Handelshøyskolen BI

GRA 19703 Master Thesis

Thesis Master of Science 100% - W

Predefinert informasjon

Startdato:	09-01-2023 09:00 CET	**Termin:**	202310
Sluttdato:	03-07-2023 12:00 CEST	**Vurderingsform:**	Norsk 6-trinns skala (A-F)
Eksamensform:	T		
Flowkode:	202310||11184||IN00||W||T		
Intern sensor:	(Anonymisert)		

Deltaker

Navn:	Victor Waage Sand og Haakon Vidbjørn Lund

Informasjon fra deltaker

Tittel *:	The Cross-Industrial Carbon Risk Premium
Navn på veileder *:	Giovanni Pagliardi

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

Gruppe

Gruppenavn:	(Anonymisert)
Gruppenummer:	213
Andre medlemmer i gruppen:	

The Cross-Industrial Carbon Risk Premium

Master Thesis

by
Victor Waage Sand and Haakon Vidbjørn Lund
MSc in Business with Major Finance

Supervisor: Giovanni Pagliardi

Oslo, July 3, 2023

ABSTRACT

This thesis investigates the presence of a carbon risk premium in stock returns from 2003 to 2022 of 8,996 companies across 66 countries. We show that firms with higher carbon emissions earn higher returns while controlling for size, book-to-market, and other return predictors. Further, we examine the time variation of the carbon risk premium, highlighting that the premium increases during political decarbonization events. Additionally, we investigate the carbon premia across various sectors and find evidence of a higher carbon premium in high-emitting sectors relative to low-emitting sectors. Finally, we illustrate how to incorporate the carbon premium in portfolio allocation.

Keywords: carbon emissions, long-term carbon-transition risk, climate change, stock returns

Acknowledgements

We want to express our great gratitude to our supervisor Giovanni Pagliardi for his unwavering support, expertise, and guidance throughout the process of writing this thesis. The encouraging discussions, dedication, and constructive feedback we have received over the six months have been instrumental in shaping this research project. This has made this experience both filled with continuous learning, but also laughter.

We also want to thank our family and loved ones for their unconditional support throughout our studies.

This thesis marks the end of our master's degree here at BI. Now new challenges await.

Thank you.

Contents

List of Tables

1 Introduction

Several studies aim to explain how companies' stock returns are impacted by aggregate risk factors such as size, book-to-market ratios, or firm-specific risk associated with identifiable firm characteristics. However, limited research has been conducted on the influence of firm-level carbon emissions on stock returns. More recently, the financial literature has begun to address this topic, as concerns over global warming due to CO2 emissions have become more salient following the December 2015 Paris Agreement (Bolton & Kacperczyk, 2021). The increasing temperatures and renewed policy initiatives aimed at reducing CO2 emissions pose the question of whether carbon emissions constitute significant risks for investors, affecting stock returns and portfolio holdings.

In this thesis, we postulate the following research questions: Is a carbon risk premium priced? Is the time variation in the carbon risk premium related to salient events? Is there a cross-section of carbon risk premia across sectors? Can investors benefit from incorporating a carbon risk premium in portfolio optimization?

First, we show evidence of a 1% statistically significant carbon risk premium priced at a global level by replicating Bolton & Kacperczyk (2022). The global carbon premium is also economically significant, with a positive coefficient of 0.081, meaning that a one standard deviation increase in carbon emissions increases stock returns by 23 bps per month or 2.7% annually. We extend the work of Bolton & Kacperczyk (2022) with a more updated sample and find that the global carbon risk premium has been increasing in recent years, specifically in 2021 and 2022.

Second, we find evidence of a time variation in the carbon risk premium due to several political initiatives. By conducting event studies, we show that the announcement of decarbonizing efforts, such as the Paris Agreement, the

German Industrial Transformation, and the US Inflation Reduction Act, all positively affects the carbon risk premium at a 1% significance level.

Third, we contribute to the work of Bolton & Kacperczyk (2021) and show that from 2016 to 2022, the period after the Paris Agreement announcement, there is a clearer categorization within high-carbon industries, creating a more distinct difference in carbon premium between high- and low-emission sectors. We propose that this disparity is a result of investors' increased awareness regarding carbon risks in high-carbon industries due to the increased occurrence and progression of political climate events.

Fourth, we show methodologically how investors can apply our extensive findings in portfolio allocation through an optimization model. This model incorporates expected returns reflecting priced carbon risk premia from various sectors.

2 Background

This thesis is motivated by the Journal of Finance studies conducted by Patrick Bolton and Marcin Kacperczyk, "Do Investors Care About Carbon-Risk?" (2021), and "Global Pricing of Transition-Risk" (2022). These papers study whether carbon emissions affect the cross-section of US and global stock returns (Bolton & Kacperczyk, 2021). Bolton and Kacperczyk highlight that firms with higher carbon emissions carry higher transition risk due to increased pressure to decarbonize following the 2015 Paris Agreement. Hence, a carbon risk premium exists in the stock market (Bolton & Kacperczyk, 2022). They test this by running cross-sectional regressions in the time period from 2005 to 2018 and find economically and statistically significant carbon risk premia in both the US (2021) and the global stock market (2022).

We find the results of the studies by Bolton and Kacperczyk fascinating, specifically as there seems to be a growing carbon risk premium due to more investor awareness of environmental changes. This implies that carbon is increasingly relevant as a risk measure for stock returns. We supplement Bolton and Kacperczyk's findings by extending the sample period, including more recent years, namely 2019 to 2022. By doing so, we can investigate whether the carbon risk premium increases as we approach the 2050 carbon-neutrality goals (UN, 2022b). If carbon is increasingly important as a measure of risk for stock returns, we will find a larger and more significant carbon risk premium in the most recent years. Additionally, we will delve deeper into how political events affect the carbon premium. This thesis analyses the following salient events: the Paris Agreement, the EU ETS price increase, the German Industrial Decarbonization Package, and the US Inflation Reduction Act.

Lastly, we find the industry analysis of Bolton & Kacperczyk (2021) compelling. Surprisingly, they find that excluding high-emitting industries from their regression sample, such as oil & gas companies, increases the carbon premium, not the opposite (Bolton & Kacperczyk, 2021). We postulate that the increasing political efforts towards carbon-neutrality (EU, 2023) could have a more substantial impact on high-carbon compared to low-carbon industries. Thus, we believe it is worthwhile investigating the carbon risk premia in different industries, including the most recent years from 2019 to 2022 as investors might be increasingly aware of firms' carbon risks.

This thesis will use related research methodology as Bolton and Kacperczyk (2021, 2022). However, we complement the research topic and provide empirical innovations by investigating the time variation in the carbon premium, the carbon premium observed in different industries, and how investors can incorporate a carbon risk premium in portfolio construction.

3 Literature review

As aforementioned, this thesis replicates and extends the work of Bolton and Kacperczyk (2021, 2022). Bolton and Kacperczyk have been pivotal in the research of the carbon risk premium, and they find statistically significant evidence of a global carbon risk premium for 14,400 companies in 77 countries from 2005 to 2018 (Bolton & Kacperczyk, 2022). Bolton and Kacperczyk show that the premium is both positive and growing after the 2015 Paris Agreement, emphasizing that investors are gradually becoming more aware of the urgency to tackle climate change. They suggest that the higher returns for high-carbon emitting firms could be explained because they carry more systematic risks, specifically carbon-transition risk (Bolton & Kacperczyk, 2022). According to Bolton and Kacpeczyk, fossil-dependent firms are exposed to carbon-transition risk as the energy transition away from fossil fuels progresses (Bolton & Kacperczyk, 2022). As we approach the 2050 climate goals (UN, 2022b), the transition risk could increase as there is a growing concern regarding climate change, which could entail a faster and potentially disorderly transition away from fossil fuels to renewable energy. Thus, transition risk encompasses the uncertain speed of adjustment toward carbon-neutrality. Also, it encapsulates the combination of investors' evolving views about the shift towards cleaner energy sources and a broad range of shocks, such as changes in climate policy, reputational impacts, shifts in market preferences, and technological innovation (Bolton & Kacperczyk, 2022).

We contribute to the work of Bolton and Kacperczyk by extending the sample period. Specifically, we investigate the global carbon risk premium in the period 2003-2022, meaning that we observe the development of the carbon risk premium in more recent years. Doing so, we investigate whether the premium increases as we approach the carbon-neutrality goals. Further, we extend the analysis of Bolton and Kacperczyk by examining the time variation in the carbon risk premium. As Bolton and Kacperczyk find that the Paris Agreement event increased the global carbon risk premium, we investigate whether more recent political climate initiatives affect the premium. We identify important environmental announcements, such as the German industrial decarbonization package and the US inflation reduction act, and analyze whether these initiatives impact the carbon risk premium.

Moreover, in their 2021 paper, Bolton and Kacperczyk examine the differences in the carbon risk premium across industries for the period 2005-2017 (Bolton & Kacperczyk, 2021). By excluding salient carbon-heavy industries from their sample, and comparing the regression results with a full sample including these carbon-heavy industries, they find that the carbon risk premium increases when excluding high-carbon industries (Bolton & Kacperczyk, 2021). Hence, Bolton and Kacperczyk conclude that investors tend to categorize firms within salient industries in a more coarse manner, where returns are less sensitive to emission differences among firms. We find these findings surprising, and we choose to further advance the research by Bolton and Kacperczyk as they investigate the period from 2005 to 2017, where investors' carbon risk awareness was more limited. Specifically, we contribute by analyzing the variation in the carbon risk premium between sectors after the Paris Agreement, namely 2016-2022. As the Paris Agreement marked a shift in climate awareness, we expect to see a clearer categorization within high-carbon industries in more recent years.

Other related studies to ours are Oestreich & Tsiakas (2015), which investigate the carbon risk premium in German stock prices from 2003 to 2009. They show an economically and statically significant carbon risk premium (Oestreich & Tsiakas, 2015). Additionally, in their newest entry to the Journal of Finance, Hsu et al. (2023) investigate the pollution premium from 1991 to 2016. They show that a long-short portfolio of US firms with high versus low emissions generates an average annual return of 4.42% from 1991 to 2016 (Hsu et al., 2023). They further highlight that these results remain significant after controlling for common risk factors, such as Fama & MacBeth (1973), and other return predictive firm characteristics. Like Bolton & Kacperczyk (2022), Hsu et al. (2023) argue that the main reason for these results is that high-polluting firms are more exposed to transition risks, such as changes in regulation and environmental policies.

Furthermore, we contribute to the current climate finance literature by demonstrating how investors can implement a carbon risk premium in portfolio optimization, following the methodology of Markowitz's Modern Portfolio Theory (Markowitz, 1952). Similar to our portfolio analysis, several papers have recently been published investigating portfolio construction with carbon risk or ESG factors. Görgen et al. (2021) show how to integrate carbon risk into portfolios using a carbon beta. Like our analysis, they measure this carbon risk as the portfolio returns generated by going long in carbon-heavy, "brown" stocks and short in "green" stocks (Görgen et al., 2021). Comparing a "brown" and a "green" portfolio with the market portfolio, Görgen et al. (2021) find that both portfolios obtain a lower Sharpe ratio relative to the market portfolio from 2010 to 2019. However, interestingly, they highlight that the Sharpe ratio of the "green" portfolio is notably lower compared to the "brown" portfolio. Further, Pedersen et al. (2021) construct an "ESG efficient frontier" showing portfolios' maximum attainable Sharpe ratio for a given ESG score. They argue that investors increasingly integrate their environmental views when picking stocks and that some investors desire to own ethical firms. Not surprisingly, Pedersen et al. (2021) show that the Sharpe ratio of the portfolios decreases when ESG constrictions are introduced (Pedersen et al., 2021).

