Handelshøyskolen BI

GRA 19703 Master Thesis

Thesis Master of Science 100% - W

Predefinert informasjon

Startdato:	16-01-2022 09:00	**Termin:**	202210
Sluttdato:	01-07-2022 12:00	**Vurderingsform:**	Norsk 6-trinns skala (A-F)
Eksamensform:	T		
Flowkode:	202210||10936||IN00||W||T		
Intern sensor:	(Anonymisert)		

Deltaker

Navn:	Haider Ali og Abubakar Khalid

Informasjon fra deltaker

Tittel *:	Carbon Risk and Expected Return
Navn på veileder *:	Espen Henriksen

Inneholder besvarelsen konfidensielt materiale?:	Nei	**Kan besvarelsen offentliggjøres?:**	Ja

Gruppe

Gruppenavn:	(Anonymisert)
Gruppenummer:	188
Andre medlemmer i gruppen:	

Carbon Risk and Expected Return

Master thesis

Haider Ali & Abubakar Khalid
MSc in Finance

Supervisor: Espen Henriksen

Oslo, June 30, 2022

ABSTRACT

This thesis examines whether climate risk and carbon emissions can be identified as separate risk factors in European listed equities. We build and extend on the methods of Bolton and Kacperczyk, by applying those methods on a broad European dataset. We apply one- and multi-factors frameworks such as the CAPM and Fama-French 3- and 5-factor models and find indications that there is a carbon premium in the period following the Paris Agreement for European listed equities.

Acknowledgements

We want to first thank our supervisor Espen Henriksen for his valuable feedback throughout this process, and importantly, for making this process not just a journey filled with learning but also one filled with laughter. This thesis marks the end of our masters programme at BI. We know that for many people with our names and our backgrounds, a high quality education is not a given. Therefore, we would like to thank our parents for making many small and important choices that has allowed us this moment. We would also like to thank our extended families and friends for their support. Special mentions go out to Haiders wife Amina, Abubakars niece and nephew Noor and Noah, our friend Akhilesh for the many late nights at the BI library, and Abubakars employers Wilstar. Finally, we would like to thank eachother for years of friendship and hard work to complete this thesis.

We can finally sleep now.

Thank you. Tusen takk. Shukriya.

Contents

List of Tables

1 Introduction

In this thesis, we ask whether climate risk and carbon emissions can be identified as separate risk factors in listed European equities and, in case, what extra expected return investors require to hold this risk. To answer this question, we also test whether traditional risk factors such as the CAPM 1-factor model, Fama-French 3-factor model, or Fama-French 5-factor model capture climate risk and carbon emissions, hence whether a separate risk factor associated with climate risk would be redundant. We build and extend on the methods used by Bolton and Kacperczyk (2020). While they analyzed carbon emissions and pricing of firms listed in the US, we have constructed a broad dataset of carbon emissions and pricing of firms listed in Europe from 2010–2019 and ask the following research question:

- To what extent do climate risk and carbon emissions represent an additional risk factor investors demand compensation for?

The determinants of equity valuations are expected cash flows and the rates used to discount these cash flows. Whether a security is associated with higher (lower) risk and lower (higher) asset price depends on expectations of future cash flows and equity risk premiums. Climate-related regulatory risk, which is the focus of this thesis, could impact equity returns in various ways, e.g., a potential carbon tax could significantly affect expected cash flows. However, investors may have become more aware of that risk, especially after the pledges made in the Paris Agreement. Since the effects of climate-related future regulation on future cash flows are uncertain, investors may require higher returns to hold the equity of firms with high carbon emissions. In this thesis, we explore whether this has been the case. If investors demand carbon risk premiums for bearing this potential additional regulatory risk, it will not imply that investors can help solve the climate crisis.

Importantly, this risk premium is a forecast of future outcomes and not necessarily a realized excess return, meaning that it should not be interpreted as a signal to take additional risk. Whether an investor takes on additional risk depends on investor mandates, wealth, and risk appetite. Typically, the average investor is risk-averse, intending to maximize expected utility by trading off risk and returns. However, the average investor may be subject to behavioural biases and capital constraints that limit their ability to leverage investments to take advantage of investment opportunities. Large institutional investors typically have greater investing capacity, can withstand financial losses, have a long-term perspective, are subject to modest future liabilities, and have steady expected cash flows. While this could mean that institutional investors may be more appropriate bearers of climate risk, they also have a fiduciary duty to be custodians of wealth for their shareholders. Therefore, arguing that one investor type is a more appropriate bearer of climate risk may not be straightforward.

With this backdrop, asset owners seem to be devoting more attention to climate risk (Fink, 2020), and many business owners are seemingly vocal about what the purpose of a business is (Business Roundtable, 2019). However, the motivation for these statements is unclear. While some investors may care deeply about climate change and want to contribute to solutions, investors in the equity market usually cannot provide meaningful contributions through their decisions as they operate in a secondary market, and their investment decisions rarely affect firm capital expenditure decisions. A potential explanation for these statements could be that investors understand the significant regulatory risk related to emissions, which may have become more evident after the Paris Agreement. Therefore, investors try to create a perception of contributing to solutions while also demanding higher risk premiums, knowing that regulatory changes are probable.

Before we present our analysis, we will focus on the background of our thesis in detail and present a structured literature review, which will motivate our hypotheses. We then describe the methods we will use to answer our research questions and, finally, the data we will use before presenting our main analysis, which will lead to a conclusion.

2 Background

Our thesis is inspired by the findings of Bolton and Kacperczyk (2020). To further support our thesis, we describe the foundations they established by discussing their results. They argue that there is a high likelihood that carbon risk may not be present in asset prices due to institutional investors' lack of consensus regarding climate change. They evaluate three hypotheses for why and how a carbon premium may arise. Using a sample of US companies from 2005–2017, they conduct a series of estimations to evaluate their hypotheses. They find statistically and economically significant carbon risk premiums and conclude that carbon emissions affect stock returns.

While they study the US market, we find their results intriguing. The fact that they can conclude that carbon emissions affect stock returns indicates that investors are putting more importance on carbon as a measure of risk. We believe that before drawing a general conclusion about the significance of carbon emissions for expected returns, we need to test these results on a European sample. Specifically, if we assume that carbon emissions may have a global implication, affecting all firms homogeneously and not just specific markets, given that all markets have the same information, these results should not differ. We also find their paper fascinating because they use different measures of carbon emissions for firms, and the resulting carbon premium has been used in a time-series regression of factor models to find a robust conclusion.

In this thesis, we use similar methods and measures for carbon emissions as Bolton and Kacperczyk (2020), but we test our hypotheses on the European equity market. In particular, we will examine whether shareholders demand compensation for exposure to climate-related risk and whether traditional risk models capture that.

3 Literature Review

Before presenting our hypotheses and analysis, we will, in this section, thoroughly review relevant and available literature explaining the relationship between carbon emissions and financial returns. We divide our review into two parts. We first present and discuss potential theoretical arguments for why we should expect to find some relationship between carbon emissions and financial returns before looking at what recent empirical research has found.

