0.22	0.22
R^2_{adj}	0.00	-0.00	0.21	0.21	0.22	0.22
N	77532	77532	77532	77532	77532	77532

*Note: t-statistics are based on standard errors employing a Newey-West (1987) correction with two lags, these are exhibited in parentheses; *p<0.10 **p<0.05 ***p<0.01*

5.4 Univariate Portfolio Sorting

The univariate portfolio sorting aims to further investigate the relationship between emission intensity and excess returns in a cross-section setting. The portfolios are first sorted by emission intensity, assigning stocks into quintile portfolios based on emission intensity within the same industry for each separate year. Portfolios are value-weighted by each company's market capitalisation. The result is the average yearly excess return of each portfolio, exhibited in Table 5. Results show that the third-highest emitter portfolio exhibits the highest returns amongst the quintile portfolios, with a return of 14.22%, followed by the fourth-highest emitter portfolio with 13.80%. The lowest-emitter portfolio exhibits a yearly return of 9.35%. The highest-emitter portfolio exhibits a return of 12.76%. Also, the long-short portfolio exhibits yearly positive returns of 3.41%. It appears that the middle portfolios do not present a consistent pattern of increasing excess returns. Overall, Table 5 provides an overview of the average returns when sorting by emission intensity, from which interesting conclusions can be drawn. It appears that high emission quintiles on average exhibit higher excess returns compared to the low emission intensity quintile, consistent with the initial prediction in H2.

Table 5. Univariate Portfolio Sorting based on emission intensity.

	Portfolio					
	L	**2**	**3**	**4**	**H**	**H-L**
Excess Return	9.35%	10.76%	14.22%	13.80%	12.76%	3.41%

This table shows the average excess returns for each quintile portfolio sorted on emission intensity (estimated emissions scaled by revenues) for the period 2010-2023. The excess return is reported over the risk-free rate. The portfolios are rebalanced on a yearly basis. Portfolio returns are value-weighted by the company's market capitalisation. H-L denotes the long-short portfolio.

Table 6 provides additional information on the composition of each quintile portfolio and its characteristics. The lowest quintile exhibits a lower mean emission intensity, and the highest quintile exhibits the highest mean emission intensity. The mean emission intensity steadily increases for every quintile. The lowest-emitter quintile and highest-emitter quintile exhibit a mean emission intensity of 0.000469 and 0.000547, respectively. Additionally, the mean market capitalization does not present a consistent pattern, further proving emission intensity is unrelated to market size. On the other hand, the mean book-to-market and return on equity are similar throughout the quintile portfolios.

Table 6. Descriptive statistics of Quintile Portfolios based on emission intensity.

	Portfolio				
Mean variable	**L**	**2**	**3**	**4**	**H**
Emission Intensity	0.000469	0.000488	0.000497	0.000515	0.000547
MV	30.6B	28.7B	28.2B	28.5B	29.4B
BM	1.33	1.34	1.30	1.30	1.31
ROE	0.08	0.08	0.08	0.08	0.08

Note: Market Capitalisation (MV) is expressed in billions of U.S. dollars. Emission intensity is calculated as estimated CO2 equivalents emission total/ revenues from business activities.

5.5 Asset Pricing Factor Tests

The asset pricing factor test investigate the extent to which the variation in average excess returns of the emission-sorted quintile portfolios is explained by the existing risk factors. The asset pricing models that are considered are the Capital Asset Pricing Model (CAPM) by Sharpe (1964) and Lintner (1965), the Fama-French three-factor model (Fama & French, 1993), and the five-factor model (Fama & French, 2015). The results are exhibited in Table 7. Furthermore, the results are interpreted in order, starting with Panel A. The standard errors of the regressions are adjusted for three lags, according to Newey and West (1987).

Panel A displays the excess returns regressed against the CAPM. The results exhibit a significant negative alpha for the lowest emitter quintile portfolio of -0.48 at the 10% level. The rest of the quintile portfolios do not exhibit significant alphas. Furthermore, the market risk factor exhibits significance in every quintile portfolio at the 1% level. Next, the long-short portfolio exhibits a positive and significant alpha of 0.44 at the 5% level. This result is interpreted as an abnormal monthly return of 0.44%. The abnormal returns are not explained by the CAPM. Thus, these returns can prove an existing and positive carbon premium.