4 Hypotheses

The literature review identifies essential risk factors linking carbon emissions to stock returns. Firms with high emissions could be more exposed to reputational risks as more and more investors avoid investing in climate-damaging industries due to ethical considerations (Pedersen et al., 2021). High-carbon firms might also carry more regulatory risk as they are more prone to carbon taxation and higher capital costs (Hsu et al., 2023). In addition, companies heavily reliant on fossil fuels might bear significant transitional risks, as they are more exposed to the technology risk from lower-cost renewable energy (Bolton & Kacperczyk, 2021). Thus, we expect our carbon risk premium analysis to yield similar results, if not stronger, relative to the global analysis done by Bolton and Kacperczyk (2022) from 2005 to 2018. This is because we choose to expand the period of study to include the most recent years from 2019 to 2022, closer to the 2050 carbon-neutrality goals (UN, 2022b). Hence, our first hypothesis is as follows:

- There is an economically and statistically significant relationship between stock returns and firms' carbon emissions. Higher carbon emissions yield higher returns.

Since the 2015 Paris Agreement, we have observed an increasing global effort towards carbon-neutrality (UN, 2020). As Bolton and Kacperczyk highlight in their paper (2022), there should be a time variation in the carbon premium as we approach the 2050 net-zero targets (UN, 2022b). Additionally, they found that the Paris Agreement affected the carbon premium and therefore concluded that salient events influence the premium. We believe that political actions favoring the net-zero targets, such as the US Inflation Reduction Act, will affect the carbon premium as it creates further pressure for firms to reduce emissions and achieve carbon-neutrality by 2050. Therefore, our second hypothesis is as follows:

- There is an economically and statistically significant relationship between political actions toward climate change and the carbon premium, creating a time variation in the carbon premium.

Although all sectors are exposed to the net-zero carbon transition, the level of exposure varies among them (McKinsey, 2022b). Specifically, decarbonization could be more challenging for industries where carbon is an integral part of the production process, called "hard-to-abate" industries like cement, chemicals, and steel (McKinsey, 2022a). In their 2021 paper, Bolton and Kacperczyk conclude that high-emission industries do not have a higher carbon premium (Bolton & Kacperczyk, 2021). However, there has been an increase in political actions towards carbon-neutrality after the Paris Agreement (EU, 2023). The price of carbon allowances in the European Union, the EU ETS, rose substantially in 2021, with an increase of 140% (Ember, 2023). Consequently, companies with high Scope 1 emissions have experienced a significant rise in production costs (Equinor, 2021). Thus, our third hypothesis is as follows:

- There is a statistically significant higher carbon premium for industries with higher carbon emissions compared to low-carbon industries.

If investors are pricing in climate risks in asset prices today, the sector-weighting of a Markowitz-constructed market portfolio should change when including a carbon risk premium (Markowitz, 1952). Therefore, when estimating expected stock returns, including a carbon risk premium together with a market risk premium should tilt the maximum Sharpe portfolio towards higher weighting in high-carbon sectors because of higher exposure to systematic risk. This is because high-carbon sectors could bear more systematic climate risks, such as transition, reputational or regulatory risks. Hence, our last hypothesis is as follows:

- The sector-weighting of the market portfolio changes towards more high-carbon sectors when including a carbon risk premium in the portfolio construction. This is because expected returns are determined not only by exposure to market risk, but also to carbon risk.

5 Methodology

In order to test the four hypotheses previously formulated, this section will demonstrate the appropriate methodology. This section is split into three parts. The first part describes the methodology used to estimate whether a carbon risk premium is present in cross-sectional stock returns. The second part will then display how we create a time series of the carbon risk premium and investigate how the carbon premium reacts to political announcements of emission reductions. Further, the third part will specify how we construct a Markowitz-constructed portfolio, including the carbon risk premium and the market risk premium from the classical CAPM.

5.1 Specification of the Regression Model

The purpose of the cross-sectional regression in this thesis is to examine if there is a relationship between stock returns and firms' relative carbon emissions. We will use firm-level carbon emissions as a proxy for companies' relative exposure to carbon emission risk to empirically test for a carbon risk premium. As Bolton and Kacperczyk discuss, the level of carbon emissions can be considered a long-term transition risk since it implies the firms' "distance" to achieving the 2050 net-zero emission targets (Bolton & Kacperczyk, 2022).

We test the first hypothesis in this thesis and replicate the results from Bolton & Kacperczyk (2022) by running the following cross-sectional regressions of companies' monthly stock returns against their total emissions while controlling for firm-specific variables and fixed effects.

$$RET_{i,t} = \beta_0 + \beta_1 TotalEmissions_{i,t-1} + \beta_2 Controls_{i,t-1} + \lambda_t + \mu_i + \delta_i + \epsilon_{i,t} \tag{1}$$

In Equation (1), the dependent variable $RET_{i,t}$ is the monthly stock returns for company i in month t. $TotalEmissions_{i,t-1}$ is the one-year lagged firm-level total emission, comprising the natural logarithm of Scope 1 and Scope 2 carbon emissions measured in tons. We choose not to include Scope 3 emissions in Equation (1), which will be further elaborated in the forthcoming section. Several firm-specific characteristics could predict stock returns which we need to control for to establish any causal inference regarding carbon emissions and stock returns (Stock & Watson, 2020). $Controls_{i,t-1}$ consists of the same control variables as proposed in Bolton & Kacperczyk (2022), namely, Momentum, Volatility, Return on Equity, Size, Book-to-Market, Investments-to-Assets, Property Plant & Equipment, and the Herfindahl Index. We also include each firm's 3-year market beta, as we want to control for market sensitivity. Like Bolton & Kacperczyk (2022), the control variables are calculated at the end of the calendar year and lagged by one year, as it may take time for these control variables to affect stock returns.

It is important to emphasize that we use panel data for our analysis, while the regression model specified in Model (1) assumes that the regression residuals are linearly independent and homoscedastic. Using panel data for firm-level variables at different points in time implies that there might be some correlation within observations for each firm across time. The result is that the standard CLRM assumptions 2 and 3 might be violated, and we observe heteroscedasticity and autocorrelation in the error terms (Brooks, 2019). If we do not correct for this, we might estimate inappropriate standard errors for the coefficient estimates, leading to wrong inference. Therefore, it is imperative to correct for autocorrelation and heteroscedasticity in the residuals, and we do this by clustering standard errors at the year and company level.

By including month-fixed effects λ_t in Model (1), we also control for effects that vary over time but are constant across firms. This works by introducing individual dummy variables for each month in the regression model, encapsulating any fluctuations in the relationship between stock returns and emissions that varies over time, but are constant across firms (Stock & Watson, 2020). Examples of such are geopolitical events or macroeconomic shocks. Further, following the same methodology, we also include industry-fixed effects μ_i in Model (1), which controls for variation across industries that are constant over time. This ensures that Model (1) does not include any bias stemming from unobserved industry-level heterogeneity, such as technological requirements, regulatory environments, or consumer preferences. Lastly, we include country-fixed effects δ_i in Model (1) to absorb potential heterogeneity between countries that are constant over time. By doing so, we control for cross-country variation, such as differences in legal and regulatory frameworks, market structures, or environmental policies. The coefficient of interest in Model (1) is β_1.

5.2 Time Series Analysis of the Carbon Risk Premium

Bolton & Kacperczyk (2022) emphasize that there should be a time variation in the carbon risk premium as firms' transition risk increases toward the 2050 net-zero climate targets. In this thesis, we perform two different analyses to investigate the time variation of the carbon premium. First, we follow the method of Bolton & Kacperczyk (2022) by dividing the sample into different time periods. They divide their dataset into two sub-samples, 2014-2015 and 2016-2017, to test the effect of the Paris Agreement on the carbon premium. We further expand the number of periods investigated by additionally including 2018-2019 and 2021-2022. The regressions for these tests follow Model (1) outlined in 5.1. Due to the COVID-19 pandemic, and the substantial noise introduced by this extraordinary event, we skip 2020 in our analysis.

Second, we investigate how the time series of the carbon risk premium, CRP, reacts to regulatory announcements of climate actions. We obtain the time series of the carbon risk premium in the stock market by constructing a global long-short portfolio that buys companies with the 20% highest carbon emissions and sells companies with the 20% lowest from 2003 to 2022. This is done by acquiring firm-level carbon emissions data for all 8,996 firms and sorting the emission levels from the 20% highest to the 20% lowest. For each month from 2003 to 2022, the portfolio re-adjusts according to the firms' emission levels, creating a dynamic measure of the carbon risk premium. We utilize this time series by running multiple event tests using dummy variable regressions.

For our first event analysis, we perform a dummy variable regression incorporating all salient events into one variable. For this thesis, we focus on the following events: the Paris Agreement, the price increase of EU ETS in 2021 (Ember, 2023), the March 2022 German announcement of industrial decarbonization (Reuters, 2022), and the August 2022 Inflation Reduction Act (UN, 2022c).

$$CRP_t = \beta_0 + \beta_1 SalientEvents_t + \beta_2 MarketPremium_t + u_t \tag{2}$$

In Equation (2), $SalientEvents_t$ denotes a dummy variable that takes on the value of 1 at the time of the event. In addition, we choose to have a zero anticipation window and a 1-month adjustment window. Thus, the month after the event has a value of 1, and 0 otherwise. In order to ensure robustness, we additionally control for market premium in the regression model, as fluctuations in the carbon risk premium might be correlated with market movements. The coefficient of interest in Model (2) is β_1.

In our second event analysis, we perform individual tests for each salient event. Model (3) illustrates the event test for the Paris Agreement, where $ParisAgreement_t$ denotes a dummy variable that takes on the value of 1 at the time of the event in December 2015 (UN, 2022a) with a zero anticipation window and a 1-month adjustment window.

$$CRP_t = \beta_0 + \beta_1 ParisAgreement_t + \beta_2 MarketPremium_t + u_t \tag{3}$$

The event test for the Inflation Reduction Act follows the exact model specification of Model (3). However, the event tests for the EU ETS and the German industrial package contain some modifications. During the events of the EU ETS price increase and the German decarbonization announcement, the oil- and natural gas prices spiked significantly. As the CRP might benefit from the rise of oil and gas prices, we control for this such that the dummy variables do not capture these effects. Controlling for these factors therefore ensures more robust results. The event tests of the EU ETS increase and the German industry announcement follows Model (4):

$$\begin{aligned} CRP_t = \beta_0 &+ \beta_1 \text{EU ETS}_t + \beta_2 \text{Market Premium}_t \\ &+ \beta_3 \text{Crude Oil} + \beta_4 \text{Natural Gas} + u_t \end{aligned} \tag{4}$$

In Equation (4), the EU ETS dummy variable takes a value of 1 in the month the price of EU ETS rose by approximately 20% with a 1-month adjustment window and 0 otherwise. We aim to investigate if the extreme effects of the EU ETS impact the carbon risk premium. The coefficient of interest is β_1.