3.1 Climate Risk Implication in Theoretical Framework

Sharpe (1964) has been central to much of the understanding in financial literature of the relationship between risk and return. He introduced the Capital Market Line (CML), a visual representation of the well-known Capital Asset Pricing Model (CAPM). Using the Sharpe argument, investors may obtain higher expected portfolio returns by taking on more risk, as long as they are well-diversified, as shown by the CML. However, if the risk is systematic, diversification may not sufficiently eliminate that risk, and therefore investors require compensation through higher expected returns for taking additional risk. Carbon emissions could be one of those systematic risk factors negatively impacting real economic output and growth, as argued by Cuervo and Ved P (1999), who explains how a carbon tax will harm global competitiveness and economic development. Islam (2022) shares those concerns by arguing that carbon taxes could affect expected returns as restructuring takes time, and increasing the price of essential natural resources may cause short-term disruptions.

While we, in this thesis, are only trying to understand if a carbon premium exists and whether traditional risk factors can explain it, this literature allows us to understand why we should expect such a relationship. Another explanation from standard finance theory may be that investors constrain themselves by not considering firms with high emissions. The mean-variance optimization theory, developed by Markowitz (1952), explains that unconstrained investors earn higher risk-adjusted returns than investors with constrained frontiers. This theoretical argument, again, gives us reason to believe that a relationship between carbon emissions and expected returns may exist, supported by recent research by Pedersen et al. (2021) who finds reduced portfolio returns for investors that constrain their portfolios due to ESG considerations.

While these theoretical arguments for the relationship between carbon emissions and financial returns are fascinating, this thesis primarily answers the question of whether investors are demanding risk premiums due to climate-related regulatory risks and not whether investors earn lower or higher returns due to constrained portfolios. Therefore, we focus the rest of this literature review on literature examining or explaining the relationship between carbon emissions and financial returns.

3.2 Climate Risk Implication on Asset Pricing

In this subsection, we turn from looking at how climate emissions could be related to financial returns in theory to looking at what relationship has been found in the existing literature.

In et al. (2017) using a long-short strategy that goes long in carbon-efficient and short in carbon-inefficient firms, find economically and statistically significant positive abnormal returns of 3.5 to 5.4% annually, using a sample of 736 public US companies between 2005–2018. Hsu et al. (2022) use a similar approach on a sample of firms between 1991–2016. They find a significant average annual return of 4.42%. This result contradicts the finding of In et al. as Hsu et al. go long firms with high emission intensity and short firms with lower emission intensity. They explain that their results result from investors demanding compensation for the increased regulatory risk of owning high-emitting firms. Chava (2014) gives further support to this argument by looking at the cost of capital and finds that investors demand a higher cost of debt and equity capital when investing in companies excluded from environmental screening due to excessive emissions. Additional support for this argument can be found in Sharfman and Fernando (2008).

Other indications that climate-related emissions and their effects may be influencing investor returns can be found in Witkowski et al. (2021) who investigate whether energy-intensive companies in Europe offer consistent carbon premiums to investors over time. They observe positive and statistically significant carbon premiums from 2003 to 2012, negative premiums from 2013 through 2015, and no premium from 2016 to 2019. Hong et al. (2019), examine extreme events affecting food crops and find that food stock prices are not adjusting to climate change threats. Further support for this argument that climate risk is mispriced is found in Daniel et al. (2016). Similarly, Baldauf et al. (2020) find adverse effects of homeowners' climate change beliefs on the prices of their properties, which may be another indication that climate is affecting financial returns. Choi et al. (2020) also indicates that climate change may be affecting returns. They argue that sell-side pressures drive prices down and increase expected returns, explaining that carbon-heavy enterprises underperform during extreme weather circumstances. Interestingly, Monasterolo and De Angelis (2020) evaluated the implications of the Paris Agreement on asset pricing, specifically if markets integrated this information by decreasing systematic risk and increasing the relative weights of low carbon-emitting indices. Consistent with Bolton and Kacperczyk (2020), they find that systematic risk for carbon-light indices decreased dramatically but did not have similar results for carbon-heavy indices.

Table 1: Summary of Literature

This table summarises relevant literature researching the relationship between carbon risk and expected returns. *Time horizon* describes the period of interest for each research paper, *Sample description* is a geographical description of the samples focus, and *Relationship* measures the relationship between carbon emissions and equity returns.

Author	(1) Time horizon	(2) Sample description	(3) Relationship
Baldauf et al. (2020)	1997–2017	U.S.	Positive
Bolton and Kacperczyk (2020)	2005–2018	Global	Positive
Bolton and Kacperczyk (2021)	2005–2017	U.S.	Positive
Chava (2014)	2000–2007	U.S.	Positive
Choi et al. (2020)	1973–2017	Global	Positive
Hong et al. (2019)	1985–2014	Global	Negative
Hsu et al. (2022)	1991–2016	U.S.	Positive
In et al. (2017)	2005–2015	U.S.	Negative
Monasterolo and De Angelis (2020)	1999–2018	Global	Positive
Pedersen et al. (2021)	2007–2019	U.S.	Negative
Sharfman and Fernando (2008)	1999–2001	U.S.	Positive
Witkowski et al. (2021)	2003–2019	Europe	Null

This literature review has shown us that firm emissions can be theoretically and empirically linked to financial returns, with research finding relationships between the two variables in practice. Theoretically, we could think of emissions as a systematic risk factor, interpreted as an unanticipated shock to economic growth, e.g., through regulation such as a carbon tax. If investors use firm emissions to restrict their investment universe, this could also affect their returns if these constraints have an additional effect. The empirical literature summarised in table 1 shows mixed results. Some researchers have found a negative carbon premium evaluating US and global equities from a time horizon spanning from 1985–2019, while other researchers found positive carbon premiums for these samples for time horizons spanning from 1973–2018. Interestingly, we find no research focused specifically on the broader European equity market and no research on any European market that has used the methods of Bolton and Kacperczyk (2020). Therefore, our thesis is a welcome addition to the existing body of literature and will allow a fresh perspective. In the next section, we will take the learnings of this literature review and start developing hypotheses for our thesis.

4 Hypotheses

In our literature review, we presented literature arguing that investors might not sufficiently be able to eliminate systematic risk through diversification and, therefore, require compensation for additional risk (Sharpe, 1964). We also saw indications that investors might have become more aware of climate-related regulatory risks, something we also argued in our introduction. Therefore, we hypothesize that regulatory interventions, such as a carbon tax, could impose a systematic risk for which investors may have started to require compensation. Some empirical results also supported this argument, especially Bolton and Kacperczyk (2020), who, using various measures for firm emissions, found positive and significant carbon premiums that standard risk factors did not explain. While they were looking at the US equity market, we assume there is no reason to expect any difference for our European sample, following the Efficient Market Hypothesis (Fama, 1970). Therefore, our first hypothesis is as follows:

- There is an economically and statistically significant relationship between carbon emissions and expected financial returns.

Multiple decision-makers pledged that they would take action to mitigate the risks of climate change as part of the Paris Agreement, leading to increased attention to climate risk. As this is a relatively new development, we hypothesize that markets may not have fully incorporated this information and that traditional risk factor models may not capture that risk, which leads to our second and final hypothesis:

- Traditional risk factors do not fully capture the relationship between carbon emissions and expected financial returns, and climate-related regulatory risk is an additional risk factor.

5 Methodology

This section will present the methods used to test the hypotheses we derived in the previous section. We have split this section into two parts, where we will first describe the method used to discover a carbon premium. If we locate a carbon premium, we will use the method presented in the second part of this section to understand whether the traditional risk factor models capture the carbon risk or whether it is an additional risk factor.

