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Price of Tomorrow? Pricing Future Carbon-Transition Risk

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Carbon Costs and Green Innovation: On the Market Pricing of Triggering and Muting Factors of Transition Risk

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Price of Tomorrow? Pricing future Carbon-Transition Risk

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Abstract

This paper estimates the stock market's pricing of future unpriced carbon costs and uncovers the firm-level future carbon-transition risk on a global sample of 8,821 unique firms. I find evidence of an annual unpriced carbon-transition risk premium of 2.5% to 3.2% related to firms' future carbon costs across the forecast years 2030, 2040, and 2050 under three carbon cost scenarios. The premium is positively associated with increases in the carbon cost scenario. However, I only find mixed evidence of a transition premium related to estimated future margin reductions due to increased carbon costs. Next, the findings suggest that particularly brown firms are systematically penalized across industries and countries, and the analysis also indicates that the ten most exposed industries are subject to heightened carbon-transition risk premiums.

JEL Codes: G3, G11, Q54

Keywords: Carbon cost, transition risk, climate risk

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1 Introduction

Are future costs of carbon priced in the stock market? In this paper, I answer the question of to what extent investors are pricing future firm-level unpriced carbon costs into stock prices. To dissect the future cost of carbon and construct a measure of scenario-level analysis, I rely on data provided by Trucost on future firm-level carbon costs for a global sample of firms. Estimations of future corporate carbon costs take the currently reported carbon emissions by firms as the basis, project the future unpriced carbon costs, and relate it to success or failure in meeting the 2-degree Celsius target set out at COP 21 in the 2015 Paris Agreement. Using this data, I examine if a relationship exists between future firm-level unpriced carbon costs and stock returns. I find that a one-standard deviation increase in the log total unpriced carbon cost is associated with an annual premium of 2.594% in a low carbon cost scenario in 2030. This effect is positively related to increases in the carbon cost scenario. In contrast, I do not find consistent results suggesting that investors require a premium based on EBIT margin reductions directly related to future unpriced carbon costs. Hence, the results imply that investors require return compensation for firms' future unpriced carbon costs, while there is only insignificant evidence for the impact on a firm's profitability. In particular, the results indicate that higher carbon cost scenarios are associated with higher premiums when analyzing the effect of unpriced scope 1 and scope 2 carbon costs. These findings are consistent for forecast years 2030, 2040, and 2050. The evidence of cost-focused and margin-level unpriced carbon premiums is more robust for firms that are estimated to be among the top 10% most exposed firms and for firms that are in a generally perceived brown industry. Further, I find results suggesting that institutional investors might be incorporating information about future unpriced carbon costs and creating downward pressure on brown stocks, indicated by possible divesting effects in firms with high future unpriced carbon costs. However, I do not find an additional effect of increased institutional ownership on the carbon-transition risk premium.

I proxy the carbon-transition premium, i.e., the excess return associated with brown companies over green companies, using a global dataset comprising estimates of the impact of future increased carbon costs on corporate costs and profitability. I dissect carbon-transition risk along three different carbon cost scenarios and three forecast years towards the 2-degree target, enabling an analysis of multiple carbon pathways and horizons. If investors incorporate information about different carbon cost scenarios into investment decisions, what carbon costs are they considering? Are stock markets pricing the short-term carbon costs or carbon costs in the medium and long term? Further, I analyze whether investors are considering unpriced costs of carbon on profitability levels or cost levels. This highlights a fundamental question essential for firms seeking to understand investors' perception of carbon-related risks: Should the focus be on mitigating the impact of unpriced carbon on margins, or are investors penalizing the carbon exposure on the cost level? Further, analyzing this question from policymakers' perspective is interesting. As the global economy transitions to a greener future, regulators need to understand the response of financial markets to different carbon cost policy decisions and scenarios. Additionally, this analysis provides a deeper understanding of the industry- and country-level exposure to carbon-transition risk over multiple carbon cost pathways.

Regulators and societal pressure to curb climate change entail a gravity towards reducing companies' carbon emissions in production and related processes. Mechanisms to curb carbon emissions include increased carbon taxes and lower emission ceilings in emission trading schemes (for example, the European Union Emission Trading Scheme). Firm-level carbon emissions impact the extent of carbon-transition risk as investors become increasingly concerned about climate change and incorporate the effect of policymakers' carbon mitigation tools. This effect can materialize through different channels. One such channel could be increased future carbon costs. Alternatively, firms that rely on brown technology are exposed to green technology disruptions, possibly rendering crucial parts of their business obsolete. Additionally, reputational consequences might lead to loss of customers and suppliers and can result in competitive disadvantages for firms not sufficiently green.

Examining the carbon-transition risk directly linked to future firm-level unpriced carbon costs is interesting on multiple dimensions. First, as exemplified by the recent success of KlimaSeniorinnen (Swiss Senior Women for Climate Protection) in the European Court of Human Rights (ECtHR), there is a continued heightened focus on combating climate change and mitigating its consequences. The ruling is a landmark for climate litigation and marks the first time a transnational specialized human rights court is directly declaring the right to climate protection. Second, from an investor perspective, it is important to understand the impact of increased carbon costs on portfolios and the risk-return profiles of assets. Carbon emissions and related costs are being incorporated into investment decisions to a more significant extent, signaling that investors are becoming increasingly concerned about climate issues. Third, the analysis of carbon-transition risk provides greater insight for policymakers on financial markets' responsiveness to different climate regulations. From a regulatory viewpoint, these insights can be valuable in decisions about the extent of carbon policy intervention and the time horizon. Hence, it is a fundamental field to understand not only for investors but also for regulators who seek to incentivize all market participants to fight climate change.

Although multiple influential papers exist on the matter, the existence of a carbon premium is disputed and inconsistently documented across time periods, geographies, and carbon risk measures. Despite this inconclusiveness, several studies document that investors increasingly price climate-related risks into stock prices. Bolton and Kacperczyk (2023) provide evidence on a carbon-transition risk premium related to firms' level of emissions as well as annual changes in emissions. In a related study, Faccini et al. (2023) show that climate policy factors are priced in U.S. stock markets, implying that investors are hedging themselves against the imminent risk of governmental intervention and not directly against climate change risks. The authors suggest that investors hedge against regulatory intervention by going long in negative climate-beta stocks, leading to increased prices and lower returns for green companies' stocks.

The academic literature presents two main arguments for why higher firm-level climate risk might be associated with higher stock returns. On the one hand, researchers argue that a firm's emission level is directly linked to the extent of carbon-transition risk that the firm faces and that carbon-heavy firms are more exposed to climate risks than carbon-lighter firms. Bearing climate-related risks should be reflected in higher stock returns as investors require sufficient compensation for increased risk. Climate-related risks can broadly materialize in two ways: First, when a company emits carbon emissions, the firm-level risk associated with the transition towards a greener economy increases. Transition risk stems from the adjustment towards a greener economy and is primarily associated with regulatory intervention and green technological development, closely tied to a company's carbon emissions. Second, firms can be exposed to varying degrees of physical risks related to increased frequency and severity of extreme weather events and natural disasters, such as the increased probability of flooding and fire, thereby imposing costs on the firm owning them (TCFD, 2017). Hence, the transition process towards a greener economy and the fact that a firm's assets can be at risk of natural disasters highlight the uncertainty surrounding how climate change will unfold on the firm level. Consequently, companies with higher carbon reliance and natural disaster exposure are expected to be subject to higher required returns from investors as compensation for holding these firms' stocks. On the other hand, it is highly plausible that investors' tastes have shifted towards making investment portfolios greener and away from holding brown companies. This can be exemplified by several strategies to make investment portfolios more climate-friendly, including negative screening, positive screening, impact investing, and thematic investing. This implies that a growing set of investors avoid investing in brown stocks on the grounds of not holding environmentally harming assets in their portfolios. As a result, a set of investors actively choose not to invest in such firms or decide to divest from them. As a result of investors shunning brown firms' stocks, it then follows that these stocks earn excess returns over greener firms' stocks.

From a practitioner's perspective, whether investors price in future unpriced carbon costs in stock prices is also interesting. Given the evidence for a carbon-transition risk premium related to unpriced carbon costs, highly exposed firms will be penalized according to their future carbon costs, leading to increased costs of equity. This effect can be seen as an additional carbon tax for the firm. It can be valuable for firms to curb the reliance on carbon to limit such an effect, and increasingly so as investors become more concerned about climate change going forward. Also, since future unpriced carbon costs encompass short-, medium- and long-term perspectives, it is increasingly important for firms to curb future carbon costs as the information on mitigation and adaptability becomes more accessible for investors, i.e., which firms are the "carbon winners and losers." Further, following the same reasoning, it might be value-creating for firms to invest in green R&D to reduce or mitigate the market-based carbon-transition risk premium.

The remainder of the paper is structured as follows: Chapter 2 reviews the most closely related literature to this paper. Chapter 3 presents the data used throughout the analysis. In Chapter 4, I detail the methodology for answering the research questions of this paper. Chapter 5 presents the main empirical results and is followed by brief interpretations. In Chapter 6, I discuss the main findings of the paper, the possible implications of the results, and the study's limitations. Lastly, Chapter 7 concludes the paper.

2 Literature review

There is limited empirical evidence on the pricing of future carbon-transition risk using forward-looking carbon scenarios. Despite the lack of scenario-based carbon-transition risk analysis, there are several influential papers on the broader topic of climate and transition risk. The literature on climate risk generally aims to uncover the relationship between firms' performance and uncertain climate-related risks, whether in the stock market or using financial metrics such as return on assets or cost of capital. In the literature review by Campiglio et al. (2023), the authors conclude that the academic sphere has largely found that financial markets tend to price climate-related risks. However, the magnitude of the risk premium varies by asset class, industry, and geographic location. Further, the authors argue that the literature has mainly focused on the effect of climate change exposure on financial assets and markets, but there is little research on whether the current climate risk compensation is efficient. As illustrated by Sautner et al. (2023b), the effect of climate change on individual stocks is highly uncertain. This arises due to uncertainties about how much carbon emissions need to be curbed and which specific measures will be implemented by regulators to achieve carbon emission reduction targets. Markets are currently trying to navigate a changing landscape related to climate policy, including uncertainty concerning levels of carbon taxes, support for green industry through the American Inflation Reduction Act (IRA) and EU's Green Deal Industrial Plan, and the expansion of emission trading schemes (ETS). The impact on firms, brown and green, remains uncertain. Hence, the uncertainty around carbon-transition risk is linked to increased carbon costs and advancements in green technology. In a related paper, Sautner et al. (2023a) show that attention to climate change exposures during firms' earnings calls predicts job creation in disruptive green technologies and green patenting. Their findings indicate that firms' concern and awareness of climate change risk is an important predictor of green innovation and technology. Arguably, it follows from this line of reasoning that companies prioritizing climate change risk mitigation through increased investments in green technological advancements and R&D will have a competitive advantage, more effective operations, and lower carbon-transition risk under a scenario of increasing carbon costs. In a study examining what drives the carbon premium in U.S. stock markets, Faccini et al. (2023) use a textual climate intensity approach to dissect climate physical risk and carbon-transition risk. Their findings suggest that it is a transition risk in the form of imminent government intervention that is priced in the U.S. stock market. In contrast, the results imply that direct physical risks are not significantly reflected in stock prices.

Further, over the unconditional realized return of S&P 500 stocks from 2005 to 2020, Sautner et al. (2023b) do not find a significant climate change risk premium. However, they find that forward-looking expected return proxies show a significant climate change risk premium of 0.5%-1% per annum. The results indicate that investors expect to earn a positive risk premium ex-ante for holding stocks with higher climate change exposure. Examining this topic, Bolton and Kacperczyk (2021) find a significant positive relationship between the level of emissions and the change in emissions and stock returns using U.S. data between 2005 and 2017. Further strengthening their results, Bolton and Kacperczyk (2023) find that higher emission levels and growth rates in emissions are associated with higher stock returns across most sectors and geographies on a sample of 14,400 firms and 77 countries. They also find that the carbon emissions premium is higher for firms located in countries with larger energy sectors, lower economic development, and less inclusive political systems. In addition, the authors find results suggesting that countries with stricter domestic climate policies are associated with higher premiums related to the level of carbon emissions.

In an early study by Matsumura et al. (2014) examining the impact of carbon emissions on firm valuation, the authors use data on the S&P 500 between 2006 and 2008 and find that higher emissions are associated with lower firm value. However, this negative firm valuation effect is mitigated by voluntary disclosures on emissions. Further, Bolton et al. (2022) find evidence for a valuation discount for companies that are large carbon emitters, as reflected in lower price-earnings ratios. Further, they find that the price-earnings discount varies significantly across industries and firm size, highlighting that higher valuation discounts are found for larger firms. In addition, the authors examine the carbon valuation discount for both U.S. and European stocks and find a discount in both geographies, albeit with higher discounts for companies covered by the EU ETS. In a forward-looking approach, Ginglinger and Moreau (2023) study the impact of firms' climate change risk exposure on leverage. Their findings suggest that firms exposed to greater climate risk become less leveraged after the 2015 Paris Agreement. The authors suggest two mechanisms for reduced leverage in firms with higher climate risk exposure: Firstly, high-ESG firms are more likely to proactively manage climate risk instead of reducing leverage than low-ESG firms. Secondly, bondholders and bankers charge higher spreads on the debt issued by high-climate risk companies.

In a cross-sectional setting, Cenedese et al. (2023) examine the relationship between expected institutional divestment, measured as the expected time to exit from a net-zero portfolio for a firm, and stock returns, as well as the time to exit from net-zero portfolios and firm value. Their findings suggest a strong negative relationship between the time to exit from net-zero portfolios and next-month stock returns. Moreover, the authors find strong support for higher valuations of companies with long time to exit. These findings support the notion that investors are increasingly incorporating carbon concerns into investment decisions, thereby requiring higher returns as carbon-risk compensation, and further, that there exists a carbon valuation discount. Coherent with these findings, Hsu et al. (2023) construct long-short portfolios from firms with high versus low toxic pollution intensity and find that heavily polluting companies are at higher regulation risk, and thereby, investors demand higher stock returns as compensation. The authors show that the pollution risk premium has materialized in a significant average annual return of 4.42%.

Nevertheless, it is important to realize that high green stock performance can emerge due to several factors. Pástor et al. (2022) suggest that recent outperformance by green stocks is due to unexpected shocks to climate concerns and that this effect emerges through two channels: Firstly, they argue that investors have a preference for green stocks over brown stocks. Second, brown stocks are highly exposed to climate risks, so green stocks are better hedge products than brown stocks. By constructing a green factor portfolio and setting the climate shock factor to zero, they find evidence indicating that green stocks' outperformance no longer holds. This finding suggests that unexpected climate concerns, leading to increased demand from investors for green stocks and consumers for green products, have driven the green stock price appreciation. Monasterolo and De Angelis (2020) investigate how financial markets price the COP 21 Paris Agreement by testing whether low-carbon indices in the EU, the U.S., and globally exhibit decreased systematic risk and lower betas after 2015. They find that the overall performance of the low-carbon indices increased after the Paris Agreement due to a significant systematic risk reduction. Moreover, the authors find evidence suggesting that the low-carbon indices' portfolio weights following standard portfolio optimization procedures increase. In contrast, the optimal portfolio weights of the carbon-intensive indices exhibit no particular effect. In a study examining the impact of ESG scores on stock performance, Pedersen et al. (2021) argue that the scores play a dual role: Firstly, they provide information on the firm's fundamentals, and secondly, they affect investor preferences. Using large datasets, they calculate the ESG efficient frontier and find that an ESG-adjusted asset pricing model determines asset prices. Similarly, in an attempt to clarify the relationship between ESG and stock market performance, Zerbib (2022) develops an asset pricing model (the S-CAPM, Sustainability-CAPM) with partial segmentation and heterogenous preferences and uses it on a sample of U.S. stocks between 1999 to 2019. The author uses this framework to argue for a taste premium and an exclusion effect. The taste premium relates to sustainable investors internalizing climate externalities and regular investors' liquidity provision to sustainable investors taking opposing positions and overweighting assets with the highest cost of externalities. The exclusion effect arises from reducing the investor base for certain brown assets, i.e., sin stocks, leading to inefficient risk-sharing effects. The author finds results suggesting a statistically significant exclusion effect that accounts for a premium of 2.79% from 1999 to 2019. However, he struggles to find similar results for the taste premium.

Delmas et al. (2015) investigate how improved environmental performance affects financial results in the U.S. using data from 2004 to 2008 under increasing likelihood of environmental regulatory intervention. They find that firms improving their environmental performance exhibit lower return on assets in the short term. However, they conclude that investors see the long-term value of such environmental improvements by firms as shown in increases in Tobin's q. Similarly, Garvey et al. (2018) document that reductions in carbon intensities are associated with increased future profitability and stock returns, arguing that carbon improvements reflect long-term heightened firm productivity and efficient use of inputs but that the market is sluggish to appreciate this over the short term. Busch et al. (2022) extends the analysis to a more comprehensive time frame and geography, and the authors confirm the finding of a positive relationship between carbon emissions and short-term financial performance. In contrast, Busch et al. (2022) find that higher carbon emissions are also strongly associated with long-term financial performance, possibly highlighting the difficulties in dissecting opaque long-term effects of carbon emissions.

The literature's efforts to dissect the short- and long-term effects of carbon emissions on firms have so far provided a mixed picture. The generally observed positive relationship between firms' carbon footprint and short-term stock price performance can have several plausible explanations. Similarly, the reason that reductions in carbon emissions are associated with lower financial performance over the short term can be related to multiple dynamics. For example, in a study on five firms in Alberta's oil sand, Slawinski and Bansal (2015) argue that savings from better carbon performance cannot be realized over the short-term horizon. Following the reasoning of Misani and Pogutz (2015), this dynamic can arise because firms can benefit from preventing capital expenditures for carbon emission mitigation technologies when competitors undertake such investments. The long-term effects of firm-level carbon emissions on financial performance have primarily been examined using an approach of assessing market-oriented measures. The intuition is that investors' perceptions of long-term carbon risk affecting earnings, margins, and other profitability metrics should be reflected in the market. However, the literature posits mixed evidence for the long-term relationship between companies' carbon emissions and financial performance, as described by Delmas et al. (2015), Busch et al. (2022), and Misani and Pogutz (2015).

Conceptually, this paper employs the equilibrium model of Pástor et al. (2022) to identify whether investors are pricing future unpriced carbon costs in stock prices. In the model, green assets are expected to have lower returns than brown assets, reflecting that investors prefer green over brown investments and that greener assets are better instruments for mitigating climate risk in investment portfolios. Central to the model is that green-realized returns may outperform brown-realized returns under scenarios of unexpected demand shifts by investors for green assets. Hence, markets may be in a disequilibrium where green stocks outperform brown stocks, reflecting unexpectedly strong increases in climate concerns and preference for green investments. The authors find that green stocks tend to outperform brown stocks when negative climate change news increases in frequency. Following this notion, this paper investigates whether stock performance is affected by future unpriced carbon costs, thereby examining if and how investors price in concerns about different carbon cost scenarios related to the 2-degree target. Importantly, given that the sample period covers the years 2017 to 2022, it is possible that stock markets in general, and green assets in particular, are in disequilibrium and that carbon-transition risk is not efficiently priced. However, focusing on global stock markets, this paper dissects to what extent investors are considering unpriced future carbon costs in investment decisions and which scenarios and horizons influence stock returns.

This paper extends the analysis of previous research on the interrelationship between carbon-transition risk and stock market performance. More specifically, this paper exploits a novel and comprehensive dataset by Trucost containing information on future firm-level carbon cost exposures. Using the approach of Bolton and Kacperczyk (2021), this paper proxies firms' exposure to carbon-transition risk with firm-level unpriced carbon costs. Moreover, building on the methodology of Bolton and Kacperczyk (2023), this paper examines the effect of firm-level unpriced carbon costs and future profitability under three scenarios related to the 2-degree target. Previous literature has largely focused on estimations of the carbon premium using contemporary carbon emissions as a proxy for carbon-transition risk. Whether in estimating the carbon premium in stock prices, short- and long-term profitability, or the cost of capital for firms, research has mainly focused on carbon emission levels, changes in carbon emissions, and carbon intensities. This paper contributes to the literature on climate finance by digging deeper into the relationships between different carbon cost scenarios and firm-level stock returns, thereby providing a more comprehensive picture of future carbon-transition risk for firms, industries, and the financial markets as a whole. Exploiting the rich forward-looking dataset by Trucost, this analysis enables nuanced insights into investor perception of carbon cost scenarios. It allows for a deeper understanding of future firm-level carbon exposure and its impact on cost and profitability in industries and countries under different carbon cost scenarios and time horizons.

3 Data description

3.1 Data on future unpriced carbon costs

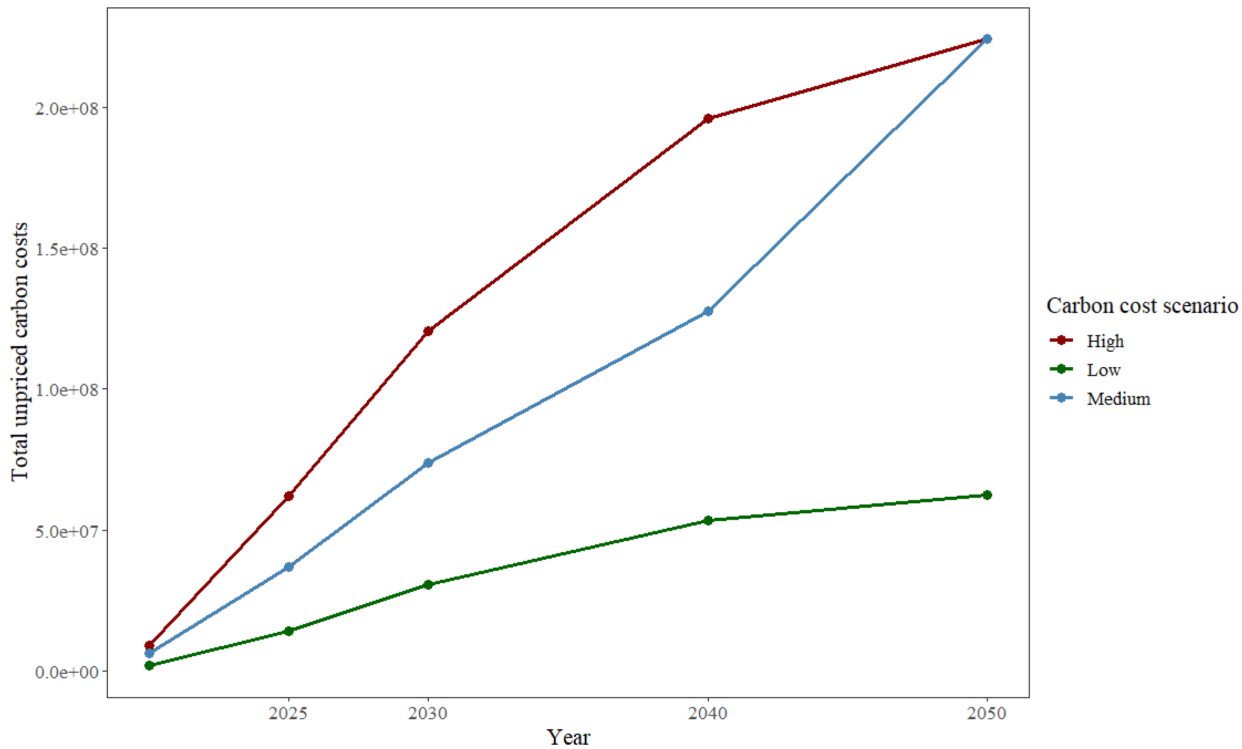
The primary database used for future unpriced carbon costs is Trucost. Trucost is a comprehensive data provider of carbon and environmental data and risk analysis. The dataset used is the Carbon Earnings at Risk data, which consists of forward-looking estimates of firms' exposure to increased carbon costs. With its distinct focus on future carbon costs, the Trucost Carbon Earnings at Risk dataset allows for isolating carbon cost risk under different assumptions and scenarios. The Carbon Earnings at Risk data includes future estimations of EBIT and EBITDA margin reductions and costs related to scope 1 and scope 2 emissions. Scope 1 emissions are defined as the direct emissions stemming from operations controlled by the firm over one year. Scope 2 emissions are defined as emissions stemming from the generation of consumed electricity and from using steam and heat. Scope 3 emissions are not included in the data. Scope 3 emissions are defined as emissions that are caused by a firm but stem from operations not controlled by the firm itself, for example, through outsourced activities. These emissions can arise in the form of, for example, emissions stemming from the purchase of input goods and waste disposal activities from third parties. Trucost's lack of inclusion of scope 3 emissions in the Carbon Earnings at Risk data limits the scope of this paper to examine the direct firm-level carbon-transition risk. However, since the data covers impacts on firm cost and profitability, it is logical that scope 3 emissions are excluded. Moreover, it is reasonable to proxy carbon-transition risk using scope 1 and scope 2 emissions, as firms are exposed to regulatory interventions targeting the direct carbon emissions of a company and its use of energy. Regulatory intervention increasing the cost of scope 3 emissions is also possible but is distinctively harder for regulators to target and less likely to emerge in practice, especially over the short and medium term. In today's regulatory landscape, the majority of the debate revolves around how to cut emissions related to the company's operations at the firm level. Therefore, scope 3 emissions are less likely to be the carbon emissions that policymakers will consider first, and scope 1 and scope 2 emissions are conceptually easier to connect to carbon-transition risk due to their direct nature. Lastly, the exclusion of scope 3 emissions reduces the vulnerability of the analysis to double counting of emissions and generally more uncertain emission estimations.

Trucost Carbon Earnings at Risk comprises data on firms' ability to absorb future carbon costs and their impacts on financial profitability. Trucost reports the effective cost of carbon in 2016 USD per ton CO2e. Central to calculating carbon earnings risk is estimating the carbon cost risk premium, defined as the additional financial cost per ton of carbon emissions from the currently prevailing carbon cost. This unpriced cost of carbon is, therefore, the difference between what carbon costs firms are subject to at the point of estimation from Trucost (i.e., from 2017 to 2022) and the cost they are projected to be subject to in the future.

The data presents three different carbon cost pathways related to limiting the global temperature increase well below 2 degrees Celsius above pre-industrial levels as set out in the 2015 Paris Agreement. These three scenarios vary according to the extent of policy action intervention and extrapolate future firm emissions from contemporary emission levels. The data, therefore, considers the shape of the transition towards a low-carbon economy and accounts for climate-related targets being reached gradually and non-disruptive or abruptly with possible higher systemic disruptions (Campiglio et al., 2023). *Low*: The low carbon cost scenario assumes that carbon emissions will follow schemes outlined in each country's Nationally Determined Contributions (NDCs). Some of these NDCs are not expected to meet the goal of the Paris Agreement, and the carbon cost will, therefore, develop slowly as time progresses. According to Robiou du Pont and Meinshausen (2018), taking the NDCs as the baseline, the expected mean temperature increase by 2100 exceeds the 2-degree target by several decimal points. *Medium*: The medium carbon cost scenario assumes reaching the target outlined in the Paris Agreement with the full implementation of policies, albeit with delayed action in the short term. In this scenario, the carbon cost will increase slowly before an abrupt price hike is needed to limit the global temperature increase to well below 2 degrees. The medium carbon cost scenario thus assumes radical shifts in the carbon cost due to, for example, abrupt increases in the carbon tax. *High*: Finally, the high carbon cost scenario assumes full implementation of policies limiting the global temperature increase to below 2 degrees. Hence, the steady 2-degree aligned scenario assumes sufficient and stable carbon cost growth in the future. Following these three pathways, Trucost provides company-level exposure to the future cost of the total, scope 1, and scope 2 carbon emissions, as depicted in Figure 1, and the related EBIT and EBITDA margin reductions, as shown in Figure 2, for the years 2030, 2040, and 2050. Given this set of parameters, the carbon cost risk premium varies according to the chosen carbon cost scenario, as well as the firm's industry, geographic location, and time horizon, allowing for estimates and analysis of scenario-based carbon-transition risk.

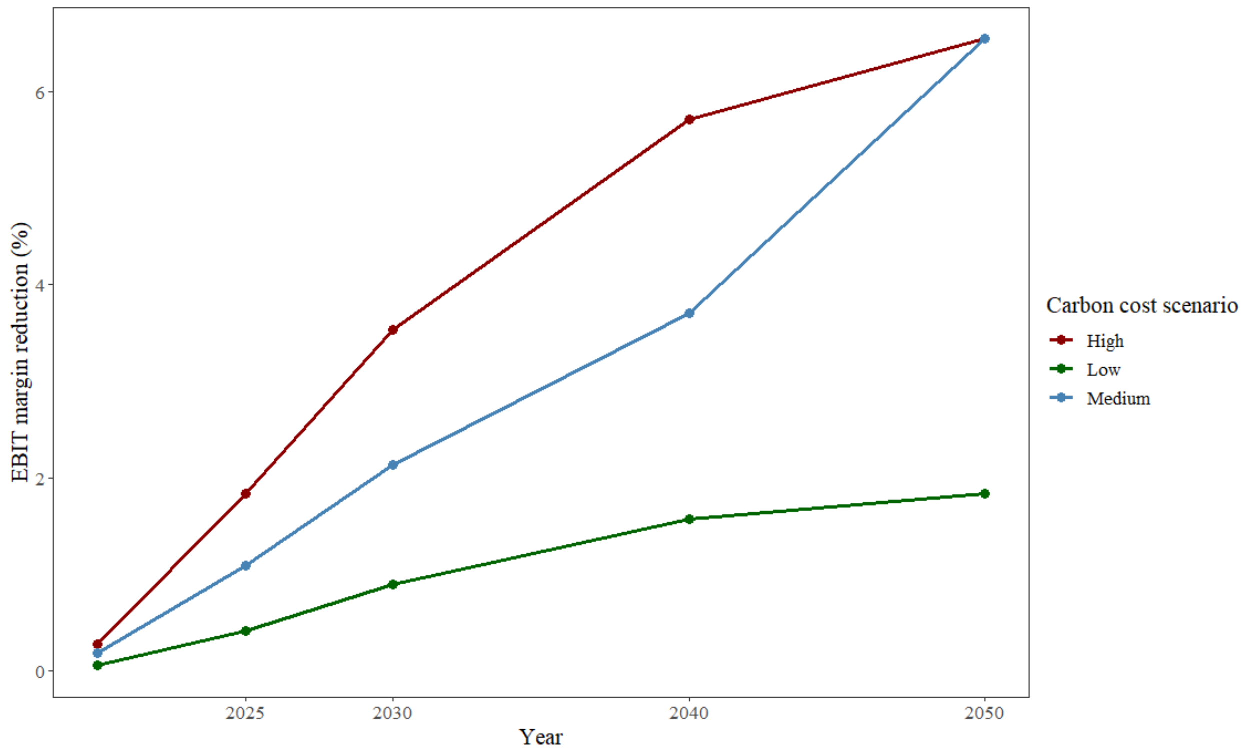
Table 1 reports descriptive statistics for the set of variables used throughout the paper. Panel A presents summary statistics on firm-level future reductions in margins directly associated with increased costs of carbon as well as estimated unpriced carbon costs measured in log

Figure 1: Total unpriced carbon cost estimations according to carbon cost scenario



USD. These summary statistics disregard forecast year and carbon costs scenario level, but they provide descriptive statistics of the aggregated effects of implementing carbon measures intended to reach the 2-degree targets set out in the Paris Agreement. Looking at the impact of increased carbon costs on profitability measures, Panel A reports estimated effects on margins on the EBIT- and EBITDA levels. The average firm in the sample is estimated to experience EBIT margin reductions and EBITDA margin reductions of 3.020% and 2.704%, respectively. This indicates that on an aggregated basis, the exposure to carbon emissions will have substantial impact on firm profitability. Note that the standard deviation for margin reduction variables is quite substantial, highlighting the fact that these statistics are estimated from margin risk data with variation stemming from different firm-level carbon exposures, carbon cost scenarios, as well as forecast years. The log total unpriced carbon cost for the average firm in the sample, disregarding forecast year and scenario level, is 17.478, with a standard deviation of 2.377. Further, the statistics show that much of the anticipated

Figure 2: Mean EBIT margin reduction estimations according to carbon cost scenario



carbon costs both stem from each firm's exposure to scope 1 and scope 2 emissions, i.e., carbon emissions directly associated with internal processes and emissions associated with the purchase of electricity, steam, heat, and cooling. This is indicated by average log scope 1 unpriced carbon cost of 16.604 with a standard deviation of 2.739 and log scope 2 unpriced carbon cost of 16.325 with a standard deviation of 2.122. It seems reasonable that the magnitude of scope 1 and scope 2 variables are similar, as they both are comparable in size when measured from current firm-level emissions (see, for example, Bolton and Kacperczyk (2021), p. 522). Further, slightly higher variation in scope 1 emissions can be reasonable given the coverage of different business models and industries and the associated emission levels in the data sample.

Table 2 presents pairwise correlations for the main emission variables used throughout the paper. Unsurprisingly, the emission variables are highly correlated. $Scope1$ is about four

Table 1: Descriptive statistics

(a) Panel A: Emission variables

Statistic	Mean	Pctl(25)	Median	Pctl(75)	St. Dev.	N
EBIT margin reduction (%)	3.020	0.250	0.486	1.236	9.068	336,565
EBITDA margin reduction (%)	2.704	0.250	0.486	1.237	6.892	336,565
LogTotal	17.478	15.883	17.242	18.905	2.377	351,120
LogScope1	16.604	14.882	16.342	18.137	2.739	351,120
LogScope2	16.325	14.944	16.256	17.698	2.122	351,120

(b) Panel B: Return variables

Statistic	Mean	Pctl(25)	Median	Pctl(75)	St. Dev.	N
Return (%)	1.133	−5.333	0.196	6.275	12.453	336,565
Log Size	6.769	5.604	6.667	7.776	1.559	336,565
Book/Market (winsorized at 2.5%)	0.838	0.330	0.631	1.112	0.717	336,565
Leverage (winsorized at 2.5%)	0.380	0.167	0.380	0.577	0.249	336,565
Momentum (%) (winsorized at 2.5%)	0.131	−0.174	0.027	0.302	0.481	336,565
Volatility (%) (winsorized at 2.5%)	34.155	21.609	30.087	41.794	18.413	336,565
Invest/Assets (winsorized at 2.5%)	0.086	0.022	0.055	0.115	0.092	336,565
ROE (%) (winsorized at 2.5%)	9.697	4.639	9.313	15.273	15.417	336,565
Log PPE	8.575	6.641	8.528	10.409	2.931	336,565

(c) Panel C: Ownership variables

Statistic	Mean	Pctl(25)	Median	Pctl(75)	St. Dev.	N
IO (%)	68.054	57.050	70.098	81.356	17.477	6,198
Invest.Co.s (%)	30.928	5.453	26.959	53.357	25.876	6,198
Advisors (%)	26.774	12.318	22.665	37.060	18.986	6,198
Public (%)	4.593	0.298	1.146	2.336	12.480	6,198
Pensions (%)	2.172	0.279	0.828	1.904	4.098	6,198
Insurance (%)	0.894	0.000	0.003	0.234	2.230	6,198
Banks (%)	0.801	0.006	0.073	0.424	2.251	6,198
Volatility (%) (winsorized at 2.5%)	33.218	20.893	29.187	40.615	17.801	6,198
Price Inverse (winsorized at 2.5%)	0.010	0.0003	0.002	0.006	0.056	6,198

Table 2: Future unpriced carbon costs and margin reductions: correlations

Pairwise correlation matrix for the emission variables used in the main analyses throughout the paper.