5.3 Portfolio Application and Asset Pricing with a Carbon Premium

The last objective of this thesis is to investigate how investors can apply the carbon risk premium. We will compare two portfolios, a portfolio including the classical CAPM and a portfolio including CAPM plus a carbon risk premium. This thesis will focus on the following: the change in expected excess returns, the change in portfolio weighting, and performance in an out-of-sample test.

The portfolios comprise the 11 GICS sectors classified by MSCI (MSCI, 2023c). These 11 GICS sectors include Energy, Materials, Industrials, Consumer Discretionary, Consumer Staples, Health Care, Financials, Information Technology, Communication Services, Utilities, and Real Estate (MSCI, 2023c).

First off, we examine how expected excess returns change when including a carbon beta in addition to the classical CAPM in a model. Therefore, in this part of the analysis, we compare two models' estimated sector excess returns using the classical CAPM (5) versus the estimated excess returns using CAPM plus a carbon beta (6). Due to CAPM theory, we set the alpha equal to zero.

$$r_{i,t}^{e} = r_{i,t}^{e,CAPM} = \alpha + \beta_i^{CAPM}(r_t^m - r_t^f) \tag{5}$$

$$r_{i,t}^{e} = r_{i,t}^{e,CAPM+CARBON} = \alpha + \beta_i^{CAPM}(r_t^m - r_t^f) + \beta_i^{CARBON}(CRP_t) \tag{6}$$

To do this, we define an in-sample period from 2016 to 2022. We elaborate on why we choose this time period in section 7. To estimate the expected excess returns, we first calculate the 5-year market beta and the 5-year carbon beta for each GICS sector for the period. The market beta for each industry, β_i^{CAPM}, is defined in regression (7) and is the slope coefficient of a regression of monthly returns of the respective GICS sector on the market-excess return.

$$r_{i,t}^{e} = \alpha + \beta_i^{CAPM}(r_t^m - r_t^f) \tag{7}$$

The market-excess return is defined as the monthly return of the MSCI International World Price Index (MSCI, 2023b) minus the US 3-month Treasury Bill (Fred, 2023).

The carbon beta, β_i^{CARBON} , is defined in regression (8) as the slope coefficient of a regression of monthly sector returns on the carbon risk premium (CRP) while controlling for the market-excess return. As outlined in subsection 5.2, CRP is defined as the return of a long-short portfolio buying global firms with the 20% highest carbon emission and selling firms with the 20% lowest emissions:

$$r_{i,t}^{e} = \alpha + \beta_i^{CAPM}(r_t^m - r_t^f) + \beta_i^{CARBON} CRP_t \tag{8}$$

For each month from 2016 to 2022, we calculate each sector's expected excess return using equations (7) and (8). Further, we compute each sector's average excess return to see if the carbon premium creates differences. If investors are pricing in carbon risk in stock prices from 2016 to 2022, carbon-heavy sectors should yield higher expected excess returns in Model (6) compared to Model (5) due to higher carbon risks, such as transition or regulatory risk. Also, on the contrary, if this argument holds, low-carbon sectors should not have higher expected excess returns in Model (6) than in Model (5).

Moreover, we compare how the weights in a portfolio change when implementing the carbon premium. In order to apply the carbon risk premium for portfolio construction, we follow the methodology of Markowitz Modern Portfolio Theory (Markowitz, 1952). This theory highlights the risk-adjusted benefits of diversification and that the optimal portfolio is obtained by maximizing the Sharpe ratio following the Markowitz framework. Using the Markowitz portfolio optimization model, we find the expected return of the max Sharpe portfolio using Formula (9):

$$E[r_p] = W^t R = \begin{bmatrix} w_1 & w_2 & \cdots & w_j \end{bmatrix} \begin{bmatrix} E(r_1) \\ E(r_2) \\ \vdots \\ E(r_j) \end{bmatrix} \tag{9}$$

Let W represent the weight vector denoting the individual sectors ranging from 1 to j, while R denotes the vector of expected returns pertaining to the individual sectors spanning from 1 to j. Further, the standard deviation of the max Sharpe portfolio is given by Formula (10):

$$\sigma_p = \sqrt{W^t S(W)} = \sqrt{\begin{bmatrix} w_1 & w_2 & \cdots & w_j \end{bmatrix} \begin{bmatrix} \sigma_{1,1} & \sigma_{1,2} & \cdots & \sigma_{1,j} \\ \sigma_{2,1} & \sigma_{2,2} & \cdots & \sigma_{2,j} \\ \vdots & \vdots & \ddots & \vdots \\ \sigma_{j,1} & \sigma_{j,2} & \cdots & \sigma_{j,j} \end{bmatrix} \begin{bmatrix} w_1 \\ w_2 \\ \vdots \\ w_j \end{bmatrix}} \tag{10}$$

Where S denotes the variance-covariance matrix of the covariances between each of the sector returns in the max Sharpe portfolio. W is defined similarly as above.

The optimal sector weights in the portfolio are the ones that maximize the Sharpe ratio for the portfolio:

$$\max \mathrm{SR}_p = \frac{r_p - r_f}{\sigma_p} \quad \text{subject to} \quad \sum_{i=1}^{j} w_i = 1, \quad 0\% < w_i < 25\% \tag{11}$$

As short-selling might be unfeasible following transaction costs, sufficient lending supply, and liquidity concerns for investors, we do not allow for it in our model setup. Further, we set the optimal portfolio's maximum weight per industry to be 25%. This is because of Markowitz optimization will, due to pure mathematics, suggest extremely large positions in some sectors. Additionally, real-world portfolios might be limited on trade- and position sizes. As this is an in-sample test, we construct the variance-covariance matrix using realized sector returns from 2016 to 2022. With the expected excess returns calculated previously, in addition to the risk-free rate, we obtain the input required to construct the optimal portfolios by utilizing the solver function in Excel. Afterwards, we compare the differences in weights between the portfolios.

Finally, we perform an out-of-sample test to observe how the carbon premium performs without look ahead bias. The out-of-sample period is also 2016-2022, and the methodology used is similar to the description above. The CAPM portfolio utilizes the 5-year CAPM beta from (7) to calculate the expected returns, while the CAPM plus carbon portfolio uses the CAPM and the carbon beta from (8). In this test, it is important to highlight that the betas and the variance-covariance matrix are estimated using rolling windows. Thus, for each month passing, a new data point enters the model and the oldest data point is removed, calculating new betas and new variance-covariance matrices to obtain new optimal weights each month. With new weights each month, we will track the performance of both portfolios.

Our primary objective in this analysis is to investigate whether the out-of-sample Sharpe ratio of the max Sharpe portfolio changes for the CAPM estimation (12) versus the CAPM including the carbon beta (13):

$$max \quad SR_{CAPM} = \frac{r_{CAPM} - r_f}{\sigma_{CAPM}} \tag{12}$$

$$max \quad SR_{CAPM+CARBON} = \frac{r_{CAPM+CARBON} - r_f}{\sigma_{CAPM+CARBON}} \tag{13}$$

If we find a higher Sharpe ratio for the carbon portfolio (13) than the CAPM portfolio (12), this could imply that including a carbon risk premium in portfolio construction could lead to better risk-adjusted portfolio performance for investors. Also, incorporating a carbon risk premium could enable the portfolio to better account for essential climate risks imposed by carbon-heavy industries, such as transitional, regulatory, or reputational risks, leading to improved risk management and presumably higher returns compared to the market beta alone. Thus, including a carbon beta could provide valuable information for portfolio construction, allowing for more effective asset allocation and potentially generating higher risk-adjusted returns.

To further evaluate the impact of including a carbon risk premium in portfolio optimization, we also analyze the weight allocation assigned to each sector in the two optimal portfolios (12) and (13). If the inclusion of carbon risk proves to be relevant for investors, we expect that the carbon portfolio (13) will display higher weights assigned to carbon-heavy industries compared to portfolio (12).

6 Data

6.1 Data Collection

Our panel data covers the period from 2003 to 2022 and consists of firm-level emissions, stock returns, and firm characteristics of 8,996 companies representing 66 countries. The panel data obtained is primarily collected from Thomson Reuters' Refinitiv Eikon database, however, Bloomberg has been used to complement the dataset and fill out missing data. Like Bolton & Kacperczyk (2022), the stock return data is obtained monthly, whereas corporate emissions and financial data are collected annually. As outlined in subsection 5.1, we lag both the emission variable and control variables by one year. Thus, our stock return data covers the period from 2003 to 2022, while the firm-level data on corporate emissions and firm characteristics cover the period from 2002 to 2021. Also, following the methodology of Bolton & Kacperczyk (2022), we transform the annual data into monthly data by assuming that the annual data point is identical for all twelve months within the same year. Specifically, if a firm reported a leverage ratio of 50% in 2022, then the leverage for all twelve months in 2022 would be 50%.

6.2 Corporate Emission Data

To obtain firm-level carbon emission data, we follow Bolton & Kacperczyk (2022) and use an industry-leading environmental, social, and governance data provider that adheres to the Greenhouse Gas Protocol (GHG, 2023). Thus, we choose Thomson Reuters' Refinitiv Eikon measures of firm-level carbon emissions for our analysis (Refinitiv, 2023). In line with the Greenhouse Gas Protocol, Refinitv Eikon separates corporate carbon emissions into three distinct types: Scope 1, Scope 2, and Scope 3 emissions. Scope 1 covers emissions that a company owns or controls directly. Scope 2 covers emissions that the firm causes indirectly through the purchase of electricity, heat, cooling, and steam. Scope 3 consists of all other indirect emissions that occur either by upstream or downstream activities for a company (GHG, 2004).

For the emission variable, it is important to emphasize that our analysis differs relative to Bolton & Kacperczyk (2022). We choose to merge Scope 1 and Scope 2 emissions into one independent variable and neglect Scope 3 emissions for three fundamental reasons.

First, we are interested in companies' total contribution to GHG emissions, and we argue that there should be no difference in firms' long-term transition risk whether these emissions originate from Scope 1 or Scope 2 emissions. Both emission types reflect the same transition risk of increased pressure to decarbonize and reach the 2050 net-zero climate targets (UN, 2022b). Thus, following this argument, the carbon risk premium should be similar for both emission types.

Second, portfolio creation to obtain a carbon risk premium will buy firms with high emissions and sell firms with low emissions. Therefore, the trade signal should therefore be based on companies' total emission of Scope 1, Scope 2, and Scope 3. However, companies differ in their GHG emission structures due to the nature of their business operations. Some companies have more Scope 1 emissions, while others have more Scope 2. Hence, creating portfolios for each scope could pose problems regarding investors' trading signals. To illustrate this issue, consider the following example: two carbon premium portfolios are created for Scope 1 and 2 emissions, respectively. A company with all emissions stemming from Scope 1 will go long in the Scope 1 portfolio. However, the Scope 2 portfolio will short the high-emission company due to its low Scope 2 emissions. Thus, to avoid this portfolio allocation problem, the trade signal should be based on total emissions.

Third, we omit Scope 3 emissions from the analysis due to the less stringent reporting requirements relative to Scope 1 and Scope 2 emissions (ThomsonReuters, 2023). Given the history of stricter reporting requirements for Scope 1 and Scope 2, there is more available data from 2002 to 2021. A 2023 MSCI ESG Research report shows that 35% of listed companies disclosed at least some of their Scope 3 emissions MSCI (2023d). As some companies report Scope 3 and other does not, including Scope 3 could inflate the emission numbers for some companies, potentially creating a bias in the emission variable.