5.1 Cross-sectional Regression

We will first estimate the following equation using a pooled linear regression model to test our hypotheses. Following Bolton and Kacperczyk (2020) we estimate three iterations of the model with different emission categories. First, we will estimate the regression using log scope one and two emissions as our independent variable before we use the year-to-year growth in emissions and, finally, the scope one and two emission intensities. All three iterations will have the same purpose of examining whether there is a relationship between firm emissions and their corresponding expected returns.

$$Return_{i,t} = \alpha_0 + \alpha_1 Emissions_{i,t} + \alpha_2 Controls_{i,t-1} + \mu_t + \epsilon_{i,t} \qquad (1)$$

A linear regression model itself does not recognise whether the data being fitted into the model is a panel data or another type of data. The linear model will fit all observations of our variables and estimate a relationship with the standard assumptions of homoscedasticity and no correlation in error terms. Knowing that these assumptions are improbable in a panel data setup of firm characteristics, as some variation in the standard deviation of firm variables over time is expected, as is the correlation of error terms across periods. To account for these shortcomings of the standard regression model, when applied to a panel data structure, we introduce time dummy variables for all but one period to account for time-fixed effects. These dummy variables will allow us to control for any variation in the relationship between firm emissions and returns that varies across time but remains constant across firms, meaning that it affects all firms the same across time, such as macroeconomic shocks. Furthermore, we cluster standard errors at a firm and year level to control for correlation in error terms across time or serial correlation in returns. While we have now controlled for time-variant unobservable factors, we still have to control for any time-invariant factors. We include industry-fixed effects to control for this unobservable variance that may differ across industries but not across time. To best account for industry fixed effects, we de-mean the variables based on industry means. This implies that, for all our variables, we subtract the industry average to obtain de-meaned variables, allowing us to also control for industry-fixed effects. While we could have used industry dummies, as we have with time, this would have resulted in artificially high R-squared values without adding much explanatory power, which we want to avoid.

In our model $Return_{i,t}$ represents the expected monthly stock return of a firm i in period t, whereas $Emissions_{i,t-1}$ represents one of the three emission categories of firm i in period t. Our control variables consist of firm-specific factors that influence financial performance, consistent with what was used in Bolton and Kacperczyk (2020) to allow for comparable results. These include Size, Book-to-Market, Momentum, Investment/Assets, HHI, PPE, Beta, Volatility, Sales growth, and EPS growth. When estimating the regression, we, as Bolton and Kacperczyk, use the annual lagged values of our control variables to account for the fact that it may take time for these variables to affect expected returns. We always include year and month fixed effects and cluster standard errors at firm and year levels to control for correlation across firms and years. These controls will ensure that our results are robust after controlling for conventional control variables that may affect expected returns.

5.2 Asset Pricing Model

To further test whether the carbon premium we may find is an additional risk factor or whether traditional risk factors capture it, we also estimate the following time-series regression.

$$\alpha_{1,t} = \alpha_0 + \beta_1 F_t + \epsilon_t \tag{2}$$

This equation represents the traditional Capital Asset Pricing Model (CAPM), developed by Sharpe (1964) and modified by Lintner (1965) and Mossin (1966). The CAPM model describes the linear relationship between systematic risk and expected equity returns. For us to argue that the CAPM captures the risk premium, we may find. The observed premium should match the model, leading to the intercept in the CAPM, commonly known as Jensen's alpha (Jensen, 1968) equalling zero. Theoretically, a significant non-zero alpha would either indicate that the asset creates value through positive abnormal returns or leads to value destruction by yielding below equilibrium returns.

Fama and French (1993) further extended the CAPM by arguing that asset returns are explained by common firm characteristics, such as Size (SMB) and Value (HML), in addition to the market risk exposure. Carhart (1997) further extended the model by adding the momentum factor, building on the work done by Jegadeesh and Titman (1993), in which they discovered that stocks that appreciated followed the same pattern over the next six to twelve months. Fama and French (2015) built on their initial work by arguing for two additional risk elements, the Quality factor (RMW) and the Investment factor (HML). Using the above equation, we will estimate all these models, using as a left-hand side variable the carbon premium we may have found in regression 1. The F represents a vector of factor-mimicking portfolios, including SMB, HML, RMW, CMA, Mkt-Rf, and momentum (WML).

As we are utilising time-series data, we expect correlation in error terms. Therefore, following Bolton and Kacperczyk (2020), we use a Newey-West procedure with 12 lags to account for possible autocorrelation. The coefficient of interest is α_0 as explained above; this coefficient shows if there is any difference between the traditional risk factors and the carbon premium that the conventional risk factors cannot explain.

Our literature review in section 3 showed us mixed results from previous research studying the relationship we are examining. However, as our sample is from a later period than most of the research we reviewed, and with the recent Bolton and Kacperczyk (2020) paper finding a positive carbon premium, we hypothesise that we will also find a positive carbon risk premium that the traditional models will not capture.

6 Data

In this section, we present our dataset by explaining the sources and data collection process before looking closer at the emission and control variables for firm characteristics. In the second part of this section, we present the variables that we will use in the factor models to estimate whether traditional risk factors capture any risk premium. Finally, we present tables with summary statistics for all variables and a table defining all variables we will use or discuss in this thesis.

6.1 Firm Level Variables

The data we use to estimate our regression is a panel consisting of 21,840 monthly observations of 182 companies across 15 countries over ten years from 2010–2019. The dataset combines the Bloomberg terminal and the Thomas Reuters Eikon Datastream platform. We started our search for data by deciding on the period we wanted to examine. We agreed that we wanted to explore the relationship between emissions and returns without the added noise of a pandemic or a financial crisis. Additionally, we understood that we needed complementing data on the classic risk factors to test whether traditional risk models captured any carbon premium we found. The 15 countries chosen were, therefore, a result of understanding what countries there were available Fama/French factors for and that those countries had developed and functioning markets. Once we decided on the period and countries, we first used Datastream to gather all closing price data to avoid the upper bound of the Bloomberg terminal data extraction limit. We used the closing prices to calculate the log of monthly expected returns for each firm in our sample. We separately used Datastream to gather the emissions data we needed and the additional control variables necessary to estimate our regressions.

Our initial dataset after extracting from Datastream consisted of 43,440 monthly observations of 362 companies across 15 countries, but with significant missing variables for certain companies in specific years, especially the beta variable had gaps from Datastream. Once we had gathered data from Datastream, we went to the Bloomberg terminal to fill data gaps and, importantly, made sure to transform any data points that used different units between the two platforms to have a consistent dataset. Finally, once we had filled all data gaps we could fill using Bloomberg, we removed all firms that had missing observations in one or more years in our period of interest. This balancing gave us a complete dataset without critical missing variables. This unique combination of the two data sources left us with a final balanced dataset of 21,840 monthly observations for 182 companies in 15 countries over ten years.

Table 4 includes the final descriptive statistics for the complete sample, with more description of the variables shown in table 5. Once we had a balanced dataset, we adjusted variables to get the final selection needed to run the regressions. This adjustment included taking the natural log of market capitalization to obtain our size variable, calculating the book-to-market ratio, and calculating the investment/assets variable. We compared our dataset to the variables used in Bolton and Kacperczyk (2020) and noticed that we were missing the Herfindahl concentration index (HHI), defined as the sum of squared market share percentages for all firms within an industry. We calculated this index as we could not find it from any data sources we used and did not have market share variables available. This computation was done by first computing the sum of revenues we had in our sample by industry and year before using the share of revenue coming from a company as their market share. Finally, we summed the square of revenues for all firms within an industry to obtain the HHI for each year.