	EBIT margin reduction	EBITDA margin reduction	Total	Scope1	Scope2
EBIT margin reduction	1.000	0.999	0.505	0.504	0.118
EBITDA margin reduction	0.999	1.000	0.502	0.502	0.119
Total	0.505	0.502	1.000	0.998	0.257
Scope1	0.504	0.502	0.998	1.000	0.191
Scope2	0.118	0.119	0.257	0.191	1.000

times more correlated with *EBIT margin reduction* than $Scope2$, signaling that much of firms' estimated margin reductions are due to increased costs in scope 1 emissions and less so from scope 2 emissions. This relationship can also be seen from the correlation between $Total$ and $Scope1$, which is substantially higher at 0.998 than the correlation between $Total$ and $Scope2$ at 0.257. Emission variables *EBIT margin reduction* and *EBITDA margin reduction* are winsorized at the 2.5% level to mitigate the effect of outliers in the Trucost data.

3.2 Data on return variables

Data on stock prices are extracted from LSEG/Refinitiv Daily Stock pricing files and subsequently computed to monthly returns adjusted for stock splits and dividends. Firm fundamental variables are extracted from LSEG/Refinitiv WRDS Worldscope on an annual basis. Panel B of Table 1 presents summary statistics for the return variables used in the regressions. In addition to $Return_{i,t}$, the estimations in regressions include several generally accepted control variables. These include: $LogSize_{i,t}$, $Book/Market_{i,t}$, $Leverage_{i,t}$, $Invest/Assets_{i,t}$, $LogPPE_{i,t}$, and $ROE_{i,t}$ as well as $Volatility_{i,t}$ and $Momentum_{i,t}$. These firm fundamental variables are extracted for each firm i in the Trucost sample at year-end in year t and are subsequently lagged by one year. Variables $Book/Market$, $Leverage$, $Invest/Assets$, ROE, $Volatility$, and $Momentum$ are winsorized at the 2.5% level. Further, following the recommendation of WRDS Research Guide on Datastream and Worldscope, I exclude observations where the monthly return exceeds 200% (Dai and Drechsler, 2021). According to Table 1, the average monthly return of the firms in the sample is 1.133% with a median of 0.196%, largely consistent with findings in previous papers (see, for example, Bolton and Kacperczyk (2023), p. 3699 for comparison). Combining the data on unpriced carbon costs and return variables renders a dataset consisting of 336,565 monthly observations for 8,821 unique firms. Note that there is a small discrepancy between the number of observations in the data samples when estimating the effect of unpriced carbon margin reductions and carbon costs. This is due to the fact that some firms in the Trucost data lack information on estimated effects on margins. This leads to a slightly larger sample with 351,120 monthly observations consisting of 9,041 unique firms when analyzing the cost of unpriced carbon.

3.3 Data on ownership variables

Data on institutional ownership is extracted from LSEG/Refinitiv Global Consolidated Ownership reports. Institutional ownership variables are calculated as follows: $IO_{i,t}$ is the aggregated percentage ownership of all institutional investors of firm i's outstanding shares at year-end in year t. Further, I create categorical ownership variables to enable an analysis of whether different institutional ownership classes behave differently according to future carbon costs. $Invest.Co.s_{i,t}$ is the ownership of investment companies of firm i's stock in year t in percent. $Advisors_{i,t}$ is the ownership of investment advisors in firm i in year t. $Public_{i,t}$ is the percentage ownership of sovereign wealth funds and public agencies in firm i in year t. $Pensions_{i,t}$ is the ownership of pension funds of firm i in year t. $Insurance_{i,t}$ is insurance companies' percentage ownership of firm i's shares in year t. Lastly, $Banks_{i,t}$ is banks' ownership of firm i's shares in year t. For the ownership analysis in section 5.5, I follow the methodology of Bolton and Kacperczyk (2021) and use the control variables $LogSize_{i,t}$, $Book/Market_{i,t}$, $Leverage_{i,t}$, $ROE_{i,t}$, $PriceInverse_{i,t}$, $Momentum_{i,t}$ and $Volatility_{i,t}$. These variables are lagged by one year. $PriceInverse_{i,t}$ is defined as the inverse of firm i's stock price at year-end in year t. Further, $Volatility_{i,t}$ and $PriceInverse_{i,t}$ are winsorized at the 2.5% level. Panel C of Table 1 presents descriptive statistics of the variables used for the ownership analysis. Note that the data of estimated margin reductions and ownership variables consists of 6,198 yearly observations, while the dataset comprising estimated future unpriced carbon costs consists of 6,385 yearly observations. Summary statistics for the ownership variables based on unpriced carbon costs can be found in the Appendix in Table 22.

4 Methodology

The analysis throughout the paper is broadly divided into four parts. First, following the methodology of Bolton and Kacperczyk (2021), I estimate the main determinants of future firm-level carbon margin reductions according to Equation 1. δ_t denote month/year-fixed effects, θ_i denote country-fixed effects and γ_i denote industry-fixed effects. The index k corresponds to the forecast years 2030, 2040, and 2050.

$$\begin{aligned} MarginReduction_{i,k} = \alpha_0 + \beta_1 \mathit{LogSize}_{i,t} + \beta_2 \mathit{Book/Market}_{i,t} + \beta_3 \mathit{Leverage}_{i,t} + \\ \beta_4 \mathit{Invest/Assets}_{i,t} + \beta_5 \mathit{LogPPE}_{i,t} + \beta_6 ROE_{i,t} + \delta_t + \theta_i + \gamma_i + \varepsilon_{i,t} \end{aligned} \tag{1}$$

In the second step, I estimate the effect of estimated margin reductions due to increasing future carbon costs on stock returns, as seen in Equation 2. The vector X of control variables includes $LogSize_{i,t}$, $Book/Market_{i,t}$, $Leverage_{i,t}$, $Invest/Assets_{i,t}$, $LogPPE_{i,t}$, $ROE_{i,t}$, $Momentum_{i,t}$, and $Volatility_{i,t}$ and is lagged by one year. Moreover, I examine the effect of future log total, log scope 1, and log scope 2 unpriced carbon on stock returns, as described in Equation 3. Therefore, I estimate the following pooled OLS regressions:

$$\mathit{Return}_{i,t} = \alpha_0 + \beta_1 \mathit{Margin\ Reduction}_{i,k} + \beta X_{i,t-1} + \delta_t + \theta_i + \gamma_i + \varepsilon_{i,t} \tag{2}$$

$$\mathit{Return}_{i,t} = \alpha_0 + \beta_1 \mathit{Unpriced\ carbon}_{i,k} + \beta X_{i,t-1} + \delta_t + \theta_i + \gamma_i + \varepsilon_{i,t} \tag{3}$$

In the third step, I look deeper at the most exposed firms, countries, and industries within the Trucost Carbon Earnings at Risk dataset. First, I examine firms estimated to have the highest future unpriced carbon costs and whether investors price in carbon-transition risk for the "brownest" firms in the sample. To explore this effect, I create a binary variable Top_decile_i equal to 1 if the company is estimated to be among the 10% firms with the highest total unpriced carbon costs in the Trucost data, and equal to 0 otherwise. Therefore, I estimate a regression according to Equation 4. Next, I examine whether the most exposed industries and countries show more substantial return effects. I create a binary variable $Salient\_industry_i$ equal to 1 if the firm operates in an industry estimated to be within the top ten most exposed industries according to EBIT margin reductions. These industries include construction materials, power producers, metals and mining, chemicals, oil, gas, and consumable fuels, electric utilities, food products, trading companies, semiconductors, and industrial conglomerates. Together, these industries account for 69.89% of all estimated EBIT margin reductions across the three forecast years and carbon cost scenarios in the Trucost data. I estimate this using regression Equation 5. Then, I do a similar estimation based on countries instead of industries. I create a binary variable $Salient\_country_i$ equal to 1 if the firm is located in a country estimated to be within the top ten most exposed countries according to EBIT margin reductions. These countries include China, India, Japan, Taiwan, Turkey, South Korea, Hong Kong, Thailand, Russia, and Saudi Arabia[1]. These ten countries account for 66.11% of the EBIT margin reductions in the dataset across forecast years and carbon cost scenarios. The salient country regressions are estimated according to Equation 6.

$$\begin{aligned} Return_{i,t} = \alpha_0 + \beta_1 Margin\ Reduction_{i,k} + \beta_2 Top\_decile_i + \\ \beta X_{i,t-1} + \delta_t + \theta_i + \gamma_i + \varepsilon_{i,t} \end{aligned} \tag{4}$$

$$\begin{aligned} Return_{i,t} = \alpha_0 + \beta_1 Margin\ Reduction_{i,k} + \beta_2 Salient\_industry_i + \\ \beta X_{i,t-1} + \delta_t + \theta_i + \varepsilon_{i,t} \end{aligned} \tag{5}$$

$$\begin{aligned} Return_{i,t} = \alpha_0 + \beta_1 Margin\ Reduction_{i,k} + \beta_2 Salient\_country_i + \\ \beta X_{i,t-1} + \delta_t + \gamma_i + \varepsilon_{i,t} \end{aligned} \tag{6}$$

[1]It is important to consider why Trucost excludes certain major carbon-emitting countries such as the U.S., Canada, United Arab Emirates, Brazil, and the EU members from the list of countries with the highest EBIT margin reductions. One potential explanation is that the prevailing carbon price in some of the most exposed countries is substantially lower than that of less exposed countries. For example, the average 2023 secondary market price in the China National ETS was \$9.65, while that of the EU ETS was \$90.25 (International Carbon Action Partnership, 2024).

In the fourth step, I estimate the effect of future carbon margin reductions on institutional ownership and future unpriced carbon costs on institutional ownership. Moreover, I introduce an interaction term between $IO_{i,t}$ and $Marginreduction_{i,k}$ to estimate the carbon-transition risk premium when institutional ownership in a firm increases. Lastly, I estimate a regression separately for each ownership category as shown in Table 1 in Panel C. The vector Z consists of control variables including $LogSize_{i,t}$, $Book/Market_{i,t}$, $Leverage_{i,t}$, $ROE_{i,t}$, $PriceInverse_{i,t}$, $Momentum_{i,t}$, and $Volatility_{i,t}$ and is lagged by one year. Therefore, I estimate the following pooled OLS regressions:

$$IO_{i,t} = \alpha_0 + \beta_1 \mathit{Margin\ Reduction}_{i,k} + \beta Z_{i,t-1} + \delta_t + \theta_i + \gamma_i + \varepsilon_{i,t} \tag{7}$$

$$IO_{i,t} = \alpha_0 + \beta_1 \mathit{Unpriced\ carbon}_{i,k} + \beta Z_{i,t-1} + \delta_t + \theta_i + \gamma_i + \varepsilon_{i,t} \tag{8}$$

$$\begin{aligned} Return_{i,t} = \alpha_0 &+ \beta_1 \mathit{Unpriced\ carbon}_{i,k} + \beta_2 IO_{i,t} + \\ &\beta_3 \mathit{Unpriced\ carbon}_{i,k} \times IO_{i,t} + \\ &\beta Z_{i,t-1} + \delta_t + \theta_i + \gamma_i + \varepsilon_{i,t} \end{aligned} \tag{9}$$

$$\mathit{IO\_category}_{i,t} = \alpha_0 + \beta_1 \mathit{Margin\ reduction}_{i,k} + \beta Z_{i,t-1} + \delta_t + \theta_i + \gamma_i + \varepsilon_{i,t} \tag{10}$$

$$\mathit{IO\_category}_{i,t} = \alpha_0 + \beta_1 \mathit{Unpriced\ carbon}_{i,k} + \beta Z_{i,t-1} + \delta_t + \theta_i + \gamma_i + \varepsilon_{i,t} \tag{11}$$

5 Results

5.1 The main determinants of future costs of carbon

Table 3 reports the main determinants of the EBIT margin reductions in 2030 related to increased costs of carbon. In turn, I regress the estimated reductions in EBIT margins for the low, medium, and high carbon cost scenarios on the following firm characteristics: *LogSize*, *Book/Market*, *Leverage*, *Invest/Assets*, *LogPPE*, and *ROE*. Note that EBIT margin reduction variables are transformed into positive, implying that higher values are associated with greater reductions in EBIT margins. Regression outputs for the forecast years 2040 and 2050 can be found in the Appendix in tables 23 and 24. All regressions include year/month-fixed effects, industry-fixed effects, and country-fixed effects to allow for systematic differences across time, industries, and countries. Industries are assigned according to the classification in the Trucost database. Standard errors are clustered at the firm- and year-level.

The firm characteristics capture much of the variation in the estimated EBIT margin reductions associated with unpriced carbon costs as shown in column (1) across month-years, countries, and industries, reflected by an R^2 of 0.171. Unsurprisingly, Table 3 provides results suggesting higher economic and statistical significance along the low, medium, and high carbon cost scenarios as described in regression specifications (1), (2), and (3). The table presents results indicating that $LogSize$ is negatively associated with estimated future EBIT margin reductions at the 1% significance level. Moving from the low carbon cost scenario to the high scenario, the size coefficient's economic significance more than triples. A 10% increase in market capitalization is approximately associated with a downsizing in EBIT margin reductions of 0.016 percentage points in the low scenario, on average. In the medium and high scenarios, a 10% increase in market capitalization is approximately associated with a cut in the EBIT margin reduction of 0.039 and 0.060 percentage points, respectively. Although relatively modest, the size variable is economically important given a median EBIT margin reduction of 0.486% in the sample. Accordingly, firms with larger market capitalizations are estimated to be less negatively affected by increased costs of carbon on the EBIT margin level. $Leverage$ and $LogPPE$ are positively associated with future reductions in EBIT margins, and they are statistically significant at the 1% level for all carbon cost scenarios. The same results hold for forecast years 2040 and 2050, as can be seen in the Appendix in Tables 23 and 24. It seems unsurprising that $LogPPE$ is positively correlated with EBIT margin reductions as it is a variable that captures the asset tangibility of firms. A 10% increase in PPE is approximately associated with an increase of

Table 3: Determinants of 2030 EBIT margin reductions

Forecast year: 2030. The dependent variables correspond to reductions of EBIT margins under the low, medium, and high carbon cost scenario for the forecast year 2030 and are transformed into positive values. I.e., the dependent variable EBIT2030Low corresponds to the reduction of EBIT margins in the low carbon cost scenario for the forecast year 2030. The sample period is 2017 to 2022. All regressions include year/month-fixed effects, country-fixed effects, and industry-fixed effects. Industries are assigned according to the classification in the Trucost database. The table reports the results for the pooled regressions with standard errors double clustered at the firm and year level (in parentheses). *** 1% significance; ** 5% significance; * 10% significance.

	Dependent variable:		
	EBIT2030Low	EBIT2030Medium	EBIT2030High
	(1)	(2)	(3)
LogSize	-0.164^{***}	-0.406^{***}	-0.632^{***}
	(0.018)	(0.043)	(0.070)
Book/Market	0.047	0.157^{**}	0.285^{**}
	(0.031)	(0.076)	(0.125)
Leverage	0.272^{***}	0.621^{***}	1.107^{***}
	(0.073)	(0.179)	(0.288)
Invest/Assets	-0.034	0.117	0.256
	(0.168)	(0.422)	(0.663)
LogPPE	0.226^{***}	0.559^{***}	0.888^{***}
	(0.014)	(0.035)	(0.056)
ROE	0.002	0.003	0.006
	(0.001)	(0.002)	(0.004)
Year/month-fixed effects	Yes	Yes	Yes
Country-fixed effects	Yes	Yes	Yes
Industry-fixed effects	Yes	Yes	Yes
Observations	336,565	336,565	336,565
R^2	0.171	0.176	0.177
Adjusted R^2	0.171	0.175	0.177
Residual Std. Error (df = 336410)	1.564	3.826	6.108
Note:			*p<0.1; **p<0.05; ***p<0.01

0.022 percentage points in the EBIT margin reduction in 2030 in the low scenario, on average. Similarly, increasing the firm's PPE by 10% is expected to lead to an increased EBIT margin reduction of approximately 0.053 and 0.085 percentage points in the medium and high scenarios, respectively. A potential explanation can be that firms with more property, plant, and equipment are generally less prepared for a green transition, possibly related to the assets being associated with brown operations. However, the strong effect of *Leverage* is more surprising, although these findings are consistent with Bolton and Kacperczyk (2023). A one-standard deviation increase in *Leverage* is associated with an increased EBIT margin reduction of 0.068 percentage points in 2030 in the low scenario. Similarly, a one-standard deviation increase in *Leverage* is associated with an increased margin reduction of 0.155 and 0.276 percentage points in the medium and high scenarios, respectively. This effect, as proposed in Bolton and Kacperczyk (2023), can potentially be related to firms with higher emissions expecting future reductions in profitability as a result of increased carbon costs, and therefore these firms consequently take on more leverage as an opposing measure. I note that the $Book/Market$ variable is less significant for the low scenario, although the economic and statistical significance increases moving to the medium and high carbon scenarios. A one-standard deviation increase in $Book/Market$ in the medium and high scenarios in 2030 is expected to lead to an increase in EBIT margin reductions of 0.113 and 0.204 percentage points, respectively. It is expected that firms with higher book value of assets are subject to increasing margin reductions because green firms typically own relatively more intangible assets. This notion is consistent with the finding of statistically significant coefficients related to $LogPPE$. Interestingly, $Invest/Assets$ and ROE are insignificant for all regression specifications. Specifically, one would expect that $Invest/Assets$ reduces the margin reductions related to unpriced carbon costs since it captures the firm's ability to renew its existing stock of assets, as is found when running similar regressions using firms' current level of emissions as the dependent variable (Bolton and Kacperczyk, 2021). Accordingly, there does not seem to be much explanatory power in the contemporary investment intensity nor the profitability of the firm on future estimated EBIT margin reductions. Similar trends can be seen for forecast years 2040 and 2050, as shown in the Appendix in tables 23 and 24. From these tables, the findings suggest that these firm characteristics' impact on the EBIT margin seem to increase over a longer horizon. In addition to increasing coefficients in this analysis for 2040 and 2050, the results are consistent with the 2030 conclusion of larger economic implications moving to higher-order carbon cost scenarios.

5.2 Effects of future unpriced carbon margin reductions on stock returns

As a first step, I estimate Equation (1) to dissect potential carbon-transition risk premiums associated with higher estimated EBIT margin reductions as a result of increased carbon costs. Table 4 presents results of the pooled regression controlling for several firm characteristics. All regression specifications include year/month-fixed effects and country-fixed effects, and specifications (4) to (6) additionally include industry-fixed effects. Table 5 presents the same regression setup using EBITDA margin reductions instead of EBIT margin reductions as proxy for carbon-transition risk. The results found in Table 5 are largely consistent with the results of Table 4, and in the remainder of the paper, I will place greater emphasis on EBIT margin reduction analyses as they tell the same story and are consistent across forecast years and carbon cost scenarios. Tables 25 and 26 in the Appendix present results of using EBITDA margin reductions instead of EBIT margin reductions as proxy for carbon-transition risk for forecast years 2040 and 2050. Moreover, the same regression setup is used on the data solely based on firms for which there exists ownership data. These tables can be found in the Appendix from Table 27 to 29. Overall, the analysis using firms with ownership data seems consistent with the results found in this section but with higher statistical significance for all carbon cost scenarios and forecast years.

Overall, the coefficients of interest are positive for all carbon cost scenarios. Note, however, that the coefficients are only partially statistically significant and only significant at the 10% level at most. Only for $EBIT2030Medium$ are the coefficients statistically significant when also including industry-fixed effects. Although not statistically significant, these coefficients signal quite substantial economic implications. For instance, a one-standard deviation in-

Table 4: Effects of 2030 carbon EBIT margin reductions on stock returns

Forecast year: 2030. The dependent variable is *Return*. EBIT margin reductions are transformed into positive values. I.e., the independent variable EBIT2030Low corresponds to the reduction of EBIT margins in the low carbon cost scenario for the forecast year 2030. The sample period is 2017 to 2022. All regressions include year/month-fixed effects, country-fixed effects, and specifications (3) to (6) additionally include industry-fixed effects. Industries are assigned according to the classification in the Trucost database. The table reports the results for the pooled regressions with standard errors double clustered at the firm and year level (in parentheses). *** 1% significance; ** 5% significance; * 10% significance.

	Dependent variable:					
	Return					
	(1)	(2)	(3)	(4)	(5)	(6)
EBIT2030Low	0.042			0.037		
	(0.028)			(0.027)		
EBIT2030Medium		0.021*			0.019*	
		(0.011)			(0.011)	
EBIT2030High			0.012*			0.011
			(0.007)			(0.007)
LogSize	−0.288***	−0.287***	−0.288***	−0.292***	−0.290***	−0.291***
	(0.066)	(0.066)	(0.066)	(0.066)	(0.066)	(0.066)
Book/Market	0.058	0.056	0.056	0.057	0.055	0.056
	(0.128)	(0.127)	(0.127)	(0.129)	(0.129)	(0.129)
Leverage	−0.220	−0.222	−0.222	−0.226	−0.227	−0.227
	(0.240)	(0.240)	(0.240)	(0.234)	(0.234)	(0.234)
Momentum	0.284	0.282	0.283	0.284	0.283	0.283
	(0.466)	(0.466)	(0.466)	(0.465)	(0.465)	(0.465)
Invest/Assets	0.908	0.905	0.904	0.906	0.903	0.902
	(0.561)	(0.562)	(0.562)	(0.555)	(0.556)	(0.556)
LogPPE	0.072	0.070	0.071	0.072	0.070	0.071
	(0.051)	(0.051)	(0.051)	(0.052)	(0.053)	(0.053)
ROE	0.005	0.005	0.005	0.005	0.005	0.005
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Volatility	0.016	0.016	0.016	0.016	0.016	0.016
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
Year/month-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Country-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry-fixed effects	No	No	No	Yes	Yes	Yes
Observations	336,565	336,565	336,565	336,565	336,565	336,565
R^2	0.130	0.130	0.130	0.130	0.130	0.130
Adjusted R^2	0.130	0.130	0.130	0.130	0.130	0.130
Residual Std. Error	11.615 (df = 336410)	11.615 (df = 336410)	11.615 (df = 336410)	11.615 (df = 336407)	11.615 (df = 336407)	11.615 (df = 336407)

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

crease in the EBIT margin reduction in 2030 under the medium carbon cost scenario is associated with an annual stock return premium of 0.965%, on average. Neglecting insignificant coefficients, a one-standard deviation increase in the EBIT margin reduction in the low scenario can be related to an annual premium of 0.765%, while that of a one-standard deviation increase in the high scenario is 0.892%.

Moreover, there is a general declining trend in the magnitude of the coefficients going from low to medium to high carbon cost scenarios. This trend can potentially be explained by investors pricing in the low-carbon scenario more than the medium- and high-carbon scenarios. Therefore, firms estimated to experience higher EBIT margin reductions might be more severely affected under lower carbon cost scenarios than higher ones. Although not statistically significant, one can imagine investors penalizing carbon margin reductions in the low scenario more as the market expects the low scenario to materialize and does not price in the medium and high scenarios to the same extent. Investors might not anticipate that stringent carbon regulations will be enforced immediately, and this effect can potentially be reflected in the downward trend in the magnitude of the coefficients between low, medium, and high carbon cost scenarios on the EBIT margin reductions.

Table 5: Effects of 2030 carbon EBITDA margin reductions on stock returns

Forecast year: 2030. The dependent variable is *Return*. EBITDA margin reductions are transformed into positive values. I.e., the independent variable EBITDA2030Low corresponds to the reduction of EBITDA margins in the low carbon cost scenario for the forecast year 2030. The sample period is 2017 to 2022. All regressions include year/month-fixed effects, country-fixed effects, and specifications (3) to (6) additionally include industry-fixed effects. Industries are assigned according to the classification in the Trucost database. The table reports the results for the pooled regressions with standard errors double clustered at the firm and year level (in parentheses). *** 1% significance; ** 5% significance; * 10% significance.

	Dependent variable:					
	Return					
	(1)	(2)	(3)	(4)	(5)	(6)
EBITDA2030Low	0.041			0.036		
	(0.028)			(0.027)		
EBITDA2030Medium		0.020*			0.018	
		(0.011)			(0.011)	
EBITDA2030High			0.012*			0.010
			(0.007)			(0.007)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year/month-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Country-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry-fixed effects	No	No	No	Yes	Yes	Yes
Observations	336,565	336,565	336,565	336,565	336,565	336,565
R^2	0.130	0.130	0.130	0.130	0.130	0.130
Adjusted R^2	0.130	0.130	0.130	0.130	0.130	0.130
Residual Std. Error	11.615 (df = 336410)	11.615 (df = 336410)	11.615 (df = 336410)	11.615 (df = 336407)	11.615 (df = 336407)	11.615 (df = 336407)

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

Table 6 shows the output of running Equation 2 using estimated EBIT margin reductions in 2040 instead of 2030. These results are highly consistent with each other as firm-level reductions in margins are connected over time. Comparably, the coefficients of interest are more pronounced for 2030 margin reductions than 2040 margin reductions, as shown by contrasting Table 4 to Table 6. However, 2030 and 2040 are similar in economic magnitude: A one-standard deviation increase in the EBIT margin reduction variable is associated with an annual premium of 0.975% in the medium scenario in 2040. As noted, the corresponding impact of 2030 medium margin reductions is 0.965%. Hence, investors seem to be pricing in carbon margin reductions similarly on short and medium horizons. Further, running the same regression on 2050 EBIT margin reductions instead of 2030 and 2040 reductions, as shown in Table 7, renders results of comparably lower coefficients associated with the EBIT margin reductions. Additionally, the statistical significance is diminishing for the 2050 forecast year. Neglecting the statistical insignificance, a one-standard deviation increase in EBIT margin reductions is related to an annual premium of 0.392% in 2050 in the medium scenario. In contrast to 2030 and 2040, there is no clear declining trend going from low to medium to high carbon cost scenarios for 2050. These results might suggest that investors' carbon concerns are priced in over the short, medium, and long term but that the effect decreases over longer forecast periods. Alternatively, one possible explanation can be that market participants' climate concerns are not well captured in the long-term carbon cost estimates from Trucost. As we move to more distant forecast years, discrepancies between investors' perceptions of carbon-transition risk and the estimates of Trucost are likely to increase. Therefore it is possible that 2050 carbon costs are less well suited to capture the market pricing of transition risk.

Table 6: Effects of 2040 carbon EBIT margin reductions on stock returns

Forecast year: 2040. The dependent variable is *Return*. EBIT margin reductions are transformed into positive values. I.e., the independent variable EBIT2040Low corresponds to the reduction of EBIT margins in the low carbon cost scenario for the forecast year 2040. The sample period is 2017 to 2022. All regressions include year/month-fixed effects, country-fixed effects, and specifications (3) to (6) additionally include industry-fixed effects. Industries are assigned according to the classification in the Trucost database. The table reports the results for the pooled regressions with standard errors double clustered at the firm and year level (in parentheses). *** 1% significance; ** 5% significance; * 10% significance.

	Dependent variable:					
	Return					
	(1)	(2)	(3)	(4)	(5)	(6)
EBIT2040Low	0.024			0.022		
	(0.016)			(0.016)		
EBIT2040Medium		0.012^{*}			0.011^{*}	
		(0.006)			(0.006)	
EBIT2040High			0.007^{*}			0.007
			(0.004)			(0.004)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year/month-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Country-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry-fixed effects	No	No	No	Yes	Yes	Yes
Observations	336,565	336,565	336,565	336,565	336,565	336,565
R^2	0.130	0.130	0.130	0.130	0.130	0.130
Adjusted R^2	0.130	0.130	0.130	0.130	0.130	0.130
Residual Std. Error	11.615 (df = 336410)	11.615 (df = 336410)	11.615 (df = 336410)	11.615 (df = 336407)	11.615 (df = 336407)	11.615 (df = 336407)

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

Table 7: Effects of 2050 carbon EBIT margin reductions on stock returns

Forecast year: 2050. The dependent variable is *Return*. EBIT margin reductions are transformed into positive values. I.e., the independent variable EBIT2050Low corresponds to the reduction of EBIT margins in the low carbon cost scenario for the forecast year 2050. The sample period is 2017 to 2022. All regressions include year/month-fixed effects, country-fixed effects, and specifications (3) to (6) additionally include industry-fixed effects. Industries are assigned according to the classification in the Trucost database. The table reports the results for the pooled regressions with standard errors double clustered at the firm and year level (in parentheses). *** 1% significance; ** 5% significance; * 10% significance.

	Dependent variable:					
	Return					
	(1)	(2)	(3)	(4)	(5)	(6)
EBIT2050Low	0.004			0.003		
	(0.003)			(0.003)		
EBIT2050Medium		0.001			0.001	
		(0.001)			(0.001)	
EBIT2050High			0.006^{*}			0.006
			(0.004)			(0.004)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year/month-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Country-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry-fixed effects	No	No	No	Yes	Yes	Yes
Observations	336,565	336,565	336,565	336,565	336,565	336,565
R^2	0.130	0.130	0.130	0.130	0.130	0.130
Adjusted R^2	0.130	0.130	0.130	0.130	0.130	0.130
Residual Std. Error	11.615 (df = 336410)	11.615 (df = 336410)	11.615 (df = 336410)	11.615 (df = 336407)	11.615 (df = 336407)	11.615 (df = 336407)

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

5.3 Effects of future unpriced carbon costs on stock returns

To dissect the impact of future unpriced carbon costs on stock returns, I regress stock returns on estimated 2030 unpriced total carbon costs according to Equation 3. The findings in Table 8 suggest that there is a positive and statistically significant relationship between future unpriced carbon and stock returns at the 1% level across low, medium, and high carbon cost scenarios, consistent with the hypothesis that higher unpriced carbon represents additional firm-level riskiness. Also, the results are economically significant: A one-standard deviation increase in the $LogTotal2030Low$ variable is associated with an annualized stock return premium of 2.594%, on average. A one-standard deviation increase in the $LogTotal2030Medium$ variable is associated with an annual premium of 2.992%. Similarly, a one-standard deviation increase in the $LogTotal2030High$ variable is associated with 3.216% higher annual stock returns. Hence, investors seem to require higher returns for holding stocks with increasing estimated future unpriced carbon costs.

Interestingly, the results presented in Table 8 suggest no clear decreasing trend going towards higher carbon cost scenarios, as was the case for margin reductions as seen in Table 4. Rather, the results indicate that market participants are pricing higher carbon cost scenarios to a larger extent than lower scenarios. These findings might be related to the fact that future unpriced carbon costs capture some of the effects of contemporary firm-level carbon emissions. Consistent with the findings of Bolton and Kacperczyk (2023), it seems that investors require higher compensation for larger carbon emissions and the related costs, as is supported by the increasing trend found in Table 8.

Tables 9 and 10 show corresponding regression outputs for the forecast years 2040 and 2050, respectively. The coefficients associated with 2040 and 2050 unpriced carbon costs are positive and significant for the three carbon scenarios. The magnitude of the coefficients is similar to 2030 estimations and implies important economic consequences. For example, a one-standard deviation increase in $LogTotal2040Medium$ is associated with 2.926% higher annual stock returns. A one-standard deviation increase in $LogTotal2050Medium$ is related to an annualized premium of 3.094%.

Table 11 presents results of a similar analysis using unpriced scope 1 carbon costs instead

Table 8: Effects of total 2030 unpriced carbon costs on stock returns

Forecast year: 2030. The dependent variable is *Return*. The sample period is 2017 to 2022. All regressions include year/month-fixed effects, country-fixed effects, and specifications (3) to (6) additionally include industry-fixed effects. Industries are assigned according to the classification in the Trucost database. The table reports the results for the pooled regressions with standard errors double clustered at the firm and year level (in parentheses). *** 1% significance; ** 5% significance; * 10% significance.

	Dependent variable:					
	Return					
	(1)	(2)	(3)	(4)	(5)	(6)
LogTotal2030Low	0.076**			0.080***		
	(0.032)			(0.029)		
LogTotal2030Medium		0.097**			0.102***	
		(0.037)			(0.035)	
LogTotal2030High			0.104***			0.111***
			(0.039)			(0.035)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year/month-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Country-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry-fixed effects	No	No	No	Yes	Yes	Yes
Observations	351,120	351,120	351,120	351,120	351,120	351,120
R^2	0.130	0.130	0.130	0.130	0.130	0.130
Adjusted R^2	0.129	0.129	0.129	0.129	0.129	0.129
Residual Std. Error	11.814 (df = 350965)	11.814 (df = 350965)	11.814 (df = 350965)	11.814 (df = 350962)	11.814 (df = 350962)	11.814 (df = 350962)
Note:						*p<0.1; **p<0.05; ***p<0.01

Table 9: Effects of total 2040 unpriced carbon costs on stock returns

Forecast year: 2040. The dependent variable is *Return*. The sample period is 2017 to 2022. All regressions include year/month-fixed effects, country-fixed effects, and specifications (3) to (6) additionally include industry-fixed effects. Industries are assigned according to the classification in the Trucost database. The table reports the results for the pooled regressions with standard errors double clustered at the firm and year level (in parentheses). *** 1% significance; ** 5% significance; * 10% significance.

	Dependent variable:					
	Return					
	(1)	(2)	(3)	(4)	(5)	(6)
LogTotal2040Low	0.079**			0.084***		
	(0.033)			(0.030)		
LogTotal2040Medium		0.096**			0.101***	
		(0.039)			(0.037)	
LogTotal2040High			0.103**			0.109***
			(0.039)			(0.036)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year/month-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Country-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry-fixed effects	No	No	No	Yes	Yes	Yes
Observations	351,120	351,120	351,120	351,120	351,120	351,120
R^2	0.130	0.130	0.130	0.130	0.130	0.130
Adjusted R^2	0.129	0.129	0.129	0.129	0.129	0.129
Residual Std. Error	11.814 (df = 350965)	11.814 (df = 350965)	11.814 (df = 350965)	11.814 (df = 350962)	11.814 (df = 350962)	11.814 (df = 350962)
Note:						*p<0.1; **p<0.05; ***p<0.01

of total unpriced carbon. Consistent with previous findings, scope 1 unpriced carbon is statistically significantly associated with stock returns for the low, medium, and high scenarios at the 5%, 1%, and 1% levels, respectively. Scope 1 unpriced carbon is also economically important: A one-standard deviation increase in $LogScope12030Low$ is associated with an annual premium of 1.815%. Similarly, a one-standard deviation increase in the variable

Table 10: Effects of total 2050 unpriced carbon costs on stock returns

Forecast year: 2050. The dependent variable is *Return*. The sample period is 2017 to 2022. All regressions include year/month-fixed effects, country-fixed effects, and specifications (3) to (6) additionally include industry-fixed effects. Industries are assigned according to the classification in the Trucost database. The table reports the results for the pooled regressions with standard errors double clustered at the firm and year level (in parentheses). *** 1% significance; ** 5% significance; * 10% significance.

	Dependent variable:					
	Return					
	(1)	(2)	(3)	(4)	(5)	(6)
LogTotal2050Low	0.080^{**}			0.084^{***}		
	(0.034)			(0.032)		
LogTotal2050Medium		0.101^{**}			0.107^{***}	
		(0.039)			(0.035)	
LogTotal2050High			0.101^{**}			0.107^{***}
			(0.039)			(0.035)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year/month-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Country-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry-fixed effects	No	No	No	Yes	Yes	Yes
Observations	351,120	351,120	351,120	351,120	351,120	351,120
R^2	0.130	0.130	0.130	0.130	0.130	0.130
Adjusted R^2	0.129	0.129	0.129	0.129	0.129	0.129
Residual Std. Error	11.814 (df = 350965)	11.814 (df = 350965)	11.814 (df = 350965)	11.814 (df = 350962)	11.814 (df = 350962)	11.814 (df = 350962)
Note:						*p<0.1; **p<0.05; ***p<0.01

$LogScope12030Medium$ is associated with 2.096% higher annual stock returns. A one-standard deviation increase in $LogScope12030High$ is related to 2.430% higher annual stock returns. Similar regression outputs for the forecast years 2040 and 2050 can be found in the Appendix in Tables 30 and 31, respectively.