Panel B displays the excess returns regressed against the Fama-French three-factor model. The regression does not exhibit significant alphas in either of the quintile portfolios, indicating that the underperformance or outperformance of the quintile portfolios is explained by the three risk factors. This explanation is supported by the high significance of the size (SMB) and value (HML) risk factors in the quintile portfolios. Furthermore, the long-short portfolio still exhibits a positive and significant alpha of 0.37 at the 10% level. Evidently, the abnormal returns have decreased in magnitude compared to the alpha exhibited in Panel A, decreasing from an abnormal monthly return of 0.44% to 0.37%. The abnormal returns remain unexplained by the Fama-French three-factor model. Thus, these returns can prove an existing positive carbon premium.

Panel C displays the excess returns regressed against the Fama-French five-factor model. The regression exhibits no significant alphas for any of the quintile portfolios. This means that the Fama-French five-factor model explains returns in the portfolios. However, the profitability and investment factors do not present a consistent pattern in terms of significance in the quintile portfolios. The market risk factor and the size factor remain highly significant in all quintile portfolios, confirming their high explanatory power. The profitability risk factor (RMW) is significant only in quintile 4 at the 5% level. On the contrary, the investment risk factor exhibits significance in the lowest emitter, highest emitter, and third-highest emitter portfolios. More importantly, the long-short portfolio no longer exhibits a significant positive alpha, meaning that adding investment and profitability factors explain the alphas. Despite this, the t-statistic of 1.61 implies a p-value of 0.11, which is very close to being significant at the 10% level.

Table 7. Asset Pricing Factor Tests.

Panel A: CAPM

	L	**2**	**3**	**4**	**H**	**H-L**
α_{CAPM}	-0.48*	-0.17	-0.05	-0.35	-0.04	0.44**
$[t]$	(-1.78)	(-0.78)	(-0.22)	(-0.55)	(-0.16)	(1.78)
MKT	1.21***	1.07***	1.14***	1.48***	1.13***	-0.08
$[t]$	(14.65)	(21.73)	(24.14)	(5.09)	(17.04)	(-1.22)
R^2	0.74	0.81	0.84	0.58	0.80	0.01
R^2_{adj}	0.73	0.81	0.84	0.57	0.80	0.00
N	156	156	156	156	156	156

Panel B: FF3

	L	**2**	**3**	**4**	**H**	**H-L**
α_{FF3}	-0.31	-0.07	0.07	-0.13	0.06	0.37*
$[t]$	(-1.47)	(-0.34)	(0.42)	(-0.30)	(0.32)	(1.78)
MKT	1.11***	1.01***	1.07***	1.35***	1.07***	-0.03
$[t]$	(18.66)	(24.81)	(32.31)	(6.47)	(20.55)	(-0.51)
SMB	0.43***	0.24***	0.25***	0.44**	0.20***	-0.24**
$[t]$	(3.96)	(4.11)	(5.96)	(2.23)	(2.84)	(-2.17)
HML	0.22***	0.16***	0.28***	0.63**	0.23***	0.01
$[t]$	(3.09)	(2.91)	(6.14)	(2.50)	(4.98)	(0.20)
R^2	0.79	0.84	0.89	0.67	0.84	0.05
R^2_{adj}	0.79	0.83	0.89	0.67	0.83	0.03
N	156	156	156	156	156	156