Following Bolton and Kacperczyk (2020) and to reduce the impact of extreme outliers, we winsorize the year-to-year growth in scope one and two emissions, scope one and two emission intensity, book-to-market, leverage, investment/assets, and return on equity at a 2.5% level, as well as momentum, volatility, sales growth, and earnings per share growth at a 0.5% level. Having winsorized the variables, we finally de-mean all variables based on the industry average as explained in section 5 to control for industry fixed effects.

In contrast to Bolton and Kacperczyk (2020), we did not find the same availability of consistent scope three emissions data and did not want to rely on estimated measures. Therefore, we employ only scope one and scope two emissions data due to the inadequate scope three data reported from 2010 to 2019 for the firms in our sample. In table 3, we have reported the mean scope one and two emissions and their intensities by year for our sample. For all categories of emissions, we see that there is a steady decline as we move through the years but that the percentage decline for levels of scope one emissions has been more prominent than the percentage decline in scope one intensity. For scope two, the opposite is true. This relationship shows that when firms have reduced their scope one emissions, their revenues have not declined proportionally. However, for scope two emissions, the revenues seemingly decline more than the reduction in emissions as the scope two emission intensity is reduced more than the scope two emissions. Table 2 shows that the correlation between scope one and two emissions and their intensities is positive and large but not perfectly correlated, as firms with very different emission levels can have the same intensity due to size. While Bolton and Kacperczyk argue that this makes emission intensity a noisy variable for emissions, we believe that while that may be true if your solving climate change, for investors, understanding how efficiently emissions are in production may be a more appropriate measure.

Table 2: Cross Correlation

This table reports the cross correlation between levels of emission and emission intensity variables in our sample.

	(1) Scope 1	(2) Scope 2	(3) Scope 1 Intensity	(4) Scope 2 Intensity
Scope 1	1.00			
Scope 2	0.46	1.00		
Scope 1 Intensity	0.54	0.23	1.00	
Scope 2 Intensity	0.15	0.55	0.26	1.00

6.2 Factor Variables

From Kennet R. French's website[1], we obtain the standard Fama-French 5-factor variables and momentum; specifically, size (SMB), which represents a long-short portfolio strategy, yielding returns obtained from going long small stocks and take short positions in large stocks. Value (HML) is a portfolio strategy that goes long firms with high book-to-market value and shorts those with relatively small book-to-value ratios. Quality (RMW) is a strategy that takes long positions in firms with solid fundamentals and shorts firms with weaker business models. The Investment factor (CMA) goes long on firms with a conservative investment approach and short on those with an aggressive investment approach, as these aggressive investing stocks tend to waste more of shareholders' wealth. Lastly, the momentum factor (WML) goes long on stocks that have experienced price appreciation over the past twelve-month window and, short, those that have depreciated during the same period. These variables will be used in the time-series regression analysis using the CAPM, 3-factor model, and the 5-factor model, including momentum.

[1] https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

Table 4 reports the descriptive statistics for these variables, as it does for all our data. While we could have added the additional factors Bolton and Kacperczyk (2020) used to conduct an even more robust control, we believe the standard 5-factor framework, including momentum, is sufficient for this thesis.

Table 3: Emissions by Year

This table reports the development of mean emissions levels and emission intensity levels for scope one and scope two by year

Year	(1) Scope 1	(2) Scope 2	(3) Scope 1 Intensity	(4) Scope 2 Intensity
2010	5,051,379	939,776.3	200.76	66.55
2011	4,791,687	980,478.7	208.88	64.27
2012	4,795,610	990,747.5	188.54	65.19
2013	4,682,778	946,253.9	243.53	64.13
2014	4,386,777	892,211	261.15	67.15
2015	4,266,616	856,384.8	256.92	70.39
2016	4,428,946	889,255.5	216.29	68.19
2017	3,708,436	884,518.9	197.11	57.32
2018	3,774,839	872,004.5	192.14	52.57
2019	3,599,976	780,487.1	175.75	44.22

Table 4: Descriptive Statistics

This table reports the summary statistics for all control variables used in our cross sectional and time series regressions. We report the total number of observation, average values, standard deviation from the mean, minimum values, and the maximum values for each variable.

Control variables	Total observations	Mean	Stdev.	Min.	Max.
Log(Scope 1)	21,804	12.11	2.86	2.25	18.89
Log(Scope 2)	21,780	12.14	1.99	4.09	16.65
ΔScope 1	19,620	-0.01	0.43	-3.97	2.56
ΔScope 2	19,596	-0.03	0.39	-5.33	3.70
Scope 1 Intensity	17,436	214.51	670.93	0.00	9854.03
Scope 2 Intensity	17,028	61.70	109.54	0.00	1041.67
Monthly Return (%)	21,840	0.32	8.30	-75.54	68.56
Size	21,840	9.30	1.36	5.26	12.68
Leverage	21,840	3.35	5.20	1.21	171.96
Momentum	21,840	1.65	17.10	-66.90	226.99
INVEST/A	21,840	0.05	0.04	0.00	0.29
ROE	21,840	0.19	0.31	-1.32	10.35
HHI	21,840	0.03	0.02	0.01	0.08
Log(PPE)	21,744	21.48	2.22	12.60	26.01
Beta	21,840	1.12	6.80	-98.63	154.72
Volatility	21,840	24.39	11.20	8.01	175.22
Sales Growth (%)	21,840	3.72	14.62	-86.67	217.06
EPS Growth (%)	21,840	3.50	11.03	-60.23	201.94

Time-Series Variables	Total observations	Mean	Stdev.	Min.	Max.
MKT-RF	120	0.57	4.70	-12.32	11.88
SMB	120	0.18	1.60	-4.35	4.68
HML	120	-0.25	2.26	-4.99	6.36
RMW	120	0.39	1.55	-3.85	3.52
CMA	120	-0.05	1.12	-3.00	2.96
WML	120	0.96	2.80	-8.99	8.94

Table 5: Variable Description

Variable	***Description***
Identifier	Stock ticker representing each specific equity.
Name	Company name.
Country	Country in which the firm has it's headquarters.
Year	Time period represented in years.
Scope 1	Direct GHG emissions from company-owned and controlled resources.
Scope 2	Indirect GHG emissions from the generation of purchased. electricity.
Scope 1 Intensity	Greenhouse gas (GHG) intensity calculated as metric tonnes of GHGs in carbon dioxide equivalent (CO2e) emitted from direct operations per million of sales revenues.
Scope 2 Intensity	Greenhouse gas (GHG) intensity calculated as metric tonnes of GHGs in carbon dioxide equivalent (CO2e) emitted from indirect operations per million of sales revenues.
Return	Percentage monthly return. Computed as the log of price at t less log of price at time t-1
Sales	Percentage change in sales revenue from year t until t+1.
Leverage	Financial leverage, measured as the ratio of average assets to average equity.
Momentum	Percentage change over the last 6 months in the one month moving average of the share price relative to a benchmark index.
B/M	Book-to-Market ratio computed as the book value of equity divided by the market value of equity.
EPS	Growth in Earnings Per Share. EPS is proportion of a company's profit allocated to each shareholder.