Table 11: Effects of scope 1 2030 unpriced carbon costs on stock returns

Forecast year: 2030. The dependent variable is *Return*. The sample period is 2017 to 2022. All regressions include year/month-fixed effects, country-fixed effects, and specifications (3) to (6) additionally include industry-fixed effects. Industries are assigned according to the classification in the Trucost database. The table reports the results for the pooled regressions with standard errors double clustered at the firm and year level (in parentheses). *** 1% significance; ** 5% significance; * 10% significance.

	Dependent variable:					
	Return					
	(1)	(2)	(3)	(4)	(5)	(6)
LogScope12030Low	0.040^{**}			0.043^{**}		
	(0.019)			(0.018)		
LogScope12030Medium		0.056^{**}			0.058^{***}	
		(0.023)			(0.021)	
LogScope12030High			0.067^{**}			0.070^{***}
			(0.025)			(0.023)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year/month-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Country-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry-fixed effects	No	No	No	Yes	Yes	Yes
Observations	351,120	351,120	351,120	351,120	351,120	351,120
R^2	0.130	0.130	0.130	0.130	0.130	0.130
Adjusted R^2	0.129	0.129	0.129	0.129	0.129	0.129
Residual Std. Error	11.815 (df = 350965)	11.814 (df = 350965)	11.814 (df = 350965)	11.814 (df = 350962)	11.814 (df = 350962)	11.814 (df = 350962)
Note:						*p<0.1; **p<0.05; ***p<0.01

Similarly, Table 12 shows results of estimating Equation 3 using scope 2 unpriced carbon costs as independent variables instead of total and scope 1 unpriced carbon. Here too, the coefficients of interest are statistically significant for all carbon cost scenarios. A one-standard deviation increase in the scope 2 unpriced carbon costs in the low carbon cost scenario in 2030 is associated with 2.114% higher annual stock returns. Moreover, a one-standard deviation increase in the variable $LogScope22030Medium$ is associated with an annualized premium of 2.611%. In the high scenario, a one-standard deviation increase in unpriced scope 2 carbon costs is related to 2.817% higher returns. Tables 32 and 33 in the Appendix show corresponding regression outputs for the forecast years 2040 and 2050, respectively.

Table 12: Effects of scope 2 2030 unpriced carbon costs on stock returns

Forecast year: 2030. The dependent variable is *Return*. The sample period is 2017 to 2022. All regressions include year/month-fixed effects, country-fixed effects, and specifications (3) to (6) additionally include industry-fixed effects. Industries are assigned according to the classification in the Trucost database. The table reports the results for the pooled regressions with standard errors double clustered at the firm and year level (in parentheses). *** 1% significance; ** 5% significance; * 10% significance.

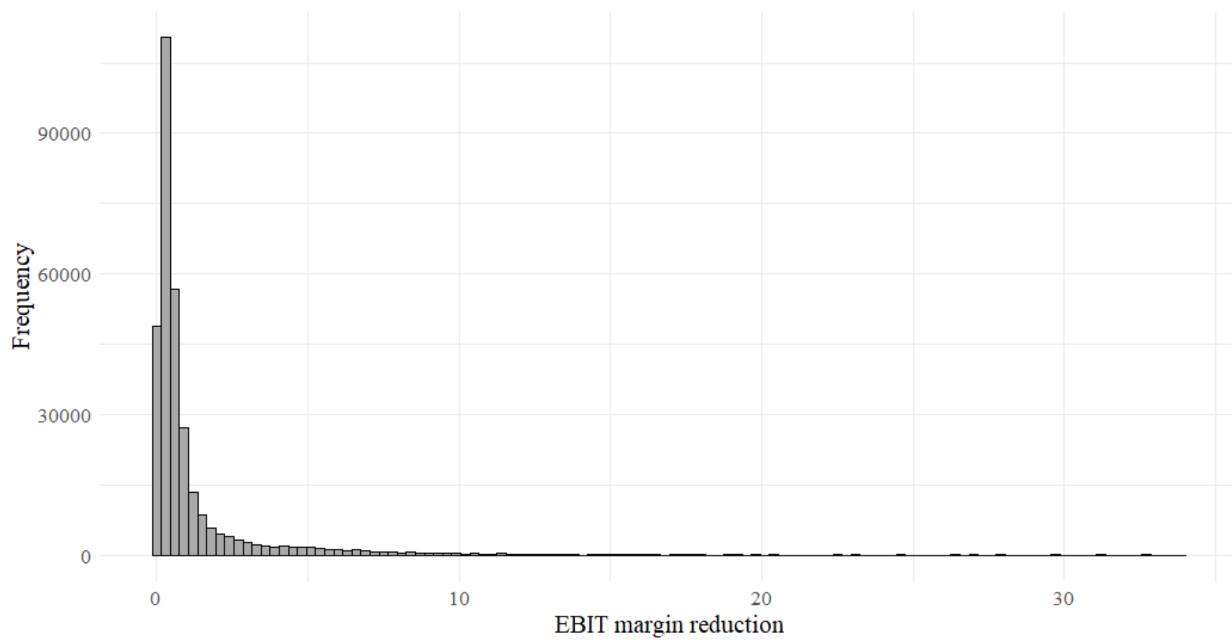
	Dependent variable:					
	Return					
	(1)	(2)	(3)	(4)	(5)	(6)
LogScope22030Low	0.057**			0.064***		
	(0.025)			(0.022)		
LogScope22030Medium		0.087**			0.100***	
		(0.034)			(0.030)	
LogScope22030High			0.095***			0.109***
			(0.035)			(0.030)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year/month-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Country-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry-fixed effects	No	No	No	Yes	Yes	Yes
Observations	351,120	351,120	351,120	351,120	351,120	351,120
R^2	0.130	0.130	0.130	0.130	0.130	0.130
Adjusted R^2	0.129	0.129	0.129	0.129	0.129	0.129
Residual Std. Error	11.815 (df = 350965)	11.814 (df = 350965)	11.814 (df = 350965)	11.814 (df = 350962)	11.814 (df = 350962)	11.814 (df = 350962)
Note:						*p<0.1; **p<0.05; ***p<0.01

5.4 Future unpriced carbon tail risk

5.4.1 The future dark-brown premium?

In a study by Ilhan et al. (2021), the authors find evidence for high carbon intensities, here measured as firms' scope 1 emissions divided by end-of-year equity market values, being clustered within a few industries and sectors. Their findings suggest that climate policy uncertainty is priced in the options market and that the cost of option protection against downside tail risk is positively related to a firm's carbon intensity: a one-standard deviation increase in a firm's log industry carbon intensity increases the implied volatility slope by 10% of the variable's standard deviation.

Figure 3: EBIT margin reduction distribution



Building on these findings, it is interesting to examine whether the firms with the highest future unpriced carbon costs are particularly penalized in the stock market. It is possible that the somewhat inconsistent findings in subsection 5.2 and Table 4 relate to investors not pricing in future carbon cost information for all firms but rather on the firms that are expected to be the most affected. One plausible explanation is that although future firm-level carbon costs are difficult to measure, it is distinctively harder to estimate this cost for firms that lay in the middle of the distribution in Figure 3 than the firms that lay to the far-right. High-emitting firms are likely the ones that are penalized due to reduced uncertainty about the reliance on carbon and increased knowledge about these firms' emissions by market participants. To examine this effect, I create a binary variable Top_decile equal to 1 if the company is estimated to be among the firms with the 10% highest total unpriced carbon costs in the Trucost data, and equal to 0 otherwise. Table 13 presents the results of running regressions according to Equation 4. The coefficients for Top_decile are consistently positive and statistically significant across all three carbon cost scenarios at either 1% or 5%. These results indicate that investors more consistently price in carbon-transition risk for the firms exposed to the highest carbon costs in the future. The top 10% exposed firms are subject to 5.095% higher annualized stock returns in the low carbon scenario using EBIT margin reductions as a proxy for carbon-transition risk. In the medium scenario, Top_decile is associated with 4.120% higher returns, while that in the high scenario is 4.920%. Tables 34 and 35 in the Appendix show results of running similar analyses on estimated EBIT margin reductions in 2040 and 2050, respectively.

Following this line of reasoning, low-emitting firms should not be expected to be subject to the same extent of carbon-transition risk premiums. From Figure 3, we can see that most firms are estimated to have small reductions in margins related to future increased costs of carbon. Moreover, according to Table 1, the median and average estimated EBIT margin reduction over forecast years 2030, 2040, and 2050 are 0.486% and 3.020%, signaling a positively skewed unpriced carbon cost distribution. Therefore, I create a binary variable $Bottom\_decile$ equal to 1 if the firm is estimated to be among the 10% lowest total unpriced carbon emitters in the Trucost data, and equal to 0 otherwise. The coefficients presented in Table 14 are consistently statistically insignificant, suggesting no clear presence of a carbon-transition risk premium for low-exposed firms in the sample.

Table 13: High unpriced carbon exposure firms - Effects of 2030 carbon EBIT margin reductions on stock returns

Forecast year: 2030. The dependent variable is *Return*. EBIT margin reductions are transformed into positive values. The sample period is 2017 to 2022. All regressions include year/month-fixed effects, country-fixed effects, and specifications (3) to (6) additionally include industry-fixed effects. Industries are assigned according to the classification in the Trucost database. The table reports the results for the pooled regressions with standard errors double clustered at the firm and year level (in parentheses). *** 1% significance; ** 5% significance; * 10% significance.

	Dependent variable:					
	Return					
	(1)	(2)	(3)	(4)	(5)	(6)
EBIT2030Low	−0.017			−0.019		
	(0.029)			(0.028)		
EBIT2030Medium		0.001			−0.001	
		(0.012)			(0.012)	
EBIT2030High			−0.003			−0.004
			(0.007)			(0.007)
Top_decile	0.436***	0.353**	0.413**	0.415***	0.337**	0.401**
	(0.153)	(0.170)	(0.167)	(0.135)	(0.158)	(0.157)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year/month-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Country-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry-fixed effects	No	No	No	Yes	Yes	Yes
Observations	336,565	336,565	336,565	336,565	336,565	336,565
R^2	0.130	0.130	0.130	0.131	0.130	0.131
Adjusted R^2	0.130	0.130	0.130	0.130	0.130	0.130
Residual Std. Error	11.615 (df = 336409)	11.615 (df = 336409)	11.615 (df = 336409)	11.615 (df = 336406)	11.615 (df = 336406)	11.615 (df = 336406)
Note:						*p<0.1; **p<0.05; ***p<0.01

Table 14: Low unpriced carbon exposure firms - Effects of 2030 carbon EBIT margin reductions on stock returns

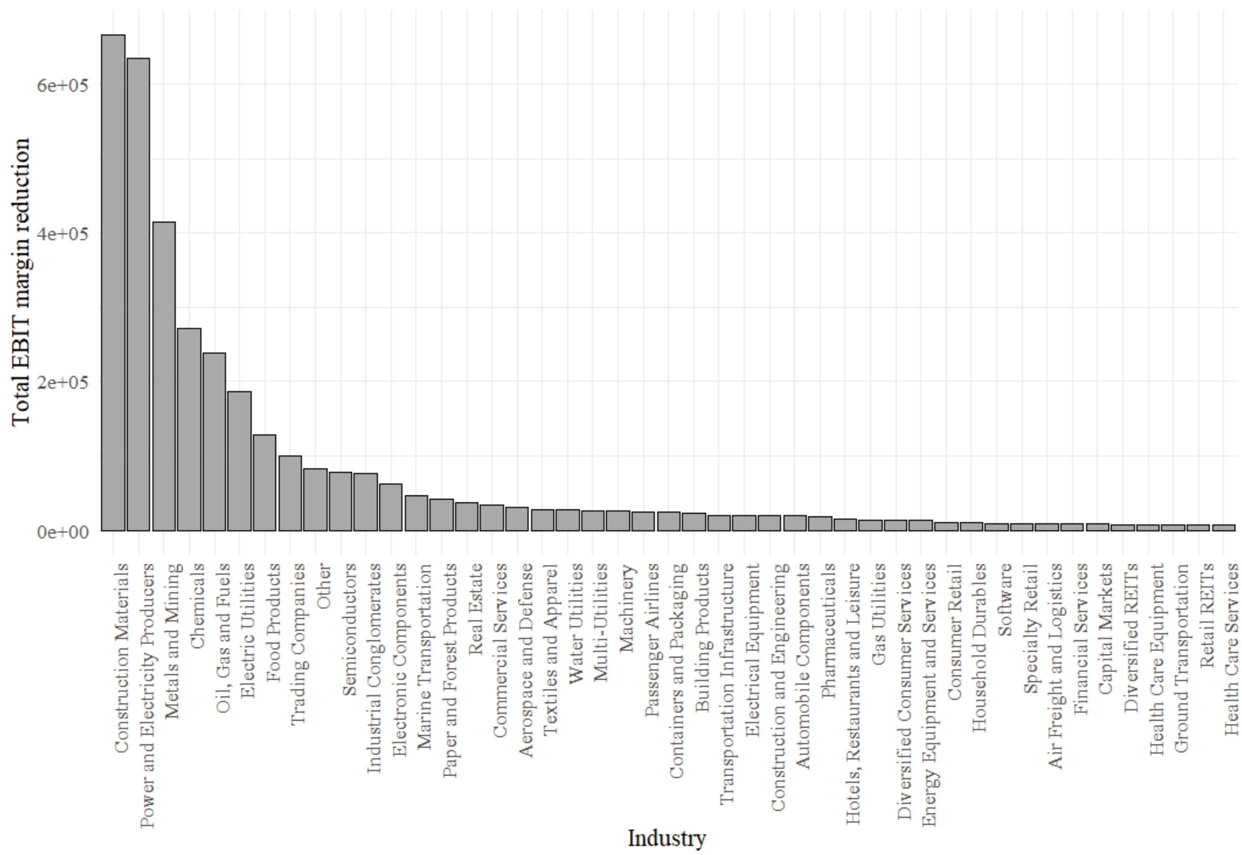
Forecast year: 2030. The dependent variable is *Return*. EBIT margin reductions are transformed into positive values. The sample period is 2017 to 2022. All regressions include year/month-fixed effects, country-fixed effects, and specifications (3) to (6) additionally include industry-fixed effects. Industries are assigned according to the classification in the Trucost database. The table reports the results for the pooled regressions with standard errors double clustered at the firm and year level (in parentheses). *** 1% significance; ** 5% significance; * 10% significance.

	Dependent variable:					
	Return					
	(1)	(2)	(3)	(4)	(5)	(6)
EBIT2030Low	0.043			0.039		
	(0.028)			(0.027)		
EBIT2030Medium		0.021*			0.019*	
		(0.011)			(0.011)	
EBIT2030High			0.012*			0.011
			(0.007)			(0.007)
Bottom_decile	0.124	0.128	0.126	0.123	0.127	0.125
	(0.100)	(0.101)	(0.100)	(0.100)	(0.100)	(0.100)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year/month-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Country-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry-fixed effects	No	No	No	Yes	Yes	Yes
Observations	336,565	336,565	336,565	336,565	336,565	336,565
R^2	0.130	0.130	0.130	0.130	0.130	0.130
Adjusted R^2	0.130	0.130	0.130	0.130	0.130	0.130
Residual Std. Error	11.615 (df = 336409)	11.615 (df = 336409)	11.615 (df = 336409)	11.615 (df = 336406)	11.615 (df = 336406)	11.615 (df = 336406)
Note:						*p<0.1; **p<0.05; ***p<0.01

5.4.2 Salient industries

According to Figures 4 and 5, the Trucost data seem to estimate future EBIT margin reductions due to unpriced carbon costs to cluster on the country- and industry-level. As discussed in section 4, the ten countries and ten industries with the highest estimated EBIT margin reductions account for 66.11% and 69.89% of all EBIT margin reductions in the sample, respectively.

Figure 4: Total EBIT margin reduction by industry



It is natural to wonder whether these industries are subject to higher carbon-transition premiums, not only because they constitute typically high-emission business models but also because investors might divest from firms based on industry criteria. For example, Norges Bank Investment Management, responsible for the management of the Norwegian sovereign wealth fund, divested from 86 companies in 2023 based on ESG criteria [2]. Typically, one of the important metrics that these investors take into account is the industry in which the company operates. Table 15 shows that the coefficients associated with $Salient\_industry$ are consistently statistically significant at the 5% level for the low, medium, and high carbon cost scenarios for the 2030 forecast year. These coefficients are economically meaningful as well: Being within the "brownest" industries is associated with annual premiums of 6.956%, 6.740%, and 6.867% in the low, medium, and high scenarios, respectively. These results indicate that the stock market is pricing in a carbon-transition premium for the firms in industries that are estimated to be heavily affected by increased carbon costs going forward. These industries can potentially be drivers of the carbon-transition premium in the sample, especially since many of the firms in these industries are also among the firms with the highest unpriced carbon costs. Interestingly, this raises the question of how firms in these industries can mitigate the premium. For example, it is possible that firms that are "best in class" within their industry can benefit from signaling to investors that they are ahead of their competitors. Table 36 and 37 in the Appendix present the corresponding regressions for the forecast years 2040 and 2050, respectively.

[2] Norges Bank Investment Management (2024)

Table 15: Salient industries - effects of 2030 carbon EBIT margin reductions on stock returns

Forecast year: 2030. The dependent variable is *Return*. The sample period is 2017 to 2022. All regressions include year/month-fixed effects and country-fixed effects. Industries are assigned according to the classification in the Trucost database. The table reports the results for the pooled regressions with standard errors double clustered at the firm and year level (in parentheses). *** 1% significance; ** 5% significance; * 10% significance.

	Dependent variable:		
	Return		
	(1)	(2)	(3)
EBIT2030Low	−0.014		
	(0.028)		
EBIT2030Medium		−0.002	
		(0.011)	
EBIT2030High			−0.002
			(0.007)
Salient_industry	0.562**	0.545**	0.555**
	(0.213)	(0.215)	(0.216)
Controls	Yes	Yes	Yes
Year/month-fixed effects	Yes	Yes	Yes
Country-fixed effects	Yes	Yes	Yes
Industry-fixed effects	No	No	No
Observations	336,565	336,565	336,565
R^2	0.131	0.131	0.131
Adjusted R^2	0.130	0.130	0.130
Residual Std. Error (df = 336409)	11.613	11.613	11.613
Note:		*p<0.1; **p<0.05; ***p<0.01	

5.4.3 Salient countries

According to the UN Emissions Gap Report (2023), the five largest greenhouse gas emitters, i.e., China, the U.S., India, the EU, and Russia accounted for about 60% of total emissions in 2021, while the G20 countries accounted for 76%. Although the Carbon Earnings at Risk data does not project the U.S. nor the EU to be within the most exposed areas for the forecast period, it is interesting to examine whether the carbon-transition premium is more pronounced for countries that are within the top ten countries estimated to experience the highest margin reductions related to increased carbon costs in the future. However, the divestment argument based on country criteria is likely weaker. Nevertheless, since much of the EBIT margins are clustered in a few countries, as shown in Figure 5, it is interesting to examine whether these countries are moving the effect. The results in Table 16 suggest that these countries are not driving a carbon-transition premium: The coefficients associated with $Salient\_country$ are insignificant across all regression specifications, while the coefficients of the EBIT margin reductions are consistently statistically significant at the 5% level. According to these results, the premium is not more pronounced inside the most exposed countries, i.e., China, India, Japan, Taiwan, Turkey, South Korea, Hong Kong, Thailand, Russia, and Saudi Arabia. One argument might be that this reflects these countries' relatively weak climate regulations. It can be that investors are expecting relaxed regulations to continue throughout the forecast period. Tables 38 and 39 show the output of running similar regressions using 2040 and 2050 estimated EBIT margin reductions instead of 2030 and can be found in the Appendix.

Figure 5: Total EBIT margin reduction by country

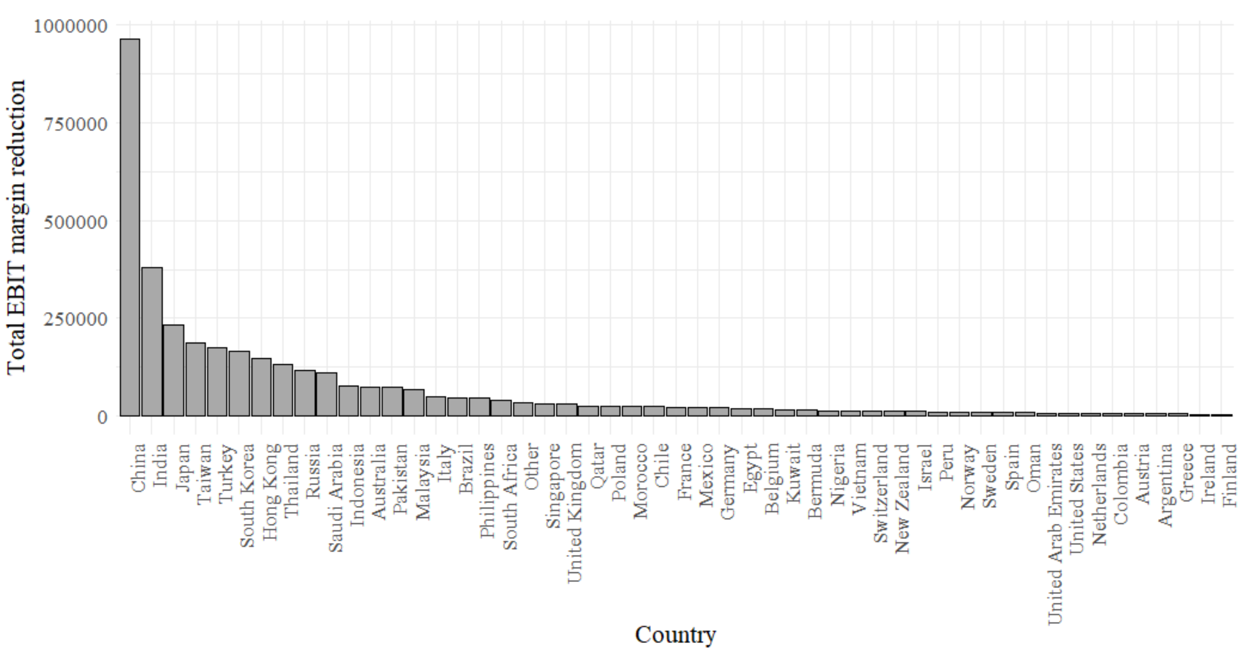


Table 16: Salient countries - Effects of 2030 carbon EBIT margin reductions on stock returns

Forecast year: 2030. The dependent variable is *Return*. EBIT margin reductions are transformed into positive values. The sample period is 2017 to 2022. All regressions include year/month-fixed effects, and specifications (3) to (6) additionally include industry-fixed effects. Industries are assigned according to the classification in the Trucost database. The table reports the results for the pooled regressions with standard errors double clustered at the firm and year level (in parentheses). *** 1% significance; ** 5% significance; * 10% significance.

	Dependent variable:					
	Return					
	(1)	(2)	(3)	(4)	(5)	(6)
EBIT2030Low	0.073**			0.069**		
	(0.032)			(0.032)		
EBIT2030Medium		0.033**			0.031**	
		(0.013)			(0.014)	
EBIT2030High			0.020**			0.019**
			(0.008)			(0.008)
Salient_country	0.036	0.048	0.041	0.044	0.055	0.048
	(0.434)	(0.433)	(0.434)	(0.435)	(0.433)	(0.434)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year/month-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Country-fixed effects	No	No	No	No	No	No
Industry-fixed effects	No	No	No	Yes	Yes	Yes
Observations	336,565	336,565	336,565	336,565	336,565	336,565
R^2	0.128	0.128	0.128	0.128	0.128	0.128
Adjusted R^2	0.128	0.128	0.128	0.128	0.128	0.128
Residual Std. Error	11.627 (df = 336493)	11.627 (df = 336493)	11.627 (df = 336493)	11.627 (df = 336490)	11.627 (df = 336490)	11.627 (df = 336490)
Note:						*p<0.1; **p<0.05; ***p<0.01

5.5 Unpriced carbon costs and institutional investors

Climate-related risks are increasingly incorporated in assessments of firms' risk exposures. Using data providers such as the Carbon Disclosure Project (CDP) and Trucost, financial analysts incorporate and take greater advantage of the increased granularity of carbon emission data. Potentially, the increased carbon awareness can put pressure on brown stocks, and it can possibly be one source of the effect seen in sections 5.2 and 5.3. For efficient market pricing, high-quality climate exposure data is needed to make informed investment decisions and pricing of the corresponding risks and opportunities (Ilhan et al., 2023). A potential explanation for a future carbon premium is that environmentally conscious investors incorporate future emission data and treat highly exposed firms as "sin stocks". According to the divestment hypothesis (Bolton and Kacperczyk, 2021), as more investors incorporate climate concerns into investment decisions, the divested firms' stocks present higher returns to the extent they are shunned. In a study by Ceccarelli et al. (2024), the authors find that mutual funds labeled as "low-carbon" after introducing Morningstar's novel carbon risk metrics experienced a significant increase in fund inflows. Moreover, the study finds that fund managers actively divested from companies with high carbon risk scores, particularly from stocks with limited diversification benefits. Rohleder et al. (2022) show that high decarbonization selling pressure sends stock prices downwards. Additionally, they show that firms subject to high decarbonization selling pressure tend to lower their emissions after the selling event. Nevertheless, investors might engage with the companies they are invested in rather than divest as a means of reducing the firm's carbon emissions. In a study conducted by Ilhan et al. (2023), the authors find evidence suggesting institutional investors demand and value climate risk disclosures and that investors actively engage in improving their portfolio firms environmentally. Moreover, Hoepner et al. (2024) find evidence for engagement being most effective at reducing downside risk when focusing on environmental issues, especially climate change. These results indicate that engagement benefits shareholders by reducing firms' downside risks. Hence, investor pressure constitutes a powerful financial mechanism for reducing firms' carbon risks. Although it is not entirely known how much investors incorporate climate data into investment decisions, especially data that relate to the future firm-level cost of carbon, it is interesting to examine whether there is systematic evidence for investors making investment decisions based on unpriced carbon costs.

Therefore, I estimate regressions according to Equation 7 to examine this potential effect. Table 17 shows that the coefficients associated with the margin reduction variables are statistically insignificant across all three carbon cost scenarios, except for the medium scenario at 10% significance. Notably, all coefficients have positive signs, reducing the strength of the divestment hypothesis as a driver of the carbon-transition risk premium related to future unpriced carbon margin reductions. Tables 40 and 41 in the Appendix present the corresponding estimates for 2040 and 2050, respectively.

Similarly, I estimate regressions according to Equation 8 to examine whether investors decrease holdings of firms estimated to have higher future carbon costs. Table 18 presents

Table 17: Effects of 2030 EBIT margin reductions on institutional ownership

Forecast year: 2030. The dependent variable is IO. The sample period is 2017 to 2022. All regressions include year/month-fixed effects, country-fixed effects, and industry-fixed effects. Industries are assigned according to the classification in the Trucost database. The table reports the results for the pooled regressions with standard errors double clustered at the firm and year level (in parentheses). *** 1% significance; ** 5% significance; * 10% significance.

	Dependent variable:		
	IO		
	(1)	(2)	(3)
EBIT2030Low	0.331		
	(0.186)		
EBIT2030Medium		0.163^{*}	
		(0.069)	
EBIT2030High			0.096
			(0.046)
Controls	Yes	Yes	Yes
Year/month-fixed effects	Yes	Yes	Yes
Industry-fixed effects	Yes	Yes	Yes
Country-fixed effects	Yes	Yes	Yes
Observations	6,198	6,198	6,198
R^2	0.383	0.384	0.383
Adjusted R^2	0.375	0.376	0.376
Residual Std. Error (df = 6119)	13.813	13.808	13.810
Note:			*p<0.1; **p<0.05; ***p<0.01

results using log total unpriced carbon costs in 2030 as the explanatory variables. The coefficients are statistically significant at the 5%, 10%, and 5% levels for the low, medium, and high carbon cost scenarios, respectively. Tables 42 and 43 in the Appendix present corresponding estimates for 2040 and 2050. These tables show similar results of negative and significant coefficients associated with future unpriced carbon costs. Although moderately, the magnitude of the coefficients for the low and medium scenarios are increasing while the coefficients for the high scenario are decreasing when taking a longer-term perspective. Tables 44 to 49 in the Appendix show the same regression setup replacing total unpriced carbon costs with scope 1 and scope 2 carbon costs. In contrast to the findings when running this analysis using estimated EBIT margin reductions, unpriced carbon costs seem negatively associated with institutional stock ownership. A 1% increase of unpriced carbon in the low scenario is associated with a reduction in institutional ownership of 0.003 percentage points. Similarly, a 1% increase in the total unpriced carbon cost in the medium scenario is associated with an average reduction of institutional ownership of 0.004 percentage points. In the high scenario, the expected reduction in institutional ownership is 0.005 percentage points. According to Tables 44 to 49 in the Appendix, institutional investors divest more consistently based on firms' scope 2 rather than scope 1 carbon costs. Note, however, that the sample size with unpriced carbon costs is slightly larger at 6,385 observations than the sample with margin reductions at 6,198 observations. This discrepancy is due to NAs in the EBIT margin sample. Moreover, the sample size is drastically reduced from 351,120 monthly observations to 6,385 yearly observations, and consequently, these results should be interpreted with caution. Further, the ownership data sample can be biased and prone to self-selection issues. It is possible that the firms included in the sample with ownership holdings have investors who are systematically more concerned about carbon emissions than firms that are excluded from the sample. Further, the findings of Bolton and Kacperczyk (2021) indicate that certain institutional investors are divesting from firms with high scope 1 intensities. Hence, my estimations may catch much of the same effects. Lastly, I estimate regressions according to Equation 9 to dissect whether an additional impact exists on the future carbon-transition risk premium due to institutional ownership. The coefficients in this analysis are insignificant across all carbon cost scenarios and forecast years, both for unpriced carbon measures as well as margin reductions, as can be seen by Tables 50 to 55 in the Appendix.

Table 18: Effects of total 2030 unpriced carbon costs on institutional ownership

Forecast year: 2030. The dependent variable is IO. The sample period is 2017 to 2022. All regressions include year/month-fixed effects, country-fixed effects, and industry-fixed effects. Industries are assigned according to the classification in the Trucost database. The table reports the results for the pooled regressions with standard errors double clustered at the firm and year level (in parentheses). *** 1% significance; ** 5% significance; * 10% significance.

	Dependent variable:		
	IO		
	(1)	(2)	(3)
LogTotal2030Low	-0.350^{**}		
	(0.100)		
LogTotal2030Medium		-0.441^{*}	
		(0.159)	
LogTotal2030High			-0.503^{**}
			(0.169)
Controls	Yes	Yes	Yes
Year/month-fixed effects	Yes	Yes	Yes
Industry-fixed effects	Yes	Yes	Yes
Country-fixed effects	Yes	Yes	Yes
Observations	6,385	6,385	6,385
R^2	0.374	0.374	0.375
Adjusted R^2	0.366	0.366	0.367
Residual Std. Error (df = 6306)	13.960	13.960	13.954
Note:			*p<0.1; **p<0.05; ***p<0.01

5.5.1 Unpriced carbon and disaggregate institutional ownership

Different classes of institutional investors are likely subject to varying degrees of pressure concerning climate change and carbon emissions. Although implementing climate assessments into investment decisions is becoming more usual, heightened climate awareness and concern can affect investor subgroups differently. For this reason, I divide the sample of firms for which ownership data exists into investor categories consisting of investment companies, insurance firms, pension funds, banks, public investors, and investment advisors. Conducting separate analyses for each of these investor types is interesting because they are expected to behave differently in relation to carbon-transition risk. For example, I expect investment companies to be under increasing pressure from clients and policymakers to comply with regulatory requirements to integrate environmental criteria into their investment portfolios. Similarly, recommendations from investment advisors should incorporate climate-related considerations to meet heightened client expectations and regulations. Integrating climate risks into investment decisions is not new for insurance companies as they need to assess climate resilience in underwriting operations and investment strategies. To secure long-term returns and coherent risk profiles, pension funds might experience rising pressure from beneficiaries and policymakers to adopt sustainable investment practices as they typically manage long-term liabilities. However, I conjecture that institutions such as banks face relatively less climate-related investor pressure than those mentioned. Yet, banks might experience growing regulatory and shareholder pressure to disclose and mitigate climate-related financial risks. For these reasons, I divide the institutional ownership variable into categories hypothesized to behave differently concerning future unpriced carbon costs. I obtain stock-level ownership data on the following categorical investment institutions and create the variables: $Banks$, $Pensions$, $Insurance$, $Invest.Co.s$, $Advisors$, and $Public$, and run regressions according to Equation 10 and 11 separately.

Table 19 presents results broken down into each owner category using 2030 EBIT margin reductions. Tables 56 and 57 in the Appendix present corresponding estimates for 2040 and 2050, respectively. In contrast, Table 20 shows regression estimates using total unpriced carbon costs. The forecast for EBIT margin reductions shows no strong divestment effects for the owner categories in the sample. The lack of significance is potentially related to the findings in the aggregated ownership analysis, in which no particular divestment effect could be uncovered for carbon margin reductions. Overall, the results presented in Table 20 show no clear divestment effects due to unpriced carbon except for investment advisors. The coefficients associated with advisors are negative and statistically significant at the 10%, 1%, and 1% levels for the low, medium, and high carbon cost scenarios, respectively. This finding suggests that investment advisors might actively divest from firms estimated to be subject to high future unpriced carbon costs and that the divestment is positively related to increases in the carbon cost scenario. Due to investment advisors' share of global stock holdings, the possible divestment effect through advisors can be substantial (Bolton and Kacperczyk, 2021). Surprisingly, although negative, the coefficients associated with pension funds are only partially significant, indicated by 10% significance for 2030 EBIT margin reductions in the medium and high carbon scenarios at most. For total unpriced carbon costs, the coefficients associated with pension funds are insignificant for all carbon scenarios. One would expect stronger results for the unpriced carbon-related divestment hypothesis for pension funds due to this investor category's long-term investment horizon. Further, insurance companies have positive and significant coefficients for all unpriced carbon cost scenarios, although only at the 10% level for the low and high scenarios. This finding contradicts the notion that insurance companies naturally incorporate carbon risks into investment decisions. Tables 58 to 65 in the Appendix present regression estimates for 2040 and 2050 and additionally replace total unpriced carbon costs with scope 1 and scope 2 unpriced carbon costs. Here too, the results are largely consistent with previous findings. Note, however, that public institutional investors seem to increase their holdings of companies based on future unpriced scope 1 carbon costs, while the effect of scope 2 unpriced carbon costs is inconclusive. Overall, the results presented here cannot verify the hypothesis that certain institutional investor subgroups divest from companies based on future unpriced carbon margin reductions or unpriced carbon costs. While the results are interesting and possibly reveal meaningful relationships between future carbon costs and institutional ownership, the underlying data might be insufficient. For example, only a small portion of the ownership holdings are assigned to pension funds, as shown in Table 1 in Panel C, which should be one of the largest institutional investor types in the global stock markets. Regardless, research uncovering investors' strategies to limit their portfolios' exposure to future carbon-transition risk can provide detailed information to firms about the consequences of remaining brown and the potential upside of becoming green.

Table 19: Effects of 2030 EBIT margin reductions on disaggregate institutional ownership

Forecast year: 2030. The dependent variables are *Banks*, *Pensions*, *Insurance*, *Invest.Co.s*, *Advisors* and *Public*. EBIT margin reductions are transformed into positive values. The sample period is 2017 to 2022. All regressions include year/month-fixed effects, country-fixed effects, and industry-fixed effects. Industries are assigned according to the classification in the Trucost database. The table reports the results for the pooled regressions with standard errors double clustered at the firm and year level (in parentheses). *** 1% significance; ** 5% significance; * 10% significance.