6.3 Corporate Financial Data

To ensure unbiased regression results, we control for firm characteristics which could predict future stock returns. We use the same control variables as Bolton & Kacperczyk (2022), namely, Leverage, Market Capitalization, Book-to-Market, Momentum, Return on Equity, Volatility, Herfindahl Concentration Index, Property, Plant and Equipment, and Investments-to-Assets. Similar to Bolton & Kacperczyk (2022), we winzorize Leverage, Book-to-Market, Momentum, Return-on-Equity, Volatility, and Investments-to-Assets at a 2.5% level and mitigate monthly return observations greater than 100% to evade the impact of outliers. Table 1 presents a description of each variable used in our cross-sectional regressions.

INSERT TABLE 1 ABOUT HERE

We choose to follow the model specification in Bolton & Kacperczyk (2022) to best replicate the global results. However, we acknowledge the importance of controlling for firms' sensitivity to movements in the market, as Bolton and Kacperczyk did in their 2021 article (Bolton & Kacperczyk, 2021). We therefore choose to include the 3-year $BETA_{i,t}$ in our model, the market beta of firm i in year t.

6.4 Data Descriptives

Table 2 displays descriptive statistics for the complete sample from 2003 to 2022. We find that the characteristics of the variables used in our cross-sectional regressions resemble the characteristics of Bolton & Kacperczyk (2022). As we investigate similar periods, regions, and the same firm-level variables, these findings are expected.

INSERT TABLE 2 ABOUT HERE

Further, we analyzed which control variables that could explain variations in firm-level emissions. Table 3 presents the regression results. As expected, market capitalization, PPE, Return-on-Equity, Book-to-Market, and leverage have both economically and statistically significant effects on firm-level carbon emissions.

INSERT TABLE 3 ABOUT HERE

7 Results and Analysis

We organize our results and analysis into four subsections. First, we investigate the relationship between stock returns and carbon emissions on a global- and regional level. We next explore the time variation for the carbon risk premium and how it is impacted by specific political events. We then turn to differences in carbon premium between sectors. Lastly, we look into the application of the carbon premium in a portfolio and its performance.

7.1 Evidence of Carbon Emissions Affecting Returns

7.1.1 Global Analysis

We begin by investigating the relationship between carbon emissions and stock returns in the global 2003-2022 dataset, using pooled OLS regressions outlined in Model (1) from the methodology. The cross-sectional regression results are reported in Table 4. Controlling for time- and country-fixed effects in column 1, we find that carbon emissions have a positive and statistically significant effect on companies' stock returns. The impact of this effect is also economically significant. If the carbon emissions increase with one standard deviation, the stock returns increase by 17 bps per month or 2.0% annually. Our results closely resemble the findings of Bolton & Kacperczyk (2022) regarding the coefficient of the carbon premium and all other control variables. We anticipated finding similar results, as we include more recent years, 2019-2022, where global initiatives towards the net-zero 2050 targets and climate awareness have been on the rise.

As discussed in subsection 5.1, there is a possibility of carbon emissions being significantly clustered within specific industries. Thus, column 2 in Table 4 controls for industry-fixed effects using Global Industry Classification Standard (GICS) methodology (MSCI, 2023a). Again, the result is as expected based on the findings from Bolton & Kacperczyk (2022). Including industry-fixed effects strengthens the effects of carbon emissions on stock returns. The coefficient of the carbon premium increases from 0.060 to 0.081 while maintaining its statistical significance at a 1% level. Hence, the economic impact increases by 35% when controlling for industry-fixed effects. If the carbon emissions increase with one standard deviation, the stock returns will increase by 23 bps per month or 2.7% annually.

INSERT TABLE 4 ABOUT HERE

7.1.2 Continental Analysis: North America, Asia & Europe

To assess the geographical differences and the magnitude of the carbon risk premium, we now divide our dataset into three regions, focusing on the North American, Asian, and European markets. The regressions conducted are identical with respect to control variables and fixed effects as Model (1). Also, given the argument made in the previous section, we include industry-fixed effects for all the regional regressions.

The regression results are reported in Table 5. We find a positive and statistically significant relationship between firm-level carbon emissions and stock returns in all three markets. North America has the most significant economic magnitude of the carbon risk premium, with one standard deviation increase in emissions leading to a 28 bps increase in stock returns or 3.4% annualized. Simultaneously, Asia has the lowest economic significance with a 13 bps return increase for one standard deviation increase in emissions or 1.5% annualized.

INSERT TABLE 5 ABOUT HERE

According to the International Monetary Fund (IMF), Asia is responsible for approximately 50% of global CO2 emissions (IMF, 2021). In addition, the region has more wealth-related disasters than other regions with increased severity and frequency (IMF, 2021). Based on this, it is surprising that Asia has the lowest carbon risk premium among the three regions. However, the relatively lower carbon premium in Asia may be attributed to the fact that China, the largest emitter in the region, had relatively few climate initiatives during the period (IMF, 2021). Few climate actions can further influence investors' awareness of the climate risks associated with high-carbon industries, thereby reducing the size of the carbon premium. Nevertheless, in September 2020, China announced that the country wants to achieve peak carbon emissions before 2030 and become carbon neutral before 2060 (UN, 2021). Hence, going forward, we might observe an increasing carbon premium in China and perhaps the whole Asian region.

7.2 Evidence of Time Variation in the Carbon Premium

7.2.1 Carbon Premium Pre & Post Paris Agreement

Based on the previous sections' evidence of a global and continental carbon risk premium from 2003-2022, an interesting question is whether this carbon premium fluctuates over time. To examine this hypothesis, we proceed following the methods of Bolton & Kacperczyk (2022). Bolton and Kacperczyk compare the worldwide carbon premium two years before the Paris Agreement, 2014-2015, with the two years after the agreement, 2016-2017. They find that the carbon premium changes following the announcement. Before the event, they report an insignificant premium. However, the premium is highly significant and positive after the event (Bolton & Kacperczyk, 2022).

We obtain similar results when performing the same analysis with our dataset. We report our regression results in Table 6. The global carbon risk premium changes from insignificant in column 1, the pre-Paris period, to economically and statistically significant after the Paris Agreement in column 2, the post-Paris period. Our results could therefore imply changes in investors' awareness regarding climate risks due to the announcement of the Paris Agreement. This might entail that investors are more concerned about carbon-related risks, such as regulatory, reputational, and transitional risks following the Paris Agreement.

INSERT TABLE 6 ABOUT HERE

7.2.2 Period with few Climate Change Initiatives

As we observed that the Paris Agreement significantly affects the carbon premium, we further test Bolton and Kacperczyk's theory that the carbon premium changes following salient events. Consequently, we investigate the period between 2018-2022. In 2018 and 2019, however, few actions toward climate change were announced. The two most notable events during this period are COP24 in Katowice (UNFCC, 2018) and COP25 in Madrid (EU, 2019). Despite keeping the global climate debate going, these events produced no major environmental impact. COP24 succeeded in finalizing many implementation guidelines for the Paris Agreement, but there were still some outstanding disagreements regarding Paris Agreement Article 6 about carbon markets (EU, 2021). This issue was also debated at COP25 in 2019, however, there was still no consensus regarding Paris Agreement Article 6 about carbon markets EU (2019). Even though a successful continuation of the climate discourse took place at COP24 and COP25, these events did not yield an equivalent impact as the Paris Agreement.

Table 7 column 1 presents the regression results from 2018-2019. Interestingly, the carbon premium changed from positive and significant in 2016-2017 to negative and significant in 2018-2019. We argue that this could reflect investors' doubts about the implementation of the Paris Agreement. Thus, the carbon premium decreases. The market expectations arising after the Paris

Agreement, which marked the start of a transition to a carbon-neutral economy, might be doubted due to the less fruitful progress following the COP24 and COP25 events. Further, if investors doubt the implementations of the Paris Agreement, it is unlikely that we will witness an incremental increase in the premium towards 2050. Alternatively, these findings suggest that the carbon premium is evolving in response to the progression of decarbonization efforts and environmental events.

INSERT TABLE 7 ABOUT HERE

7.2.3 Period of Climate Change Packages and Increasing EU ETS

Although the years following the Paris Agreement did not encompass any major climate impact, 2021 and 2022 contain several interesting events for our analysis. In 2021, the emission allowance price in the EU, EU ETS, increased by 140% (Ember, 2023), which affected the production cost for oil companies such as Equinor. Equinor's total CO2 expenses increased by 60%, from 268 USDm in 2020 to 428 USDm in 2021 (Equinor, 2021). In 2022, two major markets, Germany and USA, announced support packages to help reach the 2050 net-zero target. Germany stated that it will invest 220USDbn for industrial transformation by 2026 (Reuters, 2022). Further, the US introduced the Inflation Reduction Act, considered the most significant climate change and clean energy action in US history (UN, 2022c). For our analysis, we decide not to include the introduction of the EU taxonomy in 2020 as the financial data during this event contains considerable noise introduced by the COVID-19 pandemic.

Table 7 column 2 shows the regression results for 2021-2022. The results are as expected, the carbon premium has become positive and statistically significant. Interestingly, we observe that the magnitude of the carbon premium is much larger in 2021-2022 relative to 2016-2017. This evidence supports the argument that the carbon premium should increase as we approach the 2050 net-zero targets. Also, the fact that the coefficient of the premium has changed from negative to positive significantly highlights the previous argument that changes in carbon premium can be reflected in salient events, which increases investors' awareness of climate change and carbon risk.

7.2.4 Event Study for Robustness Check

In the preceding subsections, we find evidence of variation in the carbon risk premium and salient events in different periods. However, to strengthen the reliability of our findings, we perform event studies following the methodology outlined in subsection 5.2.

Table 8 showcases the regression results from the event study regarding all the salient events. Our findings consistently validate our earlier observations. The dummy variable, which represents salient political decarbonization initiatives, is positive and statistically significant at a 1% level, even after controlling for the market risk premium. Consequently, our regression analysis confirms Bolton and Kacperczyk's statement that salient events affect the carbon risk premium (Bolton & Kacperczyk, 2022). We contribute to this statement by highlighting that salient events also create time variation in the carbon premium. During years with fewer and less impactful environmental events, we observe a declining carbon risk premium, reaching negative values in 2018-2019.

INSERT TABLE 8 ABOUT HERE

Furthermore, Table 9 presents regression results for each individual event study. Panel A displays the findings related to the Paris Agreement and Inflation Reduction Act, while Panel B highlights the results concerning the EU ETS and the German package for industry decarbonization. It is important to note that in Panel B, we control for oil and natural gas prices as the events took place when these commodities experienced a significant price spike. By controlling for these factors in our regression model, we mitigate the potential influence of these price increases on oil and gas companies. As shown in Table 9, our results consistently support our previous findings. All the events investigated, the Paris Agreement, the EU ETS price increase, the Germany package, and the Inflation Reduction Act, have a positive and statistically significant impact on the carbon risk premium.

INSERT TABLE 9 ABOUT HERE

7.3 Evidence of Sector Variation of the Carbon Risk Premium

7.3.1 Excluding Salient High-Carbon Industries

Although decarbonization is a key priority in a majority of sectors in order to reach the 2050 net-zero target, much of the total emissions are concentrated among specific sectors. A report published in 2020 by the International Energy Agency (IEA) outlined that of the total emissions in 2018, 23% came from transportation, 23% from industry, and 40% from power production (IEA, 2020). Also, specific industries encounter more significant challenges in achieving emission neutrality due to their dependence on carbon in production, named "hard-to-abate" industries (McKinsey, 2022a). Intuitively, these industries should have a higher carbon risk premium, as higher emissions could represent more exposure to long-term transitional risk. The pressure to decarbonize operations and adjust to carbon-neutral solutions could be larger in "hard-to-abate" industries, and this pressure might increase approaching the 2050 net-zero targets.