Table 5 continued from previous page

Variable	***Description***
BVPS	Growth in Book Value Per Share.
Volatility	Annualized standard deviation of the relative price change for the one month closing price.
ROE	Return on Equity measures the profitability of a company by revealing how much profit it generates with the capital invested by shareholders.
CAPEX	Capital Expenditure, equivalent to the amount spent on purchases of tangible fixed assets.
PPE	Firm's property, plant, and equipment.
Beta	CAPM beta measured over the one year period. Beta captures the degree of comovement between market and asset returns.
Market Cap.	Market Capitalization, measured as the total number of shares outstanding multiplied by the market value per share.
HHI	Herfindahl concentration index of firms with respect to different business segments. This index represents the degree of competition within a industry.
INVEST/A	Firms capital expenditure divided by the book value of assets. The ratio measures the amount invested on fixed assets compared to the book value of total assets.
RF	Monthly risk-free rate.
MKT-RF	The market risk premium is the difference between the anticipated return of an index and the risk-free rate. It compensates an investor for the greater volatility of returns over and beyond the risk-free rate by providing a higher return.

Table 5 continued from previous page

Variable	***Description***
SMB	Size factor is determined by a company's market capitalization. SMB evaluates the historical excess return of small-cap stocks over those of large-cap stocks.
HML	The value factor shows the return differential between long positions in companies with a high book-to-market value (BM) ratio and short positions in companies with a low BM ratio.
RMW	The profitability factor is obtained from the difference in returns between long positions in (robust) firms with high profitability and short positions in (weak) firms with low profitability.
CMA	Investment factor takes long position in firms that invests with cautious (conservative) and short position in firms that invests heavily (aggressive).
WML	The momentum factor represents the difference between the returns generated by holding a long position in high-performing companies over the most recent twelve-month period and a short position in substantially underperforming equities over the same time.

7 Results

In this section, we will present the results from the regression we outlined in equation 1 for each category of firm emissions. As explained in section 5, a significant coefficient on these emission variables indicates a relationship between emissions and expected returns. Once we have analysed the regression results, we perform additional robustness tests presented in a separate section. Finally, we present results from the factor models represented by equation 2, which will allow us to understand if the traditional risk factors capture any carbon premium we may have found or whether carbon is an additional risk element.

7.1 Cross-sectional Regression

In table 6, we report the results of using the log of scope one and two emissions as the independent variables. In the first two columns, we have included all our control variables and controlled for time-fixed effects. The estimated coefficients show an inverse relationship between emissions and expected monthly returns. If we look at the first column, it shows that a one standard deviation increase in log scope one emissions leads to a $-.0018\%$ change in expected monthly returns. A similar inverse relationship is found for log scope two emissions. However, the reported coefficients are not statistically significant, judging by the t-statistic and using any of the standard p-values as a threshold. The third and fourth columns include industry-fixed effects to control for time-invariant industry-specific variation. The reported coefficients in these columns show a positive relationship between log scope emissions and expected monthly returns. These coefficients indicate the existence of a positive carbon premium in our sample, e.g., a one standard deviation increase in log scope two emissions correlates with a $.005\%$ increase in expected monthly returns. However, the coefficients are still not statistically significantly different from zero, meaning that while the data indicates a relationship, we cannot conclude that such a relationship exists. Even if the reported coefficients had been statistically significant, they are not economically significant due to the small magnitude, meaning that they would not influence investors' decision-making.

Table 6: Regression of Log Scope Emissions

This table reports the regression results from regressing the monthly expected return on the natural logarithm of firm level emissions and control variables. We report our regression output along with standard errors clustered at the year and firm level in parentheses. All regressions include year/month fixed effects, while regression 3 and 4 also takes industry fixed effects into account.

	Monthly return	Monthly return	Monthly return	Monthly return
Log(Scope 1)	-0.00180		0.00128	
	(0.0281)		(0.0432)	
Log(Scope 2)		-0.0438		0.00543
		(0.0417)		(0.0508)
_cons	4.481***	4.335***	3.031***	3.000***
(0.867)	(0.813)	(0.618)	(0.621)	
Controls	Yes	Yes	Yes	Yes
Time Fixed	Yes	Yes	Yes	Yes
Industry Fixed	No	No	Yes	Yes
N	19568	19520	19568	19520
R^2	0.315	0.315	0.316	0.317

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

While we have not found a statistically or economically significant carbon premium using emissions levels, it may be that year-to-year growth in emissions or the emission intensity is of more importance to expected returns. Therefore, in Table 7 we present estimates of equation 1 using the year-to-year growth in emissions and emission intensity as dependent variables. Table 7 indicates a negative relationship between the annual growth in emissions and expected monthly returns, also when we include industry fixed effects. If we, e.g., look at the fourth column, we see that a one standard deviation increase in the annual growth of scope two emissions correlates with a $-.21\%$ decrease in expected monthly returns. While this would have been economically significant, it is not statistically significant. For emission intensity, we find similar relationships to what we found for levels of emissions, especially for scope two emission intensity, but with the coefficients being even smaller in magnitude and still not significant.

Table 7: Regression of Emission Growth and Emission Intensity

This table reports the regression results from regressing expected monthly return on the year-to-year change on annual growth in emissions in the first panel and on emission intensity in the second panel. We always include all our control variables, standard errors clustered at the year and firm level in parentheses, and year/month fixed effects, while regression 3 and 4 also takes industry fixed effects into account.

	(1) Monthly return	(2) Monthly return	(3) Monthly return	(4) Monthly return
ΔScope 1	-0.0121		-0.0147	
	(0.228)		(0.221)	
ΔScope 2		-0.268		-0.211
		(0.223)		(0.217)
_cons	4.398***	4.484***	2.944***	3.011***
	(0.827)	(0.820)	(0.622)	(0.622)
Controls	Yes	Yes	Yes	Yes
Time Fixed	Yes	Yes	Yes	Yes
Industry Fixed	No	No	Yes	Yes
N	19532	19508	19532	19508
R^2	0.315	0.315	0.316	0.317
Scope 1 Intensity	0.0000440		0.0000164	
	(0.000184)		0.000238	
Scope 2 Intensity		-0.000375		0.00000862
		(0.000789)		0.000866
_cons	5.309***	5.004***	3.415***	3.174***
	(0.918)	(0.899)	(0.693)	(0.682)
Controls	Yes	Yes	Yes	Yes
Time Fixed	Yes	Yes	Yes	Yes
Industry Fixed	No	No	Yes	Yes
N	16001	15593	16001	15593
R^2	0.302	0.304	0.304	0.305

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

7.2 Robustness Tests

Our results have, so far, provided no significant indication of a relationship between carbon emissions and expected monthly returns. We have not found an economically significant carbon premium in our sample. We conduct further robustness tests presented in this subsection to confidently conclude that there is an indication of no carbon premium within the sample of European firms we are examining for 2010–2019 period. These robustness tests include testing for a potential salience effect and a Paris Agreement effect.

7.2.1 Salience Effect

In the literature review presented in section 3, we discussed literature looking at specific markets or industries and found significant relationships between carbon emissions and returns. This includes Witkowski et al. (2021), Hong et al. (2019), and Baldauf et al. (2020) amongst others. Therefore, we want to explore whether the firm's industry impacts a potential carbon premium rather than being universal for all industries. To that end, we will follow Bolton and Kacperczyk (2020) and split our sample by whether the firms are operating in salient or non-salient industries. We determine salience as being in one of the three industries with the highest sum of log scope one and two emissions in our sample: Construction Materials, Metals & Mining, and Oil, Gas & Consumable Fuels.