	Dependent variable:																	
		Banks			Pensions			Insurance			Invest.Co.s			Advisors			Public	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
EBIT2030Low	0.035			−0.075			0.049			0.515			−0.308			−0.046		
	(0.030)			(0.039)			(0.032)			(0.328)			(0.167)			(0.185)		
EBIT2030Medium		0.013			−0.034*			0.017			0.215			−0.139*			0.026	
		(0.013)			(0.014)			(0.012)			(0.125)			(0.060)			(0.079)	
EBIT2030High			0.012			−0.022*			0.010			0.136			−0.080			−0.005
			(0.012)			(0.009)			(0.008)			(0.083)			(0.040)			(0.053)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year/month-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,198	6,198	6,198	6,198	6,198	6,198	6,198	6,198	6,198	6,198	6,198	6,198	6,198	6,198	6,198	6,198	6,198	6,198
R^2	0.238	0.238	0.238	0.495	0.495	0.495	0.268	0.267	0.267	0.340	0.340	0.340	0.449	0.449	0.449	0.304	0.304	0.304
Adjusted R^2	0.228	0.228	0.228	0.489	0.489	0.489	0.258	0.258	0.258	0.332	0.332	0.332	0.442	0.442	0.442	0.295	0.295	0.295
Residual Std. Error (df = 6119)	1.978	1.978	1.977	2.930	2.930	2.930	1.921	1.921	1.921	21.155	21.152	21.153	14.186	14.184	14.186	10.481	10.481	10.481

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

Table 20: Effects of total 2030 unpriced carbon costs on disaggregate institutional ownership

Forecast year: 2030. The dependent variables are *Banks*, *Pensions*, *Insurance*, *Invest.Co.s*, *Advisors* and *Public*. The sample period is 2017 to 2022. All regressions include year/month-fixed effects, country-fixed effects, and industry-fixed effects. Industries are assigned according to the classification in the Trucost database. The table reports the results for the pooled regressions with standard errors double clustered at the firm and year level (in parentheses). *** 1% significance; ** 5% significance; * 10% significance.

	Dependent variable:																	
	Banks			Pensions			Insurance			Invest.Co.s			Advisors			Public		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
LogTotal2030Low	0.038			−0.009			0.035*			−0.237			−0.391*			0.140		
	(0.019)			(0.022)			(0.013)			(0.184)			(0.170)			(0.094)		
LogTotal2030Medium		0.052*			−0.043			0.057**			−0.056			−0.747***			0.205	
		(0.019)			(0.026)			(0.019)			(0.252)			(0.144)			(0.153)	
LogTotal2030High			0.053**			−0.044			0.056*			−0.114			−0.754***			0.214
			(0.019)			(0.026)			(0.020)			(0.261)			(0.151)			(0.155)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year/month-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,385	6,385	6,385	6,385	6,385	6,385	6,385	6,385	6,385	6,385	6,385	6,385	6,385	6,385	6,385	6,385	6,385	6,385
R^2	0.237	0.237	0.237	0.491	0.491	0.491	0.268	0.269	0.269	0.338	0.337	0.337	0.448	0.451	0.451	0.301	0.301	0.301
Adjusted R^2	0.227	0.227	0.227	0.485	0.485	0.485	0.259	0.260	0.260	0.329	0.329	0.329	0.442	0.444	0.444	0.292	0.292	0.292
Residual Std. Error (df = 6306)	1.963	1.963	1.963	2.915	2.914	2.914	1.908	1.907	1.907	21.173	21.180	21.179	14.215	14.179	14.179	10.466	10.464	10.464

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

6 Discussion

This study's findings have shown that estimated carbon margin reductions are not consistently priced into stock prices. Instead, investors seem to be pricing future unpriced carbon costs. These findings might be related to future unpriced carbon costs capturing some of the effects of contemporary firm-level carbon emissions. However, the results presented here indicate that investors are skeptical of firms' ability to improve environmentally. As noted, it seems that 2050 carbon costs are as significant for market participants as 2030 carbon costs, indicating a somewhat static view of firms' ability to become greener and reduce carbon costs in the future. The investor notion appears to be that firms will continue on their emissions paths with little probability of reducing carbon emissions going forward. Thus, investors seem to be generally pessimistic about firms' ability to cut future carbon costs.

One interesting line of thought is whether unpriced carbon cost is a better proxy for long-term carbon-transition risk while the impact of increased carbon costs on margins is more suitable as a proxy for short-term transition risk. If this holds true, carbon margin reductions should show significant effects as time progresses because they will likely become more important as investors increasingly incorporate information on the impact of carbon costs on profitability over the short term. That is, since investors already have information on current and future carbon emission costs, margin reductions may be priced in when investors view this information not exclusively as an indication of future risks but also as increasingly important indicators of present profitability. Therefore, carbon margin reductions may be better suited as a proxy for short-term transition risk, while unpriced carbon costs are more suitable for capturing long-term transition risk.

Going forward, I expect carbon margin reductions to become more significantly priced into stock prices. As time progresses and global temperatures continue to rise, the probability of abrupt carbon price hikes increases. Such abrupt carbon price hikes will likely become more severely priced into stock prices, reflecting an increased probability of adjacent profitability reductions for firms highly exposed to short-term transition risk. Further, abrupt price hikes will be especially harmful to brown firms as they are less well-suited to manage climate risks. As the probability of carbon price hikes increases, it will become clearer to the market which firms are "carbon winners and losers". Brown firms will experience substantial negative impacts on their margins as they have little expertise in managing heightened carbon costs, and even more so in a constrained time frame. It is, therefore, likely that investors will require return premiums for brown firms both on the level of margin reductions and high unpriced carbon costs in the near future.

Moreover, assuming that regulators are slow in adjusting the carbon price over the short term, the dramatic carbon price change, as depicted in the medium carbon cost scenario, will become more important as we progress closer to the 2050 net-zero commitments. Consequently, it is likely that higher carbon costs will be more severely priced into stock markets. This effect should emerge for both carbon margin reductions and unpriced carbon costs. Hence, firms that are highly exposed to carbon cost increases will be penalized according to their inability to adapt. Therefore, with time I expect higher carbon cost scenarios to exponentially require increased stock returns for brown firms, reflecting these firms' sluggish green transformations. In contrast, companies that successfully reduce carbon emissions will be less exposed to increased required returns in higher carbon cost scenarios, reflecting a higher likelihood of effectively managing the transition to a low-carbon economy.

A central limitation of the analysis of this paper is the uncertainty regarding the underlying data on the future unpriced cost of carbon. First, the Trucost Carbon Earnings at Risk data can be critiqued for insufficient transparency of the methodology and assumptions underlying the estimated carbon costs. Second, forward-looking estimations and predictions are notoriously harder to produce than using backward-looking data to assess climate-related risks. Using assumptions to produce scenarios about the future is a way to deal with the uncertainties of future unpriced carbon costs. In this paper, I have used a methodology to estimate the future cost of carbon emissions by using unclear but conceivable carbon cost outcomes and horizons.

As illustrated by Sautner et al. (2023a), as climate change exposure is becoming an increasingly important risk factor for investors, it follows that expected future climate risk will need to be compensated for. However, Trucost's estimations of future unpriced carbon costs might not accurately capture carbon-transition risk as market participants perceive it. Therefore, one interesting extension of this paper is to analyze the framework and its underlying assumptions used in estimating future firm-level carbon cost exposure.

Further, the analysis concerning institutional ownership and future unpriced carbon must be interpreted with caution. Possibly, the ownership data is not representative outside of the sample of investors that are required to document such data, and there can be some external validity issues in this section. With greater access to larger and more granular ownership data, further research on institutional ownership and future carbon costs can uncover important investor mechanisms in the fight against climate change. Moreover, an interesting topic for further research is exploring retail investors' perception of carbon-transition risk, possibly using a similar approach to this paper.

7 Conclusion

Reaching a net-zero economy by 2050 requires substantial reductions in carbon emissions. Whether the reductions will be a smooth or abrupt process is highly uncertain. In this paper, I provide a glimpse into the pricing of future unpriced carbon costs under different assumptions of carbon cost scenarios and time horizons. I have analyzed the firm-level future carbon-transition risk on a global sample of 8,821 unique firms. I find results suggesting the existence of an unpriced carbon-transition risk premium related to firms' future carbon costs for the forecast years 2030, 2040, and 2050 within the range of 2.5% to 3.2% on an annual basis. This premium is economically important and positively related to increases in the carbon cost scenario. However, evidence of a transition premium related to estimated future margin reductions associated with increased carbon costs is mixed. Still, the premium becomes highly significant and economically meaningful for firms estimated to be within the top 10% exposed companies, both on the cost and margin levels. These findings suggest that particularly brown firms are systematically penalized across industries and countries. Further, the analysis presents results suggesting that the ten most exposed industries in the data are subject to heightened carbon-transition risk premiums. Looking at the ten most exposed countries, the effect of a carbon-transition risk on stock returns is nonexistent. Lastly, using a smaller sample of companies reporting ownership data, I find some indications of divestment dynamics related to unpriced carbon costs for all three forecast years and carbon cost scenarios. Also, these effects differ for institutional ownership categories, although the results are somewhat inconsistent with the theory. The EBIT margin reductions and institutional ownership results are inconsistent and do not support the notion that investors are divesting from firms highly exposed to future unpriced carbon margin reductions.

This paper is relevant in a regulatory discussion about carbon costs, especially concerning the means of carbon taxes and emission trading schemes. As investors incorporate unpriced carbon into investment decisions, policymakers have a pivotal role in deciding which carbon scenario to realize. Regulators have the authority to influence the uncertainty regarding how abruptly or smoothly the cost of carbon will unfold to reach the temperature targets. Also, this paper is useful for firms because the unpriced carbon-related increased costs of equity can be considered as an additional carbon tax for firms. Therefore, the question of green signaling and mitigation efforts becomes even more relevant. It is interesting to examine whether investments in green projects, signaling green outlooks and reduced carbon costs to the market, can mitigate the carbon-transition premium. Future research related to green investments, innovation, and patents will be interesting and a rewarding contribution to the literature on the carbon-transition risk.

This study is not without empirical issues. The pressing challenge is the "black box" nature of the Trucost Carbon Earnings at Risk data and the underlying assumptions used to estimate future unpriced carbon costs and their impact on margins. It is not given that these estimations are representative of the actual realized future carbon costs for firms, nor is it certain that it is representative of investors' perceptions of firm-level carbon exposure. Further, since the data sample consists of monthly returns covering the years post-2015, it can be that the results are biased as the stock markets might have overreacted during this particular period to the Paris Agreement (Bolton and Kacperczyk, 2023). Nevertheless, the persistent scientific evidence of global rising temperatures suggests that climate concerns are not a temporary shock. As we continue to emit carbon and reach record temperature levels, it becomes increasingly difficult to accomplish the net-zero commitments by 2050. Thus, it is probably more precise to say that the carbon-transition risk will become even more important in the future.

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References

Bolton, P., Z. Halem, and M. Kacperczyk (2022). The financial cost of carbon. *Journal of Applied Corporate Finance 34*(2), 17–29.

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

Bolton, P. and M. Kacperczyk (2023). Global pricing of carbon-transition risk. *The Journal of Finance 78*(6), 3677–3754.

Busch, T., A. Bassen, S. Lewandowski, and F. Sump (2022). Corporate carbon and financial performance revisited. *Organization & Environment 35*(1), 154–171.

Campiglio, E., L. Daumas, P. Monnin, and A. von Jagow (2023). Climate-related risks in financial assets. *Journal of Economic Surveys 37*(3), 950–992.

Ceccarelli, M., S. Ramelli, and A. F. Wagner (2024). Low carbon mutual funds. *Review of Finance 28*(1), 45–74.

Cenedese, G., S. Han, and M. T. Kacperczyk (2023). Carbon-transition risk and net-zero portfolios. *Available at SSRN*.

Dai, R. and Q. F. S. Drechsler (2021). Research guide for datastream and worldscope at wharton research data services. *Research Guide for Datastream and Worldscope at Wharton Research Data Services (May 11, 2021).*

Delmas, M. A., N. Nairn-Birch, and J. Lim (2015). Dynamics of environmental and financial performance: The case of greenhouse gas emissions. *Organization & Environment 28*(4), 374–393.

Faccini, R., R. Matin, and G. Skiadopoulos (2023). Dissecting climate risks: Are they reflected in stock prices? *Journal of Banking & Finance 155*, 106948.

Garvey, G. T., M. Iyer, and J. Nash (2018). Carbon footprint and productivity: Does the" e" in esg capture efficiency as well as environment? *Journal of Investment Management 16*(1), 59–69.

Ginglinger, E. and Q. Moreau (2023). Climate risk and capital structure. *Management Science 69*(12), 7492–7516.

Hoepner, A. G., I. Oikonomou, Z. Sautner, L. T. Starks, and X. Y. Zhou (2024). Esg shareholder engagement and downside risk. *Review of Finance 28*(2), 483–510.

Hsu, P.-H., K. Li, and C.-Y. Tsou (2023). The pollution premium. *The Journal of Finance 78*(3), 1343–1392.

Ilhan, E., P. Krueger, Z. Sautner, and L. T. Starks (2023). Climate risk disclosure and institutional investors. *The Review of Financial Studies 36*(7), 2617–2650.

Ilhan, E., Z. Sautner, and G. Vilkov (2021). Carbon tail risk. *The Review of Financial Studies 34*(3), 1540–1571.

International Carbon Action Partnership (2024). Compare EU ETS and China National ETS. `https://icapcarbonaction.com/en/compare/55/43`, Accessed: June 5, 2024.

Matsumura, E. M., R. Prakash, and S. C. Vera-Munoz (2014). Firm-value effects of carbon emissions and carbon disclosures. *The accounting review 89*(2), 695–724.

Misani, N. and S. Pogutz (2015). Unraveling the effects of environmental outcomes and processes on financial performance: A non-linear approach. *Ecological economics 109*, 150–160.

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

Norges Bank Investment Management (2024). Divesting from companies. `https://www.nbim.no/en/responsible-investment/divesting-from-companies/`, Accessed: May 24, 2024.

Pástor, L., R. F. Stambaugh, and L. A. Taylor (2022). Dissecting green returns. *Journal of Financial Economics 146*(2), 403–424.

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

Robiou du Pont, Y. and M. Meinshausen (2018). Warming assessment of the bottom-up paris agreement emissions pledges. *Nature communications 9*(1), 4810.

Rohleder, M., M. Wilkens, and J. Zink (2022). The effects of mutual fund decarbonization on stock prices and carbon emissions. *Journal of Banking & Finance 134*, 106352.

Sautner, Z., L. Van Lent, G. Vilkov, and R. Zhang (2023a). Firm-level climate change exposure. *The Journal of Finance 78*(3), 1449–1498.

Sautner, Z., L. Van Lent, G. Vilkov, and R. Zhang (2023b). Pricing climate change exposure. *Management Science 69*(12), 7540–7561.

Slawinski, N. and P. Bansal (2015). Short on time: Intertemporal tensions in business sustainability. *Organization Science 26*(2), 531–549.

TCFD (2017). Recommendations of the task force on climate-related financial disclosures. https://assets.bbhub.io/company/sites/60/2021/10/FINAL-2017-TCFD-Report.pdf, Accessed: May 4, 2024.

UN Emissions Gap Report (2023). Broken record - temperatures hit new highs, yet world fails to cut emissions (again). *UN Environment Programme*. https://doi.org/10.59117/20.500.11822/43922.

Zerbib, O. D. (2022). A sustainable capital asset pricing model (s-capm): Evidence from environmental integration and sin stock exclusion. *Review of Finance 26*(6), 1345–1388.

Table 21: Declaration of use of language models

Language model AI tool	Usage	Affected sections
ChatGPT	Grammar, vocabulary, and sentence structure improvement	Section 1-7
Grammarly	Grammar, vocabulary, and sentence structure improvement	Section 1-7

A Appendix

A.1 Supplementary tables

Table 22: Ownership descriptive statistics - For regressions using unpriced carbon costs

This table reports descriptive statistics for the data used in regression estimating the impact of future unpriced carbon costs on institutional ownership variables.

Statistic	Mean	Pctl(25)	Median	Pctl(75)	St. Dev.	N
IO (%)	67.928	56.855	69.989	81.296	17.538	6,385
Invest.Co.s (%)	31.018	5.629	27.173	53.395	25.857	6,385
Advisors (%)	26.669	12.166	22.519	37.061	19.023	6,385
Public (%)	4.557	0.265	1.127	2.315	12.437	6,385
Pensions (%)	2.136	0.262	0.800	1.861	4.061	6,385
Insurance (%)	0.880	0.000	0.002	0.210	2.217	6,385
Banks (%)	0.792	0.005	0.072	0.420	2.233	6,385
Volatility (winsorized at 2.5%)	33.702	21.060	29.553	41.177	18.232	6,385
Price Inverse (winsorized at 2.5%)	0.006	0.0003	0.002	0.006	0.014	6,385

Table 23: Determinants of 2040 EBIT margin reductions

Forecast year: 2040. The dependent variables correspond to reductions of EBIT margins under the low, medium, and high carbon cost scenario for the forecast year 2040 and are transformed into positive values. The sample period is 2017 to 2022. All regressions include year/month-fixed effects, country-fixed effects, and industry-fixed effects. Industries are assigned according to the classification in the Trucost database. The table reports the results for the pooled regressions with standard errors double clustered at the firm and year level (in parentheses). *** 1% significance; ** 5% significance; * 10% significance.

	Dependent variable:		
	EBIT2040Low	EBIT2040Medium	EBIT2040High
	(1)	(2)	(3)
LogSize	-0.289^{***}	-0.707^{***}	-1.031^{***}
	(0.031)	(0.076)	(0.113)
Book/Market	0.089	0.277^{**}	0.432^{**}
	(0.054)	(0.133)	(0.201)
Leverage	0.476^{***}	1.080^{***}	1.751^{***}
	(0.128)	(0.314)	(0.468)
Invest/Assets	-0.079	0.113	0.248
	(0.296)	(0.740)	(1.079)
LogPPE	0.396^{***}	0.969^{***}	1.438^{***}
	(0.025)	(0.062)	(0.091)
ROE	0.003	0.006	0.009
	(0.002)	(0.004)	(0.006)
Year/month-fixed effects	Yes	Yes	Yes
Country-fixed effects	Yes	Yes	Yes
Industry-fixed effects	Yes	Yes	Yes
Observations	336,565	336,565	336,565
R^2	0.173	0.177	0.178
Adjusted R^2	0.173	0.176	0.177
Residual Std. Error (df = 336410)	2.726	6.671	9.828
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 24: Determinants of 2050 EBIT margin reductions

Forecast year: 2050. The dependent variables correspond to reductions of EBIT margins under the low, medium, and high carbon cost scenario for the forecast year 2050 and are transformed into positive values. The sample period is 2017 to 2022. All regressions include year/month-fixed effects, country-fixed effects, and industry-fixed effects. Industries are assigned according to the classification in the Trucost database. The table reports the results for the pooled regressions with standard errors double clustered at the firm and year level (in parentheses). *** 1% significance; ** 5% significance; * 10% significance.

	Dependent variable:		
	EBIT2050Low	EBIT2050Medium	EBIT2050High
	(1)	(2)	(3)
LogSize	-0.688^{***}	-2.260^{***}	-1.191^{***}
	(0.087)	(0.284)	(0.130)
Book/Market	0.015	0.258	0.494^{**}
	(0.155)	(0.505)	(0.231)
Leverage	0.891^{**}	3.107^{**}	1.991^{***}
	(0.377)	(1.262)	(0.540)
Invest/Assets	-0.712	-1.650	0.195
	(1.062)	(3.511)	(1.247)
LogPPE	0.786^{***}	2.652^{***}	1.657^{***}
	(0.074)	(0.239)	(0.104)
ROE	0.004	0.012	0.011
	(0.004)	(0.013)	(0.007)
Year/month-fixed effects	Yes	Yes	Yes
Country-fixed effects	Yes	Yes	Yes
Industry-fixed effects	Yes	Yes	Yes
Observations	336,565	336,565	336,565
R^2	0.094	0.094	0.178
Adjusted R^2	0.093	0.094	0.178
Residual Std. Error (df = 336410)	9.265	31.018	11.300
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 25: Effects of 2040 carbon EBITDA margin reductions on stock returns

Forecast year: 2040. The dependent variable is *Return*. EBITDA margin reductions are transformed into positive values. I.e., the independent variable EBITDA2040Low corresponds to the reduction of EBITDA margins in the low carbon cost scenario for the forecast year 2040. The sample period is 2017 to 2022. All regressions include year/month-fixed effects, country-fixed effects, and specifications (3) to (6) additionally include industry-fixed effects. Industries are assigned according to the classification in the Trucost database. The table reports the results for the pooled regressions with standard errors double clustered at the firm and year level (in parentheses). *** 1% significance; ** 5% significance; * 10% significance.

	Dependent variable:					
	Return					
	(1)	(2)	(3)	(4)	(5)	(6)
EBITDA2040Low	0.024			0.021		
	(0.016)			(0.016)		
EBITDA2040Medium		0.012^{*}			0.011^{*}	
		(0.006)			(0.006)	
EBITDA2040High			0.007^{*}			0.006
			(0.004)			(0.004)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year/month-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Country-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry-fixed effects	No	No	No	Yes	Yes	Yes
Observations	336,565	336,565	336,565	336,565	336,565	336,565
R^2	0.130	0.130	0.130	0.130	0.130	0.130
Adjusted R^2	0.130	0.130	0.130	0.130	0.130	0.130
Residual Std. Error	11.615 (df = 336410)	11.615 (df = 336410)	11.615 (df = 336410)	11.615 (df = 336407)	11.615 (df = 336407)	11.615 (df = 336407)
Note:						*p<0.1; **p<0.05; ***p<0.01

Table 26: Effects of 2050 carbon EBITDA margin reductions on stock returns

Forecast year: 2050. The dependent variable is *Return*. EBITDA margin reductions are transformed into positive values. I.e., the independent variable EBITDA2050Low corresponds to the reduction of EBITDA margins in the low carbon cost scenario for the forecast year 2050. The sample period is 2017 to 2022. All regressions include year/month-fixed effects, country-fixed effects, and specifications (3) to (6) additionally include industry-fixed effects. Industries are assigned according to the classification in the Trucost database. The table reports the results for the pooled regressions with standard errors double clustered at the firm and year level (in parentheses). *** 1% significance; ** 5% significance; * 10% significance.

	Dependent variable:					
	Return					
	(1)	(2)	(3)	(4)	(5)	(6)
EBITDA2050Low	0.020			0.018		
	(0.013)			(0.013)		
EBITDA2050Medium		0.006^{*}			0.005	
		(0.004)			(0.004)	
EBITDA2050High			0.006^{*}			0.005
			(0.004)			(0.004)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year/month-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Country-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry-fixed effects	No	No	No	Yes	Yes	Yes
Observations	336,565	336,565	336,565	336,565	336,565	336,565
R^2	0.130	0.130	0.130	0.130	0.130	0.130
Adjusted R^2	0.130	0.130	0.130	0.130	0.130	0.130
Residual Std. Error	11.615 (df = 336410)	11.615 (df = 336410)	11.615 (df = 336410)	11.615 (df = 336407)	11.615 (df = 336407)	11.615 (df = 336407)
Note:						*p<0.1; **p<0.05; ***p<0.01

Table 27: Effects of 2030 carbon EBIT margin reductions on stock returns - Ownership data only

Forecast year: 2030. Data is solely based on firms for which there exists ownership data. The dependent variable is *Return*. EBIT margin reductions are transformed to positive values. The sample period is 2017 to 2022. All regressions include year/month-fixed effects, country-fixed effects, and specifications (3) to (6) additionally include industry-fixed effects. Industries are assigned according to the classification in the Trucost database. The table reports the results for the pooled regressions with standard errors double clustered at the firm and year level (in parentheses). *** 1% significance; ** 5% significance; * 10% significance.

	Dependent variable:					
	Return					
	(1)	(2)	(3)	(4)	(5)	(6)
EBIT2030Low	0.146***			0.145***		
	(0.026)			(0.025)		
EBIT2030Medium		0.044***			0.043**	
		(0.008)			(0.012)	
EBIT2030High			0.031**			0.030**
			(0.010)			(0.011)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year/month-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Country-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry-fixed effects	No	No	No	Yes	Yes	Yes
Observations	6,198	6,198	6,198	6,198	6,198	6,198
R^2	0.210	0.210	0.210	0.210	0.210	0.210
Adjusted R^2	0.200	0.200	0.200	0.200	0.200	0.200
Residual Std. Error	8.658 (df = 6121)	8.659 (df = 6121)	8.659 (df = 6121)	8.660 (df = 6118)	8.661 (df = 6118)	8.661 (df = 6118)
Note:						*p<0.1; **p<0.05; ***p<0.01

Table 28: Effects of 2040 carbon EBIT margin reductions on stock returns - Ownership data only

Forecast year: 2040. Data is solely based on firms for which there exists ownership data. The dependent variable is *Return*. EBIT margin reductions are transformed into positive values. I.e., the independent variable EBIT2030Low corresponds to the reduction of EBIT margins in the low carbon cost scenario for the forecast year 2030. The sample period is 2017 to 2022. All regressions include year/month-fixed effects, country-fixed effects, and specifications (3) to (6) additionally include industry-fixed effects. Industries are assigned according to the classification in the Trucost database. The table reports the results for the pooled regressions with standard errors double clustered at the firm and year level (in parentheses). *** 1% significance; ** 5% significance; * 10% significance.

	Dependent variable:					
	Return					
	(1)	(2)	(3)	(4)	(5)	(6)
EBIT2040Low	0.083***			0.082***		
	(0.015)			(0.015)		
EBIT2040Medium		0.024**			0.023**	
		(0.005)			(0.008)	
EBIT2040High			0.018**			0.017*
			(0.005)			(0.007)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year/month-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Country-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry-fixed effects	No	No	No	Yes	Yes	Yes
Observations	6,198	6,198	6,198	6,198	6,198	6,198
R^2	0.210	0.210	0.210	0.210	0.210	0.210
Adjusted R^2	0.200	0.200	0.200	0.200	0.200	0.200
Residual Std. Error	8.658 (df = 6121)	8.659 (df = 6121)	8.659 (df = 6121)	8.660 (df = 6118)	8.661 (df = 6118)	8.661 (df = 6118)
Note:						*p<0.1; **p<0.05; ***p<0.01

Table 29: Effects of 2050 carbon EBIT margin reductions on stock returns - Ownership data only

Forecast year: 2050. Data is solely based on firms for which there exists ownership data. The dependent variable is *Return*. EBIT margin reductions are transformed to positive values. The sample period is 2017 to 2022. All regressions include year/month-fixed effects, country-fixed effects, and specifications (3) to (6) additionally include industry-fixed effects. Industries are assigned according to the classification in the Trucost database. The table reports the results for the pooled regressions with standard errors double clustered at the firm and year level (in parentheses). *** 1% significance; ** 5% significance; * 10% significance.

	Dependent variable:					
	Return					
	(1)	(2)	(3)	(4)	(5)	(6)
EBIT2050Low	0.011			0.011		
	(0.007)			(0.008)		
EBIT2050Medium		0.003			0.003	
		(0.002)			(0.002)	
EBIT2050High			0.015^{**}			0.015^{*}
			(0.005)			(0.006)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year/month-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Country-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry-fixed effects	No	No	No	Yes	Yes	Yes
Observations	6,198	6,198	6,198	6,198	6,198	6,198
R^2	0.210	0.209	0.210	0.210	0.210	0.210
Adjusted R^2	0.200	0.200	0.200	0.199	0.199	0.200
Residual Std. Error	8.660 (df = 6121)	8.660 (df = 6121)	8.659 (df = 6121)	8.662 (df = 6118)	8.662 (df = 6118)	8.661 (df = 6118)
Note:						*p<0.1; **p<0.05; ***p<0.01

Table 30: Effects of scope 1 2040 unpriced carbon costs on stock returns

Forecast year: 2040. The dependent variable is *Return*. The sample period is 2017 to 2022. All regressions include year/month-fixed effects, country-fixed effects, and specifications (3) to (6) additionally include industry-fixed effects. Industries are assigned according to the classification in the Trucost database. The table reports the results for the pooled regressions with standard errors double clustered at the firm and year level (in parentheses). *** 1% significance; ** 5% significance; * 10% significance.

	Dependent variable:					
	Return					
	(1)	(2)	(3)	(4)	(5)	(6)
LogScope12040Low	0.051^{**}			0.054^{**}		
	(0.022)			(0.021)		
LogScope12040Medium		0.065^{**}			0.068^{***}	
		(0.026)			(0.025)	
LogScope12040High			0.074^{***}			0.078^{***}
			(0.028)			(0.025)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year/month-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Country-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry-fixed effects	No	No	No	Yes	Yes	Yes
Observations	351,120	351,120	351,120	351,120	351,120	351,120
R^2	0.130	0.130	0.130	0.130	0.130	0.130
Adjusted R^2	0.129	0.129	0.129	0.129	0.129	0.129
Residual Std. Error	11.814 (df = 350965)	11.814 (df = 350965)	11.814 (df = 350965)	11.814 (df = 350962)	11.814 (df = 350962)	11.814 (df = 350962)
Note:						*p<0.1; **p<0.05; ***p<0.01

Table 31: Effects of scope 1 2050 unpriced carbon costs on stock returns

Forecast year: 2050. The dependent variable is *Return*. The sample period is 2017 to 2022. All regressions include year/month-fixed effects, country-fixed effects, and specifications (3) to (6) additionally include industry-fixed effects. Industries are assigned according to the classification in the Trucost database. The table reports the results for the pooled regressions with standard errors double clustered at the firm and year level (in parentheses). *** 1% significance; ** 5% significance; * 10% significance.

	Dependent variable:					
	Return					
	(1)	(2)	(3)	(4)	(5)	(6)
LogScope12050Low	0.053**			0.055**		
	(0.023)			(0.021)		
LogScope12050Medium		0.076***			0.081***	
		(0.029)			(0.026)	
LogScope12050High			0.076***			0.081***
			(0.029)			(0.026)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year/month-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Country-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry-fixed effects	No	No	No	Yes	Yes	Yes
Observations	351,120	351,120	351,120	351,120	351,120	351,120
R^2	0.130	0.130	0.130	0.130	0.130	0.130
Adjusted R^2	0.129	0.129	0.129	0.129	0.129	0.129
Residual Std. Error	11.814 (df = 350965)	11.814 (df = 350965)	11.814 (df = 350965)	11.814 (df = 350962)	11.814 (df = 350962)	11.814 (df = 350962)
Note:						*p<0.1; **p<0.05; ***p<0.01

Table 32: Effects of scope 2 2040 unpriced carbon costs on stock returns

Forecast year: 2040. The dependent variable is *Return*. The sample period is 2017 to 2022. All regressions include year/month-fixed effects, country-fixed effects, and specifications (3) to (6) additionally include industry-fixed effects. Industries are assigned according to the classification in the Trucost database. The table reports the results for the pooled regressions with standard errors double clustered at the firm and year level (in parentheses). *** 1% significance; ** 5% significance; * 10% significance.

	Dependent variable:					
	Return					
	(1)	(2)	(3)	(4)	(5)	(6)
LogScope22040Low	0.062**			0.070***		
	(0.027)			(0.025)		
LogScope22040Medium		0.085**			0.098***	
		(0.035)			(0.030)	
LogScope22040High			0.092**			0.106***
			(0.036)			(0.030)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year/month-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Country-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry-fixed effects	No	No	No	Yes	Yes	Yes
Observations	351,120	351,120	351,120	351,120	351,120	351,120
R^2	0.130	0.130	0.130	0.130	0.130	0.130
Adjusted R^2	0.129	0.129	0.129	0.129	0.129	0.129
Residual Std. Error	11.815 (df = 350965)	11.814 (df = 350965)	11.814 (df = 350965)	11.814 (df = 350962)	11.814 (df = 350962)	11.814 (df = 350962)
Note:						*p<0.1; **p<0.05; ***p<0.01

Table 33: Effects of scope 2 2050 unpriced carbon costs on stock returns

Forecast year: 2050. The dependent variable is *Return*. The sample period is 2017 to 2022. All regressions include year/month-fixed effects, country-fixed effects, and specifications (3) to (6) additionally include industry-fixed effects. Industries are assigned according to the classification in the Trucost database. The table reports the results for the pooled regressions with standard errors double clustered at the firm and year level (in parentheses). *** 1% significance; ** 5% significance; * 10% significance.

	Dependent variable:					
	Return					
	(1)	(2)	(3)	(4)	(5)	(6)
LogScope22050Low	0.061^{**}			0.068^{***}		
	(0.027)			(0.025)		
LogScope22050Medium		0.090^{**}			0.104^{***}	
		(0.035)			(0.030)	
LogScope22050High			0.090^{**}			0.104^{***}
			(0.035)			(0.030)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year/month-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Country-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry-fixed effects	No	No	No	Yes	Yes	Yes
Observations	351,120	351,120	351,120	351,120	351,120	351,120
R^2	0.130	0.130	0.130	0.130	0.130	0.130
Adjusted R^2	0.129	0.129	0.129	0.129	0.129	0.129
Residual Std. Error	11.815 (df = 350965)	11.814 (df = 350965)	11.814 (df = 350965)	11.814 (df = 350962)	11.814 (df = 350962)	11.814 (df = 350962)
Note:						*p<0.1; **p<0.05; ***p<0.01

Table 34: High unpriced carbon exposure firms - Effects of 2040 carbon EBIT margin reductions on stock returns

Forecast year: 2040. The dependent variable is *Return*. EBIT margin reductions are transformed into positive values. The sample period is 2017 to 2022. All regressions include year/month-fixed effects, country-fixed effects, and specifications (3) to (6) additionally include industry-fixed effects. Industries are assigned according to the classification in the Trucost database. The table reports the results for the pooled regressions with standard errors double clustered at the firm and year level (in parentheses). *** 1% significance; ** 5% significance; * 10% significance.

	Dependent variable:					
	Return					
	(1)	(2)	(3)	(4)	(5)	(6)
EBIT2040Low	−0.011			−0.012		
	(0.016)			(0.016)		
EBIT2040Medium		0.002			0.001	
		(0.007)			(0.007)	
EBIT2040High			−0.002			−0.003
			(0.005)			(0.005)
Top_decile	0.444^{***}	0.330^{*}	0.414^{**}	0.425^{***}	0.315^{*}	0.403^{**}
	(0.152)	(0.173)	(0.166)	(0.137)	(0.162)	(0.156)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year/month-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Country-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry-fixed effects	No	No	No	Yes	Yes	Yes
Observations	336,565	336,565	336,565	336,565	336,565	336,565
R^2	0.130	0.130	0.130	0.131	0.130	0.131
Adjusted R^2	0.130	0.130	0.130	0.130	0.130	0.130
Residual Std. Error	11.615 (df = 336409)	11.615 (df = 336409)	11.615 (df = 336409)	11.615 (df = 336406)	11.615 (df = 336406)	11.615 (df = 336406)
Note:						*p<0.1; **p<0.05; ***p<0.01

Table 35: High unpriced carbon exposure firms - Effects of 2050 carbon EBIT margin reductions on stock returns

Forecast year: 2050. The dependent variable is *Return*. EBIT margin reductions are transformed into positive values. The sample period is 2017 to 2022. All regressions include year/month-fixed effects, country-fixed effects, and specifications (3) to (6) additionally include industry-fixed effects. Industries are assigned according to the classification in the Trucost database. The table reports the results for the pooled regressions with standard errors double clustered at the firm and year level (in parentheses). *** 1% significance; ** 5% significance; * 10% significance.