Panel C: FF5						
	L	**2**	**3**	**4**	**H**	**H-L**
α_{FF5}	-0.30	-0.09	-0.00	-0.25	-0.01	0.30
$[t]$	(-1.57)	(-0.43)	(-0.02)	(-0.63)	(-0.03)	(1.61)
MKT	1.14***	1.02***	1.09***	1.29***	1.10***	-0.04
$[t]$	(17.92)	(25.50)	(29.97)	(8.14)	(20.69)	(-0.54)
SMB	0.38***	0.25***	0.33***	0.69***	0.25***	-0.12
$[t]$	(3.50)	(3.49)	(6.77)	(3.13)	(3.26)	(-1.06)
HML	0.13	0.01	0.14**	0.68	0.07	-0.06
$[t]$	(1.18)	(1.44)	(2.14)	(1.64)	(0.84)	(-0.65)
RMW	-0.20	-0.01	0.11	0.70**	0.06	0.26
$[t]$	(-0.85)	(-0.06)	(1.28)	(2.16)	(0.65)	(1.07)
CMA	0.27**	0.14	0.28***	-0.34	0.34**	0.07
$[t]$	(2.05)	(1.49)	(3.02)	(-0.61)	(2.56)	(0.61)
R^2	0.80	0.84	0.90	0.70	0.85	0.07
R^2_{adj}	0.79	0.83	0.90	0.69	0.84	0.04
N	156	156	156	156	156	156

*Note: t-statistics are based on standard errors employing a Newey-West (1987) correction with four lags, these are exhibited in parentheses; This table shows the asset pricing tests for each quintile portfolio sorted on emission intensity (estimated emissions scaled by revenues) and the long-short portfolio for the period 2010-2023. The results are exhibited at a monthly frequency. Each quintile portfolio's monthly excess returns are regressed in a time series against the CAPM in Panel A, the Fama-French three-factor model in Panel B, and the Fama-French five-factor model in Panel C. *p<0.10 **p<0.05 ***p<0.01*

There are additional interesting conclusions to be drawn from these tests. The market risk factor remains significant at the 1% level for all quintile portfolios. However, the coefficients for the market factor do not exhibit a clear pattern, as the values vary from portfolio to portfolio but all have values above one. Notably, in Panel C, the lowest- and highest-emitter quintiles exhibit a similar market risk factor with 1.14 and 1.10, respectively. Similarly, the size risk factor remains significant at the 1% level for all quintile portfolios. The size factor coefficients in Panel C for the lowest-emitter and highest-emitter quintiles are 0.38 and 0.25, respectively. This difference suggests that the lowest quintile has more exposure to the size factor compared to the highest quintile, indicating a higher weight on small stocks. Another interesting conclusion is the investment risk factor coefficient differences between the lowest and highest quintiles, exhibiting coefficients of 0.27 and 0.34, respectively, as displayed in Panel C. This difference suggests that the highest quintile portfolio is more exposed to the investment risk factor compared to the lowest quintile, indicating a higher weight on more conservative stocks.

At last, it is clear that the third quintile portfolio returns are best explained by the Fama-French five-factor model, attaining an R_{adj}^2 of 0.90. Meanwhile, the fourth quintile portfolio returns are the least explained by the model, with an R_{adj}^2 of 0.69. Notably, the portfolio returns from the lowest and highest quintiles exhibit an R_{adj}^2 of 0.79 and 0.84, respectively when tested against the Fama-French five-factor model. It can be argued, that a considerable part of the variation is explained by the model. This argument can be supported by the slightly increasing explanatory power from the three-factor model to the five-factor model.

6 Discussion

In this section, the main results from the conducted regression analyses are discussed and interpreted according to previous literature on the carbon premium topic. In addition, the hypotheses and their conclusions are stated.

The first hypothesis states there is no significant relationship between emission intensity (carbon risk) and stock returns in the U.S. over the period 2010-2023. However, the results in Table 4 show that emission intensity positively predicts future stock returns considering each Fama-MacBeth regression, as the significance of the coefficient remains throughout the six models. Overall, the regression results suggest that the positive relationship between emission intensity and a stock's excess return has its own predictive power, as its significance cannot be explained by the rest of the variables. These results suggest that firms with higher emission intensity exhibit higher stock returns throughout the period 2010-2023, accounting for the Fama-French five-factor model. Thus, I reject the null hypothesis. Consequently, the alternative hypothesis, which states there is a significant positive relationship, is supported. The result aligns with the findings from Huij et al. (2021), as emission intensity scaled by revenues is significant in the emission-return relationship. Similarly, the results align with the findings from Hsu et al. (2023), despite the emission intensity being scaled differently. At the same time, this result contradicts the findings from Bolton and Kacperczyk (2021), which link carbon premium to total emissions and annual change in emissions but find no association with emission intensity.