Table 8, 9, and 10 present the results of estimating the same regression as earlier on our three categories of emissions, on these sub-samples. Running the regression on these sub-samples gave us similar results to what we have already found. We still have not found a statistically and economically significant carbon premium for our sample of European firms from 2010–2019, even after we split the sample by salience. The fourth column of table 9 presents a significant carbon premium coefficient at a 10% significance level for the year-to-year growth in scope two emissions. It is also an economically significant result, showing that a one standard deviation increase in the annual growth in scope two emissions is related to a –1.62% change in expected monthly returns. While this could indicate a negative carbon premium in our sample, we note that the regression has been estimated on a relatively smaller sample of firms, making up only 1,620 monthly observations, as seen in the table. This sub-sample provides some conflicting results, and the salient industry firms do not make up a sufficiently large number of monthly observations. Therefore, we run additional robustness tests where we split our sample into percentiles based on scope one and two emissions. We now determine emission salient firms as firms with emissions above the 60th percentile. The result of estimating our regression on this sub-sample is found in the appendix and shows no economically and statistically significant carbon premium.

Table 8: Regression of Log Scope Emissions with Salient Industry Effect

This table reports the regression results from regressing the expected monthly return on the log of scope one and two emissions splitting the sample by industry salience. We always include all control variables, standard errors clustered at the year and firm level in parentheses, year/month fixed effects, as well as industry fixed effects.

	(1) Monthly return	(2) Monthly return	(3) Monthly return	(4) Monthly return
Log(Scope 1)	0.00537		-0.0826	
	(0.0548)		(0.0847)	
Log(Scope 2)		-0.0374		0.1006
		(0.0714)		(0.0852)
_cons	2.518**	2.459**	3.712***	3.642***
	(0.835)	(0.842)	(0.913)	(0.914)
Salient Industry	No	No	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Time Fixed	Yes	Yes	Yes	Yes
Industry Fixed	Yes	Yes	Yes	Yes
N	17,940	17,892	1,620	1,620
R^2	0.31	0.44	0.31	0.33

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 9: Regression of Growth in Emissions with Salient Industry Effect

This table reports the regression results from regressing the expected monthly return on the year-to-year growth of scope one and two emissions splitting the sample by industry salience. We always include all control variables, standard errors clustered at the year and firm level in parentheses, year/month fixed effects, as well as industry fixed effects.

	(1) Monthly returns	(2) Monthly returns	(3) Monthly returns	(4) Monthly returns
ΔScope 1	0.065		-2.535	
	(0.2166)		(1.961)	
ΔScope 2		-0.108		-1.624*
		(0.2137)		(0.834)
_cons	2.81***	4.30*	2.88***	4.430**
	(0.65)	(2.184)	(0.649)	(2.234)
Salient Industry	No	No	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Time Fixed	Yes	Yes	Yes	Yes
Industry Fixed	Yes	Yes	Yes	Yes
N	17,904	17,904	1,620	1,620
R^2	0.32	0.32	0.44	0.44

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 10: Regression on Emission Intensities with Salient Industry Effect

This table reports the regression results from regressing the expected monthly return on the scope one and two emission intensities splitting the sample by industry salience. We always include all control variables, standard errors clustered at the year and firm level in parentheses, year/month fixed effects, as well as industry fixed effects.

	(1) Monthly returns	(2) Monthly returns	(3) Monthly returns	(4) Monthly returns
Scope 1 Intensity	-0.000082		-0.00055	
	(0.00024)		(0.0017)	
Scope 2 Intensity		0.000055		-0.0054
		(0.0008)		(0.0064)
_cons	3.317***	3.076***	4.169	4.22
	(0.716)	(0.697)	(2.67)	(2.87)
Salient Industry	No	No	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Time Fixed	Yes	Yes	Yes	Yes
Industry Fixed	Yes	Yes	Yes	Yes
N	14,796	14,520	1,200	1,068
R^2	0.30	0.30	0.43	0.46

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

7.2.2 Paris Agreement Effect

Going back to the literature presented in section 3, some of the research argued that the effect of emissions on firm returns might have become more critical after the Paris Agreement. Therefore, following Bolton and Kacperczyk (2020) and Witkowski et al. (2021), we split our sample depending on whether we analyse firms before or after COP 21. This split allows an additional robustness test. We control for a potential Paris Agreement effect in our sample and findings to analyse if this gives us results challenging what we have already found.

Once again, we find no significant carbon premium using log emissions as independent variables or using the year-to-year growth in emissions. The tables presenting these results can be found in the appendix. However, for the regression on emission intensity, the results are different. As seen in the second and fourth column of table 11, we find a significant carbon premium, both for the pre-Paris sample (2011–2015) and the post-Paris sample (2016–2019).

Interestingly, the estimated relationships differ depending on the period. Column two of table 11 relates a one standard deviation increase in the scope two emission intensity of a firm with a –0.0022% change in expected monthly returns. This result implies that in the period before the Paris Agreement, there may have existed a negative relationship between firm emissions intensity and expected monthly returns. However, the fourth column of table 11 shows that a one standard deviation increase in the scope two emission intensity of a firm is related to a .003% change in expected monthly returns. This result indicates that the relationship between emission intensity and monthly returns has become positive in the period after the Paris Agreement.

Our results from this sub-sample indicate that investors may have become more aware of climate-related regulatory risk and are demanding a risk premium, reflecting that investor perception of climate risk related to regulation might have changed after COP 21. Interestingly, this is another difference from Bolton and Kacperczyk (2020), who found significant premiums for levels of emissions and year-to-year growth but not for emission intensity. This difference may indicate that European investors, in contrast to American investors, are focused not on total emissions or changes in total emissions but on how efficiently firms use emissions per million of revenue. If the emissions-to-sales level grows, they expect compensation for the additional risk, which might describe a difference in European investors' understanding of carbon risk. However, it is also important to note that Bolton and Kacperczyk did have some arguments that emission intensity might be a more noisy indicator compared to the other indicators. For investors, we argue that emission intensity may be a more appropriate indicator to understand risk, as it accounts for size compared to levels of emissions, which may be more vital if we are trying to curb climate change.

By examining our sample before and after the Paris Agreement, we found significant carbon premiums, indicating a potential "Paris effect". However, we still need to understand whether these present an additional carbon emission risk factor or whether traditional risk factors such as the CAPM 1-factor model, Fama-French 3-factor model, or Fama-French 5-factor model, including momentum, capture that risk.

Table 11: Emission Intensity Regression with Paris Effect

This table reports the regression results from regressing the expected monthly return on the scope one and two emission intensities splitting the sample by year. We always include all control variables, standard errors clustered at the year and firm level in parentheses, year/month fixed effects, as well as industry fixed effects.

	(1) Monthly returns	(2) Monthly returns	(3) Monthly returns	(4) Monthly returns
Scope 1 Intensity	-0.0002		0.0003	
	(0.0004)		(0.0003)	
Scope 2 Intensity		-0.0022**		0.003**
		(0.001)		(0.0013)
_cons	3.023***	3.055***	-7.024***	-7.162***
	(0.723)	(0.685)	(0.728)	(0.752)
Time Period	2011-2015	2011-2015	2016-2019	2016-2019
Controls	Yes	Yes	Yes	Yes
Time Fixed	Yes	Yes	Yes	Yes
Industry Fixed	Yes	Yes	Yes	Yes
N	8352	8220	7644	7368
R^2	0.338	0.344	0.26	0.259

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

7.3 Carbon Premium and Risk Factors

This section presents results from running our factor models using the time-series regression represented by equation 2. These models allow us to examine whether the carbon premiums we found in the previous section represent an additional carbon risk or whether these traditional risk factor models capture them. To estimate the regression, we follow Bolton and Kacperczyk (2020) and use a Newey-West procedure with 12 lags to account for autocorrelation in the error terms. As explained in section 5, a significant non-zero alpha from these regressions indicates that the factors included in the model cannot define the carbon premium and that some underlying risk might not be captured in the models.