	Dependent variable:					
	Return					
	(1)	(2)	(3)	(4)	(5)	(6)
EBIT2050Low	−0.002			−0.002		
	(0.003)			(0.003)		
EBIT2050Medium		−0.0005			−0.001	
		(0.001)			(0.001)	
EBIT2050High			−0.002			−0.003
			(0.004)			(0.004)
Top_decile	0.384**	0.386**	0.428**	0.362**	0.364**	0.418***
	(0.151)	(0.153)	(0.167)	(0.143)	(0.146)	(0.157)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year/month-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Country-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry-fixed effects	No	No	No	Yes	Yes	Yes
Observations	336,565	336,565	336,565	336,565	336,565	336,565
R^2	0.130	0.130	0.130	0.131	0.131	0.131
Adjusted R^2	0.130	0.130	0.130	0.130	0.130	0.130
Residual Std. Error	11.615 (df = 336409)	11.615 (df = 336409)	11.615 (df = 336409)	11.615 (df = 336406)	11.615 (df = 336406)	11.615 (df = 336406)

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

Table 36: Salient industries - effects of 2040 carbon EBIT margin reductions on stock returns

Forecast year: 2040. The dependent variable is *Return*. The sample period is 2017 to 2022. All regressions include year/month-fixed effects and country-fixed effects. Industries are assigned according to the classification in the Trucost database. The table reports the results for the pooled regressions with standard errors double clustered at the firm and year level (in parentheses). *** 1% significance; ** 5% significance; * 10% significance.

	Dependent variable:		
	Return		
	(1)	(2)	(3)
EBIT2040Low	−0.008		
	(0.016)		
EBIT2040Medium		−0.0004	
		(0.007)	
EBIT2040High			−0.001
			(0.004)
Salient_industry	0.562**	0.540**	0.554**
	(0.213)	(0.216)	(0.216)
Controls	Yes	Yes	Yes
Year/month-fixed effects	Yes	Yes	Yes
Country-fixed effects	Yes	Yes	Yes
Industry-fixed effects	No	No	No
Observations	336,565	336,565	336,565
R^2	0.131	0.131	0.131
Adjusted R^2	0.130	0.130	0.130
Residual Std. Error (df = 336409)	11.613	11.613	11.613
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 37: Salient industries - effects of 2050 carbon EBIT margin reductions on stock returns

Forecast year: 2050. The dependent variable is *Return*. The sample period is 2017 to 2022. All regressions include year/month-fixed effects and country-fixed effects. Industries are assigned according to the classification in the Trucost database. The table reports the results for the pooled regressions with standard errors double clustered at the firm and year level (in parentheses). *** 1% significance; ** 5% significance; * 10% significance.

	Dependent variable:		
	Return		
	(1)	(2)	(3)
EBIT2050Low	−0.002		
	(0.004)		
EBIT2050Medium		−0.001	
		(0.001)	
EBIT2050High			−0.001
			(0.004)
Salient_industry	0.548***	0.548***	0.557**
	(0.205)	(0.206)	(0.216)
Controls	Yes	Yes	Yes
Year/month-fixed effects	Yes	Yes	Yes
Country-fixed effects	Yes	Yes	Yes
Industry-fixed effects	No	No	No
Observations	336,565	336,565	336,565
R^2	0.131	0.131	0.131
Adjusted R^2	0.130	0.130	0.130
Residual Std. Error (df = 336409)	11.613	11.613	11.613
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 38: Salient countries - Effects of 2040 carbon EBIT margin reductions on stock returns

Forecast year: 2040. The dependent variable is *Return*. EBIT margin reductions are transformed into positive values. The sample period is 2017 to 2022. All regressions include year/month-fixed effects and specifications (3) to (6) additionally include industry-fixed effects. Industries are assigned according to the classification in the Trucost database. The table reports the results for the pooled regressions with standard errors double clustered at the firm and year level (in parentheses). *** 1% significance; ** 5% significance; * 10% significance.

	Dependent variable:					
	Return					
	(1)	(2)	(3)	(4)	(5)	(6)
EBIT2040Low	0.043**			0.040**		
	(0.019)			(0.019)		
EBIT2040Medium		0.020**			0.019**	
		(0.008)			(0.008)	
EBIT2040High			0.013**			0.012**
			(0.005)			(0.005)
Salient_country	0.037	0.047	0.041	0.044	0.054	0.048
	(0.434)	(0.434)	(0.434)	(0.435)	(0.434)	(0.434)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year/month-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Country-fixed effects	No	No	No	No	No	No
Industry-fixed effects	No	No	No	Yes	Yes	Yes
Observations	336,565	336,565	336,565	336,565	336,565	336,565
R^2	0.128	0.128	0.128	0.128	0.128	0.128
Adjusted R^2	0.128	0.128	0.128	0.128	0.128	0.128
Residual Std. Error	11.627 (df = 336493)	11.627 (df = 336493)	11.627 (df = 336493)	11.627 (df = 336490)	11.627 (df = 336490)	11.627 (df = 336490)
Note:						*p<0.1; **p<0.05; ***p<0.01

Table 39: Salient countries - Effects of 2050 carbon EBIT margin reductions on stock returns

Forecast year: 2050. The dependent variable is *Return*. EBIT margin reductions are transformed to positive values. The sample period is 2017 to 2022. All regressions include year/month-fixed effects and specifications (3) to (6) additionally include industry-fixed effects. Industries are assigned according to the classification in the Trucost database. The table reports the results for the pooled regressions with standard errors double clustered at the firm and year level (in parentheses). *** 1% significance; ** 5% significance; * 10% significance.

	Dependent variable:					
	Return					
	(1)	(2)	(3)	(4)	(5)	(6)
EBIT2050Low	0.009**			0.008**		
	(0.004)			(0.004)		
EBIT2050Medium		0.003**			0.002**	
		(0.001)			(0.001)	
EBIT2050High			0.011**			0.010**
			(0.004)			(0.004)
Salient_country	0.020	0.022	0.041	0.027	0.029	0.048
	(0.435)	(0.435)	(0.434)	(0.436)	(0.436)	(0.434)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year/month-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Country-fixed effects	No	No	No	No	No	No
Industry-fixed effects	No	No	No	Yes	Yes	Yes
Observations	336,565	336,565	336,565	336,565	336,565	336,565
R^2	0.128	0.128	0.128	0.128	0.128	0.128
Adjusted R^2	0.128	0.128	0.128	0.128	0.128	0.128
Residual Std. Error	11.627 (df = 336493)	11.627 (df = 336493)	11.627 (df = 336493)	11.627 (df = 336490)	11.627 (df = 336490)	11.627 (df = 336490)
Note:						*p<0.1; **p<0.05; ***p<0.01

Table 40: Effects of 2040 EBIT margin reductions on institutional ownership

Forecast year: 2040. The dependent variable is *IO*. The sample period is 2017 to 2022. All regressions include year/month-fixed effects, country-fixed effects, and industry-fixed effects. Industries are assigned according to the classification in the Trucost database. The table reports the results for the pooled regressions with standard errors double clustered at the firm and year level (in parentheses). *** 1% significance; ** 5% significance; * 10% significance.

	Dependent variable:		
	IO		
	(1)	(2)	(3)
EBIT2040Low	0.225 (0.107)		
EBIT2040Medium		0.105^{*} (0.040)	
EBIT2040High			0.064^{*} (0.027)
Controls	Yes	Yes	Yes
Year/month-fixed effects	Yes	Yes	Yes
Industry-fixed effects	Yes	Yes	Yes
Country-fixed effects	Yes	Yes	Yes
Observations	6,198	6,198	6,198
R^2	0.383	0.384	0.384
Adjusted R^2	0.376	0.376	0.376
Residual Std. Error (df = 6119)	13.810	13.805	13.808
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 41: Effects of 2050 EBIT margin reductions on institutional ownership

Forecast year: 2050. The dependent variable is *IO*. The sample period is 2017 to 2022. All regressions include year/month-fixed effects, country-fixed effects, and industry-fixed effects. Industries are assigned according to the classification in the Trucost database. The table reports the results for the pooled regressions with standard errors double clustered at the firm and year level (in parentheses). *** 1% significance; ** 5% significance; * 10% significance.

	Dependent variable:		
	IO		
	(1)	(2)	(3)
EBIT2050Low	0.129**		
	(0.035)		
EBIT2050Medium		0.041**	
		(0.011)	
EBIT2050High			0.058*
			(0.023)
Controls	Yes	Yes	Yes
Year/month-fixed effects	Yes	Yes	Yes
Industry-fixed effects	Yes	Yes	Yes
Country-fixed effects	Yes	Yes	Yes
Observations	6,198	6,198	6,198
R^2	0.384	0.384	0.384
Adjusted R^2	0.377	0.377	0.376
Residual Std. Error (df = 6119)	13.800	13.799	13.806
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 42: Effects of total 2040 unpriced carbon costs on institutional ownership

Forecast year: 2040. The dependent variable is *IO*. The sample period is 2017 to 2022. All regressions include year/month-fixed effects, country-fixed effects, and industry-fixed effects. Industries are assigned according to the classification in the Trucost database. The table reports the results for the pooled regressions with standard errors double clustered at the firm and year level (in parentheses). *** 1% significance; ** 5% significance; * 10% significance.

	Dependent variable:		
	IO		
	(1)	(2)	(3)
LogTotal2040Low	-0.399^{**}		
	(0.113)		
LogTotal2040Medium		-0.467^{*}	
		(0.173)	
LogTotal2040High			-0.493^{**}
			(0.171)
Controls	Yes	Yes	Yes
Year/month-fixed effects	Yes	Yes	Yes
Industry-fixed effects	Yes	Yes	Yes
Country-fixed effects	Yes	Yes	Yes
Observations	6,385	6,385	6,385
R^2	0.375	0.374	0.375
Adjusted R^2	0.367	0.367	0.367
Residual Std. Error (df = 6306)	13.955	13.958	13.955
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 43: Effects of total 2050 unpriced carbon costs on institutional ownership

Forecast year: 2050. The dependent variable is *IO*. The sample period is 2017 to 2022. All regressions include year/month-fixed effects, country-fixed effects, and industry-fixed effects. Industries are assigned according to the classification in the Trucost database. The table reports the results for the pooled regressions with standard errors double clustered at the firm and year level (in parentheses). *** 1% significance; ** 5% significance; * 10% significance.

	Dependent variable:		
	IO		
	(1)	(2)	(3)
LogTotal2050Low	-0.386^{**}		
	(0.118)		
LogTotal2050Medium		-0.488^{**}	
		(0.171)	
LogTotal2050High			-0.488^{**}
			(0.171)
Controls	Yes	Yes	Yes
Year/month-fixed effects	Yes	Yes	Yes
Industry-fixed effects	Yes	Yes	Yes
Country-fixed effects	Yes	Yes	Yes
Observations	6,385	6,385	6,385
R^2	0.374	0.375	0.375
Adjusted R^2	0.367	0.367	0.367
Residual Std. Error (df = 6306)	13.959	13.956	13.956
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 44: Effects of scope 1 2030 unpriced carbon costs on institutional ownership

Forecast year: 2030. The dependent variable is *IO*. The sample period is 2017 to 2022. All regressions include year/month-fixed effects, country-fixed effects, and industry-fixed effects. Industries are assigned according to the classification in the Trucost database. The table reports the results for the pooled regressions with standard errors double clustered at the firm and year level (in parentheses). *** 1% significance; ** 5% significance; * 10% significance.

	Dependent variable:		
	IO		
	(1)	(2)	(3)
LogScope12030Low	−0.127		
	(0.089)		
LogScope12030Medium		−0.160	
		(0.114)	
LogScope12030High			−0.245
			(0.119)
Controls	Yes	Yes	Yes
Year/month-fixed effects	Yes	Yes	Yes
Industry-fixed effects	Yes	Yes	Yes
Country-fixed effects	Yes	Yes	Yes
Observations	6,385	6,385	6,385
R^2	0.373	0.373	0.373
Adjusted R^2	0.365	0.365	0.366
Residual Std. Error (df = 6306)	13.976	13.976	13.968
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 45: Effects of scope 1 2040 unpriced carbon costs on institutional ownership

Forecast year: 2040. The dependent variable is *IO*. The sample period is 2017 to 2022. All regressions include year/month-fixed effects, country-fixed effects, and industry-fixed effects. Industries are assigned according to the classification in the Trucost database. The table reports the results for the pooled regressions with standard errors double clustered at the firm and year level (in parentheses). *** 1% significance; ** 5% significance; * 10% significance.

	Dependent variable:		
	IO		
	(1)	(2)	(3)
LogScope12040Low	-0.214^{*}		
	(0.092)		
LogScope12040Medium		-0.242	
		(0.120)	
LogScope12040High			-0.309^{*}
			(0.125)
Controls	Yes	Yes	Yes
Year/month-fixed effects	Yes	Yes	Yes
Industry-fixed effects	Yes	Yes	Yes
Country-fixed effects	Yes	Yes	Yes
Observations	6,385	6,385	6,385
R^2	0.373	0.373	0.374
Adjusted R^2	0.366	0.366	0.366
Residual Std. Error (df = 6306)	13.968	13.969	13.962
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 46: Effects of scope 1 2050 unpriced carbon costs on institutional ownership

Forecast year: 2050. The dependent variable is *IO*. The sample period is 2017 to 2022. All regressions include year/month-fixed effects, country-fixed effects, and industry-fixed effects. Industries are assigned according to the classification in the Trucost database. The table reports the results for the pooled regressions with standard errors double clustered at the firm and year level (in parentheses). *** 1% significance; ** 5% significance; * 10% significance.

	Dependent variable:		
	IO		
	(1)	(2)	(3)
LogScope12050Low	-0.212^{*}		
	(0.090)		
LogScope12050Medium		-0.318^{*}	
		(0.129)	
LogScope12050High			-0.318^{*}
			(0.129)
Controls	Yes	Yes	Yes
Year/month-fixed effects	Yes	Yes	Yes
Industry-fixed effects	Yes	Yes	Yes
Country-fixed effects	Yes	Yes	Yes
Observations	6,385	6,385	6,385
R^2	0.373	0.374	0.374
Adjusted R^2	0.366	0.366	0.366
Residual Std. Error (df = 6306)	13.969	13.962	13.962
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 47: Effects of scope 2 2030 unpriced carbon costs on institutional ownership

Forecast year: 2030. The dependent variable is *IO*. The sample period is 2017 to 2022. All regressions include year/month-fixed effects, country-fixed effects, and industry-fixed effects. Industries are assigned according to the classification in the Trucost database. The table reports the results for the pooled regressions with standard errors double clustered at the firm and year level (in parentheses). *** 1% significance; ** 5% significance; * 10% significance.

	Dependent variable:		
	IO		
	(1)	(2)	(3)
LogScope22030Low	-0.331^{**}		
	(0.075)		
LogScope22030Medium		-0.574^{**}	
		(0.142)	
LogScope22030High			-0.622^{**}
			(0.141)
Controls	Yes	Yes	Yes
Year/month-fixed effects	Yes	Yes	Yes
Industry-fixed effects	Yes	Yes	Yes
Country-fixed effects	Yes	Yes	Yes
Observations	6,385	6,385	6,385
R^2	0.374	0.375	0.376
Adjusted R^2	0.367	0.367	0.368
Residual Std. Error (df = 6306)	13.957	13.949	13.944
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 48: Effects of scope 2 2040 unpriced carbon costs on institutional ownership

Forecast year: 2040. The dependent variable is *IO*. The sample period is 2017 to 2022. All regressions include year/month-fixed effects, country-fixed effects, and industry-fixed effects. Industries are assigned according to the classification in the Trucost database. The table reports the results for the pooled regressions with standard errors double clustered at the firm and year level (in parentheses). *** 1% significance; ** 5% significance; * 10% significance.

	Dependent variable:		
	IO		
	(1)	(2)	(3)
LogScope22040Low	-0.389^{**}		
	(0.098)		
LogScope22040Medium		-0.598^{**}	
		(0.145)	
LogScope22040High			-0.614^{**}
			(0.144)
Controls	Yes	Yes	Yes
Year/month-fixed effects	Yes	Yes	Yes
Industry-fixed effects	Yes	Yes	Yes
Country-fixed effects	Yes	Yes	Yes
Observations	6,385	6,385	6,385
R^2	0.375	0.375	0.375
Adjusted R^2	0.367	0.368	0.368
Residual Std. Error (df = 6306)	13.954	13.948	13.946
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 49: Effects of scope 2 2050 unpriced carbon costs on institutional ownership

Forecast year: 2050. The dependent variable is *IO*. The sample period is 2017 to 2022. All regressions include year/month-fixed effects, country-fixed effects, and industry-fixed effects. Industries are assigned according to the classification in the Trucost database. The table reports the results for the pooled regressions with standard errors double clustered at the firm and year level (in parentheses). *** 1% significance; ** 5% significance; * 10% significance.

	Dependent variable:		
	IO		
	(1)	(2)	(3)
LogScope22050Low	-0.386^{**}		
	(0.096)		
LogScope22050Medium		-0.609^{**}	
		(0.145)	
LogScope22050High			-0.609^{**}
			(0.145)
Controls	Yes	Yes	Yes
Year/month-fixed effects	Yes	Yes	Yes
Industry-fixed effects	Yes	Yes	Yes
Country-fixed effects	Yes	Yes	Yes
Observations	6,385	6,385	6,385
R^2	0.375	0.375	0.375
Adjusted R^2	0.367	0.368	0.368
Residual Std. Error (df = 6306)	13.954	13.946	13.946
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 50: Interaction effects of total 2030 unpriced carbon costs and institutional ownership on stock returns

Forecast year: 2030. The dependent variable is *Return*. The sample period is 2017 to 2022. All regressions include year/month-fixed effects, country-fixed effects, and industry-fixed effects. Industries are assigned according to the classification in the Trucost database. The table reports the results for the pooled regressions with standard errors double clustered at the firm and year level (in parentheses). *** 1% significance; ** 5% significance; * 10% significance.

	Dependent variable:		
	Return		
	(1)	(2)	(3)
IO	−0.035	−0.038	−0.040
	(0.038)	(0.050)	(0.056)
LogTotal2030Low:IO	0.003		
	(0.003)		
LogTotal2030Medium:IO		0.003	
		(0.003)	
LogTotal2030High:IO			0.003
			(0.003)
Year/month-fixed effects	Yes	Yes	Yes
Industry-fixed effects	Yes	Yes	Yes
Country-fixed effects	Yes	Yes	Yes
Observations	6,385	6,385	6,385
R^2	0.203	0.203	0.203
Adjusted R^2	0.193	0.193	0.193
Residual Std. Error (df = 6303)	8.916	8.913	8.914
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 51: Interaction effects of total 2040 unpriced carbon costs and institutional ownership on stock returns

Forecast year: 2040. The dependent variable is *Return*. The sample period is 2017 to 2022. All regressions include year/month-fixed effects, country-fixed effects, and industry-fixed effects. Industries are assigned according to the classification in the Trucost database. The table reports the results for the pooled regressions with standard errors double clustered at the firm and year level (in parentheses). *** 1% significance; ** 5% significance; * 10% significance.

	Dependent variable:		
	Return		
	(1)	(2)	(3)
IO	−0.032	−0.038	−0.041
	(0.042)	(0.053)	(0.055)
LogTotal2040Low:IO	0.003		
	(0.003)		
LogTotal2040Medium:IO		0.003	
		(0.003)	
LogTotal2040High:IO			0.003
			(0.003)
Year/month-fixed effects	Yes	Yes	Yes
Industry-fixed effects	Yes	Yes	Yes
Country-fixed effects	Yes	Yes	Yes
Observations	6,385	6,385	6,385
R^2	0.203	0.203	0.203
Adjusted R^2	0.193	0.193	0.193
Residual Std. Error (df = 6303)	8.916	8.913	8.913
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 52: Interaction effects of total 2050 unpriced carbon costs and institutional ownership on stock returns

Forecast year: 2050. The dependent variable is *Return*. The sample period is 2017 to 2022. All regressions include year/month-fixed effects, country-fixed effects, and industry-fixed effects. Industries are assigned according to the classification in the Trucost database. The table reports the results for the pooled regressions with standard errors double clustered at the firm and year level (in parentheses). *** 1% significance; ** 5% significance; * 10% significance.

	Dependent variable:		
	Return		
	(1)	(2)	(3)
IO	−0.035	−0.042	−0.042
	(0.043)	(0.054)	(0.054)
LogTotal2050Low:IO	0.003		
	(0.003)		
LogTotal2050Medium:IO		0.003	
		(0.003)	
LogTotal2050High:IO			0.003
			(0.003)
Year/month-fixed effects	Yes	Yes	Yes
Industry-fixed effects	Yes	Yes	Yes
Country-fixed effects	Yes	Yes	Yes
Observations	6,385	6,385	6,385
R^2	0.203	0.203	0.203
Adjusted R^2	0.193	0.193	0.193
Residual Std. Error (df = 6303)	8.915	8.913	8.913
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 53: Interaction effects of 2030 EBIT margin reductions and institutional ownership on stock returns

Forecast year: 2030. The dependent variable is *Return*. The sample period is 2017 to 2022. All regressions include year/month-fixed effects, country-fixed effects, and industry-fixed effects. Industries are assigned according to the classification in the Trucost database. The table reports the results for the pooled regressions with standard errors double clustered at the firm and year level (in parentheses). *** 1% significance; ** 5% significance; * 10% significance.

	Dependent variable:		
	Return		
	(1)	(2)	(3)
IO	0.006	0.006	0.006
	(0.010)	(0.009)	(0.009)
EBIT2030Low:IO	0.003		
	(0.003)		
EBIT2030Medium:IO		0.001	
		(0.002)	
EBIT2030High:IO			0.001
			(0.001)
Year/month-fixed effects	Yes	Yes	Yes
Industry-fixed effects	Yes	Yes	Yes
Country-fixed effects	Yes	Yes	Yes
Observations	6,198	6,198	6,198
R^2	0.210	0.210	0.210
Adjusted R^2	0.200	0.200	0.200
Residual Std. Error (df = 6116)	8.660	8.661	8.661
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 54: Interaction effects of 2040 EBIT margin reductions and institutional ownership on stock returns

Forecast year: 2040. The dependent variable is *Return*. The sample period is 2017 to 2022. All regressions include year/month-fixed effects, country-fixed effects, and industry-fixed effects. Industries are assigned according to the classification in the Trucost database. The table reports the results for the pooled regressions with standard errors double clustered at the firm and year level (in parentheses). *** 1% significance; ** 5% significance; * 10% significance.

	Dependent variable:		
	Return		
	(1)	(2)	(3)
IO	0.006	0.006	0.006
	(0.010)	(0.009)	(0.009)
EBIT2040Low:IO	0.002		
	(0.002)		
EBIT2040Medium:IO		0.001	
		(0.001)	
EBIT2040High:IO			0.001
			(0.001)
Year/month-fixed effects	Yes	Yes	Yes
Industry-fixed effects	Yes	Yes	Yes
Country-fixed effects	Yes	Yes	Yes
Observations	6,198	6,198	6,198
R^2	0.210	0.210	0.210
Adjusted R^2	0.200	0.200	0.200
Residual Std. Error (df = 6116)	8.660	8.661	8.661
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 55: Interaction effects of 2050 EBIT margin reductions and institutional ownership on stock returns

Forecast year: 2050. The dependent variable is *Return*. The sample period is 2017 to 2022. All regressions include year/month-fixed effects, country-fixed effects, and industry-fixed effects. Industries are assigned according to the classification in the Trucost database. The table reports the results for the pooled regressions with standard errors double clustered at the firm and year level (in parentheses). *** 1% significance; ** 5% significance; * 10% significance.

	Dependent variable:		
	Return		
	(1)	(2)	(3)
IO	0.008	0.008	0.006
	(0.010)	(0.010)	(0.009)
EBIT2050Low:IO	0.0003		
	(0.001)		
EBIT2050Medium:IO		0.0002	
		(0.0004)	
EBIT2050High:IO			0.001
			(0.0005)
Year/month-fixed effects	Yes	Yes	Yes
Industry-fixed effects	Yes	Yes	Yes
Country-fixed effects	Yes	Yes	Yes
Observations	6,198	6,198	6,198
R^2	0.210	0.210	0.210
Adjusted R^2	0.199	0.199	0.200
Residual Std. Error (df = 6116)	8.662	8.662	8.661
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 56: Effects of 2040 EBIT margin reductions on disaggregate institutional ownership

Forecast year: 2040. The dependent variables are *Banks*, *Pensions*, *Insurance*, *Invest.Co.s*, *Advisors* and *Public*. EBIT margin reductions are transformed to positive values. The sample period is 2017 to 2022. All regressions include year/month-fixed effects, country-fixed effects and industry-fixed effects. Industries are assigned according to the classification in the Trucost database. The table reports the results for the pooled regressions with standard errors double clustered at the firm and year level (in parentheses). *** 1% significance; ** 5% significance; * 10% significance.

	Dependent variable:																	
	Banks			Pensions			Insurance			Invest.Co.s			Advisors			Public		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
EBIT2040Low	0.029			−0.047*			0.029			0.305			−0.179			−0.014		
	(0.024)			(0.021)			(0.018)			(0.190)			(0.095)			(0.115)		
EBIT2040Medium		0.008			−0.020*			0.011			0.115			−0.075*			0.023	
		(0.008)			(0.008)			(0.007)			(0.074)			(0.034)			(0.048)	
EBIT2040High			0.007			−0.014*			0.007			0.082			−0.048			−0.0001
			(0.007)			(0.005)			(0.005)			(0.050)			(0.024)			(0.032)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year/month-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,198	6,198	6,198	6,198	6,198	6,198	6,198	6,198	6,198	6,198	6,198	6,198	6,198	6,198	6,198	6,198	6,198	6,198
R^2	0.238	0.238	0.238	0.495	0.495	0.495	0.268	0.268	0.267	0.340	0.340	0.340	0.449	0.449	0.449	0.304	0.304	0.304
Adjusted R^2	0.228	0.228	0.228	0.489	0.489	0.489	0.258	0.258	0.258	0.332	0.332	0.332	0.442	0.442	0.442	0.295	0.295	0.295
Residual Std. Error (df = 6119)	1.977	1.978	1.977	2.930	2.930	2.930	1.921	1.921	1.921	21.154	21.154	21.153	14.186	14.185	14.186	10.481	10.480	10.481

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

Table 57: Effects of 2050 EBIT margin reductions on disaggregate institutional ownership

Forecast year: 2050. The dependent variables are *Banks*, *Pensions*, *Insurance*, *Invest.Co.s*, *Advisors* and *Public*. EBIT margin reductions are transformed into positive values. The sample period is 2017 to 2022. All regressions include year/month-fixed effects, country-fixed effects, and industry-fixed effects. Industries are assigned according to the classification in the Trucost database. The table reports the results for the pooled regressions with standard errors double clustered at the firm and year level (in parentheses). *** 1% significance; ** 5% significance; * 10% significance.

	Dependent variable:																	
	Banks			Pensions			Insurance			Invest.Co.s			Advisors			Public		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
EBIT2050Low	0.004			−0.013			0.012			0.143*			−0.030			−0.020		
	(0.007)			(0.007)			(0.007)			(0.064)			(0.039)			(0.046)		
EBIT2050Medium		0.002			−0.005*			0.003			0.045*			−0.012			−0.003	
		(0.003)			(0.002)			(0.002)			(0.020)			(0.012)			(0.015)	
EBIT2050High			0.006			−0.012*			0.006			0.071			−0.041			0.001
			(0.006)			(0.004)			(0.004)			(0.043)			(0.021)			(0.028)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year/month-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,198	6,198	6,198	6,198	6,198	6,198	6,198	6,198	6,198	6,198	6,198	6,198	6,198	6,198	6,198	6,198	6,198	6,198
R^2	0.237	0.237	0.238	0.495	0.495	0.495	0.268	0.267	0.268	0.340	0.340	0.340	0.448	0.448	0.449	0.304	0.304	0.304
Adjusted R^2	0.228	0.228	0.228	0.488	0.488	0.489	0.258	0.258	0.258	0.332	0.332	0.332	0.441	0.441	0.442	0.295	0.295	0.295
Residual Std. Error (df = 6119)	1.978	1.978	1.977	2.931	2.931	2.930	1.921	1.921	1.921	21.151	21.150	21.153	14.192	14.191	14.186	10.480	10.481	10.481

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

Table 58: Effects of total 2040 unpriced carbon costs on disaggregate institutional ownership

Forecast year: 2040. The dependent variables are *Banks*, *Pensions*, *Insurance*, *Invest.Co.s*, *Advisors* and *Public*. The sample period is 2017 to 2022. All regressions include year/month-fixed effects, country-fixed effects, and industry-fixed effects. Industries are assigned according to the classification in the Trucost database. The table reports the results for the pooled regressions with standard errors double clustered at the firm and year level (in parentheses). *** 1% significance; ** 5% significance; * 10% significance.

	Dependent variable:																	
	Banks			Pensions			Insurance			Invest.Co.s			Advisors			Public		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
LogTotal2040Low	0.039			−0.009			0.037^{*}			−0.283			-0.440^{*}			0.175		
	(0.020)			(0.023)			(0.014)			(0.206)			(0.169)			(0.102)		
LogTotal2040Medium		0.052^{*}			−0.048			0.062^{**}			−0.107			-0.783^{***}			0.262	
		(0.019)			(0.027)			(0.020)			(0.266)			(0.152)			(0.159)	
LogTotal2040High			0.053^{**}			−0.048			0.058^{**}			−0.114			-0.765^{***}			0.233
			(0.019)			(0.026)			(0.020)			(0.265)			(0.153)			(0.157)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year/month-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,385	6,385	6,385	6,385	6,385	6,385	6,385	6,385	6,385	6,385	6,385	6,385	6,385	6,385	6,385	6,385	6,385	6,385
R^2	0.237	0.237	0.237	0.491	0.492	0.492	0.268	0.269	0.269	0.338	0.337	0.337	0.449	0.452	0.451	0.301	0.301	0.301
Adjusted R^2	0.227	0.227	0.227	0.485	0.485	0.485	0.259	0.260	0.260	0.330	0.329	0.329	0.442	0.445	0.445	0.292	0.293	0.292
Residual Std. Error (df = 6306)	1.963	1.963	1.963	2.915	2.914	2.914	1.908	1.907	1.907	21.171	21.179	21.179	14.210	14.174	14.177	10.464	10.460	10.463

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

Table 59: Effects of total 2050 unpriced carbon costs on disaggregate institutional ownership

Forecast year: 2050. The dependent variables are *Banks*, *Pensions*, *Insurance*, *Invest.Co.s*, *Advisors* and *Public*. The sample period is 2017 to 2022. All regressions include year/month-fixed effects, country-fixed effects and industry-fixed effects. Industries are assigned according to the classification in the Trucost database. The table reports the results for the pooled regressions with standard errors double clustered at the firm and year level (in parentheses). *** 1% significance; ** 5% significance; * 10% significance.

	Dependent variable:																	
	Banks			Pensions			Insurance			Invest.Co.s			Advisors			Public		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
LogTotal2050Low	0.040			−0.014			0.041^{**}			−0.189			-0.510^{**}			0.171		
	(0.020)			(0.023)			(0.015)			(0.186)			(0.140)			(0.110)		
LogTotal2050Medium		0.053^{**}			−0.048			0.060^{**}			−0.115			-0.767^{***}			0.241	
		(0.019)			(0.026)			(0.020)			(0.266)			(0.153)			(0.158)	
LogTotal2050High			0.053^{**}			−0.048			0.060^{**}			−0.115			-0.767^{***}			0.241
			(0.019)			(0.026)			(0.020)			(0.266)			(0.153)			(0.158)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year/month-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,385	6,385	6,385	6,385	6,385	6,385	6,385	6,385	6,385	6,385	6,385	6,385	6,385	6,385	6,385	6,385	6,385	6,385
R^2	0.237	0.237	0.237	0.491	0.492	0.492	0.268	0.269	0.269	0.337	0.337	0.337	0.449	0.451	0.451	0.301	0.301	0.301
Adjusted R^2	0.227	0.227	0.227	0.485	0.485	0.485	0.259	0.260	0.260	0.329	0.329	0.329	0.443	0.445	0.445	0.292	0.292	0.292
Residual Std. Error (df = 6306)	1.963	1.963	1.963	2.915	2.914	2.914	1.908	1.907	1.907	21.176	21.179	21.179	14.202	14.177	14.177	10.465	10.462	10.462

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

Table 60: Effects of scope 1 2030 unpriced carbon costs on disaggregate institutional ownership

Forecast year: 2030. The dependent variables are *Banks*, *Pensions*, *Insurance*, *Invest.Co.s*, *Advisors* and *Public*. The sample period is 2017 to 2022. All regressions include year/month-fixed effects, country-fixed effects and industry-fixed effects. Industries are assigned according to the classification in the Trucost database. The table reports the results for the pooled regressions with standard errors double clustered at the firm and year level (in parentheses). *** 1% significance; ** 5% significance; * 10% significance.

	Dependent variable:																	
	Banks			Pensions			Insurance			Invest.Co.s			Advisors			Public		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
LogScope12030Low	0.026			−0.012			0.018			−0.105			-0.205^{**}			0.131^{*}		
	(0.014)			(0.016)			(0.013)			(0.125)			(0.069)			(0.059)		
LogScope12030Medium		0.034^{**}			−0.033			0.030			−0.034			-0.410^{***}			0.203^{*}	
		(0.012)			(0.017)			(0.014)			(0.158)			(0.086)			(0.076)	
LogScope12030High			0.036^{*}			−0.035			0.034			−0.105			-0.483^{***}			0.256^{**}
			(0.013)			(0.019)			(0.016)			(0.169)			(0.100)			(0.084)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year/month-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,385	6,385	6,385	6,385	6,385	6,385	6,385	6,385	6,385	6,385	6,385	6,385	6,385	6,385	6,385	6,385	6,385	6,385
R^2	0.236	0.237	0.237	0.491	0.492	0.492	0.267	0.268	0.268	0.337	0.337	0.337	0.448	0.450	0.450	0.301	0.302	0.303
Adjusted R^2	0.227	0.227	0.227	0.485	0.485	0.485	0.258	0.259	0.259	0.329	0.329	0.329	0.441	0.443	0.444	0.292	0.293	0.294
Residual Std. Error (df = 6306)	1.963	1.963	1.963	2.915	2.914	2.914	1.909	1.908	1.908	21.177	21.180	21.178	14.227	14.199	14.189	10.462	10.456	10.450

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

Table 61: Effects of scope 1 2040 unpriced carbon costs on disaggregate institutional ownership

Forecast year: 2040. The dependent variables are *Banks*, *Pensions*, *Insurance*, *Invest.Co.s*, *Advisors* and *Public*. The sample period is 2017 to 2022. All regressions include year/month-fixed effects, country-fixed effects, and industry-fixed effects. Industries are assigned according to the classification in the Trucost database. The table reports the results for the pooled regressions with standard errors double clustered at the firm and year level (in parentheses). *** 1% significance; ** 5% significance; * 10% significance.

	Dependent variable:																	
	Banks			Pensions			Insurance			Invest.Co.s			Advisors			Public		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
LogScope12040Low	0.021			−0.012			0.017			−0.186			-0.264^{**}			0.166^{*}		
	(0.014)			(0.020)			(0.015)			(0.139)			(0.075)			(0.064)		
LogScope12040Medium		0.037^{*}			−0.035			0.041^{*}			−0.109			-0.508^{***}			0.271^{**}	
		(0.014)			(0.019)			(0.016)			(0.177)			(0.103)			(0.095)	
LogScope12040High			0.039^{*}			−0.038			0.039^{*}			−0.163			-0.528^{***}			0.282^{**}
			(0.014)			(0.020)			(0.017)			(0.185)			(0.110)			(0.096)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year/month-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,385	6,385	6,385	6,385	6,385	6,385	6,385	6,385	6,385	6,385	6,385	6,385	6,385	6,385	6,385	6,385	6,385	6,385
R^2	0.236	0.237	0.237	0.491	0.492	0.492	0.267	0.269	0.268	0.338	0.337	0.337	0.448	0.451	0.451	0.301	0.303	0.303
Adjusted R^2	0.226	0.227	0.227	0.485	0.485	0.485	0.258	0.260	0.259	0.329	0.329	0.329	0.441	0.444	0.444	0.293	0.294	0.294
Residual Std. Error (df = 6306)	1.964	1.963	1.963	2.915	2.914	2.913	1.909	1.907	1.908	21.173	21.178	21.176	14.221	14.186	14.185	10.459	10.449	10.449

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

Table 62: Effects of scope 1 2050 unpriced carbon costs on disaggregate institutional ownership

Forecast year: 2050. The dependent variables are *Banks*, *Pensions*, *Insurance*, *Invest.Co.s*, *Advisors* and *Public*. The sample period is 2017 to 2022. All regressions include year/month-fixed effects, country-fixed effects and industry-fixed effects. Industries are assigned according to the classification in the Trucost database. The table reports the results for the pooled regressions with standard errors double clustered at the firm and year level (in parentheses). *** 1% significance; ** 5% significance; * 10% significance.