Bolton & Kacperczyk (2021) investigate the differences in the carbon premium across industries in the period 2005-2017. They construct a sample excluding salient high-carbon industries such as oil & gas, utilities, and transportation, based on the industries' respective GICS codes. Then they run two regressions, one including all industries and one which excludes these salient industries (Bolton & Kacperczyk, 2021). Their idea was that the carbon premium should be significantly smaller by excluding salient industries. However, surprisingly, excluding the salient high-carbon sectors led to stronger results, meaning that the firm-level carbon premium increased. According to Bolton & Kacperczyk (2021), these findings suggest that investors tend to categorize companies within salient industries in a coarser manner, where returns are less sensitive to emission differences among companies.

We find the results of Bolton & Kacperczyk (2021) surprising, given the initial discussion in this section. However, as they examined the period 2005-2017, where investors' awareness of carbon risk was more limited, we postulate that replicating this study for the years after the Paris Agreement could yield different results. The evidence of a time variation in the carbon premium after the Paris Agreement, provided by our event studies, highlights that several political initiatives have increased the carbon premium. Therefore, we expect to see a clearer categorization within salient high-carbon industries in more recent years, and we choose to conduct this industry analysis for the period 2016-2022.

Table 10 displays our regression results for four different regressions. The regressions conducted in columns 1 and 2 represent our replication of Bolton and Kacperczyk's study (2021) for the same sample period, 2005-2017. Column 1 includes all industries, while column 2 excludes the following salient industries; oil & gas, utilities, and transportation, similar to Bolton & Kacperczyk (2021). Looking at column 2, we see that the carbon premium increases when excluding the salient industries from 2005-2017. Thus, our results are equivalent to Bolton & Kacperczyk (2021), and we agree that this implies a more coarse categorization within salient industries.

INSERT TABLE 10 ABOUT HERE

Further, columns 3 and 4 represent regressions in the sample period of 2016-2022. Column 3 includes all industries, while column 4 excludes salient industries. Interestingly, for the period 2016-2022, we observe an opposite effect compared to earlier. In line with our original expectations, the carbon premium decreases when we exclude salient high-carbon industries from the sample. Thus, we argue that political efforts such as the German decarbonization package and the US Inflation Reduction Act, with the substantial price increase in the EU ETS, make returns for firms in salient industries more sensitive to differences in emissions.

7.3.2 Robustness Check - Sector Variation of the Carbon Premium

In order to ensure that these findings are robust, we conduct sector-based regressions following regression Model (1) from the methodology. This regression analysis compares the carbon risk premium for the different sectors. Hence, we run separate regressions for each of the 11 GICS sectors classified by MSCI in the period 2016-2022 (MSCI, 2023c). We expect the sectors with high emissions to have a positive and significant premium and the low-emission sectors to have an insignificant premium.

In May 2023, MSCI published a report stating the highest carbon-emitting GICS sectors, where they argue that the industries Utilities, Materials Transportation, Energy, and Food, Beverages, and Tobacco are the most emission-intensive (MSCI, 2023d). MSCI categorizes the Transportation industry as belonging to the GICS sector Industrials, while other industries, such as Food, Beverages, and Tobacco, are classified as Consumer Staples (MSCI, 2023a). In addition, BlackRock also released an emission report in 2023, tracking the percentage of total Scope 1 and Scope 2 emissions from each GICS sector among their clients' equity holdings (BlackRock, 2023). See Table 11 for the breakdown. Even though the BlackRock report only represents 1000 companies, we find it consistent with the comments from MSCI, making it a valuable source concerning which sectors we would expect to have a significant carbon premium. Based on these reports, we expect the high-carbon sectors, Energy, Industrials, Materials, Utilities, and Consumer Staples, to have a positive and significant carbon premium. Similarly, we argue that the other sectors will not have a statistically significant premium.

INSERT TABLE 11 ABOUT HERE

Table 12 showcases our regression results of the 11 different GICS sectors. In accordance with MSCI's report, the sectors Energy, Industrials, and Consumer Staples all have a positive and statistically significant carbon risk premium. What is more puzzling is the fact that the carbon premium for Materials and Utilities is statistically insignificant, while the carbon premium for Financials is positive and statistically significant. However, BlackRock reports that the financial sector is the fifth highest emitting sector, accounting for 6% of Scope 1 and Scope 2 emissions (BlackRock, 2023). This could therefore potentially explain why Financials have a statistically and economically significant carbon premium. According to our expectations, we find that the remaining low-emitting sectors in Table 12 all have statistically insignificant carbon premia.

INSERT TABLE 12 ABOUT HERE

Although we initially expected Materials and Utilities to be positive and significant, we still observe an overall trend in our results. The high-emission sectors generally display a positive and statistically significant relationship between carbon emissions and stock returns. Meanwhile, we do not find evidence that low emissions sectors generally reflect a carbon premium. Thus, we confirm our previous results and find additional evidence of cross-sector differences in the carbon premium.

7.4 Application of the Carbon Risk Premium

In this thesis, we have found that carbon risk premium rises during events related to climate change and that the premium differs between sectors. In general, the carbon risk premium is reflected more in high emissions sectors. The implication is that we should be able to benefit from this premium, as there is more systematic risk in high-emission sectors relative to low-emission sectors.

7.4.1 Expected Excess Returns

With higher exposure to systematic risk, investors will require additional compensation in terms of higher expected returns (Sharpe, 1964). In Table 13, we report the expected excess return for each GICS sector based on the Capital Asset Pricing Theory (CAPM) and the expected excess return based on CAPM plus a carbon risk premium. We proceed using the same sample period of 2016-2022 as before, since we found evidence of a shift in carbon premium between sectors in this time horizon.

INSERT TABLE 13 ABOUT HERE

Our results highlight that adding a carbon risk premium creates differences in the expected excess return. As anticipated, the high emissions sectors reflect a higher expected return, while the low emissions sectors do the opposite. Furthermore, all sectors where we found a positive and statistically significant carbon premium yield a higher expected excess return. Most notable is Energy, which increases expected excess returns with a delta of 1.58%, and

Communication service, with a fall in the expected excess return of a delta of 1.31%.

Table 13 also shows consistent results relative to our surprising findings regarding our earlier cross-sector carbon premium analysis. We observe that Materials and Utilities experience lower expected excess returns with a delta of -0.41% and -0.56%, respectively. Further, Financials' expected excess return increases with a delta of 1.43%, which is the second-highest increase.

7.4.2 Markowitz Portfolio Optimization and Sector Weights

With differences in expected excess returns, we should observe changes in the sector weighting when implementing Markowitz portfolio optimization. Table 14 presents the optimal weighting of each sector between two portfolios using Markowitz portfolio optimization. The first portfolio uses CAPM to calculate expected returns, while the second portfolio uses CAPM plus the carbon premium to calculate expected returns. Again, we use the same sample period of 2016-2022.

INSERT TABLE 14 ABOUT HERE

As projected, the second portfolio tilts more toward high-carbon sectors, which we found to have positive and statistically significant carbon premia. For Energy, the weight increased from 11.75% to 21.59% when including the carbon premium. Additionally, Industrials initially had 0% weight but increased to 3.41% in the carbon portfolio. Notably, the more surprising results were the weight changes observed for Consumer Staples and Materials. The weight of Consumer Staples increased from 0% to 25%, while Materials had a corresponding decrease from 25% to 0%.

We find that implementing a carbon premium changes the Markowitz portfolio optimization and buys more high-emission sectors. With these weight-changes, we again find consistency relative to our analysis. The interesting question now is to investigate if investors actually can benefit from incorporating a carbon premium in portfolio construction. We will now test the out-of-sample performance of a CAPM plus carbon portfolio relative to a CAPM portfolio.

7.4.3 Out-of-Sample Testing

We test the two portfolio constructions with an out-of-sample test in the period of 2016-2022, creating new optimal weights for the upcoming month using Markowitz portfolio optimization. Table 15 displays the performance of the two portfolios, the CAPM portfolio, Portfolio 1, and the CAPM plus carbon premium portfolio, Portfolio 2. We observe that adding a carbon premium slightly increases the Sharpe ratio from 0.40 to 0.44. The expected return is mainly unchanged, however, the standard deviation of the excess return falls from 17.76% to 16.32%, corresponding to an 8.1% decrease. Hence, we can conclude that the inclusion of a carbon premium slightly enhances the portfolio performance, representing an increase in the Sharpe ratio of 0.04. With carbon emissions still growing (IEA, 2022), the transition risk in high-carbon sectors could continue to rise. As a result, it is likely that the carbon premium will increase in the future, which could entail even better improvements in the Sharpe ratio when implementing this trading strategy. These findings illustrate that investors incorporating a carbon risk premium in portfolio construction could enable portfolios to better encapsulate important climate risks imposed by high-carbon sectors, such as reputational, transitional, or regulatory risks. This could result in improved risk management and potentially better risk-adjusted performance.

INSERT TABLE 15 ABOUT HERE

The concluding part of this thesis is to observe the shift in portfolio weights among the sectors. Table 16 displays the optimal weighting of each sector. Overall, we observe that including a carbon premium in the portfolio induces higher weight for high emitting sectors in the max Sharpe portfolio. For instance, the portfolio has higher weights in the sectors Energy, Materials, Consumer Staples, and Utilities. A consequence of buying more high-emission sectors is that the portfolio reduces its positions in lower-emission sectors such as Information technology, Health Care, Consumer Discretionary, and Real Estate. Also, surprisingly, the portfolio reduces weights in Financials and Industrials as well, however, the weight of Communication Service increases, which is inconsistent with our previous findings. Despite the presence of some outliers, it is evident that the shift in sector weights aligns with our previous analysis.

INSERT TABLE 16 ABOUT HERE

8 Conclusion

Do investors care about climate change and the transition risk that high-carbon companies face toward a carbon-neutral economy? Extending the work of Bolton and Kacperczyk, we have investigated the pricing of carbon transition risk at the firm level from 2003-2022 across a diverse range of 8,996 companies in 66 countries. We found evidence of a global and significant carbon risk premium, indicating that firms with higher emissions achieve higher stock returns. Further, we tested whether a time variation in the carbon risk premium exists. In line with Bolton and Kacperczyk's findings, we show that the carbon risk premium changes after the implementation of the Paris Agreement. Prior to the agreement, we observed a statistically insignificant premium, but following the agreement, the premium became both positive and significant. We propose that this shift is attributable to investors becoming more aware of global carbon-transition risk.

Additionally, our findings reveal an increase in the carbon premium during the period of 2021-2022. We argue that this surge can be attributed to increased climate change awareness caused by several salient events, such as the price increase of the EU ETS, the German Industrial Transformation Package, and the Inflation Reduction Act. To substantiate this claim, we conducted formal event tests, which provided evidence suggesting a positive and statistically significant relationship between announcements of decarbonization initiatives and the carbon premium. Thus, we conclude that there is not only a time variation in the carbon premium, it is also significantly affected by salient political events concerning climate change.