As revealed by Table 4, Model 5 and Model 6 exhibit an emission intensity coefficient of 0.38 and 0.51, respectively. Specifically, the Fama-MacBeth regressions suggest that one standard deviation increase in the logarithmic emission intensity variable will increase excess returns by 0.38 or 0.51 percentage points, depending on the model. The R^2_{adj} remains the same between Models 5 and 6, indicating identical explanatory power. However, accounting for the parsimonious principle and adhering to asset pricing theory and its empirically proven models, then Model 5 is the better model. Nevertheless, since I am replicating the methodology by Hsu et al. (2023), which includes firm characteristics that may drive stock returns in emission portfolio returns, Model 6 is a more complete model for this purpose. This can be further supported by the significance of the term ROE. However, the terms BM, ROE, and MV were significant in the research conducted by Hsu et al., while MV and BM remain insignificant in my results. In sum, the results presented align with the results by Hsu et al., as both models show a significant positive relationship while differing in magnitude.

It is valuable to first discuss the results obtained from the univariate portfolio sorting based on emission intensity before addressing the second hypothesis and its results. The univariate portfolio results in Table 5 show there is a difference between high-emitter and low-emitter portfolio returns. Despite the highest-emitter portfolio not being the quintile portfolio exhibiting the highest returns, it yields a return of 12.76% annually, which is substantially greater than the lowest-emitter portfolio yielding 9.35%. This difference causes the long-short portfolio to have a positive return of 3.41% annually. A positive return is obtained when constructing a long-short position on portfolios, aligning with the findings of Huij et al. (2021), Bua et al. (2024), and Hsu et al. (2023). However, to fully align with these researchers, it is essential to test for its significance. Next, the second hypothesis is discussed to further elaborate on the economic meaning of these portfolio returns and whether they are significant.

The second hypothesis states that the long-short portfolio based on emission intensity will not yield significant abnormal returns on the cross-section of stock returns in the U.S. over the period 2010-2023, after controlling for the Fama-French five-factor model. As previously mentioned, the long-short portfolio yields positive returns; however, it is essential to investigate if the returns are explained by some of the most prevalent asset pricing models or if they indeed are abnormal returns.

Firstly, it is necessary to determine the best performing model to correctly interpret the results and their implications for this thesis. The results in Table 7 exhibit the corresponding R_{adj}^2 of each model for each portfolio. Evidently, the Fama-French five-factor model outperforms the other models in terms of explanatory power, closely followed by the Fama-French three-factor model and the CAPM with the lowest explanatory power among the asset pricing models. These results are consistent with the findings from Fama and French (1993, 2015).

To summarise, Table 7 exhibits the abnormal returns (alpha) with the three selected asset pricing models. The long-short portfolio returns are tested first against the CAPM, yielding an abnormal monthly return of 0.44% at the 5% significance level. Similarly, the second model tests these returns against the Fama-French three-factor model, yielding an abnormal monthly return of 0.37% but now at the 10% significance level. However, the significance of the alpha disappears after regressing against the Fama-French five-factor model. As previously discussed, the five-factor model has the best explanatory power, meaning that the abnormal returns previously obtained are now successfully explained by the model. Namely, I fail to reject the second null hypothesis as the significant abnormal returns fail to persist when tested against the Fama-French five-factor model. This insignificance of the carbon premium on the long-short portfolio partially contradicts the findings from Huij et al. (2021), Bua et al. (2024), and Hsu et al. (2023), as I fail to prove that the positive return is indeed an abnormal return.