	Dependent variable:																	
	Banks			Pensions			Insurance			Invest.Co.s			Advisors			Public		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
LogScope12050Low	0.032*			−0.016			0.031*			−0.158			−0.307**			0.158*		
	(0.014)			(0.021)			(0.012)			(0.134)			(0.076)			(0.067)		
LogScope12050Medium		0.039*			−0.039			0.047**			−0.168			−0.552***			0.290**	
		(0.015)			(0.021)			(0.015)			(0.191)			(0.111)			(0.101)	
LogScope12050High			0.039*			−0.039			0.047**			−0.168			−0.552***			0.290**
			(0.015)			(0.021)			(0.015)			(0.191)			(0.111)			(0.101)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year/month-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,385	6,385	6,385	6,385	6,385	6,385	6,385	6,385	6,385	6,385	6,385	6,385	6,385	6,385	6,385	6,385	6,385	6,385
R^2	0.237	0.237	0.237	0.491	0.492	0.492	0.268	0.269	0.269	0.338	0.337	0.337	0.448	0.451	0.451	0.301	0.303	0.303
Adjusted R^2	0.227	0.227	0.227	0.485	0.485	0.485	0.259	0.260	0.260	0.329	0.329	0.329	0.442	0.444	0.444	0.293	0.294	0.294
Residual Std. Error (df = 6306)	1.963	1.963	1.963	2.915	2.913	2.913	1.908	1.907	1.907	21.175	21.176	21.176	14.215	14.183	14.183	10.461	10.448	10.448

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

Table 63: Effects of scope 2 2030 unpriced carbon costs on disaggregate institutional ownership

Forecast year: 2030. The dependent variables are *Banks*, *Pensions*, *Insurance*, *Invest.Co.s*, *Advisors* and *Public*. The sample period is 2017 to 2022. All regressions include year/month-fixed effects, country-fixed effects, and industry-fixed effects. Industries are assigned according to the classification in the Trucost database. The table reports the results for the pooled regressions with standard errors double clustered at the firm and year level (in parentheses). *** 1% significance; ** 5% significance; * 10% significance.

	Dependent variable:																	
	Banks			Pensions			Insurance			Invest.Co.s			Advisors			Public		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
LogScope22030Low	0.012			0.007			0.017			0.013			−0.351*			−0.094		
	(0.010)			(0.010)			(0.009)			(0.187)			(0.141)			(0.091)		
LogScope22030Medium		0.026			0.014			0.048*			0.094			−0.685**			−0.188	
		(0.022)			(0.025)			(0.019)			(0.253)			(0.177)			(0.153)	
LogScope22030High			0.027			0.015			0.044*			0.052			−0.677**			−0.196
			(0.022)			(0.026)			(0.019)			(0.255)			(0.177)			(0.158)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year/month-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,385	6,385	6,385	6,385	6,385	6,385	6,385	6,385	6,385	6,385	6,385	6,385	6,385	6,385	6,385	6,385	6,385	6,385
R^2	0.235	0.235	0.235	0.491	0.491	0.491	0.267	0.268	0.268	0.337	0.337	0.337	0.448	0.450	0.450	0.300	0.301	0.301
Adjusted R^2	0.226	0.226	0.226	0.485	0.485	0.485	0.258	0.259	0.259	0.329	0.329	0.329	0.442	0.443	0.443	0.292	0.292	0.292
Residual Std. Error (df = 6306)	1.965	1.965	1.964	2.915	2.915	2.915	1.909	1.908	1.909	21.180	21.179	21.180	14.214	14.196	14.198	10.468	10.466	10.466

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

Table 64: Effects of scope 2 2040 unpriced carbon costs on disaggregate institutional ownership

Forecast year: 2040. The dependent variables are *Banks*, *Pensions*, *Insurance*, *Invest.Co.s*, *Advisors* and *Public*. The sample period is 2017 to 2022. All regressions include year/month-fixed effects, country-fixed effects and industry-fixed effects. Industries are assigned according to the classification in the Trucost database. The table reports the results for the pooled regressions with standard errors double clustered at the firm and year level (in parentheses). *** 1% significance; ** 5% significance; * 10% significance.

	Dependent variable:																	
	Banks			Pensions			Insurance			Invest.Co.s			Advisors			Public		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
LogScope22040Low	0.014			0.016			0.022			−0.073			−0.373*			−0.079		
	(0.010)			(0.014)			(0.012)			(0.178)			(0.167)			(0.113)		
LogScope22040Medium		0.028			0.013			0.052*			0.054			−0.711**			−0.152	
		(0.023)			(0.027)			(0.019)			(0.265)			(0.181)			(0.160)	
LogScope22040High			0.029			0.014			0.047*			0.044			−0.679**			−0.183
			(0.022)			(0.026)			(0.019)			(0.263)			(0.179)			(0.160)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year/month-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,385	6,385	6,385	6,385	6,385	6,385	6,385	6,385	6,385	6,385	6,385	6,385	6,385	6,385	6,385	6,385	6,385	6,385
R^2	0.235	0.236	0.236	0.491	0.491	0.491	0.267	0.268	0.268	0.337	0.337	0.337	0.448	0.450	0.450	0.300	0.300	0.300
Adjusted R^2	0.226	0.226	0.226	0.485	0.485	0.485	0.258	0.259	0.259	0.329	0.329	0.329	0.441	0.443	0.443	0.291	0.292	0.292
Residual Std. Error (df = 6306)	1.965	1.964	1.964	2.915	2.915	2.915	1.909	1.908	1.908	21.179	21.180	21.180	14.217	14.194	14.198	10.469	10.468	10.466

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

Table 65: Effects of scope 2 2050 unpriced carbon costs on disaggregate institutional ownership

Forecast year: 2050. The dependent variables are *Banks*, *Pensions*, *Insurance*, *Invest.Co.s*, *Advisors* and *Public*. The sample period is 2017 to 2022. All regressions include year/month-fixed effects, country-fixed effects, and industry-fixed effects. Industries are assigned according to the classification in the Trucost database. The table reports the results for the pooled regressions with standard errors double clustered at the firm and year level (in parentheses). *** 1% significance; ** 5% significance; * 10% significance.

	Dependent variable:																	
	Banks			Pensions			Insurance			Invest.Co.s			Advisors			Public		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
LogScope22050Low	0.015			0.016			0.023			−0.076			−0.375*			−0.073		
	(0.010)			(0.013)			(0.012)			(0.176)			(0.163)			(0.112)		
LogScope22050Medium		0.030			0.014			0.048*			0.042			−0.680**			−0.176	
		(0.023)			(0.026)			(0.019)			(0.265)			(0.179)			(0.160)	
LogScope22050High			0.030			0.014			0.048*			0.042			−0.680**			−0.176
			(0.023)			(0.026)			(0.019)			(0.265)			(0.179)			(0.160)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year/month-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,385	6,385	6,385	6,385	6,385	6,385	6,385	6,385	6,385	6,385	6,385	6,385	6,385	6,385	6,385	6,385	6,385	6,385
R^2	0.235	0.236	0.236	0.491	0.491	0.491	0.267	0.268	0.268	0.337	0.337	0.337	0.448	0.450	0.450	0.300	0.300	0.300
Adjusted R^2	0.226	0.226	0.226	0.485	0.485	0.485	0.258	0.259	0.259	0.329	0.329	0.329	0.441	0.443	0.443	0.291	0.292	0.292
Residual Std. Error (df = 6306)	1.965	1.964	1.964	2.915	2.915	2.915	1.909	1.908	1.908	21.179	21.180	21.180	14.216	14.198	14.198	10.469	10.467	10.467

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

A.2 Supplementary figures

Figure 6: Log total unpriced carbon cost distribution

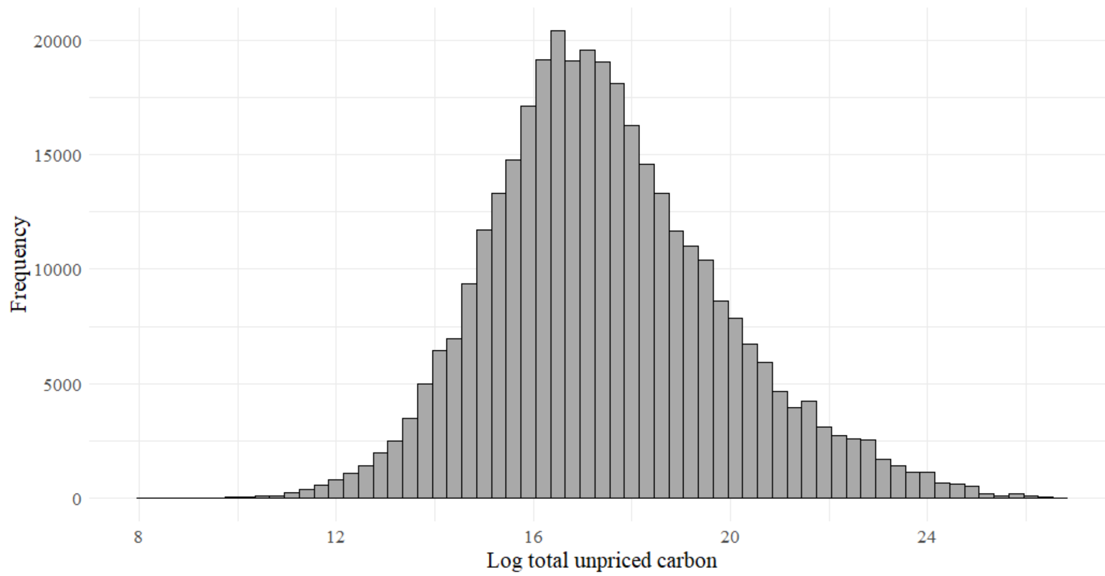


Figure 7: Log scope 1 unpriced carbon cost distribution

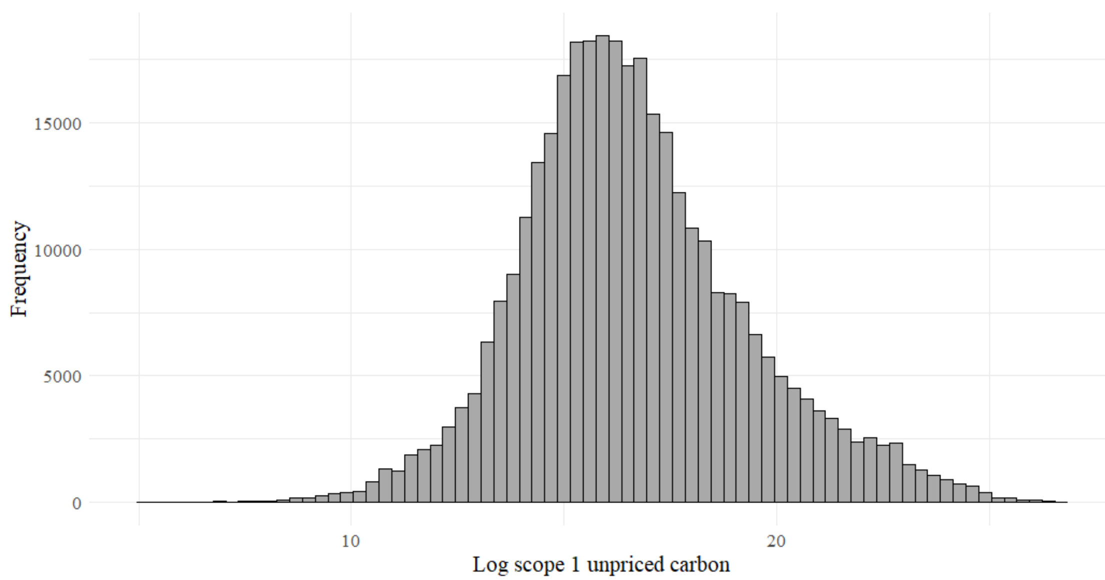


Figure 8: Log scope 2 unpriced carbon cost distribution

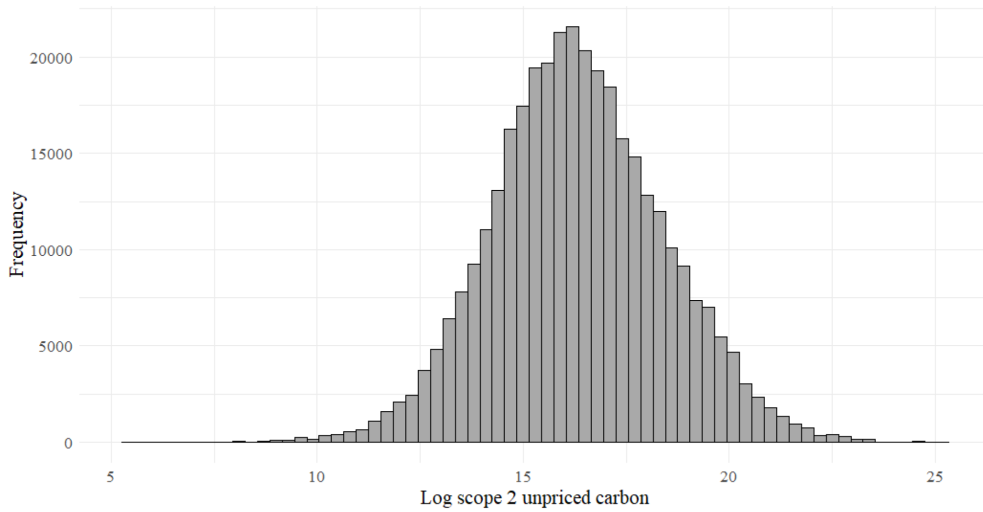


Figure 9: Return distribution

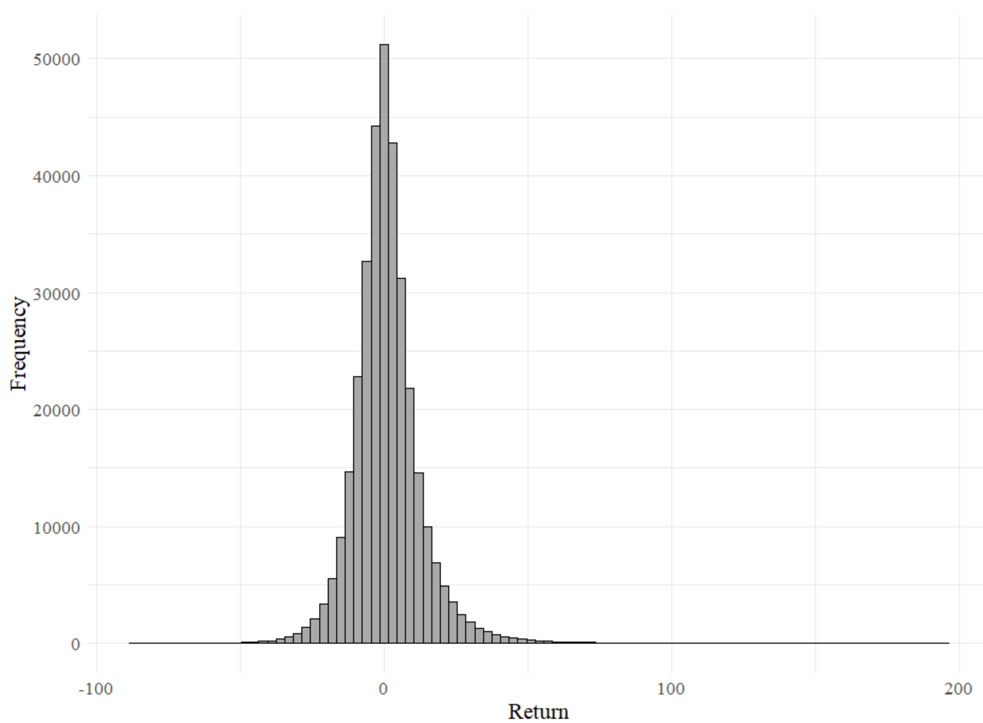


Figure 10: Institutional ownership distribution (%)

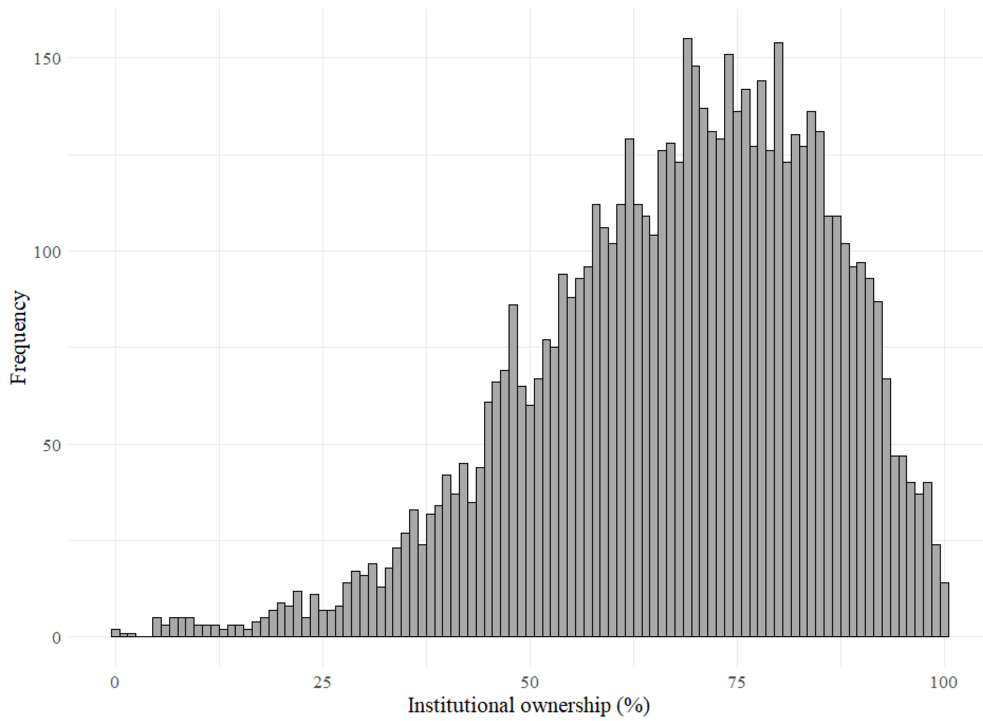
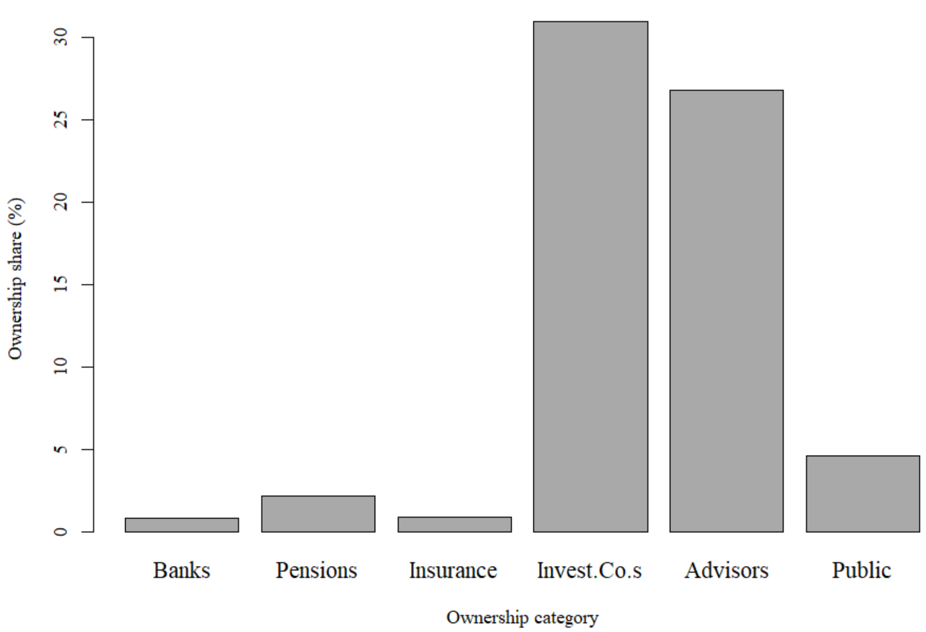


Figure 11: Categorical ownership mean share holdings (%)



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- that all parts of the thesis produced with the help of aids have been precisely declared;
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Carbon Costs and Green Innovation:

On the Market Pricing of Triggering and Muting Factors of Transition Risk

Erik Audun Sørensen*‡

24846

September 28, 2024

Abstract

In this paper, I estimate whether firm-level green innovation constitutes a significant mitigating factor in the pricing of carbon-transition risk using stock market data on 3,404 unique firms in 70 countries between 2016 and 2022. The results imply that green innovation does not significantly reduce the carbon-transition premium related to future carbon costs. Narrowing the focus to firms within the top five industries most exposed to carbon price increases according to Trucost, I find results indicating that the best green innovators within these brown industries experience a muting effect on the carbon-transition premium. However, the evidence diminishes when controlling for time-invariant country characteristics, underscoring the variability of countries' exposures and regulations related to climate change.

JEL Codes: G30, Q55

Keywords: Carbon cost, innovation, climate risk, transition risk

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†I would like to thank Prof. Anders Anderson for providing constructive guidance and suggestions throughout the work of this thesis

‡This paper is an extension of my thesis "Price of Tomorrow? Pricing future Carbon-Transition Risk"

1 Introduction

To what extent can green innovation mitigate the carbon-transition premium widely witnessed in global stock markets? In this paper, I estimate the effect of firm-level green innovativeness on the stock market's pricing of future carbon-transition risk. Using data consisting of estimated future carbon costs for the forecast years 2030, 2040, and 2050 under low, medium, and high carbon price scenarios as a proxy for carbon-transition risk together with data on firms' green innovation, I present an analysis aimed at uncovering the mitigating effects on the stock market-based carbon-transition premium. Taking advantage of a global dataset comprising 3,404 unique firms from 70 countries between 2016 and 2022, I find no conclusive results on the effect of green innovation in reducing the carbon-transition risk premium in the stock market. However, focusing solely on firms within the brownest industries in the sample, measured as the top five industries most severely exposed to increased future carbon costs, I find indications of reduced carbon-transition premiums due to firm-level green innovativeness. This finding is less robust when controlling for country-specific time-invariant effects, indicating that factors related to countries' characteristics and their perspectives on climate change are important drivers in pricing green innovation and carbon-transition risk. Despite this, the results imply that stock market investors view the best green innovators within these brown industries as different from the rest, signaled by insignificant results for firms within the low and middle ranges of green innovation.

The findings of this study complement the literature on climate-related risks in general and carbon-transition risk in particular. First, the findings outlined here offer additional insights into the muting factors of the carbon-transition premium. Bolton and Kacperczyk (2023) show that the level and growth in carbon emissions are consistently priced in the stock market due to investors' increasing climate awareness and risks related to the transition to carbon neutrality. Building on these findings, this paper indicates that green innovation is only weakly important in the stock market pricing of transition risk. Second, investors increasingly incorporate climate risks into investment decisions and aim to reduce portfolio carbon footprints by actively engaging with or divesting from firms. Several recent studies emphasize the heightened importance of climate risk, both physical risk and carbon-transition risk, in investment decisions and pricing of assets (Bolton and Kacperczyk, 2021; Bolton et al., 2022; Campiglio et al., 2023; Sautner et al., 2023b; Pástor et al., 2022; Sørensen, 2024), but corresponding analyses on green innovation is scarce. Hence, increasing climate awareness and concern yields the need to understand the impact of green innovation on the pricing of carbon-transition risk.

This study is interesting due to at least three reasons: First, the severity and frequency of extreme weather events, such as the 2024 California wildfires, is just one example of climate change's disturbing consequences. Year after year, it becomes increasingly evident that climate change poses one of the most significant challenges. If not addressed with the appropriate attention and actions, it will yield dire consequences. Politicians and national and supranational-level regulators will continue implementing policies to curb climate change. Along this path, risks and opportunities rise for firms: On the one hand, firms lagging will be subject to increasing carbon costs and heightened transition risk. Carbon-transition risk occurs as a result of increasing climate-related regulatory intervention and green technological advances putting brown technology at risk of becoming obsolete. For some firms, physical risks are also expected to increase as firms' assets are at risk of devaluation due to changing climate and extreme weather. On the other hand, opportunities are created for firms to be carbon leaders and green innovators. As climate regulations continue to tighten, green innovation is key to firms' successful climate transitions and can result in sustainable competitive advantages. Second, this paper's explicit focus on brown industries provides valuable insights for firms highly exposed to regulatory climate change risk. As we progress closer to the temperature increase limit set out at COP 21 in the 2015 Paris Agreement, policies to mitigate climate change and reduce carbon emissions are expected to increase in importance and frequency. Brown firms are especially prone to policy measures such as lowered emission ceilings in emission trading schemes (ETSs) and carbon taxes, increasing the importance of green innovation efforts. Third, in a broad sense, the paper is interesting for firms, investors, and regulators because it uncovers relationships between climate politics, corporate green innovation, costs of carbon emissions, and firms' costs of equity in a scenario-based context toward the net-zero commitments in the 2015 Paris Agreement.

The subsequent sections of the paper are organized as follows: Section 2 reviews and summarizes related research papers on green innovation and carbon-transition risk. Section 3 details the data used in the estimations. Section 4 demonstrates the methodology used in the paper and the regression setup. In Section 5, I present the results alongside brief analyses. In Section 6, I discuss possible driving factors behind the results and implications. Finally, the paper is concluded in Section 7.

2 Literature review

Do investors value green innovation? Extending on the conceptual framework of Pástor et al. (2022), stocks of firms with high levels of green innovation should trade at higher prices and exert lower returns in equilibrium. According to the framework, carbon-heavy firms are more risky than carbon-light firms, reflecting that brown firms need to drastically change their operations and be subject to increasing carbon costs going forward. In disequilibrium, green stocks can exert high returns, as has been the case in previous years. However, the authors show that this outperformance is due to unexpectedly strong increases in environmental concerns and not expected returns. If markets are in equilibrium, green stocks should exert lower returns on a medium- and long-term basis reflecting these firms' viability under increasing climate change. However, short-term price appreciation is likely to occur as investors increasingly incorporate and value firms' efforts to reduce carbon emissions. For this reason, the horizon on which the analysis is based can play a role in whether brown stocks are subject to increased carbon-transition premiums or not. In addition to the risk-based argument, a growing body of literature has uncovered investors' tastes for green assets. According to Siemroth and Hornuf (2023), using a decision experiment with crowd funders, retail investors invest in green projects because they prefer positive environmental impact over higher returns, conditional on a large enough impact. Can firms mitigate market participants' increasing climate-related return requirement by investing in green projects and R&D?

The pricing of climate-related risks and opportunities has been studied by several researchers and continues to gain momentum within the academic and professional spheres. Still, the literature remains inconsistent on the pricing of carbon-transition risk. As mentioned in the introduction, this risk can occur because of climate-related regulatory intervention and advances in green technology and innovation. Campiglio et al. (2023) conclude that most of the literature find that financial markets price climate-related risks. However, the risk premium varies across asset class, geography, and industry. Bolton and Kacperczyk (2021) find results implying that firms with higher levels and growth in carbon emissions experience higher stock returns and that traditional risk factors cannot explain this premium. In a later and related study, Bolton and Kacperczyk (2023) find similar results indicating that higher levels and growth in emissions are associated with higher stock returns and, further, that the carbon-emission growth premium is more significant in countries with lower economic development, larger energy sectors, and less inclusive political systems. Using the introduction of the Paris Agreement, the EU Green Deal, and the first climate strike, Alessi et al. (2023) conclude that European stock market investors tend to accept lower stock returns and hold greener and more transparent assets during credible green transition shifts. In a study conducted by Faccini et al. (2023), the authors explore climate change-related news from 2000 to 2018 and estimate the pricing of climate physical risk and carbon-transition risk. The authors conclude that regulatory risk, in the form of risks related to imminent government intervention, is priced in the U.S. stock market, while the results for physical risks remain insignificant. Similarly, Ramiah et al. (2016) study climate policy shocks' effect on British stock prices from 2003 to 2012 and find that environmental regulations increase volatility and generate abnormal returns, and further, that environmental policy affects the short- and long-run systematic risk of businesses.

Can green innovation mute the carbon-transition premium? The literature on this topic is inconclusive and can uncover important dynamics that are valuable for policymakers, investors, and firms. Technological innovations can reduce firms' carbon footprint by developing better solutions for clean energy and more energy-effective production. According to Popp (2011), a firm can reduce its carbon footprint in two ways: First, it can reduce its carbon intensity of energy use. That is, reducing carbon emissions per unit of energy consumed, for example, through greener energy sources such as wind and solar instead of fossil fuels. Second, firms can reduce their carbon footprint by reducing their energy intensity. This ratio constitutes a measure of a firm's energy efficiency, as Popp defines it as energy usage per dollar of output. More energy-efficient technologies contribute to higher output and GDP from a given amount of energy consumed. Calel (2020) shows that firms covered by the European Emissions Trading System (EU ETS) are incentivized to apply for low-carbon patents and increase related R&D expenditures. Similarly, Aghion et al. (2016) study innovation in the automobile industry and conclude that firms tend to innovate more in green technologies when subject to increasing tax-inclusive fuel prices. Using a global dataset, Cohen et al. (2020) show that the quantity and quality of green patenting are higher for firms in the energy sector than firms outside of it. Further, their results indicate that firms within the energy sector are often first-movers, are not easily substitutable, and produce foundational technology on which alternative energy sectors build. Also, the authors conclude that green patents produced by energy firms have a particular impact outside the traditional energy sectors, showcased by patents cited frequently and mimicked by green innovators. Using a machine learning keyword discovery algorithm to dissect firms' earnings calls, Sautner et al. (2023a) find a strong positive connection between attention paid to climate-related risks and job creation in green technologies and green patenting. Castro et al. (2021) study the relationship between stock market firm values from 2005 to 2017 in 16 European countries and environmental performance. The authors conclude that environmental performance is value-relevant, except during particularly pronounced market downturns. Moreover, their results indicate that green patents have a significant positive effect on the relationship between environmental performance and market values.

In a recent study by De Haas and Popov (2023) using a large panel consisting of countries and sectors from 1990 to 2015, the authors find results indicating a strong relationship between the financial structure of economies and carbon emission reductions. Specifically, the paper presents results showing that economies with financial structures with larger shares of equity-based financing are more successful at reducing carbon emissions. Further, they find that carbon-intensive industries emit relatively less in economies with deeper stock markets. Additionally, the authors conclude that deeper stock markets are related to higher green innovation within carbon-intensive industries. Hence, financial systems with larger shares of stock market financing seem to be better at enabling reductions in carbon emissions than financial systems with larger shares of bank-based financing. Importantly, deeper stock markets are related to increased green innovation in carbon-heavy sectors, possibly highlighting the stock market's ability in capital allocation and pricing of climate-related risks and opportunities. In a similar study using data on 38 countries, Brown et al. (2017) find a strong association between a country's stock market development and the size of its high-tech sector. Their findings support that deeper stock markets enable faster growth in innovation-heavy, high-tech industries, while credit markets foster growth in physical capital-heavy industries.

Using stock market data from 2013 to 2022 and the delayed introduction of the Chinese carbon trading markets, Chen et al. (2024) find that firms with low green innovation suffer more from the introduction of the carbon market, while firms with high green innovation are profitable. This effect can be understood in the context of the trade-off between "crowdingin effects”, in which environmental regulation is perceived as an additional constraint on the firms’ aim of profit maximization, and “compensatory effects”, in which green firms are compensated by, for example, selling surplus carbon credits in emission trading markets. In a related study, Chen et al. (2021) explore the relationship between green innovation and introducing carbon emission trading pilot programs in China. They find results suggesting that companies choose to reduce output rather than increase green innovation to meet carbon emission reduction targets and, further, that firms tend to reduce investments in R&D due to decreased expected cash flow and earnings.

Studying the impact of carbon taxes on green innovation, Fried (2018) concludes that carbon taxes induce significant changes in innovation and, further, that the innovation’s response to the carbon tax increases the effectiveness of the policy at reducing emissions. For example, the author shows that due to green innovation, the required size of the carbon tax decreases by almost 20 percent to reduce carbon emissions by 30 percent in 20 years. Similarly, Horbach et al. (2012) study the climate-related motivations for firms and conclude that regulatory intervention is an important factor in firms’ efforts to reduce emissions, avoid hazardous substances, and reduce water pollution and noise. Additionally, their study shows that cost saving remains a critical factor for firms in reducing energy and materials use, highlighting the importance of energy prices and carbon taxes in driving green innovation.

3 Data description

Green innovation scores and green innovation values are collected from LSEG/Refinitiv between 2016 and 2022. LSEG/Refinitiv collects over 630 firm-level ESG measures that form the overall firm assessment and scoring for over 12,500 firms globally. Generally, the ESG scores are metrics that measure firms’ performance based on verifiable public information, and these are calculated based on information collected from annual reports, company websites, stock exchange files, NGO websites, CSR reports, and news sources. The green innovation scores are determined from the green innovation values, which range from 0 to 1. Higher green innovation values correspond to better innovation scores. Green innovation scores range from A to D, where A corresponds to the highest innovation values and D to the lowest. Environmental innovation assessments are based on data on firms' product innovation, green revenues, green R&D, and green capital expenditures. LSEG/Refinitiv thus assigns firms a score that should capture the extent to which firms are green innovation leaders or laggards. The innovation scores reflect a firm's ability to reduce customer environmental costs and its capacity to create new green technology and open markets. Future unpriced carbon costs are taken from Trucost's Carbon Earnings at Risk dataset and consist of estimated corporate carbon costs in 2030, 2040, and 2050 under three different carbon price scenarios: Low, medium, and high. Annual firm fundamental variables are extracted from LSEG/Refinitiv WRDS Worldscope. Finally, monthly stock returns are computed from daily stock prices taken from LSEG/Refinitiv daily stock pricing files, which are adjusted for stock splits and dividends. Matching the data of future unpriced carbon costs and the green innovation scores renders a dataset consisting of 121,330 monthly firm observations, covering 3,404 unique firms from 70 countries. The firm-fundamental characteristics $LogSize_{i,t}$, $Book/Market_{i,t}$, $Leverage_{i,t}$, $Invest/Assets_{i,t}$, $LogPPE_{i,t}$, and $ROE_{i,t}$ are extracted for each firm i in the Trucost sample at year-end in year t. The variables are subsequently lagged by one year. $Volatility_{i,t}$ and $Momentum_{i,t}$ are calculated over a 12-month rolling window. Variables $Book/Market$, $Leverage$, $Invest/Assets$, ROE, $Volatility$, and $Momentum$ are winsorized at the 2.5% level to account for outliers. To account for exceptionally high returns and potential calculation errors in the stock pricing files, I follow the recommendation of WRDS Research Guide on Datastream and Worldscope and exclude observations where the monthly return exceeds 200% (Dai and Drechsler, 2021).