Building on these findings, we contribute to the work of Bolton and Kacperczyk. They investigated the differences in the carbon risk premia across industries in the period of 2005-2017 and found that excluding the salient high-carbon industries from the sample led to a stronger carbon premium. We found these results interesting and conducted the same analysis in a newer sample period due to our previous evidence that several political initiatives have increased the carbon premium. Notably, in the period of 2016-2022, we found evidence of a clearer categorization within high-carbon industries. This means that investors are pricing in higher carbon-transition risk in high-carbon emitting industries relative to low-carbon emitting industries.

Finally, based on our extensive findings, we demonstrated that an out-of-sample test of an optimal portfolio including a carbon risk premium yields a slightly higher Sharpe ratio and higher weights in high-carbon sectors relative to a CAPM-constructed portfolio. Considering the ongoing increase in CO2 levels, we might observe that the carbon risk premium will escalate in the future as a result of higher transition risk. Thus, investors integrating a carbon risk premium in portfolio construction might enhance portfolios' ability to capture significant climate risks associated with high-carbon sectors, such as transitional, regulatory, and reputational risks. Consequently, this could lead to improved risk management and potentially better risk-adjusted performance.

9 Further Research

For further research, we believe examining differences in the carbon premium among smaller regions would be interesting. As companies continue to report new and more detailed data on their greenhouse gas emissions, new research could focus on changes in the carbon premium levels between Asia, North America, and Europe or cross-country comparisons. We highlighted that Asia accounts for approximately 50% of all global emissions, and the region has experienced more wealth-related disasters compared to other regions (IMF, 2021). As Asia currently has the lowest carbon premium, the premium in Asia could increase significantly relative to North America and Europe in the future.

Moreover, our thesis sorts firms into the 11 GICS sectors defined by MSCI, however the GICS also uses narrower definitions. GICS consists of 11 sectors that MSCI further sorts into 25 industry groups, which again divide into 74 industries and 163 sub-industries (MSCI, 2023c). Therefore, another research idea would be to investigate the carbon premium among all these industry levels.

Finally, following (Bolton & Kacperczyk, 2022), we have stated that companies' carbon emissions are a potential measure of climate risk. A last idea would therefore be to consider other measures related to climate performance which potentially could be a source of climate risk. By doing so, one can obtain a better understanding of how markets price climate performance and risk.

REFERENCES

BlackRock. (2023). *Blackrock: Climate focus universe.* Retrieved from https://www.blackrock.com/corporate/literature/publication/blk-climate-focus-universe.pdf. (Accessed 2023-02-18)

Bolton, P., & Kacperczyk, M. (2021). Do investors care about carbon risk? *Journal of Financial Economics*, *142*(3), 517-549. doi: doi:10.1016/j.jfineco.2021.05.008

Bolton, P., & Kacperczyk, M. (2022). Global pricing of carbon-transition risk. *Journal of Finance, forthcoming*. doi: doi:https://dx.doi.org/10.2139/ssrn.3550233

Brooks, C. (2019). Introductory econometrics for finance. *Cambridge University*.

Ember. (2023). *The price of emission allowances in the eu and uk.* Retrieved from https://ember-climate.org/data/data-tools/carbon-price-viewer/. (Accessed 2023-03-20)

Equinor. (2021). *Equinor annual report 2021.* Retrieved from https://cdn.equinor.com/files/h61q9gi9/global/83ce4c64e602e203100e1ce2c5de9b2d42ff8192.pdf?equinor-2021-annual-report-and-form-20-f.pdf. (Accessed 2023-02-01)

EU. (2019). *European comission, closing statement by the finnish presidency and the european commission on behalf of the eu and its member states at cop25.* Retrieved from https://ec.europa.eu/commission/presscorner/detail/en/statement_19_6779. (Accessed 2023-03-22)

EU. (2021). *European parliament - cop24 climate change conference outcomes.* Retrieved from https://www.europarl.europa.eu/RegData/etudes/ATAG/2019/633139/EPRS_ATA(2019)633139_EN.pdf. (Accessed 2023-03-22)

EU. (2023). *European parliament - what is carbon neutrality and how can it be achieved by 2050.* Retrieved from www.europarl.europa.eu/news/en/headlines/society/20190926STO62270/what-is-carbon-neutrality-and-how-can-it-be-achieved-by-2050. (Accessed 2023-01-19)

Fama, E. F., & MacBeth, J. D. (1973). Risk, return, and equilibrium: Empirical tests. *Journal of Political Economy*, *81*(3), 607-636.

Fred. (2023). *Board of governors of the federal reserve system (us), 3-month treasury bill secondary market rate, discount basis [dtb3], retrieved from fred.* Retrieved from https://fred.stlouisfed.org/series/DTB3. (Accessed 2023-03-07)

GHG. (2004). *The greenhouse gas protocol - a corporate accounting and reporting standard.* Retrieved from https://ghgprotocol.org/sites/default/files/standards/ghg-protocol-revised.pdf. (Accessed 2023-02-13)

GHG. (2023). *Greenhouse gas protocol: Standards to measure and manage emissions.* Retrieved from https://ghgprotocol.org/. (Accessed 2023-02-13)

Görgen, M., Jacob, A., & Nerlinger, M. (2021). Get green or die trying? carbon risk integration into portfolio management. *The Journal of Portfolio Management*, *47*(3), 77-93. doi: doi:https://doi.org/10.3905/jpm.2020.1.200

Hsu, P.-H., Li, K., & Tsou, C.-Y. (2023). The pollution premium. *Journal of Finance*, *78*(3), 1343-1392. doi: doi:https://doi.org/10.1111/jofi.13217

IEA. (2020). *The role of ccus in low-carbon power systems.* Retrieved from https://www.iea.org/reports/the-role-of-ccus-in-low-carbon-power-systems. (Accessed 2023-03-28)

IEA. (2022). *8th annual global conference on energy efficiency.* Retrieved from https://www.iea.org/reports/co2-emissions-in-2022?fbclid=IwAR10DliBDSY50ic0_oMNadqrxq4jdaBim8sWWGlFemfH7welacDnz78eJS0. (Accessed 2023-02-13)

IMF. (2021). *International monetary fund - asia's climate emergency.* Retrieved from https://www.imf.org/en/Publications/fandd/issues/2021/09/asia-climate-emergency-role-of-fiscal-policy-IMF-dabla. (Accessed 2023-04-10)

Markowitz, H. (1952). Portfolio selection. *Journal of Finance*, *7*(1), 77-91. doi: doi:https://doi.org/10.2307/2975974

McKinsey. (2022a). *The economic transformation: What would change in the net-zero transition.* Retrieved from https://www.mckinsey.com/capabilities/sustainability/our-insights/the-economic-transformation-what-would-change-in-the-net-zero-transition?fbclid=IwAR0RiiAXl0CrLwG7qyruIHslaWkVc0QixDW5Q7QJr1Ysdy6UeIKUYdWYK2Y. (Accessed 2023-03-10)

McKinsey. (2022b). *Sectors are unevenly exposed in the net-zero transition.* Retrieved from https://www.mckinsey.com/capabilities/sustainability/our-insights/sectors-are-unevenly-exposed-in-the-net-zero-transition. (Accessed 2023-03-10)

MSCI. (2023a). *Msci: Global industry classification standard methodology.* Retrieved from https://www.msci.com/documents/1296102/11185224/GICS+Methodology+2023.pdf. (Accessed 2023-03-13)

MSCI. (2023b). *Msci international world price index.* Retrieved from https://www.msci.com/end-of-day-history?chart=regional&priceLevel=0&scope=R&style=C&asOf=May%2029,%202023&currency=15&size=36&indexId=106. (Accessed 2023-03-13)

MSCI. (2023c). *Msci: The global industry classification standard (gics).* Retrieved from https://www.msci.com/our-solutions/indexes/gics. (Accessed 2023-03-13)

MSCI. (2023d). *Msci: The msci net-zero tracker.* Retrieved from https://www.msci.com/documents/1296102/38217127/NetZero-Tracker-May.pdf. (Accessed 2023-03-13)

Oestreich, M., & Tsiakas, I. (2015). Carbon emissions and stock returns: Evidence from the eu emissions trading scheme. *Journal of Banking and Finance*, *58*, 294-308. doi: doi:https://doi.org/10.1016/j.jbankfin.2015.05.005

Pedersen, L., Fitzgibbons, S., & Pomorski, L. (2021). Responsible investing: The esg-efficient frontier. *Journal of Financial Economics*, *142*, 527-597. doi: doi:https://doi.org/10.1016/j.jfineco.2020.11.001

Refinitiv. (2023). *Refinitiv: An overview of environmental, social and corporate governance - esg.* Retrieved from https://www.refinitiv.com/en/financial-data/company-data/esg-data. (Accessed 2023-01-24)

Reuters. (2022). *Germany to spend 220 billion usd for industrial transformation by 2026.* Retrieved from https://www.reuters.com/business/sustainable-business/germany-has-earmarked-220-billion-industrial-transformation-by-2026-2022-03-06/. (Accessed 2023-02-05)

Sharpe, W. F. (1964). Capital asset prices a theory of market equilibirum under conditions of risk. *Journal of Finance*, *19*, 425-442. doi: doi:https://doi.org/10.1111/j.1540-6261.1964.tb02865.x

Stock, M., & Watson, J. (2020). Introduction to econometrics. 4th edition. *Pearson*.

ThomsonReuters. (2023). *Thomson reuters regulation scope 3 emissions.* Retrieved from https://www.thomsonreuters.com/en-us/posts/esg/double-counting-scope-3-emissions/. (Accessed 2023-04-14)

UN. (2020). *Carbon neutrality by 2050: The world's most urgent mission.* Retrieved from https://www.un.org/sg/en/content/sg/articles/2020-12-11/carbon-neutrality-2050-the-world%E2%80%99s-most-urgent-mission. (Accessed 2023-01-20)

UN. (2021). *China headed towards carbon neutrality by 2060.* Retrieved from https://news.un.org/en/story/2021/09/1100642. (Accessed 2023-05-15)

UN. (2022a). *United nations climate change - the paris agreement, what is the paris agreement.* Retrieved from https://unfccc.int/process-and-meetings/the-paris-agreement. (Accessed 2023-01-20)

UN. (2022b). *United nations - net-zero commitments must be backed by credible action.* Retrieved from https://www.un.org/en/climatechange/net-zero-coalition. (Accessed 2023-01-23)

UN. (2022c). *The white house - inflation reduction act.* Retrieved from https://www.whitehouse.gov/cleanenergy/inflation-reduction-act-guidebook/. (Accessed 2023-02-10)

UNFCC. (2018). *United nations climate change - the katowice climate package: Making the paris agreement work for all.* Retrieved from https://unfccc.int/process-and-meetings/the-paris-agreement/katowice-climate-package#2019-and-beyond. (Accessed 2023-02-20)

TABLES

Table 1: Description of Regression Variables

Table 1 displays the description of variables used in all cross-sectional regressions. The data is collected from Thomson Reuters' Refinitiv Eikon, due to industry-leading financial and ESG databases, as well as its compliance with the Greenhouse Gas Protocol. Bloomberg has been used to supplement the dataset.

