Pricing of carbon-transition risk with geographical and industrial carbon dispersion

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Abstract

The transition towards a net-zero economy faces a finite timeline, which increases the level of carbon-transition risk for high-polluting companies. In line with recent research, we find that companies with higher carbon emissions experience higher stock returns and lower firm value. Firms that voluntarily disclose a comprehensive breakdown of their carbon emissions across geographic regions and industrial sectors may signal the complexity and pressure they face in reducing their carbon footprint. This breakdown also enables investors to adjust the carbon-transition risk incorporated into their valuations. We investigate the impact of geographical and industrial carbon dispersion on the pricing of carbon-transition risk by analyzing data from the Carbon Disclosure Project (CDP) on a worldwide level for the period 2010-2020. The results that investors are exposed to greater carbon-transition risk when firms exhibit higher geographical and industrial carbon dispersion. This evidence suggests that spreading negative climate impacts across regions and sectors is costly for polluting firms.

Keywords: Carbon emissions, stock returns, firm value, geographical carbon dispersion, industrial carbon dispersion, climate change.

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1. Introduction

We study carbon-transition risk by focusing on the possible differential impacts of the extent to which firms spread their carbon emissions across countries (*geographical dispersion*) and across industry sectors (*industrial dispersion*). We investigate the influence of geographical and industrial carbon dispersion on sensitivities of stock returns and firm value to corporate carbon emissions by utilizing a large set of global companies that are subject to varying levels of this sensitivity. This is important because the pricing of carbon-transition risk in financial markets plays a crucial role in determining the likelihood and speed of the transition towards a low-carbon economy. Despite its importance, the existing literature is still in its early stages and we currently only have fragmented evidence regarding the pricing of carbon-transition risk, especially concerning its diverse sources (Bolton & Kacperczyk, 2023).

The current and anticipated future developments related to climate change have led to an increase in carbon-transition risk and the costs associated with managing carbon emissions. Given that stock markets are fundamentally focused on future expectations, it is natural to ask whether and to what degree stock returns and firm value reflect the presence of carbon-transition risk. Since the current developments (e.g. carbon control regulations, technological disruptions, changes in market preferences and norms) differ across geographical regions and industrial sectors, varying levels of geographical and industrial carbon dispersion may result in different levels of carbon-transition risk.

A growing body of research documents a positive relationship between carbon emissions and stock returns (Bolton & Kacperczyk, 2021, 2023), and find that carbon emissions decrease firm value (Matsumura et al., 2014; Bolton & Kacperczyk, 2023). These findings align with the concept that high-emitting firms encounter a higher cost of equity, indicating that financial markets incorporate carbon-transition risk into their pricing. The impact of geographical and industrial carbon dispersion on the pricing of carbon-transition risk remains an area of limited research and is unclear ex ante. Related literature suggests that geographically or industrially dispersed operations increase the complexity for firms in meeting the environmental expectations of various stakeholders (Marano et al., 2017; Park, 2018; Gómez-Bolaños et al., 2020), which could potentially lead to an elevated level of carbon-transition risk. Bolton & Kacperczyk (2023) expected to observe clear differences in the pricing of carbon-transition risk among firms with geographically or industrially dispersed operations due to varying policy frameworks, different technological innovations, or different perceptions of the threat of climate change. However, their results are inconclusive, indicating that the level of geographical and industrial carbon dispersion could not be a driver of the carbon premium. Therefore, the extent to which geographical and industrial carbon dispersion affect the sensitivities of stock returns and firm value with respect to corporate carbon emissions remains an area of limited research and is unclear ex ante. Additionally, the voluntary nature of carbon disclosure, coupled with firms' discretion in choosing the level of detail, introduces critical considerations regarding self-selection bias and the accuracy of carbon information. We utilize a novel dataset that offers a unique feature, enabling us to explore the extent to which the carbon emissions of firms participating in the survey are disaggregated by country or region, as well as by business division.

We utilize dataset provided by the Carbon Disclosure Project (CDP), which includes reported carbon emissions from firms participating in the survey across various countries or regions, and business divisions. This provides direct insight into firms' actual pollution at the micro-level, encompassing both Scope 1 and Scope 2 emissions. To quantify the levels of geographical and industrial carbon dispersion, we computed distinct Gini-Simpson indices for each. We perform our empirical analysis using an international sample consisting of 1,937 firms from 39 countries for the period 2010–2020. In addition to ordinary least squares (OLS) regressions, we tackle endogeneity concerns by employing two-stage least-squares (2SLS), propensity score matching (PSM) and firm-fixed effects. Additionally, we conducted several sensitivity tests, including the use of firms' carbon intensity instead of absolute carbon emissions, analyzing different time periods, exploring continent-level differences, and considering the influence of country-level development. We also separated the effect of direct (Scope 1) and indirect (Scope 2) emissions, and used alternative proxies to measure geographical carbon dispersion.