Table 1 presents descriptive statistics for the main variables used in the analyses in this paper. The table shows that LSEG/Refinitiv assigns 52.5% of the firms in the sample Green Innovation Score D. Green Innovation Score C, B, and A are assigned to 20.8%, 14.5%, and

Table 1: Descriptive statistics

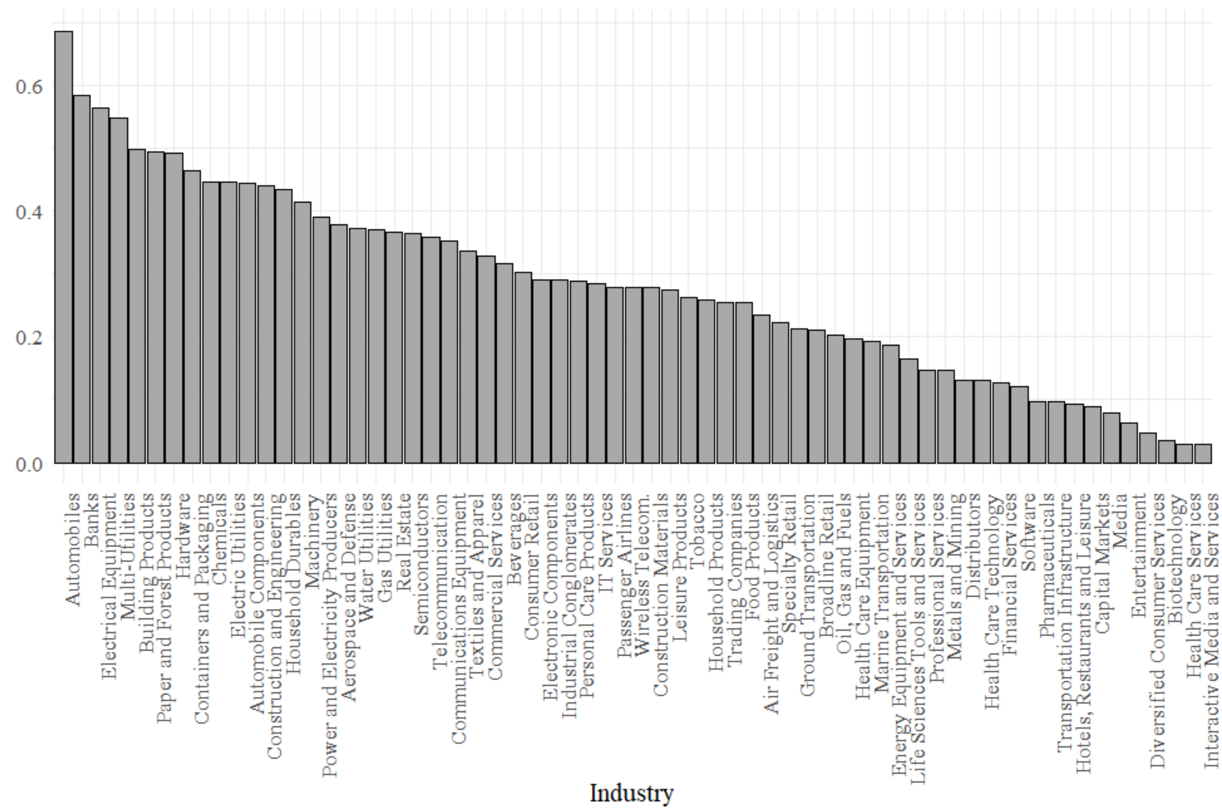
This table presents descriptive statistics for the variables used throughout the paper. Green innovation scores are extracted from LSEG/Refinitiv and transformed into binary variables. Future firm-level unpriced carbon costs are taken from Trucost Carbon Earnings at Risk. The future carbon costs are projected for the years 2030, 2040, and 2050. Three carbon price scenarios are presented relative to the 2-degree target set out in the 2015 Paris Agreement: Low, medium, and high. Firm fundamental variables are extracted from LSEG/Refinitiv WRDS Worldscope, while monthly returns are calculated from LSEG/Refinitiv daily stock pricing files adjusted for stock splits and dividends.

Statistic	Mean	Pctl(25)	Median	Pctl(75)	St. Dev.	N
LogTotal	16.190	14.511	16.136	17.839	2.583	121,330
LogScope1	15.146	13.197	15.028	17.064	3.102	121,330
LogScope2	14.853	13.425	15.082	16.607	2.497	121,330
GreenInnovationScoreA	0.121	0	0	0	0.326	121,330
GreenInnovationScoreB	0.145	0	0	0	0.352	121,330
GreenInnovationScoreC	0.208	0	0	0	0.406	121,330
GreenInnovationScoreD	0.525	0	1	1	0.499	121,330
Return (%)	1.004	−5.072	0.419	6.281	11.460	121,330
LogSize	8.038	7.131	8.082	8.925	1.396	121,330
Book/Market (winsorized at 2.5%)	0.722	0.280	0.556	0.963	0.624	121,330
Leverage (winsorized at 2.5%)	0.378	0.193	0.373	0.555	0.231	121,330
Momentum (%) (winsorized at 2.5%)	0.137	−0.153	0.049	0.313	0.453	121,330
Volatility (%) (winsorized at 2.5%)	32.007	20.831	28.492	38.984	16.473	121,330
Invest/Assets (winsorized at 2.5%)	0.076	0.022	0.050	0.100	0.079	121,330
ROE (%) (winsorized at 2.5%)	10.237	5.024	10.146	16.508	17.843	121,330
LogPPE	8.992	6.698	8.779	11.213	3.274	121,330

12.1% of the firms in the sample, respectively. The average monthly return for the firms in the sample is 1.004% with a median of 0.419%. Figure 1 shows the average green innovation value grouped by industry. According to the data, the automobile industry, banks, electrical equipment, multi-utilities, building products, and paper products have the highest green innovation values. According to the descriptions by LSEG/Refinitiv, these scores partially reflect firms' ability to reduce environmental costs and burdens for their customers, which might be one reason why many industries typically viewed as innovative are excluded from the top industries, such as biotechnology. In the right tail of Figure 1, presenting industries with the lowest green innovation values in the data, we find industries such as media, health care, biotechnology, consumer services, entertainment, and capital markets. Important carbon-emitting sectors such as oil and gas, airline, and industrial companies are located in the middle of the figure. Potentially, these industries are not located to the right in the figure because they are subject to significant environmental focus and pressure from regulators and society in general to reduce their carbon footprints.

Figure 1: Green innovation values grouped by industry

This figure describes the average green innovation value for each industry in the dataset. Innovation values are extracted from LSEG/Refinitiv between 2016 and 2022 and range from 0 to 1. The green innovation scores are assigned based on the green innovation values. Higher green innovation values correspond to better innovation scores. Green innovation scores range from A to D, where A corresponds to the highest innovation values and D to the lowest.



4 Methodology

In the first step, to analyze the impact of firm-level green innovativeness on the pricing of future carbon-transition risk, I estimate regressions according to Equation 1, inspired by the methodology of Bolton and Kacperczyk (2021) and Bolton and Kacperczyk (2023). In the regressions, $LogTotal$ corresponds to the log transformation of firms' estimated future total carbon costs in the forecast years 2030, 2040, and 2050 under the three carbon price scenarios low, medium, and high, as outlined in Section 3. The time index k corresponds to the forecast years 2030, 2040, and 2050. To estimate the mitigating effect of green innovation, I introduce an interaction term between future carbon costs and green innovation scores. The green innovation scores are transformed into binary variables. In Equations 1 and 2, δ_t denote month/year-fixed effects, θ_i denote country-fixed effects, and γ_i denote industry-fixed effects. X is a vector of control variables which includes $LogSize_{i,t}$, $Book/Market_{i,t}$, $Leverage_{i,t}$, $Invest/Assets_{i,t}$, $LogPPE_{i,t}$, $ROE_{i,t}$, $Momentum_{i,t}$, and $Volatility_{i,t}$. The firm-specific variables are lagged by one year, and $Momentum_{i,t}$ and $Volatility_{i,t}$ are computed over a 12-month rolling window. In the second step, providing some robustness to the analysis, I introduce a variable capturing firms' environmental product offerings, which serves as an alternative proxy for green innovation. The variable *GreenProducts* ranges from 0 to 1, with 0 corresponding to the lowest green product score and 1 to the highest. Green products might better signal successful green innovation to market participants than the green innovation scores because the latter is less prone to uncertain assumptions about green R&D and investments. Therefore, I estimate the following pooled OLS regressions to analyze the effect of green innovation scores and green products on the pricing of future carbon-transition risk, as seen in Equation 1 and 2.

$$\begin{aligned}Return_{i,t} = \alpha_0 + \beta_1 LogTotal_{i,k} + \beta_2 Green\ Innovation\ Score + \\ \beta_3 LogTotal_{i,k} \times Green\ Innovation\ Score + \beta X_{i,t-1} \\ + \delta_t + \theta_i + \gamma_i + \varepsilon_{i,t}\end{aligned} \tag{1}$$

$$\begin{aligned}Return_{i,t} = \alpha_0 + \beta_1 LogTotal_{i,k} + \beta_2 Green\ Products + \\ \beta_3 LogTotal_{i,k} \times Green\ Products + \beta X_{i,t-1} \\ + \delta_t + \theta_i + \gamma_i + \varepsilon_{i,t}\end{aligned} \tag{2}$$

The coefficient of interest is β_3, which should capture the impact of firm-level green innovation on the stock market's pricing of carbon-transition risk related to future expected increases in firms' carbon costs. If green innovation mitigates the carbon-transition risk premium, then the sign associated with β_3 should be negative. I hypothesize that environmental innovation scores capture firms' abilities to adjust their carbon emissions and, therefore, that the incremental impact of being a green innovator should reduce investors' climate-related risk premium. Further, since green innovation score A represents a higher level of environmental innovation than green innovation score D, I hypothesize that higher-order innovation will be more effective at reducing the carbon-transition premium.

5 Results

5.1 The effect of green innovativeness on the pricing of carbon-transition risk

To estimate whether the stock market price in an effect of firms' environmental innovation on the carbon-transition premium, I run pooled regressions according to Equation 1. The results using unpriced carbon costs in 2030 as proxy for carbon-transition risk are presented in Table 2. The base score for green innovation is set to D, which corresponds to the lowest green innovation value. The regressions include year/month-, country-, and industry-fixed effects. Standard errors are clustered at the firm and year level. Table 7 and 8 in the Appendix present the corresponding estimates for 2040 and 2050 unpriced carbon costs, respectively.

Importantly, the significance of the coefficients associated with unpriced carbon cost is lost when estimating this regression on the sample of firms for which green innovation data exists from LSEG/Refinitiv. Therefore, it seems that the carbon-transition risk premium is less robust for these firms on an aggregated basis than what is found when using a sample of firms not restricted to having innovation scores reported by LSEG/Refinitiv (Bolton and Kacperczyk, 2023; Sørensen, 2024). However, the signs of the coefficients related to unpriced carbon costs remain positive, while the signs of the coefficients representing green innovation scores are negative for all scores except for C in the low carbon cost scenario. Despite the correct hypothesized signs of the coefficients, all coefficients associated with green innovation are without statistical significance at any reasonable level. Comparing the interaction term coefficients, the magnitude differs for different environmental innovation scores. Somewhat surprisingly, environmental innovation score B seems to present the most negative effect on the pricing of the carbon-transition risk premium, while coefficients for green innovation score A and C are less negative. A similar trend is found for the forecast years 2040 and 2050, which can be seen in the Appendix in Tables 7 and 8. Comparing the coefficients of the interaction term across carbon cost scenarios, the table presents a general negative trend. From columns (1) to (3), the coefficients for each innovation score become more negative as one moves to higher 2030 carbon cost scenarios. Neglecting the statistical insignificance, such a trend can be explained by the relative importance of firm-level green R&D and technology development under more severe carbon cost scenarios. For example, the high carbon cost scenario assumes that regulators implement policies that increase the 2030 carbon price abruptly and drastically enough to be on the trajectory to reach the 2-degree Celsius target set out in the 2015 Paris Agreement. The greatest carbon emitters face the most significant transition risk, particularly in such a scenario, increasing the relative importance of green innovation efforts and their potential to mitigate the heightened carbon costs.

The main finding from the analysis and results presented in Table 2 is that, overall, green innovation does not reduce the stock market's pricing of the carbon-transition premium. Investigating the reasons for this conclusion is interesting because it can help firms and investors understand the mechanisms that undermine innovation's capacity to reduce the transition premium. One possible explanation is related to the nature of transition risk and its tight coupling with regulatory risk. Despite a firm being a green innovator, market participants might have the belief that innovation isolated does not reduce climate-related regulation risk. Policymakers are primarily concerned about reducing carbon emissions, and

Table 2: Effects of green innovation on the pricing of total 2030 unpriced carbon costs

The table presents fixed effects regressions with a firm's monthly stock return as the dependent variable. The main independent variables are estimated firm-level carbon costs for the forecast year 2030 and green innovation scores. Columns (1), (2), and (3) represent the low, medium, and high carbon cost scenarios, respectively. The sample period is 2017 to 2022. All regressions include year/month-fixed effects, country-fixed effects, and industry-fixed effects. Green innovation scores are collected from LSEG/Refinitiv, range from A to D, and are transformed into binary variables. Green innovation score A corresponds to the highest green innovation score and D to the lowest. Firm control variables include $LogSize_{i,t}$, $Book/Market_{i,t}$, $Leverage_{i,t}$, $Invest/Assets_{i,t}$, $LogPPE_{i,t}$, $ROE_{i,t}$, $Momentum_{i,t}$, and $Volatility_{i,t}$. The firm characteristic variables are lagged by one year, and $Momentum_{i,t}$ and $Volatility_{i,t}$ are computed over a 12-month rolling window. Industries are assigned according to the classification in the Trucost database. The table reports the results for the pooled regressions with standard errors double clustered at the firm and year level (in parentheses). *** 1% significance; ** 5% significance; * 10% significance.

	Dependent variable:		
	Return		
	(1) Low	(2) Medium	(3) High
LogTotal2030	0.025	0.048	0.062*
	(0.023)	(0.033)	(0.037)
LogTotal2030 × GreenInnovationScoreA	−0.002		
	(0.031)		
LogTotal2030 × GreenInnovationScoreB	−0.028		
	(0.028)		
LogTotal2030 × GreenInnovationScoreC	0.008		
	(0.024)		
LogTotal2030 × GreenInnovationScoreA		−0.007	
		(0.043)	
LogTotal2030 × GreenInnovationScoreB		−0.049	
		(0.038)	
LogTotal2030 × GreenInnovationScoreC		−0.0001	
		(0.035)	
LogTotal2030 × GreenInnovationScoreA			−0.013
			(0.043)
LogTotal2030 × GreenInnovationScoreB			−0.054
			(0.041)
LogTotal2030 × GreenInnovationScoreC			−0.010
			(0.033)
Controls	Yes	Yes	Yes
Year/month-fixed effects	Yes	Yes	Yes
Country-fixed effects	Yes	Yes	Yes
Industry-fixed effects	Yes	Yes	Yes
Observations	121,330	121,330	121,330
R^2	0.170	0.170	0.170
Adjusted R^2	0.169	0.169	0.169
Residual Std. Error (df = 121181)	10.446	10.446	10.446
Note:			*p<0.1; **p<0.05; ***p<0.01

it is, therefore, logical that the level of carbon emissions is of first-order importance for investors while less importance is given to green innovation. Another explanation is related to the ambiguous nature of innovation. It is unclear what technology will succeed and what regulation will emerge to reduce carbon emissions going forward. For example, disruptive green technology can prompt paradigm shifts for industries, but it is not clear whether LSEG/Refinitiv is able to "predict" and capture this in its assessments. Hence, the green innovation scores might not accurately reflect the innovation that enables carbon reductions for firms but rather innovation potentially aligning with climate change in a broader sense. Lastly, it can be that green innovation does not enable mitigation of a carbon-transition premium for all firms in all industries in the data. Potentially, green innovation is most relevant for reducing carbon-transition risk for the firms that are most exposed to carbon emissions to start with.

5.2 Brown industries

The aggregated analysis using all firms for which Trucost estimates the future cost of carbon and LSEG/Refinitiv assigns a green innovation score does not show any support for green innovation being a muting factor for the carbon-transition risk premium. This can be related to multiple factors. It can be that overall, green innovation is not consistently accounted for in the pricing of carbon-transition risk, but firms within certain industries can still see a stock market effect of increased green investments. Therefore, it is interesting to examine whether there exists some variation between industries. The question is whether carbon-heavy industries, which conceptually are greater subjects to climate-related risks, are different than firms in moderate carbon-emitting industries. Possibly, a carbon-heavy firm can show investors that although its current carbon footprint is extensive, the firm has devoted funds, attention, and effort to green projects and innovation to adjust and reduce its future carbon emissions. Moreover, firms within brown industries are becoming more greatly penalized on the stock market as investors' climate awareness and concern increases, and, therefore, it is likely valuable for these firms to differentiate themselves from other firms in the same industry. Thus, it is an important channel of differentiation for the firms in the brownest industries to invest more in green R&D and green projects, signaling to the market that the firm has intentions of adjusting towards the net-zero economy. The brownest industries are especially interesting because the literature seems to find that these industries are subject to increasing carbon-transition risk premiums, see for instance Bolton and Kacperczyk (2021), Bolton and Kacperczyk (2023), and (Sørensen, 2024), and further, there is likely large differences between firms in these industries.

For these reasons, I run similar regressions as in Section 5.1, but solely on a dataset consisting of the top 5 industries that are estimated to be the most exposed to EBIT margin reductions (and also future unpriced carbon costs) according to Trucost. These industries are construction materials, energy producers, metals and mining, chemicals, and oil, gas and fuels. Figure 2 and 3 in the Appendix presents the estimated total future carbon costs and EBIT margin reductions by Trucost grouped by industry and forms the decision on which industries to include in this analysis. Table 3 presents the results of running pooled regressions on a sample consisting of 18,884 monthly observations on 514 unique companies. All regressions in the table include year/month-fixed effects, and specifications (4) to (6) additionally include country-fixed effects. Tables 9 and 10 in the Appendix present the corresponding regression estimates for 2040 and 2050, respectively.

The findings in Table 3 show a somewhat different effect than what was uncovered in Tables 2, 7, and 8 using the overall sample of firms. For firms within commonly considered brown industries, there seems to be some relationship between green innovation scores and future unpriced carbon costs on stock returns. Interestingly, green innovation score A is associated with a decrease in the carbon-transition premium related to future unpriced carbon costs, on average. This also holds when including country-fixed effects, as shown in column (4), although the statistical significance drops from 1% to 10%. However, only green innovation

Table 3: Brown industries - Effects of green innovation on the pricing of total 2030 unpriced carbon costs

The table presents fixed effects regressions with a firm's monthly stock return as the dependent variable. The main independent variables are estimated firm-level carbon costs for the forecast year 2030 and green innovation scores. The columns represent the three different carbon price scenarios in the Trucost data. The sample period is 2017 to 2022. The sample includes firms estimated to be the most exposed to increased carbon costs according to Trucost. The industries included are construction materials, power producers, metals and mining, chemicals, oil, gas, and fuels. All regressions include year/month-fixed effects and specifications (4) to (6) additionally include country-fixed effects. Green innovation scores are collected from LSEG/Refinitiv, range from A to D, and are transformed into binary variables. Green innovation score A corresponds to the highest green innovation score and D to the lowest. Firm control variables include $LogSize_{i,t}$, $Book/Market_{i,t}$, $Leverage_{i,t}$, $Invest/Assets_{i,t}$, $LogPPE_{i,t}$, $ROE_{i,t}$, $Momentum_{i,t}$, and $Volatility_{i,t}$. The firm characteristic variables are lagged by one year, and $Momentum_{i,t}$ and $Volatility_{i,t}$ are computed over a 12-month rolling window. Industries are assigned according to the Trucost classification. The table reports the results for the pooled regressions with standard errors double clustered at the firm and year level (in parentheses). *** 1% significance; ** 5% significance; * 10% significance.

	Dependent variable:					
	Return					
	(1)	(2)	(3)	(4)	(5)	(6)
	Low	Medium	High	Low	Medium	High
LogTotal2030	0.052	0.066	0.077	−0.047	−0.047	−0.033
	(0.055)	(0.091)	(0.089)	(0.065)	(0.098)	(0.096)
LogTotal2030 × GreenInnovationScoreA	−0.173***			−0.119*		
	(0.061)			(0.064)		
LogTotal2030 × GreenInnovationScoreB	−0.066			0.002		
	(0.092)			(0.092)		
LogTotal2030 × GreenInnovationScoreC	−0.001			0.002		
	(0.070)			(0.064)		
LogTotal2030 × GreenInnovationScoreA		−0.185*			−0.136	
		(0.099)			(0.100)	
LogTotal2030 × GreenInnovationScoreB		−0.124			−0.077	
		(0.136)			(0.118)	
LogTotal2030 × GreenInnovationScoreC		−0.047			−0.027	
		(0.077)			(0.070)	
LogTotal2030 × GreenInnovationScoreA			−0.192*			−0.133
			(0.099)			(0.095)
LogTotal2030 × GreenInnovationScoreB			−0.140			−0.081
			(0.123)			(0.105)
LogTotal2030 × GreenInnovationScoreC			−0.060			−0.036
			(0.079)			(0.071)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year/month-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Country-fixed effects	No	No	No	Yes	Yes	Yes
Industry-fixed effects	No	No	No	No	No	No
Observations	18,884	18,884	18,884	18,884	18,884	18,884
R^2	0.195	0.195	0.195	0.199	0.199	0.199
Adjusted R^2	0.192	0.192	0.192	0.194	0.194	0.194
Residual Std. Error	11.275 (df = 18810)	11.275 (df = 18810)	11.275 (df = 18810)	11.260 (df = 18759)	11.260 (df = 18759)	11.260 (df = 18759)

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

score A seems to have a somewhat consistent muting effect on the transition premium related to 2030 unpriced carbon costs. For other innovation scores, the coefficients lose statistical significance when controlling for time-invariant country characteristics. Moreover, using the estimates in columns (1) to (3), the magnitude of the coefficient related to green innovation score A in the interaction term is stable with a slight increase as one moves to higher carbon cost scenarios, although the statistical significance is diminishing. Note, also, that the premium related to future unpriced carbon costs remain statistically insignificant, similarly as in Section 5.1.

The results presented here indicate that the best green innovators within the most exposed industries to increased carbon costs can somewhat mitigate the carbon-transition premium. The significance is somewhat robust for green innovation score A, but adding country-fixed effects reduces the significance substantially for all scores, as shown in columns (4) to (6). Although it is reasonable that the best green innovators are more effective at reducing the transition premium, it is interesting to explore why lower green innovation firms, especially those with green innovation score B, seem not to be gaining much from their green innovation efforts from a stock market perspective. This finding relates to at least two arguments: First, investors might require firms to be sufficiently green. That is, firms need to be at least over a certain threshold for investors to believe that the firm can adjust itself toward a more carbon-light future. Following this notion, firms need to be proven green innovators with an increased likelihood of succeeding in reducing their carbon emissions, which can be a reason why there is little room for deviation from the green innovation threshold. Second, because this analysis solely focuses on firms in brown industries, the argument about "carbon leaders and laggards" is likely stronger than for other industries. Green innovation is one way firms in these industries can differentiate themselves from the rest of their competitors, and logically, this diversification channel applies only to those firms that are innovation outliers.

5.3 Green products

The inconsistent findings of the impact of green innovation on the pricing of future carbon-transition risk might be related to scores not capturing investors' perceptions of corporate carbon mitigation. For instance, one possible scenario is that this information is less accessible to investors, or alternatively, investors have a pessimistic view of firms' ability to reduce future carbon emissions by being innovative. Another potential explanation is that investors do not view green innovation itself as a factor that reduces firms' exposure to transition risk as we move closer to 2050. Rather, it might be that investors use other information when analyzing firms' carbon emission exposure. To test this, I take advantage of LSEG/Refinitiv and its rich firm-level environmental data. From there, I extract data on firms' green product offerings. The green products variable captures firms' green product innovation with a value score ranging from 0 to 1. Using this data, I end up with a dataset consisting of 59,528 monthly observations with 1,732 unique firms.

According to Table 4, consistent with the findings in Section 5.1, the coefficients associated with the interaction term between future unpriced carbon costs and green product innovation are insignificant, implying that green product innovation has an insignificant impact on the pricing of carbon-transition risk in stock markets. These results suggest that efforts aimed at developing green products do not mitigate a potential carbon-transition risk premium associated with future carbon costs. Supporting results are found in Tables 11 and 12 in the Appendix showing estimates for 2040 and 2050 carbon costs, respectively. The lack of significant results is likely related to the same underlying dynamics as for the aggregated results using green innovation scores instead of the green product innovation variable. However, one can argue that green product innovation should be a weaker factor in muting the carbon-transition premium as it only constitutes one dimension of green innovation efforts. Therefore, it is somewhat unexpected that this analysis presents no evidence for green product innovation as a mitigating factor in pricing the transition premium.

Table 4: Effects of green product innovation on the pricing of total 2030 unpriced carbon costs

The table presents fixed effects regressions with a firm's monthly stock return as the dependent variable. The main independent variables are estimated firm-level carbon costs for the forecast year 2030 and green product innovation values. Columns (1), (2), and (3) represent the low, medium, and high carbon cost scenarios, respectively. The sample period is 2017 to 2022. All regressions include year/month-fixed effects, country-fixed effects, and industry-fixed effects. Firm control variables include $LogSize_{i,t}$, $Book/Market_{i,t}$, $Leverage_{i,t}$, $Invest/Assets_{i,t}$, $LogPPE_{i,t}$, $ROE_{i,t}$, $Momentum_{i,t}$, and $Volatility_{i,t}$. The firm characteristic variables are lagged by one year, and $Momentum_{i,t}$ and $Volatility_{i,t}$ are computed over a 12-month rolling window. Green product innovation data is extracted from LSEG/Refinitiv and ranges from 0 to 1, with 1 corresponding to the highest green product innovation value and 0 to the lowest. Industries are assigned according to the classification in the Trucost database. The table reports the results for the pooled regressions with standard errors double clustered at the firm and year level (in parentheses). *** 1% significance; ** 5% significance; * 10% significance.

	Dependent variable:		
	Return		
	(1)	(2)	(3)
	Low	Medium	High
LogTotal2030	0.029	0.044	0.060
	(0.107)	(0.145)	(0.142)
LogTotal2030 × GreenProducts	−0.022	−0.050	−0.068
	(0.131)	(0.192)	(0.185)
Controls	Yes	Yes	Yes
Year/month-fixed effects	Yes	Yes	Yes
Country-fixed effects	Yes	Yes	Yes
Industry-fixed effects	Yes	Yes	Yes
Observations	59,528	59,528	59,528
R^2	0.206	0.206	0.206
Adjusted R^2	0.204	0.204	0.204
Residual Std. Error (df = 59397)	9.649	9.649	9.649
Note:	*p<0.1; **p<0.05; ***p<0.01		

6 Discussion

The results obtained in Section 5.1 have shown that green innovation scores, as reported by LSEG/Refinitiv's ESG metrics and data, do not significantly reduce the carbon-transition premium in stock markets related to future increases in the cost of carbon. Because green innovation scores capture firms' product innovation, green revenues, green R&D, and green capital expenditures, these results can possibly serve as preliminary indications of a somewhat static and pessimistic investor perspective on firms' capacity to reduce carbon emissions by investing in green projects and technology. Potentially, investors incorporate information about carbon emissions while giving little importance to green innovation. At the extreme, this can lead to a dichotomous investor dynamic in which firms are either perceived to be "carbon leaders or losers" entirely based on current emission levels with little belief in environmental improvement. These results can be explained by the fact that the green innovation scores reported by LSEG/Refinitiv only reflect the current firm-level innovation and are less suited to proxy firms' future ability to reduce carbon costs. A related explanation supporting the findings of Faccini et al. (2023) is that regulatory risk is primarily a consequence of firm-level carbon emissions and does not include potential channels of emission reductions. Generally, policymakers do not account for green innovation but look at carbon emissions independently when forming climate policies. Therefore, regulatory risk remains viable even if a firm is environmentally innovative.

Further, in contrast to a major group of research papers, see, for instance, Bolton and Kacperczyk (2023), Cenedese et al. (2023), and Faccini et al. (2023), this paper struggles to find a consistent underlying transition premium for the aggregated sample of firms. This finding can be related to at least two factors: First, it can be explained by potential sample issues. It is possible that firms assigned with a green innovation score by LSEG/Refinitiv are systematically different than the firms without such scores, and further, that if a firm is assigned a green innovation score, the carbon-transition premium diminishes just by the fact that these firms have innovation data. Investors might require carbon-risk compensation from firms that lack green innovation data, while the firms that are included in the LSEG/Refinitiv database are less prone to this penalty because they can show efforts related to the green transition. Presumably, firms with green innovation data might be more transparent in annual reports and company presentations about their efforts to reduce carbon emissions by means of green innovation. If investors view this information as a critical factor in dissecting firms and their carbon-transition risks, it can explain the insignificant results related to the carbon-transition premium for this particular sample of firms. Second, a potential explanation for why any consistent carbon-transition premium related to future carbon costs could not be uncovered is connected to the time frame of this analysis. Following the model of Pástor et al. (2022), no consistent significant carbon-transition premium can be explained by stock markets not being in equilibrium. If this is true, green firms can see higher returns than brown firms, in contrast to the model's theoretical predictions. This occurs, according to the authors, under scenarios of unexpectedly high climate concerns. Since the data sample covers the period succeeding the 2015 Paris Agreement, one can imagine that high climate change concerns have resulted in upward pressure on green stocks, possibly reflected in the lack of consistent significance for the carbon-transition premium in the regressions. This argumentation aligns with the theoretical framework of Pástor et al. (2022), in which short-term price appreciation can occur for green assets. However, brown assets should trade at lower prices and exert higher returns over the medium and long term. Once stock markets reach equilibrium, I expect brown assets to be increasingly punished for lack of climate change readiness, leading to growing evidence of a systematic carbon-transition premium.

This raises the question of why firms in the brownest industries in the Trucost data seem to benefit from being green innovators, as shown in Section 5.2, standing in stark contrast to the aggregated results. There can be several reasons behind this insight, and it is likely a mix of multiple driving factors. One explanation is related to the significant pressure from policymakers, investors, and the public on brown firms to reduce their carbon emissions. Investing in green R&D and developing green products is likely one way brown firms can signal to stakeholders that the company is adjusting itself toward a net-zero economy. Additionally, brown firms are increasingly incentivized to be relatively greener than their competitors. This effect can materialize in two ways: Directly due to expected increases in firm-level carbon costs in the future, providing a cost benefit over the firm's competitors, and indirectly due to strategic reasons such as increasing investor and customer climate concerns and preference for greener products and services.

Lastly, it is interesting to explore why the effect of green innovation on the carbon-transition premium diminishes for brown firms when country-fixed effects are controlled for in the regressions. Because countries put varying degrees of importance on climate change and have different political agendas and regulatory frameworks related to carbon emissions, it is unsurprising that country-fixed effects impact the coefficients in the regressions and that the effect of green innovation is not uniform across countries. Most likely, adding country-fixed effects controls for the impact of different national carbon regulations. Since the coefficients become insignificant, country-specific regulatory environments might drive the relationship between green innovation and carbon-transition risk rather than green innovation alone. Further, countries are exposed to varying levels of physical risks, such as rising sea levels, wildfires, and drought, which could affect the pricing of carbon-transition risk and green innovation in stock markets. Insignificant findings are reasonable if, for example, investors view green innovation as an important mitigating channel on the carbon-transition premium solely in countries with high degrees of physical and/or regulatory climate change risk, while the same does not hold for countries with little exposure to such risks.

7 Conclusion

Expanding upon the growing body of literature on climate-related risks and opportunities, I have examined whether firm-level green innovation affects the stock market's pricing of carbon-transition risk. The underlying hypothesis is that better green technology should reflect firms' ability to reduce their reliance on processes emitting carbon in the future. Specifically, the insights uncovered throughout the analysis point to the direction that green innovation cannot mitigate the carbon-transition premium for all firms but that it can play a significant role for firms in carbon-heavy industries. Therefore, brown firms can potentially benefit from being the best green innovators, while on an aggregated basis, no muting effect could be found from green innovation on the pricing of carbon-transition risk.

The green innovation data collected, analyzed, and reported by LSEG/Refinitiv is far from perfect in reflecting a firm's ability to reduce its future costs of carbon. For example, the scores used throughout this paper cannot mirror more than current firm-level green innovation, limiting the appropriateness of this metric as a proxy for future carbon reductions. Since innovation can change abruptly, other proxies for firms' capabilities in carbon emission reduction may exist. Finding suitable and practical proxies for future carbon-neutrality alignment can extend this research further and will provide a valuable understanding of the factors that can help firms align with the 2-degree target set out in Paris in 2015. For example, using green patents was discussed during the development phase of this paper, and this data can potentially be valuable in similar analyses. However, due to the nature of patents clustering within a few industries, it was deemed less useful in this context. Moreover, further research on firms' approach to carbon emission reduction strategies related to the two fundamental pillars of energy efficiency and renewable energy is interesting and provides important insights for investors and regulators. Discovering and digging deeper into the driving factors behind each of the two pillars is relevant and a valuable contribution to the literature on the energy transition.

Much uncertainty exists around which scenarios will play out in the coming 30 years. Yet, it is clear that climate change mitigation will need to be at the forefront of investors', firms', and regulators' agenda to fulfill the net-zero commitments. Rising global temperatures and the continuing growth in climate awareness and concerns will lead to regulatory interventions such as increased carbon taxes and expanded ETSs aiming to raise the cost of carbon for firms. As carbon costs continue to rise, firms are increasingly punished for not reducing their emissions, spurring the need for green technological developments. Going forward, the pressure on firms to become green innovators will be a necessary parallel force along traditional carbon regulations. It is, therefore, in the best interest to formulate policies that foster firm-level green innovation and reductions in carbon emissions. After all, these stakeholders play a crucial role in shaping the future of carbon emissions.

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References

Aghion, P., A. Dechezleprêtre, D. Hemous, R. Martin, and J. Van Reenen (2016). Carbon taxes, path dependency, and directed technical change: Evidence from the auto industry. *Journal of Political Economy 124*(1), 1–51.

Alessi, L., E. Ossola, and R. Panzica (2023). When do investors go green? evidence from a time-varying asset-pricing model. *International review of financial analysis 90*, 102898.

Bolton, P., Z. Halem, and M. Kacperczyk (2022). The financial cost of carbon. *Journal of Applied Corporate Finance 34*(2), 17–29.

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

Bolton, P. and M. Kacperczyk (2023). Global pricing of carbon-transition risk. *The Journal of Finance 78*(6), 3677–3754.

Bose, S., K. Minnick, and S. Shams (2021). Does carbon risk matter for corporate acquisition decisions? *Journal of Corporate Finance 70*, 102058.

Brown, J. R., G. Martinsson, and B. C. Petersen (2017). Stock markets, credit markets, and technology-led growth. *Journal of Financial Intermediation 32*, 45–59.

Busch, T., A. Bassen, S. Lewandowski, and F. Sump (2022). Corporate carbon and financial performance revisited. *Organization & Environment 35*(1), 154–171.

Calel, R. (2020). Adopt or innovate: Understanding technological responses to cap-and-trade. *American Economic Journal: Economic Policy 12*(3), 170–201.

Campiglio, E., L. Daumas, P. Monnin, and A. von Jagow (2023). Climate-related risks in financial assets. *Journal of Economic Surveys 37*(3), 950–992.

Castro, P., C. Gutiérrez-López, M. T. Tascón, and F. J. Castaño (2021). The impact of environmental performance on stock prices in the green and innovative context. *Journal of Cleaner Production 320*, 128868.

Ceccarelli, M., S. Ramelli, and A. F. Wagner (2024). Low carbon mutual funds. *Review of Finance 28*(1), 45–74.

Cenedese, G., S. Han, and M. T. Kacperczyk (2023). Carbon-transition risk and net-zero portfolios. *Available at SSRN*.

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

Chen, F., Z. Chen, and X. Zhang (2024). Belated stock returns for green innovation under carbon emissions trading market. *Journal of Corporate Finance 85*, 102558.

Chen, Z., X. Zhang, and F. Chen (2021). Do carbon emission trading schemes stimulate green innovation in enterprises? evidence from china. *Technological Forecasting and Social Change 168*, 120744.

Cohen, L., U. G. Gurun, and Q. H. Nguyen (2020). The esg-innovation disconnect: Evidence from green patenting. Technical report, National Bureau of Economic Research.