Variable	Description
$RET_{i,t}$	Monthly stock return of company i in month t. We collect stock returns as monthly data, with the advantage of capturing more short-term dynamics and increasing the data points, relative to using quarterly or annual stock returns.
$LOG\ CARBON\ EMISSIONS_{i,t}$	The natural logarithm of annual Scope 1 and Scope 2 emissions for company i in year t.
$LEVERAGE_{i,t}$	The ratio of the debt-to-book value of assets of company i at the end of year t.
$LOG\ SIZE_{i,t}$	The natural logarithm of the market capitalization of company i, meaning the shares outstanding times price at the end of year t. To ensure a distribution that more closely resembles a normal distribution, we employ the natural logarithm of the market capitalization.
$B/M_{i,t}$	The book-to-market ratio of the equity of company i at the end of year t.
$MOM_{i,t}$	Momentum is the average of the most recent twelve months stock return for company i, including month $t - 1$.
$ROE_{i,t}$	Return on equity of company i, calculated as annual net income divided by the book value of equity at the end of year t.
$VOLAT_{i,t}$	The idiosyncratic risk of company i, measured as the standard deviation of the past 12 months' stock return.

Continued on next page

Table 1 – continued from previous page

Variable	Description
$HHI_{i,t}$	Herfindahl concentration index of the firm to control for market concentration. We calculated the Herfindahl concentration index, as our data providers do not collect measures of HHI. HHI is defined as the sum of squared market share percentages for all firms within an industry, where the market share of company i is defined as the comapny revenue divided by the total revenue generated within the specific GICS industry in year t.
$LOG\ PPE_{i,t}$	The stock of physical capital for company i, calculated as the natural logarithm of the property, plant and equipment of company i in year t.
$INVEST/A_{i,t}$	Measure for capital expenditures, which is calculated as the capital expenditures of company i in year t divided by the book value of assets.
$BETA_{i,t}$	The 3-year market beta of company i in year t, calculated regressing monthly returns of company i on the market-excess return. The market-excess return is calculated using the monthly return of the MSCI World Price Index minus the 3-month yield on a US treasury bond.

Table 2: Summary Statistics

Panel A displays summary statistics for all variables used in the cross-sectional regressions. We report the total observations, mean, standard deviation, and median of all variables. The final global panel dataset spanning 2003-2022 contains 769,044 observations. The dependent variable, monthly stock returns, is expressed in percentage. The reported monthly returns in Panel A are annualized. Monthly returns observations greater than 100% are winzorized to evade the impact of outliers. The variables B/M, MOM, ROE, VOLAT, and INVEST/A are winzorized at a 2.5% level. The variables MOM and VOLAT are expressed in monthly terms. **Panel B** displays summary statistics of the carbon premium portfolio constructed by purchasing stocks with the 20% highest emissions and selling stocks with the 20% lowest emissions from the sample of 8,996 companies spanning the period 2010-2022. Henry Hub Natural Gas spot prices and Brent spot prices are obtained from U.S. Energy Information Administration, covering the same period as the carbon premium portfolio. The returns are calculated from spot price movements. The EU ETS monthly data covers 2021 and is collected from Refinitiv Eikon. All reported returns are annualized. **Panel C** displays monthly returns of GICS sectors classified by MSCI. The data is obtained from MSCI indexes from Refinitv Eikon. The sample period is 2016-2022. The reported returns are annualized.

PANEL A - Cross-Sectional Regression Variables

Variable	Total Obs.	Mean	Std. Dev.	Median
Monthly Return (%)	1,982,563	12.84	44.99	7.56
Log Emissions	931,356	11.19	2.92	11.24
Leverage	2,150,952	0.23	0.19	0.19
Log Size	1,976,268	20.75	1.97	20.85
B/M	1,961,784	0.73	0.62	0.56
MOM	1,962,732	0.01	0.04	0.01
ROE	2,146,704	0.07	0.28	0.10
Beta	1,612,092	0.92	0.66	0.84
Volat	1,954,404	0.11	0.07	0.09
Invest/A	2,057,016	0.04	0.05	0.03
Log PPE	2,030,592	18.77	2.72	18.98
HHI	2,122,140	1.89	6.71	0.01

PANEL B - Descriptives of Variables in Event Tests

Variable	Total Obs.	Mean	Std. Dev.	Median
Carbon Premium Portfolio (%)	156	2.28	12.50	1.87
Return Natural Gas Spot Prices (%)	156	12.94	52.74	-6.86
Return on Brent Spot Prices (%)	156	7.94	37.86	17.93
Return on EU ETS (%)	12	89.80	32.26	88.28

PANEL C - Descriptives of MSCI Sector Returns

Variable	Total Obs.	Mean	Std. Dev.	Median
GICS 10, Energy	84	8.53	27.98	9.94
GICS 15, Materials	84	9.37	19.56	17.64
GICS 20, Industrials	84	8.06	18.36	15.96
GICS 25, Consumer Discretionary	84	7.71	19.48	12.34
GICS 30, Consumer Staples	84	4.42	12.11	5.42
GICS 35, Health Care	84	9.53	14.13	14.37
GICS 40, Financials	84	6.53	20.14	19.49
GICS 45, Information Tech.	84	17.12	20.15	29.77
GICS 50, Communication Services	84	1.09	16.44	8.47
GICS 55, Utilities	84	5.49	14.14	7.64
GICS 60, Real Estate	84	1.83	16.26	9.49

Table 3: Determinants of Corporate Carbon Emissions

Table 3 displays regression results from the 2003-2022 global dataset containing firms in all continents: Asia, America, Europe, Oceania & Africa. The dependent variable is the log carbon emissions. The table report results from the pooled regression with standard errors clustered at year- and firm-level. The regressions also include month- and country-fixed effects. Column (2) include industry-fixed effects.

DEPENDENT VARIABLE: Log Carbon Emissions

Variable	(1)	(2)
Intercept	-6.154***	-7.469***
	(0.491)	(0.264)
MOM	1.395**	-1.250**
	(0.563)	(0.596)
Beta	0.003	0.003
	(0.028)	(0.040)
Leverage	1.099***	0.709***
	(0.113)	(0.076)
Log Size	0.136***	0.460***
	(0.021)	(0.025)
B/M	0.095**	0.471***
	(0.046)	(0.033)
Volat	-0.541	-0.0001
	(0.334)	(0.011)
Invest/A	0.002***	-0.002***
	(0.0005)	(0.0002)
ROE	0.245***	0.161***
	(0.064)	(0.068)
Log PPE	0.901***	0.466***
	(0.064)	(0.021)
HHI	0.0002*	0.00004***
	(0.00012)	(0.0001)
Time-Fixed Effects	YES	YES
Country-Fixed Effects	YES	YES
Industry-Fixed Effects	NO	YES
R-squared	0.6490	0.7950
Observations	770,481	770,413

Note: ***1% significance, **5% significance, *10% significance

Table 4: Global Carbon Risk Premium Analysis

Table 4 displays regression results from the 2003-2022 global dataset, containing firms in all continents: Asia, America, Europe, Oceania & Africa. The dependent variable is monthly stock returns. The variable of interest is log carbon emissions. We report results from the pooled regressions with standard errors clustered at year- and firm-level. The regressions also include month-fixed effects and country-fixed effects. In column (2), we include industry-fixed effects.

DEPENDENT VARIABLE: Monthly Returns

Variable	(1)	(2)
Intercept	15.380***	15.750***
	(0.665)	(0.578)
Log Carbon Emissions	0.060***	0.081***
	(0.011)	(0.015)
MOM	1.643***	1.599***
	(0.641)	(0.013)
Beta	0.211***	0.175***
	(0.025)	(0.027)
Leverage	-0.167***	-0.071
	(0.079)	(0.089)
Log Size	-0.145***	-0.158***
	(0.019)	(0.020)
B/M	0.210***	0.276***
	(0.032)	(0.038)
Volat	0.125	0.123
	(0.097)	(0.096)
Invest/A	-0.017	-0.017
	(0.020)	(0.020)
ROE	0.634***	0.601***
	(0.087)	(0.089)
Log PPE	-0.001	-0.006
	(0.011)	(0.013)
HHI	<0.001	< 0.001
	(0.0009)	(0.0009)
Time-Fixed Effects	YES	YES
Country-Fixed Effects	YES	YES
Industry-Fixed Effects	NO	YES
R-squared	0.1685	0.1689
Observations	769,044	768,660

Table 5: Continental Carbon Risk Premium Analysis

Table 5 displays regression results from North America, Asia, and Europe. The sample period is 2003-2022. The dependent variable is monthly stock returns. The variable of interest is the natural logarithm of total firm emissions. We report results from the pooled regressions with standard errors clustered at year- and firm-level. The regressions include month-fixed effects, country-fixed effects, and industry-fixed effects.

DEPENDENT VARIABLE: Monthly Returns

	North-America	Asia	Europe
Variable	(1)	(2)	(3)
Log Carbon Emissions	0.100***	0.052***	0.061***
	(0.019)	(0.018)	(0.019)
Intercept	13.221***	3.070	16.467***
	(0.851)	(2.179)	(1.077)
Control Variables	YES	YES	YES
Time-Fixed Effects	YES	YES	YES
Country-Fixed Effects	YES	YES	YES
Industry-Fixed Effects	YES	YES	YES
R-squared	0.213	0.154	0.236
Observations	273,753	231,085	186,057

Note: ***1% significance, **5% significance, *10% significance.

Table 6: Comparison: Pre vs. Post Paris Agreement

Table 6 displays the comparison of the pre- vs. post-Paris agreement with global sub-samples of 2014-2015 and 2016-2017. The dependent variable is monthly stock returns. The variable of interest is the natural logarithm of total firm emissions. We report results from the pooled regression with standard errors clustered at year- and firm-level. The regressions also include month-fixed effects, country-fixed effects, and industry-fixed effects.

DEPENDENT VARIABLE: Monthly Returns

	Global: Pre-Paris	Global: Post-Paris
Variable	2014-2015 (1)	2016-2017 (2)
Log Carbon Emissions	0.011	0.060**
	(0.033)	(0.030)
Intercept	2.613***	9.374***
	(1.012)	(1.189)
Control Variables	YES	YES
Time-Fixed Effects	YES	YES
Country-Fixed Effects	YES	YES
Industry-Fixed Effects	YES	YES
R-squared	0.1070	0.0740
Observations	74,410	94,546

Note: ***1% significance, **5% significance, *10% significance.

Table 7: Carbon Risk Premium from 2018 to 2022

Table 7 displays the relationship between carbon emissions and stock returns with sub-samples of 2018-2019 and 2021-2022. The dependent variable is monthly stock returns. The variable of interest is the natural logarithm of total firm emissions. We report results from the pooled regression with standard errors clustered at year- and firm-level. The regressions also include month-fixed effects, country-fixed effects, and industry-fixed effects.

DEPENDENT VARIABLE: Monthly Returns

Variable	2018-2019 (1)	2021-2022 (2)
Log Carbon Emissions	-0.064*** (0.024)	0.112*** (0.021)
Intercept	2.247*** (0.891)	9.061*** (0.761)
Control Variables	YES	YES
Time-Fixed Effects	YES	YES
Country-Fixed Effects	YES	YES
Industry-Fixed Effects	YES	YES
R-squared	0.1316	0.1095
Observations	128,912	178,464

Note: ***1% significance, **5% significance, *10% significance.

Table 8: Relationship between Carbon Risk Premium and Salient Events

Table 8 displays the impact of specific climate change efforts on the carbon premium. The sample period is 2010-2022. The dependent variable is the monthly carbon premium from the long-short carbon risk portfolio. The variable of interest is the event dummy, representing following events taking place: the Paris Agreement, the EU ETS price increase, the German Decarbonization Package, and the US Inflation Reduction Act. Mkt-rf denotes the monthly market risk premium.