It is necessary to summarise the main findings and attempt to find possible explanations for them, as the results have several implications for this thesis. Firstly, the Fama-Macbeth shows emission intensity has an independent predictive power of stock returns. Secondly, when constructing the long-short portfolio based on emission intensity, it yields a positive return. Lastly, the positive return is explained by the Fama-French five-factor model, yielding no abnormal returns. Interestingly, these results lie in between the evidence supporting the existence of a carbon premium and its non-existence while showing a weak positive predictive power of emission intensity on stock returns but failing to yield abnormal returns when constructing a long-short portfolio. However, I will discuss next the most plausible explanation for my results.

The Fama-Macbeth regression exhibits a significant positive emission intensity coefficient at the 10% level. It is possible that the number of observations for the emission intensity data (data is only provided in a yearly frequency) and the chosen significance level of 10% may not yield robust results and just provide weak evidence of a positive and significant existing emission-return relationship. If the threshold is a significance of 5%, this would drastically change the significance of the relationship, implying emission intensity has no predictive power . This argument would be consistent with the fact that when constructing the long-short portfolio, the positive returns are explained by the Fama-French five-factor model, as the predictive power of emission intensity is weak while the explanatory power of the Fama-French five-factor model is considerably high, supported by the variation explained throughout the quintile portfolio regressions.

At last, my results contribute to the current literature on the carbon premium topic by providing evidence that stocks with higher emission intensity tend to have higher excess returns compared to stocks with lower emission intensity; however, this difference is successfully explained by the Fama-French five-factor model throughout the period 2010-2023 in American stocks. This thesis neither agrees with the existence of a positive carbon premium supported by Huij et al. (2021), Bua et al. (2024), and Hsu et al. (2023), nor with the existence of a negative carbon premium supported by Li and Zheng (2024), Wang (2024), and Enders et al. (2023). Actually, my research lies in between these two theses by recognising the positive association between emission intensity and excess returns while finding no significant carbon premium in any direction. This result further supports market efficiency as emission intensity is considered when pricing a stock but yields no abnormal returns.

Although the obtained results partially align with previous research proving the significance of the metric emission intensity, they must be interpreted with caution. The results regarding the existence of a carbon premium suggest that there is no existing carbon premium, fitting between the research that argue in favour of a significant negative carbon premium and a significant positive carbon premium. Therefore, this thesis provides evidence of another explanation for assessing the carbon premium. Clearly, more evidence needs to be provided to reach a consensus regarding the carbon premium topic in the U.S., Europe, and the world.

7 Conclusion

The carbon emission premium and pricing of carbon risk literature have not yet reached a consensus on its existence, as researchers offer different explanations for the emission-return relationship. My thesis provides new evidence for the U.S. by studying this relationship in a recent period by combining the approaches from Hsu et al. (2023) and Enders et al. (2023) while employing the Datastream/LSEG database. The objective of this research is to study the stock returns and determine if a positive carbon premium exists and if it yields abnormal returns. This thesis answers the research question: *What impact, if any, does carbon risk (transition risk) exposure have on stock returns in the U.S. in the period 2010-2023?*

The first hypothesis states there is no significant relationship between emission intensity (carbon risk) and stock returns in the U.S. over the period 2010-2023. To test this, I conduct a Fama-Macbeth regression to evaluate the emission- return relationship while controlling for the traditional risk factors and firm characteristics that can serve as an explanation for cross-section variation in the emission portfolio's returns, according to Hsu et al. (2023). The results provide weak evidence that emission intensity has a positive and significant predictive power on stock returns, rejecting the null hypothesis. Specifically, the Fama-MacBeth regressions suggest that one standard deviation increase in the logarithmic emission intensity variable will increase excess returns by 0.51 percentage points. The second hypothesis states that the long-short portfolio based on emission intensity will not yield significant abnormal returns on the cross-section of stock returns in the U.S. over the period 2010-2023, after controlling for the Fama-French five-factor model. To test this, I assign stocks into quintile portfolios based on emission intensity within the same industry to separate high emitters from low emitters. After assigning stocks into quintiles, I calculate the value-weighted return for each quintile. In addition to the five portfolios, I construct a long-short portfolio that yields a positive return of 3.41% per year. However, this portfolio yields no abnormal returns.