Table 12 presents the results of running the different factor models, using the coefficient we found on our pre-Paris Agreement sample. In the first column, we present results from running the CAPM model and see that once we control for the market risk, the negative carbon premium we found for the pre-Paris sample is insignificant. In column two, we run the Fama-French 3-factor model and find a positive coefficient on the size factor, indicating that size may explain the negative carbon premium we found. This indication remains the case when we include momentum in the third column, run the Fama-French 5-factor model in the fourth column, and run the Fama-French 5-factor model, including momentum in the fifth column. This result indicates that the traditional risk factor models capture the negative carbon premium we found.

Table 12: Factor Model Regression (pre-Paris Sample)

In this table, we report results from the factor models. The dependent variable is the monthly carbon premium obtained from running the cross sectional return regression on scope two intensity. We regress our dependent variable on the 1-factor model (CAPM), 3-factor model (FF3), 3-factor model + Momentum (FF3 + MOM), 5-factor model (FF5), and the 5-factor model + Momentum (FF5 + MOM) using a Newey-West procedure including 12 lags.

	CAPM	FF3	FF3 + MOM	FF5	FF5 + MOM
MktRF	-0.0000526	0.000107	0.000110	0.000317	0.000318
	(0.000198)	(0.000293)	(0.000266)	(0.000342)	(0.000334)
SMB		0.00127**	0.00127**	0.00135**	0.00137**
		(0.000401)	(0.000403)	(0.000436)	(0.000426)
HML		-0.000172	-0.000148	-0.00191	-0.00201
		(0.000600)	(0.000820)	(0.00108)	(0.00113)
WML			0.0000435		-0.000194
			(0.000535)		(0.000440)
RMW				-0.00122	-0.00110
				(0.00101)	(0.00105)
CMA				0.00295	0.00310
				(0.00206)	(0.00200)
_cons	-0.00121	-0.00153	-0.00157	-0.00146	-0.00135
	(0.000883)	(0.00123)	(0.00108)	(0.00110)	(0.000983)
N	60	60	60	60	60

Standard errors in parentheses.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 13 presents the results for the positive and significant carbon premium we found for the post-Paris sample. In the first column, we again show results from running the CAPM model, but this time observe that controlling for market risk does not make the carbon premium we have found insignificant. Running the 3-factor model in the second column yields the same result. Whether we include momentum in the 3-factor model, run a 5-factor model, or run a 5-factor model including momentum, the α remains positive and significant, meaning that investors are receiving a premium for the additional carbon risk. These results indicate that the positive carbon premium we have found for the post-Paris sample represents an additional risk element not captured by the traditional risk models.

Table 13: Carbon Premium (Post-Paris Sample)

In this table, we report results from the factor models. The dependent variable is the monthly carbon premium obtained from running the cross sectional return regression on scope two intensity. We regress our dependent variable on the 1-factor model (CAPM), 3-factor model (FF3), 3-factor model + Momentum (FF3 + MOM), 5-factor model (FF5), and the 5-factor model + Momentum (FF5 + MOM) using a Newey-West procedure including 12 lags.

	CAPM	FF3	FF3 + MOM	FF5	FF5 + MOM
MktRF	0.00000808	0.000195	0.000227	0.000394	0.000387
	(0.000329)	(0.000333)	(0.000318)	(0.000386)	(0.000354)
SMB		-0.00245	-0.00247	-0.00247	-0.00246
		(0.00139)	(0.00138)	(0.00137)	(0.00132)
HML		-0.000615	-0.000565	-0.00215	-0.00219
		(0.000412)	(0.000473)	(0.00108)	(0.00138)
WML			0.000133		-0.0000493
			(0.000446)		(0.000564)
RMW				-0.00168	-0.00170
				(0.00123)	(0.00136)
CMA				0.00140	0.00144
				(0.000920)	(0.00116)
_cons	0.00237***	0.00247***	0.00238**	0.00265***	0.00269**
	(0.000668)	(0.000620)	(0.000805)	(0.000641)	(0.000914)
N	48	48	48	48	48

Standard errors in parentheses.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

8 Conclusion

In this thesis, we identified a significant carbon risk premium in our unique sample of European firms from 2010–2019 by building and extending on the methods of Bolton and Kacperczyk (2020). The carbon premium was identified by splitting the sample based on whether we examined a period before or after the Paris Agreement. Interestingly, we found a negative premium for the pre-Paris sample and a positive one for the post-Paris sample, indicating that carbon emissions negatively affected expected monthly returns before COP 21 but that investors started requiring compensation for risk after the Paris Agreement. While the negative premium we found in the pre-Paris sample was captured by the traditional risk models, particularly by the size factor, conventional risk factor models could not explain the positive premium found in the post-Paris sample.

This result could imply that investors incorporated the information available after 2015 on climate-related regulatory risks, potentially resulting from government pledges to curb emissions. However, we did not find any significant carbon premium for emissions levels, the year-to-year growth of emissions, or emission intensity. Splitting the sample by salience also did not yield a consistent significant result. Even when breaking it into a pre- and post-Paris sample, only when we used scope two emission intensity did we find a statistically significant carbon premium, but not when we used any of our other emission indicators.

To conclude, most of our estimates were insignificant and did not yield a significant carbon premium. Therefore, more research on this topic may be necessary for the external validity of our results beyond our sample and for an even more robust conclusion. However, we did find some indications that investors are starting to acknowledge an increased climate-related regulatory risk by requiring a carbon premium after the Paris Agreement.

References

Baldauf, M., Garlappi, L., & Yannelis, C. (2020). Does climate change affect real estate prices? only if you believe in it. *The Review of Financial Studies*, *33*(3), 1256–1295.

Bolton, P., & Kacperczyk, M. (2021). Do investors care about carbon risk? *Journal of financial economics*, *142*(2), 517–549.

Bolton, P., & Kacperczyk, M. T. (2020). Carbon premium around the world.

Carhart, M. M. (1997). On persistence in mutual fund performance. *The Journal of finance*, *52*(1), 57–82.

Chava, S. (2014). Environmental externalities and cost of capital. *Management science*, *60*(9), 2223–2247.

Choi, D., Gao, Z., & Jiang, W. (2020). Attention to global warming. *The Review of Financial Studies*, *33*(3), 1112–1145.

Cuervo, J., & Ved P, G. (1999). Carbon taxes: Their macroeconomic effects and prospects for global adoption. a survey of the literature. *Revista Desarrollo y Sociedad*, (43), 132–171.

Daniel, K. D., Litterman, R. B., & Wagner, G. (2016). *Applying asset pricing theory to calibrate the price of climate risk* (tech. rep.). National Bureau of Economic Research.

Fama, E. F. (1970). Efficient capital markets: A review of theory and empirical work. *The Journal of Finance*, *25*(2), 383–417.

Fama, E. F., & French, K. R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of financial economics*, *33*(1), 3–56.

Fama, E. F., & French, K. R. (2015). A five-factor asset pricing model. *Journal of financial economics*, *116*(1), 1–22.