DEPENDENT VARIABLE: Monthly Carbon Premium

Variable	All Salient Events
Event Dummy	0.038***
	(0.008)
Mkt - Rf	-0.037
	(0.040)
Time-Fixed Effects	YES
Country-Fixed Effects	YES
Industry-Fixed Effects	YES
R-squared	0.13
Observations	156

Note: ***1% significance, **5% significance, *10% significance.

Table 9: Carbon Risk Premium and Individual Salient Events

Table 9 displays the individual effects specific climate change efforts have on the carbon premium. The sample period is 2010-2022. The dependent variable is the monthly carbon premium from the long-short carbon risk portfolio. **Panel A** reports the results of the individual dummy variable regressions for the Paris Agreement and the US Inflation Reduction Act. Panel A panel includes the variable of interest, a dummy variable for when the event takes place, and monthly market risk premium as a control variable. **Panel B** reports the results of the individual dummy variable regressions for the EU ETS price increase and the German Decarbonization Package. Panel B includes the monthly market risk premium and oil and natural gas returns as control variables.

PANEL A - DEPENDENT VARIABLE: Monthly Carbon Premium

Variable	Paris Agreement (1)	Inflation Reduction Act (2)
Event Dummy	0.026**	0.024**
	(0.011)	(0.011)
Mkt - rf	-0.051	-0.058
	(0.032)	(0.041)
R-squared	0.12	0.04
Observations	156	156

Note: ***1% significance, **5% significance, *10% significance.

PANEL B - DEPENDENT VARIABLE: Monthly Carbon Premium

Variable	EU ETS (1)	Germany Package (2)
Event Dummy	0.033**	0.035**
	(0.011)	(0.016)
Mkt - rf	-0.055	-0.040
	(0.043)	(0.043)
Crude Oil	-0.007	-0.011
(Brent)	(0.017)	(0.018)
Natural Gas	0.018	0.012
(Henry Hub)	(0.012)	(0.012)
R-squared	0.08	0.05
Observations	156	156

Note: ***1% significance, **5% significance, *10% significance.

Table 10: Carbon Risk Premium: Excluding Salient Industries

Table 10 displays regression results from excluding salient industries. There are two sample periods. In columns (1) and (2), the sample period is 2005-2017. In columns (3) and (4), the sample period is 2016-2022. In column (2) and (4), companies in the oil & gas, utilities, and transportation industries are excluded from the sample. The dependent variable is monthly stock returns. The variable of interest is the natural logarithm of total firm emissions. We report results from the pooled regression with standard errors clustered at year- and firm-level. The regressions also include month-fixed effects, country-fixed effects, and industry-fixed effects.

DEPENDENT VARIABLE: Monthly Returns

	2005-2017: All Industries (1)	2005-2017: Excluding Salient Industries (2)	2016-2022: All Industries (3)	2016-2022: Excluding Salient Industries (4)
Log Carbon Emissions	0.106***	0.110***	0.051***	0.044***
	(0.015)	(0.017)	(0.013)	(0.014)
Intercept	10.331***	3.920***	6.981***	6.604***
	(0.777)	(0.949)	(0.551)	(0.556)
Control Variables	YES	YES	YES	YES
Time-Fixed Effects	YES	YES	YES	YES
Country-Fixed Effects	YES	YES	YES	YES
Industry-Fixed Effects	YES	YES	YES	YES
R-squared	0.1610	0.1690	0.1624	0.1646
Observations	370,162	328,187	482,312	437,112

Note: ***1% significance, **5% significance, *10% significance.

Table 11: Breakdown of Greenhouse Gas Emissions by GICS sectors

Table 11 displays the reported percentage of Greenhouse gas (GHG) emissions of global Scope 1 and Scope 2 by the GICS sectors. Note that the representation does not encompass all emitting companies. The dataset comprises over 1,000 publicly traded carbon-intensive companies and covers approximately 90% of emissions associated with the equity holdings of BlackRock's clients.

Sector (GICS)	Share Total GHG Emissions %
Energy	17%
Materials	29%
Industrials	16%
Consumer Staples	5%
Health Care	1%
Information Technology	3%
Consumer Discretionary	5%
Financials	6%
Utilities	17%
Real Estate	1%
Communication Services	2%

Table 12: Carbon Risk Premium in different GICS Sectors

Table 12 displays regression results from each GICS sector. The sample period is 2016-2022. The dependent variable is monthly stock returns. The variable of interest is the natural logarithm of total firm emissions. We report results from the pooled regression with standard errors clustered at year- and firm-level. The regressions also include month-fixed effects, country-fixed effects, and industry-fixed effects. **Panel A** contains regression results from sectors Energy (GICS 10), Materials (GICS 15), Industrials (GICS 20), and Consumer Discretionary (GICS 25). **Panel B** contains regression results from sectors Consumer Staples (GICS 30), Health care (GICS 35), Financials (GICS 40), and Information Technology (GICS 45). **Panel C** contains regression results sectors Communication Services (GICS 50), Utilities (GICS 55), and Real Estate (GICS 60).

PANEL A - DEPENDENT VARIABLE: Monthly Returns

Variable	Energy, GICS 10	Materials, GICS 15	Industrials, GICS 20	Consumer Discretionary, GICS 25
Log Carbon Emissions	0.146**	-0.013	0.063**	-0.005
	(0.063)	(0.045)	(0.031)	(0.050)
Intercept	15.094***	13.355***	7.294***	3.409*
	(2.208)	(1.920)	(1.225)	(1.864)
Control Variables	YES	YES	YES	YES
Time-Fixed Effects	YES	YES	YES	YES
Country-Fixed Effects	YES	YES	YES	YES
Industry-Fixed Effects	YES	YES	YES	YES
R-squared	0.3246	0.1845	0.2151	0.2252
Observations	24,225	46,161	85,899	57,379

Note: ***1% significance, **5% significance, *10% significance.

PANEL B - DEPENDENT VARIABLE: Monthly Returns

Variable	Consumer Staples, GICS 30	Health Care, GICS 35	Financials, GICS 40	Information Technology, GICS 45
Log Carbon Emissions	0.135**	0.069	0.083**	-0.018
	(0.062)	(0.068)	(0.035)	(0.049)
Intercept	6.208***	12.381***	5.171***	3.715
	(1.838)	(3.756)	(1.077)	(2.798)
Control Variables	YES	YES	YES	YES
Time-Fixed Effects	YES	YES	YES	YES
Country-Fixed Effects	YES	YES	YES	YES
Industry-Fixed Effects	YES	YES	YES	YES
R-squared	0.1041	0.1187	0.2563	0.1968
Observations	31,083	44,759	70,976	48,354

Note: ***1% significance, **5% significance, *10% significance.

PANEL C - DEPENDENT VARIABLE: Monthly Returns

Variable	Communication Servies, GICS 50	Utilities, GICS 55	Real Estate, GICS 60
Log Carbon Emissions	0.005	-0.019	0.065
	(0.081)	(0.037)	(0.046)
Intercept	6.310***	0.626	6.927***
	(2.020)	(1.861)	(2.152)
Control Variables	YES	YES	YES
Time-Fixed Effects	YES	YES	YES
Country-Fixed Effects	YES	YES	YES
Industry-Fixed Effects	YES	YES	YES
R-squared	0.1433	0.1452	0.2490
Observations	24,842	20,230	27,020

Note: ***1% significance, **5% significance, *10% significance.

Table 13: GICS Expected Excess Returns - CAPM vs. CAPM plus Carbon Premium

Table 13 displays the annualized expected excess return for each GICS sector based on CAPM in column 1. Column 2 presents the annualized expected excess return based on CAPM plus a carbon premium. The in-sample test period is 2016-2022.

Sector (GICS)	r^e: CAPM (1)	r^e: CAPM + Carbon Premium (2)	Δ (2-1)
Energy	9.05%	10.63%	1.58%
Materials	7.71%	7.30%	-0.41%
Industrials	7.08%	7.60%	0.51%
Consumer Staples	4.09%	5.01%	0.92%
Health Care	5.14%	5.66%	0.51%
Information Technology	6.72%	5.55%	-1.17%
Consumer Discretionary	7.92%	6.70%	-0.59%
Financials	8.00%	9.42%	1.43%
Utilities	3.48%	2.93%	-0.56%
Real Estate	5.52%	5.49%	-0.03%
Communication Services	5.26%	3.95%	-1.31%

Table 14: Comparing Sector Portfolio Weights CAPM vs. CAPM plus Carbon Premium

Table 14 displays the optimal weighting of each sector within two portfolios constructed using Markowitz portfolio optimization. The in-sample test period is 2016-2022. The variance-covariance matrix is based on realized returns. Portfolio 1 uses CAPM to estimate the expected returns for each sector. Portfolio 2 uses CAPM plus a carbon premium to estimate the expected returns for each sector.

Sector (GICS)	Portfolio 1	Portfolio 2	Δ (2-1)
Energy	11.75%	21.59%	9.84%
Materials	25.00%	0.00%	-25.00%
Industrials	0.00%	3.41%	3.41%
Consumer Staples	0.00%	25.00%	25.00%
Health Care	22.17%	25.00%	2.83%
Information Technology	0.00%	0.00%	0.00%
Consumer Discretionary	16.08%	0.00%	-16.08%
Financials	25.00%	25.00%	0.00%
Utilities	0.00%	0.00%	0.00%
Real Estate	0.00%	0.00%	0.00%
Communication Services	0.00%	0.00%	0.00%
Total	100%	100%	

Table 15: Comparison Portfolio Performance - Out-of-Sample test

Table 15 displays the portfolio performance for portfolio 1 and portfolio 2. The out-of-sample test period is 2016-2022. Portfolio 1 uses CAPM to calculate expected returns. Portfolio 2 uses CAPM plus a carbon premium to calculate expected returns. The annualized risk-free rate is the US 3month treasury bill collected from the federal reserve in the period 2016-2022.

	Portfolio 1	Portfolio 2	Δ (2-1)
Annualized Return	8.16%	8.21%	0.05%
Annualized RF	1.11%	1.11%	
Annualized Standard Dev.	17.76%	16.32%	-1.44%
Sharpe Ratio	0.40	0.44	0.04

Table 16: Average Portfolio Sector Weights: Out-of-Sample Period 2016-2022

Table 16 displays the average optimal sector weights in two portfolio constructed using Markowitz portfolio optimization. The out-of-sample test period is 2016-2022. The variance-covariance matrix is based on realized returns. Portfolio 1 uses CAPM to estimate the expected returns for each sector. Portfolio 2 uses CAPM plus a carbon premium to estimate the expected returns for each sector.

Sector (GICS)	Portfolio 1	Portfolio 2	Δ (2-1)
Energy	8.89%	12.33%	3.44%
Materials	7.48%	23.93%	16.46%
Industrials	15.85%	10.66%	-5.19%
Consumer Staples	4.69%	11.64%	6.59%
Health Care	8.25%	0.00%	-8.25%
Information Technology	17.45%	3.54%	-13.91%
Consumer Discretionary	18.05%	5.52%	-12.53%
Financials	16.06%	12.32%	-3.73%
Utilities	0.93%	8.55%	7.63%
Real Estate	0.48%	0.00%	-0.48%
Communication Services	1.88%	11.50%	9.63%
Total	100%	100%	