This thesis neither agrees with the existence of a positive carbon premium supported by Huij et al. (2021), Bua et al. (2024), and Hsu et al. (2023), nor with the existence of a negative carbon premium supported by Li and Zheng (2024), Wang (2024), and Enders et al. (2023). Actually, my research lies in between these two theses, recognising the positive association between emission intensity and excess returns while finding no significant carbon premium in any direction. Further research needs to be conducted to reach a consensus regarding the carbon premium topic in the U.S., Europe, and the world.

8 Limitations and future research

The first obstacle I encountered when conducting this research was the limited availability of estimated carbon emission data on the Datastream/LSEG database. Also, when retrieving the data, it was evident that there was a substantial amount of firm-level data with missing values, making it difficult to have a more representative number of companies and industries. As previously mentioned, the number of industries in my research is 49 out of the 61 contemplated industries by the TRBC codes in the Datastream/LSEG database. This underrepresentation of industries can make my findings not entirely generalisable to every industry or to the population of American companies. Another limitation derives from the carbon emission data annual frequency, which makes it require longer periods to compensate for the fewer observations, while carbon emission reporting varies from year to year, so including more years could result in fewer complete observations at the firm level.

The emission intensity variable was constructed utilising estimated CO2 equivalent emissions, which are calculated with a method composed of four models, each giving one value. The models are based on reported emissions, the CO2 model, the energy model, and the median model. This means estimates can be inaccurate and based on incorrect assumptions, possibly leading to self-selection bias or measurement errors. Further data concerns are highlighted by Aswani et al. (2024), stating that 70% of standard U.S. emissions data is vendor-estimated rather than disclosed by firms. Aswani et al. have found empirical evidence of systematic differences between estimated data and disclosed emissions data.

Future research investigating a different dataset with more companies can provide a better understanding of the topic, especially if the dataset provides carbon emission data at the scope 1, 2, and 3 levels. This data feature allows researchers to differentiate between direct and indirect emissions, making the data more accurate. However, the availability of direct and indirect emissions is not so easily available, especially in the Datastream/LSEG database.

Also, this thesis exclusively focuses on the American stock market, while it is valuable to investigate if the obtained results hold in a North American, European, or emerging market context. My research includes a limited number of asset pricing models to test my hypotheses. Therefore, testing my hypothesis with other asset pricing models that have been proven to be empirically accurate can generate different results, offering valuable insights when trying to understand the emission-return relationship.

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APPENDIX A. Preliminary tests.

***Table A 1*. Variance inflation factor test for multicollinearity (VIF).**

Variable	**VIF**	**1/VIF**
HML	2.102	0.476
CMA	1.921	0.521
SMB	1.647	0.607
ROE	1.341	0.746
RMW	1.337	0.748
MV	1.26	0.794
MKT	1.233	0.811
Emission Intensity	1.09	0.918
BM	1.032	0.969
Mean VIF	1.44	

This table shows the VIF scores to test for multicollinearity in the models used in this thesis.

Table A 2. Correlation matrix with the Fama-French factors.

Variable	Excess Return	MKT	SMB	HML	RMW	CMA
Excess Return	1.000					
MKT	0.432	1.000				
SMB	0.224	0.354	1.000			
HML	0.118	0.059	0.287	1.000		
RMW	-0.032	-0.079	-0.431	0.079	1.000	
CMA	0.003	-0.181	0.005	0.645	0.151	1.000

This table shows the correlation matrix of excess returns and the Fama-French five factors over the period 2010-2023.

Table A 3. Correlation matrix with firm characteristics.

Variable	Excess Return	Emission Int.	MV	ROE	BM
Excess Return	1.000				
Emission Int.	-0.100	1.000			
MV	0.045	-0.004	1.000		
ROE	-0.009	-0.222	-0.430	1.000	
BM	0.031	0.095	-0.062	-0.060	1.000

This table shows the correlation matrix of excess returns and firm characteristics over the period 2010-2023.