Fink, L. (2020). *A fundamental reshaping of finance*. https://www.blackrock.com/us/individual/larry-fink-ceo-letter (accessed: 23.06.2022)

Hong, H., Li, F. W., & Xu, J. (2019). Climate risks and market efficiency. *Journal of econometrics*, *208*(1), 265–281.

Hsu, P.-H., Li, K., & Tsou, C.-Y. (2022). The pollution premium. *Journal of Finance, Forthcoming.*

In, S. Y., Park, K. Y., & Monk, A. (2017). Is “being green” rewarded in the market? an empirical investigation of decarbonization risk and stock returns. *International Association for Energy Economics (Singapore Issue)*, *46*(48).

Islam, R. (2022). *What a carbon tax can do and why it cannot do it all.* https://blogs.worldbank.org/energy/what-carbon-tax-can-do-and-why-it-cannot-do-it-all (accessed: 08.06.2022)

Jegadeesh, N., & Titman, S. (1993). Returns to buying winners and selling losers: Implications for stock market efficiency. *The Journal of finance*, *48*(1), 65–91.

Jensen, M. C. (1968). The performance of mutual funds in the period 1945-1964. *The Journal of finance*, *23*(2), 389–416.

Lintner, J. (1965). Security prices, risk, and maximal gains from diversification. *The journal of finance*, *20*(4), 587–615.

Markowitz, H. (1952). Portfolio selection. *The Journal of Finance*, *7*(1), 77–91.

Monasterolo, I., & De Angelis, L. (2020). Blind to carbon risk? an analysis of stock market reaction to the paris agreement. *Ecological Economics*, *170*, 106571.

Mossin, J. (1966). Equilibrium in a capital asset market. *Econometrica: Journal of the econometric society*, 768–783.

Pedersen, L. H., Fitzgibbons, S., & Pomorski, L. (2021). Responsible investing: The esg-efficient frontier. *Journal of Financial Economics*, *142*(2), 572–597.

Roundtable, B. (2019). *Business roundtable redefines the purpose of a corporation to promote 'an economy that serves all americans'*. https://www.businessroundtable.org/business-roundtable-redefines-the-purpose-of-a-corporation-to-promote-an-economy-that-serves-all-americans (accessed: 23.06.2022)

Sharfman, M. P., & Fernando, C. S. (2008). Environmental risk management and the cost of capital. *Strategic management journal*, *29*(6), 569–592.

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

Witkowski, P., Adamczyk, A., & Franek, S. (2021). Does carbon risk matter? evidence of carbon premium in eu energy-intensive companies. *Energies*, *14*(7), 1855.

APPENDIX

Table 14: Regression of Log Scope Emissions with Salient industry effect

This table reports the regression results from regressing the expected monthly return on the log of scope one and two emissions splitting the sample by industry salience based on percentiles. We always include all control variables, standard errors clustered at the year and firm level in parentheses, year/month fixed effects, as well as industry fixed effects.

	(1) Monthly returns	(2) Monthly returns	(3) Monthly returns	(4) Monthly returns
Log(Scope 1)	-0.0133		-0.0534	
	(0.0439)		(0.2468)	
Log(Scope 2)		-0.0181		0.1545
		(0.0511)		(0.3184)
_cons	2.913***	2.879***	4.356**	4.305*
	(0.835)	(0.842)	(0.913)	(0.914)
Salient Industry	No	No	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Time Fixed	Yes	Yes	Yes	Yes
Industry Fixed	Yes	Yes	Yes	Yes
N	11760	11712	7800	7800
R^2	0.31	0.311	0.35	0.35

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 15: Regression on Change in Emissions with Salient industry effect

This table reports the regression results from regressing the expected monthly return on the year-to-year growth of scope one and two emissions splitting the sample by industry salience based on percentiles. We always include all control variables, standard errors clustered at the year and firm level in parentheses, year/month fixed effects, as well as industry fixed effects.

	(1) mthretpct	(2) mthretpct	(3) mthretpct	(4) mthretpct
ΔScope 1	0.020		-0.5418	
	(0.2208)		(0.3761)	
ΔScope 2		-0.2853		-0.1553
		(0.2273)		(0.289)
_cons	2.018**	2.151**	3.522***	3.478***
	(0.885)	(0.887)	(0.937)	(0.936)
Salient Industry	No	No	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Time Fixed	Yes	Yes	Yes	Yes
Industry Fixed	Yes	Yes	Yes	Yes
N	11724	11736	7800	7788
R^2	0.316	0.317	0.359	0.36

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 16: Emission Intensity Regression with Salient industry effect

This table reports the regression results from regressing the expected monthly return on the scope one and two emission intensities splitting the sample by industry salience based on percentiles. We always include all control variables, standard errors clustered at the year and firm level in parentheses, year/month fixed effects, as well as industry fixed effects.

	(1) mthretpct	(2) mthretpct	(3) mthretpct	(4) mthretpct
Scope 1 Intensity	0.0002		-0.0002	
	(0.0038)		(0.0002)	
Scope 2 Intensity		0.0007		-0.0015*
		(0.0012)		(0.0009)
_cons	3.112***	2.698**	3.140**	3.089**
	(0.9757)	(0.929)	(1.092)	(1.1100)
Salient Industry	No	No	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Time Fixed	Yes	Yes	Yes	Yes
Industry Fixed	Yes	Yes	Yes	Yes
N	9492	9240	6504	6348
R^2	0.30	0.303	0.355	0.359

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 17: Regression of Log Scope Emissions with Paris effect

This table reports the regression results from regressing the expected monthly return on the log of scope one and two emission splitting the sample by year. We always include all control variables, standard errors clustered at the year and firm level in parentheses, year/month fixed effects, as well as industry fixed effects.

	(1) Monthly returns	(2) Monthly returns	(3) Monthly returns	(4) Monthly returns
Log(Scope 1)	-0.0837		0.0525	
	(0.1319)		(0.1680)	
Log(Scope 2)		-0.0837		0.0525
		(0.1319)		(0.1680)
_cons	2.6479***	2.6479***	-7.473***	-7.473***
	(0.650)	(0.650)	(0.676)	(0.676)
Time Period	2011-2015	2011-2015	2016-2019	2016-2019
Controls	Yes	Yes	Yes	Yes
Time Fixed	Yes	Yes	Yes	Yes
Industry Fixed	Yes	Yes	Yes	Yes
N	10800	10800	8712	8712
R^2	0.36	0.36	0.273	0.273

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 18: Regression of Growth in Emissions with Paris effect

This table reports the regression results from regressing the expected monthly return on the year-to-year growth of scope one and two emissions splitting the sample by year. We always include all control variables, standard errors clustered at the year and firm level in parentheses, year/month fixed effects, as well as industry fixed effects.

	(1) Monthly returns	(2) Monthly returns	(3) Monthly returns	(4) Monthly returns
ΔScope 1	-0.0440		-0.1598	
	(0.2362)		(0.3168)	
ΔScope 2		-0.4473		-0.1149
		(0.2727)		(0.2353)
_cons	2.569***	2.655***	-7.475***	-7.471***
	(0.648)	(0.650)	(0.676)	(0.676)
Time Period	2011-2015	2011-2015	2016-2019	2016-2019
Controls	Yes	Yes	Yes	Yes
Time Fixed	Yes	Yes	Yes	Yes
Industry Fixed	Yes	Yes	Yes	Yes
N	10788	10788	8736	8736
R^2	0.359	0.361	0.273	0.273

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$