Dai, R. and Q. F. S. Drechsler (2021). Research guide for datastream and worldscope at wharton research data services. *Research Guide for Datastream and Worldscope at Wharton Research Data Services (May 11, 2021)*.

De Haas, R. and A. Popov (2023). Finance and green growth. *The Economic Journal 133*(650), 637–668.

Delmas, M. A., N. Nairn-Birch, and J. Lim (2015). Dynamics of environmental and financial performance: The case of greenhouse gas emissions. *Organization & Environment 28*(4), 374–393.

Faccini, R., R. Matin, and G. Skiadopoulos (2023). Dissecting climate risks: Are they reflected in stock prices? *Journal of Banking & Finance 155*, 106948.

Fried, S. (2018). Climate policy and innovation: A quantitative macroeconomic analysis. *American Economic Journal: Macroeconomics 10*(1), 90–118.

Garvey, G. T., M. Iyer, and J. Nash (2018). Carbon footprint and productivity: Does the" e" in esg capture efficiency as well as environment? *Journal of Investment Management 16*(1), 59–69.

Ginglinger, E. and Q. Moreau (2023). Climate risk and capital structure. *Management Science 69*(12), 7492–7516.

Hoepner, A. G., I. Oikonomou, Z. Sautner, L. T. Starks, and X. Y. Zhou (2024). Esg shareholder engagement and downside risk. *Review of Finance 28*(2), 483–510.

Horbach, J., C. Rammer, and K. Rennings (2012). Determinants of eco-innovations by type of environmental impact—the role of regulatory push/pull, technology push and market pull. *Ecological economics 78*, 112–122.

Hsu, P.-H., K. Li, and C.-Y. Tsou (2023). The pollution premium. *The Journal of Finance 78*(3), 1343–1392.

Ilhan, E., P. Krueger, Z. Sautner, and L. T. Starks (2023). Climate risk disclosure and institutional investors. *The Review of Financial Studies 36*(7), 2617–2650.

Ilhan, E., Z. Sautner, and G. Vilkov (2021). Carbon tail risk. *The Review of Financial Studies 34*(3), 1540–1571.

International Carbon Action Partnership (2024). Compare EU ETS and China National ETS. https://icapcarbonaction.com/en/compare/55/43, Accessed: June 5, 2024.

Matsumura, E. M., R. Prakash, and S. C. Vera-Munoz (2014). Firm-value effects of carbon emissions and carbon disclosures. *The accounting review 89*(2), 695–724.

Misani, N. and S. Pogutz (2015). Unraveling the effects of environmental outcomes and processes on financial performance: A non-linear approach. *Ecological economics 109*, 150–160.

Mitschke, L., P. Spielberger, and E. A. Sørensen (2024). The role of environmental innovativeness in the pricing of carbon-transition risk. *Research Seminar paper submitted at HSG in April 2024, 3 ECTS*.

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

Nordhaus, W. D. (1993). Optimal greenhouse-gas reductions and tax policy in the" dice" model. *The American Economic Review 83*(2), 313–317.

Norges Bank Investment Management (2024). Divesting from companies. https://www.nbim.no/en/responsible-investment/divesting-from-companies/, Accessed: May 24, 2024.

Pástor, L., R. F. Stambaugh, and L. A. Taylor (2022). Dissecting green returns. *Journal of Financial Economics 146*(2), 403–424.

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

Popp, D. (2011). International technology transfer, climate change, and the clean development mechanism. *Review of Environmental Economics and Policy*.

Ramiah, V., T. Morris, I. Moosa, M. Gangemi, and L. Puican (2016). The effects of announcement of green policies on equity portfolios: Evidence from the united kingdom. *Managerial Auditing Journal 31*(2), 138–155.

Robiou du Pont, Y. and M. Meinshausen (2018). Warming assessment of the bottom-up paris agreement emissions pledges. *Nature communications 9*(1), 4810.

Rohleder, M., M. Wilkens, and J. Zink (2022). The effects of mutual fund decarbonization on stock prices and carbon emissions. *Journal of Banking & Finance 134*, 106352.

Sautner, Z., L. Van Lent, G. Vilkov, and R. Zhang (2023a). Firm-level climate change exposure. *The Journal of Finance 78*(3), 1449–1498.

Sautner, Z., L. Van Lent, G. Vilkov, and R. Zhang (2023b). Pricing climate change exposure. *Management Science 69*(12), 7540–7561.

Siemroth, C. and L. Hornuf (2023). Why do retail investors pick green investments? a lab-in-the-field experiment with crowdfunders. *Journal of Economic Behavior & Organization 209*, 74–90.

Slawinski, N. and P. Bansal (2015). Short on time: Intertemporal tensions in business sustainability. *Organization Science 26*(2), 531–549.

Sørensen, E. A. (2024). Price of tomorrow? Pricing future carbon-transition risk. *Master thesis submitted at HSG in June 2024, 18 ECTS*.

TCFD (2017). Recommendations of the task force on climate-related financial disclosures. https://assets.bbhub.io/company/sites/60/2021/10/FINAL-2017-TCFD-Report.pdf, Accessed: May 4, 2024.

UN Emissions Gap Report (2023). Broken record - temperatures hit new highs, yet world fails to cut emissions (again). *UN Environment Programme*. https://doi.org/10.59117/20.500.11822/43922.

Zerbib, O. D. (2022). A sustainable capital asset pricing model (s-capm): Evidence from environmental integration and sin stock exclusion. *Review of Finance 26*(6), 1345–1388.

Table 5: Declaration of use of language models

Language model AI tool	Usage	Affected sections
ChatGPT	Grammar, vocabulary, and sentence structure improvement	Section 1-7
Grammarly	Grammar, vocabulary, and sentence structure improvement	Section 1-7

A Appendix

A.1 Supplementary tables

Table 6: Green innovation values and green products variables: Correlations

	(1)	**(2)**
(1) Green Innovation Value	1.000	0.093
(2) Green Products	0.093	1.000

Note. Pairwise correlation matrix for the innovation variables used in the main analyses throughout this paper.

Table 7: Effects of green innovation on the pricing of total 2040 unpriced carbon costs

The table presents fixed effects regressions with a firm's monthly stock return as the dependent variable. The main independent variables are estimated firm-level carbon costs for the forecast year 2040 and green innovation scores. Columns (1), (2), and (3) represent the low, medium, and high carbon cost scenarios, respectively. The sample period is 2017 to 2022. All regressions include year/month-fixed effects, country-fixed effects, and industry-fixed effects. Green innovation scores are collected from LSEG/Refinitiv, range from A to D, and are transformed into binary variables. Green innovation score A corresponds to the highest green innovation score and D to the lowest. Firm control variables include $LogSize_{i,t}$, $Book/Market_{i,t}$, $Leverage_{i,t}$, $Invest/Assets_{i,t}$, $LogPPE_{i,t}$, $ROE_{i,t}$, $Momentum_{i,t}$, and $Volatility_{i,t}$. The firm characteristic variables are lagged by one year, and $Momentum_{i,t}$ and $Volatility_{i,t}$ are computed over a 12-month rolling window. Industries are assigned according to the classification in the Trucost database. The table reports the results for the pooled regressions with standard errors double clustered at the firm and year level (in parentheses). *** 1% significance; ** 5% significance; * 10% significance.

	Dependent variable:		
	Return		
	(1) Low	(2) Medium	(3) High
LogTotal2040	0.031	0.052	0.061
	(0.024)	(0.038)	(0.038)
LogTotal2040 × GreenInnovationScoreA	−0.004		
	(0.032)		
LogTotal2040 × GreenInnovationScoreB	−0.036		
	(0.029)		
LogTotal2040 × GreenInnovationScoreC	0.010		
	(0.027)		
LogTotal2040 × GreenInnovationScoreA		−0.010	
		(0.045)	
LogTotal2040 × GreenInnovationScoreB		−0.054	
		(0.042)	
LogTotal2040 × GreenInnovationScoreC		−0.002	
		(0.035)	
LogTotal2040 × GreenInnovationScoreA			−0.015
			(0.043)
LogTotal2040 × GreenInnovationScoreB			−0.056
			(0.041)
LogTotal2040 × GreenInnovationScoreC			−0.008
			(0.033)
Controls	Yes	Yes	Yes
Year/month-fixed effects	Yes	Yes	Yes
Country-fixed effects	Yes	Yes	Yes
Industry-fixed effects	Yes	Yes	Yes
Observations	121,330	121,330	121,330
R^2	0.170	0.170	0.170
Adjusted R^2	0.169	0.169	0.169
Residual Std. Error (df = 121181)	10.446	10.446	10.446
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 8: Effects of green innovation on the pricing of total 2050 unpriced carbon costs

The table presents fixed effects regressions with a firm's monthly stock return as the dependent variable. The main independent variables are estimated firm-level carbon costs for the forecast year 2050 and green innovation scores. Columns (1), (2), and (3) represent the low, medium, and high carbon cost scenarios, respectively. The sample period is 2017 to 2022. All regressions include year/month-fixed effects, country-fixed effects, and industry-fixed effects. Green innovation scores are collected from LSEG/Refinitiv, range from A to D, and are transformed into binary variables. Green innovation score A corresponds to the highest green innovation score and D to the lowest. Firm control variables include $LogSize_{i,t}$, $Book/Market_{i,t}$, $Leverage_{i,t}$, $Invest/Assets_{i,t}$, $LogPPE_{i,t}$, $ROE_{i,t}$, $Momentum_{i,t}$, and $Volatility_{i,t}$. The firm characteristic variables are lagged by one year, and $Momentum_{i,t}$ and $Volatility_{i,t}$ are computed over a 12-month rolling window. Industries are assigned according to the classification in the Trucost database. The table reports the results for the pooled regressions with standard errors double clustered at the firm and year level (in parentheses). *** 1% significance; ** 5% significance; * 10% significance.

	Dependent variable:		
	Return		
	(1) Low	(2) Medium	(3) High
LogTotal2050	0.027	0.060	0.060
	(0.026)	(0.038)	(0.038)
LogTotal2050 × GreenInnovationScoreA	−0.005		
	(0.034)		
LogTotal2050 × GreenInnovationScoreB	−0.036		
	(0.032)		
LogTotal2050 × GreenInnovationScoreC	0.005		
	(0.028)		
LogTotal2050 × GreenInnovationScoreA		−0.015	
		(0.043)	
LogTotal2050 × GreenInnovationScoreB		−0.056	
		(0.041)	
LogTotal2050 × GreenInnovationScoreC		−0.007	
		(0.033)	
LogTotal2050 × GreenInnovationScoreA			−0.015
			(0.043)
LogTotal2050 × GreenInnovationScoreB			−0.056
			(0.041)
LogTotal2050 × GreenInnovationScoreC			−0.007
			(0.033)
Controls	Yes	Yes	Yes
Year/month-fixed effects	Yes	Yes	Yes
Country-fixed effects	Yes	Yes	Yes
Industry-fixed effects	Yes	Yes	Yes
Observations	121,330	121,330	121,330
R^2	0.170	0.170	0.170
Adjusted R^2	0.169	0.169	0.169
Residual Std. Error (df = 121181)	10.446	10.446	10.446
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 9: Brown industries - Effects of green innovation on the pricing of total 2040 unpriced carbon costs

The table presents fixed effects regressions with a firm's monthly stock return as the dependent variable. The main independent variables are estimated firm-level carbon costs for the forecast year 2040 and green innovation scores. The columns represent the three different carbon price scenarios in the Trucost data. The sample period is 2017 to 2022. The sample includes firms estimated to be the most exposed to increased carbon costs according to Trucost. The industries included are construction materials, power producers, metals and mining, chemicals, oil, gas, and fuels. All regressions include year/month-fixed effects and specifications (4) to (6) additionally include country-fixed effects. Green innovation scores are collected from LSEG/Refinitiv, range from A to D, and are transformed into binary variables. Green innovation score A corresponds to the highest green innovation score and D to the lowest. Firm control variables include $LogSize_{i,t}$, $Book/Market_{i,t}$, $Leverage_{i,t}$, $Invest/Assets_{i,t}$, $LogPPE_{i,t}$, $ROE_{i,t}$, $Momentum_{i,t}$, and $Volatility_{i,t}$. The firm characteristic variables are lagged by one year, and $Momentum_{i,t}$ and $Volatility_{i,t}$ are computed over a 12-month rolling window. Industries are assigned according to the Trucost classification. The table reports the results for the pooled regressions with standard errors double clustered at the firm and year level (in parentheses). *** 1% significance; ** 5% significance; * 10% significance.

	Dependent variable:					
	Return					
	(1)	(2)	(3)	(4)	(5)	(6)
	Low	Medium	High	Low	Medium	High
LogTotal2040	0.070	0.076	0.084	−0.024	−0.046	−0.034
	(0.060)	(0.094)	(0.093)	(0.067)	(0.102)	(0.101)
LogTotal2040 × GreenInnovationScoreA	−0.194**			−0.150*		
	(0.083)			(0.082)		
LogTotal2040 × GreenInnovationScoreB	−0.073			−0.009		
	(0.095)			(0.095)		
LogTotal2040 × GreenInnovationScoreC	−0.017			−0.009		
	(0.076)			(0.069)		
LogTotal2040 × GreenInnovationScoreA		−0.192*			−0.145	
		(0.101)			(0.103)	
LogTotal2040 × GreenInnovationScoreB		−0.132			−0.088	
		(0.143)			(0.123)	
LogTotal2040 × GreenInnovationScoreC		−0.046			−0.027	
		(0.078)			(0.071)	
LogTotal2040 × GreenInnovationScoreA			−0.197*			−0.140
			(0.101)			(0.099)
LogTotal2040 × GreenInnovationScoreB			−0.137			−0.082
			(0.128)			(0.108)
LogTotal2040 × GreenInnovationScoreC			−0.061			−0.036
			(0.078)			(0.069)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year/month-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Country-fixed effects	No	No	No	Yes	Yes	Yes
Industry-fixed effects	No	No	No	No	No	No
Observations	18,884	18,884	18,884	18,884	18,884	18,884
R^2	0.195	0.195	0.195	0.199	0.199	0.199
Adjusted R^2	0.192	0.192	0.192	0.194	0.194	0.194
Residual Std. Error	11.275 (df = 18810)	11.275 (df = 18810)	11.275 (df = 18810)	11.260 (df = 18759)	11.260 (df = 18759)	11.260 (df = 18759)

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

Table 10: Brown industries - Effects of green innovation on the pricing of total 2050 unpriced carbon costs

The table presents fixed effects regressions with a firm's monthly stock return as the dependent variable. The main independent variables are estimated firm-level carbon costs for the forecast year 2050 and green innovation scores. The columns represent the three different carbon price scenarios in the Trucost data. The sample period is 2017 to 2022. The sample includes firms estimated to be the most exposed to increased carbon costs according to Trucost. The industries included are construction materials, power producers, metals and mining, chemicals, oil, gas, and fuels. All regressions include year/month-fixed effects and specifications (4) to (6) additionally include country-fixed effects. Green innovation scores are collected from LSEG/Refinitiv, range from A to D, and are transformed into binary variables. Green innovation score A corresponds to the highest green innovation score and D to the lowest. Firm control variables include $LogSize_{i,t}$, $Book/Market_{i,t}$, $Leverage_{i,t}$, $Invest/Assets_{i,t}$, $LogPPE_{i,t}$, $ROE_{i,t}$, $Momentum_{i,t}$, and $Volatility_{i,t}$. The firm characteristic variables are lagged by one year, and $Momentum_{i,t}$ and $Volatility_{i,t}$ are computed over a 12-month rolling window. Industries are assigned according to the Trucost classification. The table reports the results for the pooled regressions with standard errors double clustered at the firm and year level (in parentheses). *** 1% significance; ** 5% significance; * 10% significance.

	Dependent variable:					
	Return					
	(1)	(2)	(3)	(4)	(5)	(6)
	Low	Medium	High	Low	Medium	High
LogTotal2050	0.066	0.084	0.084	−0.042	−0.038	−0.038
	(0.067)	(0.094)	(0.094)	(0.075)	(0.102)	(0.102)
LogTotal2050 × GreenInnovationScoreA	−0.193**			−0.141		
	(0.087)			(0.087)		
LogTotal2050 × GreenInnovationScoreB	−0.069			0.004		
	(0.099)			(0.101)		
LogTotal2050 × GreenInnovationScoreC	−0.015			0.003		
	(0.077)			(0.069)		
LogTotal2050 × GreenInnovationScoreA		−0.199*			−0.143	
		(0.102)			(0.100)	
LogTotal2050 × GreenInnovationScoreB		−0.136			−0.082	
		(0.129)			(0.110)	
LogTotal2050 × GreenInnovationScoreC		−0.060			−0.035	
		(0.078)			(0.069)	
LogTotal2050 × GreenInnovationScoreA			−0.199*			−0.143
			(0.102)			(0.100)
LogTotal2050 × GreenInnovationScoreB			−0.136			−0.082
			(0.129)			(0.110)
LogTotal2050 × GreenInnovationScoreC			−0.060			−0.035
			(0.078)			(0.069)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year/month-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Country-fixed effects	No	No	No	Yes	Yes	Yes
Industry-fixed effects	No	No	No	No	No	No
Observations	18,884	18,884	18,884	18,884	18,884	18,884
R^2	0.195	0.195	0.195	0.199	0.199	0.199
Adjusted R^2	0.192	0.192	0.192	0.194	0.194	0.194
Residual Std. Error	11.275 (df = 18810)	11.275 (df = 18810)	11.275 (df = 18810)	11.260 (df = 18759)	11.260 (df = 18759)	11.260 (df = 18759)

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

Table 11: Effects of green product innovation on the pricing of total 2040 unpriced carbon costs

The table presents fixed effects regressions with a firm's monthly stock return as the dependent variable. The main independent variables are estimated firm-level carbon costs for the forecast year 2040 and green product innovation values. Columns (1), (2), and (3) represent the low, medium, and high carbon cost scenarios, respectively. The sample period is 2017 to 2022. All regressions include year/month-fixed effects, country-fixed effects, and industry-fixed effects. Firm control variables include $LogSize_{i,t}$, $Book/Market_{i,t}$, $Leverage_{i,t}$, $Invest/Assets_{i,t}$, $LogPPE_{i,t}$, $ROE_{i,t}$, $Momentum_{i,t}$, and $Volatility_{i,t}$. The firm characteristic variables are lagged by one year, and $Momentum_{i,t}$ and $Volatility_{i,t}$ are computed over a 12-month rolling window. Green product innovation data is extracted from LSEG/Refinitiv and ranges from 0 to 1, with 1 corresponding to the highest green product innovation value and 0 to the lowest. Industries are assigned according to the classification in the Trucost database. The table reports the results for the pooled regressions with standard errors double clustered at the firm and year level (in parentheses). *** 1% significance; ** 5% significance; * 10% significance.

	Dependent variable:		
	Return		
	(1)	(2)	(3)
	Low	Medium	High
LogTotal2040	0.043	0.046	0.058
	(0.109)	(0.144)	(0.141)
LogTotal2040 × GreenProducts	−0.040	−0.059	−0.068
	(0.137)	(0.194)	(0.187)
Controls	Yes	Yes	Yes
Year/month-fixed effects	Yes	Yes	Yes
Country-fixed effects	Yes	Yes	Yes
Industry-fixed effects	Yes	Yes	Yes
Observations	59,528	59,528	59,528
R^2	0.206	0.206	0.206
Adjusted R^2	0.204	0.204	0.204
Residual Std. Error (df = 59397)	9.649	9.649	9.649
Note:	*p<0.1; **p<0.05; ***p<0.01		

Table 12: Effects of green product innovation on the pricing of total 2050 unpriced carbon costs

The table presents fixed effects regressions with a firm's monthly stock return as the dependent variable. The main independent variables are estimated firm-level carbon costs for the forecast year 2050 and green product innovation values. Columns (1), (2), and (3) represent the low, medium, and high carbon cost scenarios, respectively. The sample period is 2017 to 2022. All regressions include year/month-fixed effects, country-fixed effects, and industry-fixed effects. Firm control variables include $LogSize_{i,t}$, $Book/Market_{i,t}$, $Leverage_{i,t}$, $Invest/Assets_{i,t}$, $LogPPE_{i,t}$, $ROE_{i,t}$, $Momentum_{i,t}$, and $Volatility_{i,t}$. The firm characteristic variables are lagged by one year, and $Momentum_{i,t}$ and $Volatility_{i,t}$ are computed over a 12-month rolling window. Green product innovation data is extracted from LSEG/Refinitiv and ranges from 0 to 1, with 1 corresponding to the highest green product innovation value and 0 to the lowest. Industries are assigned according to the classification in the Trucost database. The table reports the results for the pooled regressions with standard errors double clustered at the firm and year level (in parentheses). *** 1% significance; ** 5% significance; * 10% significance.

	Dependent variable:		
	Return		
	(1)	(2)	(3)
	Low	Medium	High
LogTotal2050	0.052	0.053	0.053
	(0.116)	(0.141)	(0.141)
LogTotal2050 × GreenProducts	−0.059	−0.063	−0.063
	(0.143)	(0.187)	(0.187)
Controls	Yes	Yes	Yes
Year/month-fixed effects	Yes	Yes	Yes
Country-fixed effects	Yes	Yes	Yes
Industry-fixed effects	Yes	Yes	Yes
Observations	59,528	59,528	59,528
R^2	0.206	0.206	0.206
Adjusted R^2	0.204	0.204	0.204
Residual Std. Error (df = 59397)	9.649	9.649	9.649
Note:	*p<0.1; **p<0.05; ***p<0.01		

A.2 Supplementary figures

Figure 2: Total unpriced carbon cost grouped by industry

This figure presents the total unpriced carbon cost for each industry in the dataset. Unpriced carbon costs are extracted from Trucost for the forecast years 2030, 2040, and 2050. Each industry's total unpriced carbon costs are calculated on an aggregated basis, i.e., across all three forecast years in the dataset.

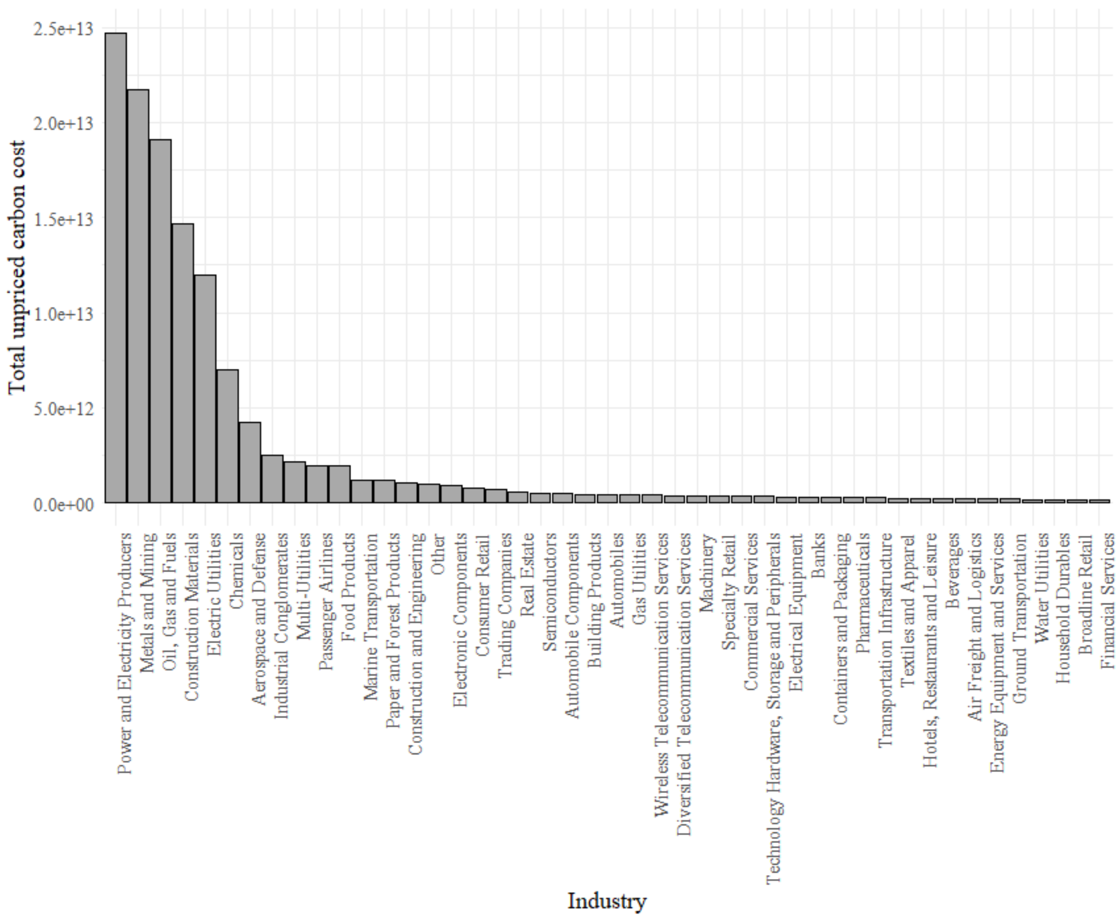

Figure 3: Total EBIT margin reduction grouped by industry

This figure presents the total EBIT margin reduction related to increased future carbon costs for each industry in the dataset. Carbon-related EBIT margin reductions are extracted from Trucost for the forecast years 2030, 2040, and 2050. Each industry's EBIT margin reductions are calculated on an aggregated basis, i.e., across all three forecast years in the dataset.

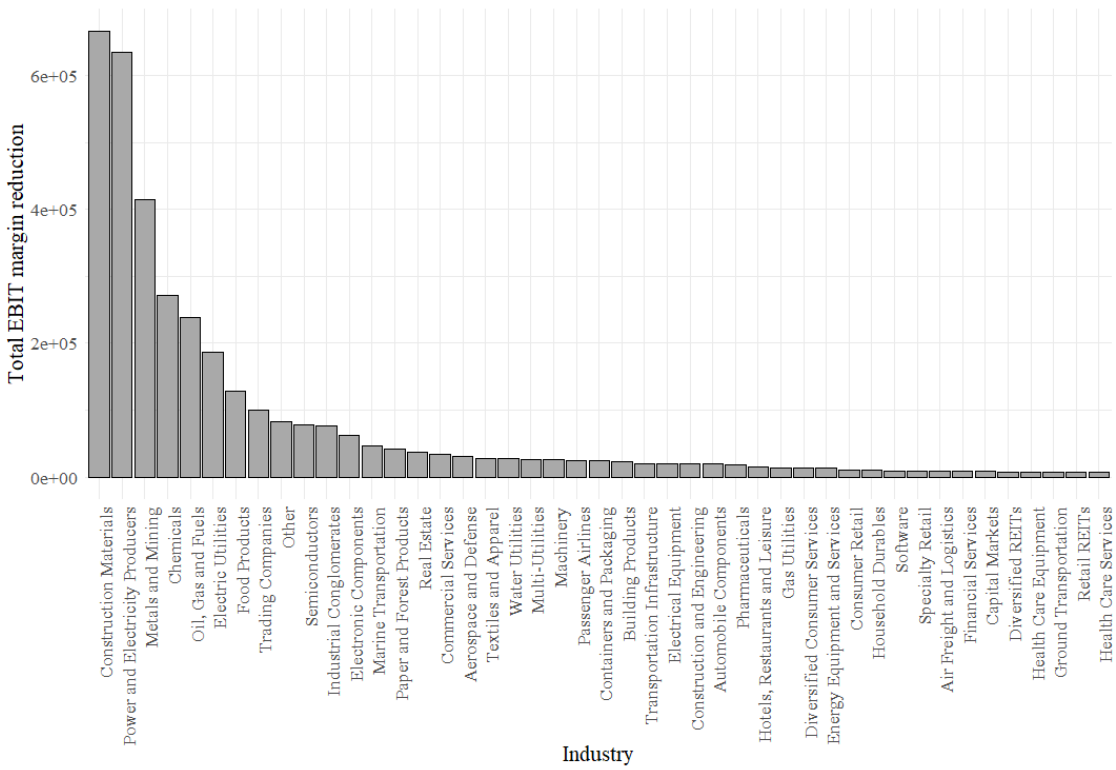

Figure 4: Log total unpriced carbon cost distribution

This figure presents the log total unpriced carbon cost distribution for the firms in the dataset on an aggregated basis for the forecast years 2030, 2040, and 2050.

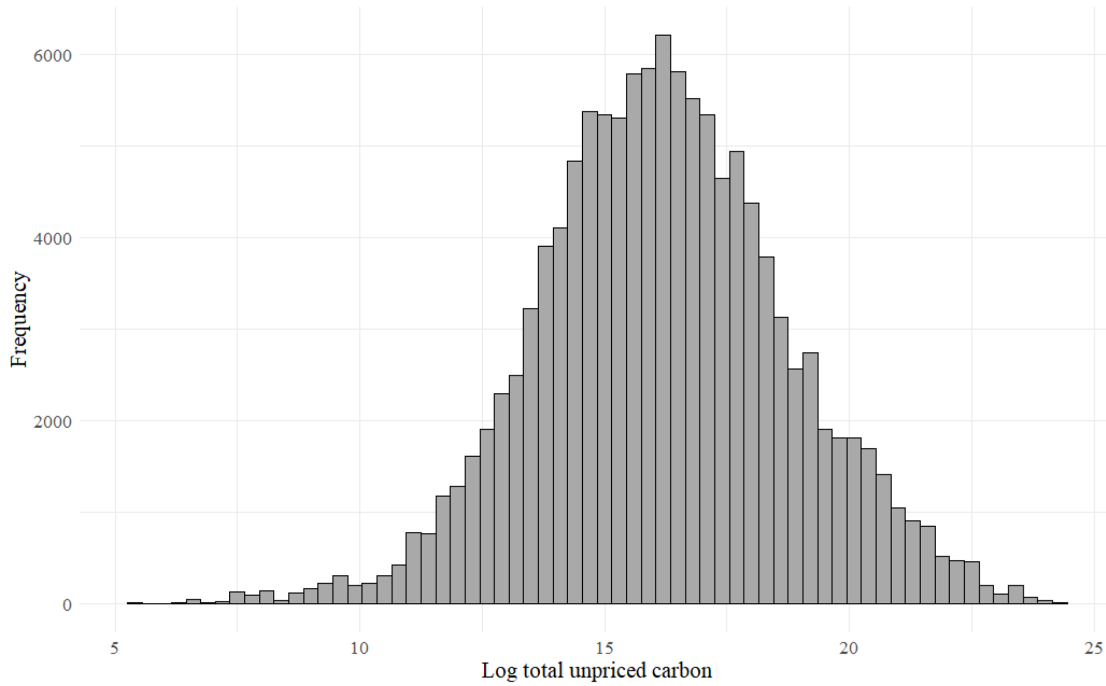

Figure 5: Log scope 1 unpriced carbon cost distribution

This figure presents the log total scope 1 unpriced carbon cost distribution for the firms in the dataset on an aggregated basis for the forecast years 2030, 2040, and 2050.

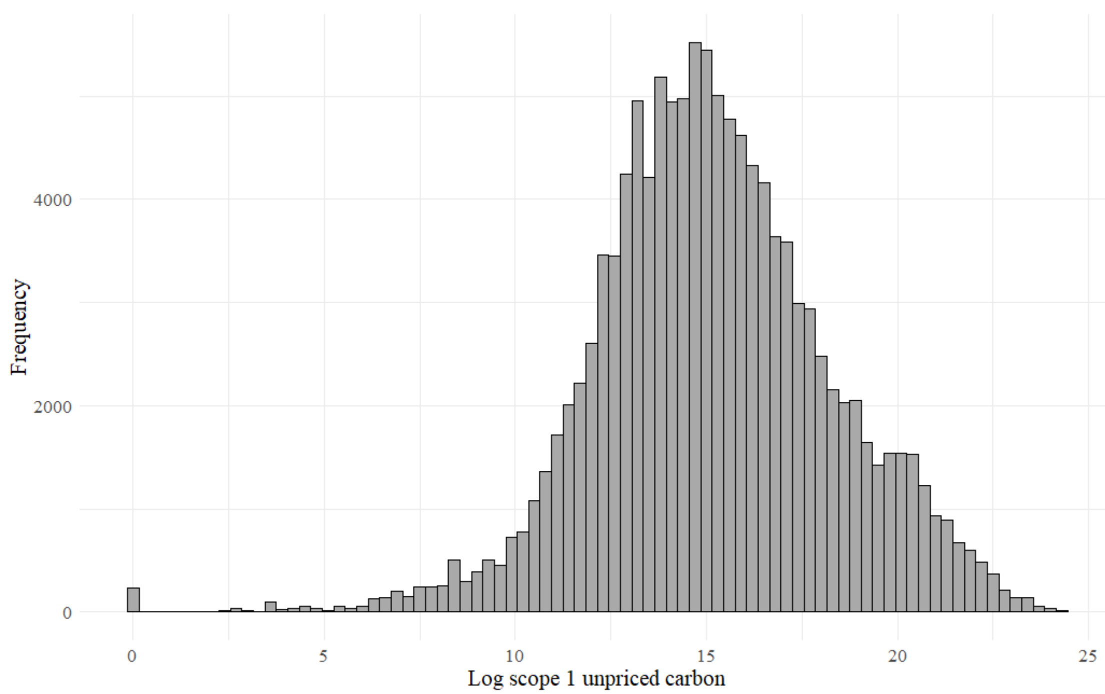

Figure 6: Log scope 2 unpriced carbon cost distribution

This figure presents the log total scope 2 unpriced carbon cost distribution for the firms in the dataset on an aggregated basis for the forecast years 2030, 2040, and 2050.

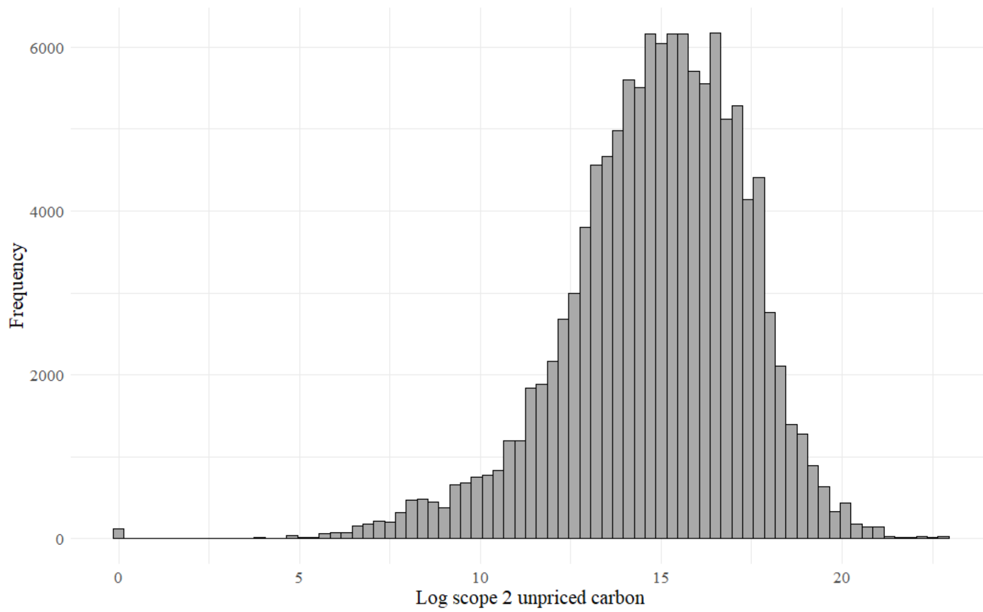

Figure 7: Return distribution

This figure presents the distribution of monthly stock returns for the firms in the dataset. Monthly stock returns are computed from daily stock prices taken from LSEG/Refinitiv daily stock pricing files, which are adjusted for stock splits and dividends. Firms' monthly stock returns are used as the dependent variable in the fixed effects regressions throughout the analysis in this paper. Following the recommendation of Dai and Drechsler (2021) to mitigate the impact of outliers and data errors, the variable is capped at a monthly stock return of 200%.