We argue that firms with a higher level of geographical or industrial carbon dispersion experience increased pressures to reduce carbon emissions, assuming increased complexity for these dispersed firms. In addition, we argue that firms exposed to higher carbon-transition risk are more likely to provide a detailed breakdown of their carbon emissions across geographical regions and industrial sectors, assuming that firms facing higher public pressure (associated with greater environmental impact) tend to provide more information about their carbon emissions to avoid scrutiny and maintain legitimacy (Chu et al., 2013; Pitrakkos and Maroun, 2020). Moreover, investors may perceive detailed carbon disclosure as a signal for accurate overall carbon information. This enables them to make well-informed investment decisions, allowing them to incorporate carbon-transition risk into their pricing (Krueger et al., 2020).

Taken together, we hypothesize that geographical and industrial carbon dispersion are associated with an increase in the firms' carbon-transition risk.

We present robust evidence suggesting that financial markets reflect carbon-transition risk through increased stock returns and reduced firm value for companies with substantial carbon emissions. Our findings indicate that firm value decreases more significantly with increased levels of geographical and industrial carbon dispersion. However, this conclusion is only applicable to companies headquartered in Europe and Asia. Our analysis also reveals limited evidence supporting the role of geographical carbon dispersion in strengthening the carbon-transition risk premium incorporated into annual stock returns. When we perform estimations using 2SLS and PSM, limit the sample to European firms, and use a subsample from the period 2010-2014, we find that the role of geographical, but not industrial, carbon dispersion exists. Despite this, the results of the alternative estimations are quantitatively highly comparable. Additionally, PSM suggests that the UK's mandatory carbon reporting policy leads to reduced uncertainty and pricing effects regarding UK firms' exposure to carbon-transition risk. Furthermore, when high-polluting UK firms expand their operations internationally, they experience relatively larger carbon pricing effects than non-UK firms. This may be attributed to the mandatory carbon reporting policy in the UK.

This study contributes to the existing literature by investigating the global pricing of carbon-transition risk. Building upon the insights and methodologies of the recent and influential studies conducted by Bolton & Kacperczyk (2021, 2023), our research extends their findings by providing additional evidence supporting the idea that carbon emissions increase stock returns and reduce firm value. While Bolton & Kacperczyk (2021) and Matsumura et al. (2014) focus solely on US firms, our study presents evidence from a global and more recent dataset. Although Bolton & Kacperczyk (2023) utilize a global sample, their dataset does not provide information on firms' carbon emissions across geographical regions or industrial sectors. In contrast, we leverage a distinctive dataset that adds a unique dimension to the current body of knowledge by introducing the concept of geographical and industrial carbon dispersion as one of the potential mechanisms driving the pricing of carbon-transition risk. Finally, we shed light on the impact of UK's mandatory carbon reporting policy.

The remainder of this paper is structured as follows. Section 2 reviews the literature and develops the hypotheses. Section 3 describes the data and the empirical methodology employed in the analysis. Section 4 provides the empirical results, discussions and suggestions for future research. Finally, Section 5 concludes the study by offering implications for investors, policymakers, managers, and other stakeholders.

2. Background and Hypotheses Development

2.1. Carbon-Transition Risk

The issue of climate change is among the most extensive and ongoing debates in contemporary times. Reducing net greenhouse gas (GHG) emissions, particularly carbon dioxide (CO2) emissions (henceforth referred to as carbon emissions) by mid-century is becoming necessary.

Terms such as "carbon risk", "environmental risk", "carbon-transition risk" and "climate change risk" are often used interchangeably. We follow the definition of Bolton & Kacperczyk (2023) and adopt the term carbon-transition risk. According to their definition, carbon-transition risk, when viewed from a company's perspective, encompasses the unpredictability surrounding the transition towards carbon neutrality. This unpredictability can manifest in various ways, including risks associated with high carbon emissions, such as carbon pricing, customer preferences, environmental scrutiny, regulatory interventions, and shifts in technology towards renewable energy sources. Due to a lack of consensus, this unpredictability is particularly relevant for firms operating across diverse geographical regions and industrial sectors. From an investor's perspective, carbon-transition risk also encompasses the influence of the changing socio-economic environment in shaping investor preferences and their expectations regarding climate change and the shift to cleaner energy. Moreover, the transition to a net-zero economy is constrained by a finite timeframe. Therefore, as the end date approaches (e.g. 2050), a company faces higher risks in striving for the same emission levels due to increasing pressure to eliminate emissions (Bolton and Kacperczyk, 2023).

2.2. Carbon Emissions, Stock Returns and Firm Value

Researchers reveal that an increasing number of investors demonstrate interest in understanding how firms contribute to reducing carbon emissions due to their belief that carbon-transition risk could result in financial implications for their portfolio companies (Van Duuren et al., 2016; Krueger et al., 2020; Bolton & Kacperczyk, 2021). Since a firm's exposure to carbon-transition risk increases the risk of its future cash flows, arising from both known and currently unidentified regulatory, physical, and business hazards, investors might require compensation for holding the stocks of companies with disproportionately high carbon emissions and the associated elevated carbon-transition risk they expose themselves to (Sharfman & Fernando, 2008). This phenomenon gives rise to a positive correlation in the cross-section of a company's carbon emissions and its stock returns. Bolton & Kacperczyk (2021, 2023) refer to this phenomenon as the carbon risk premium hypothesis. They note, however, that the existing literature is still in its early stages and there is only scarce evidence regarding the pricing of carbon-transition risk, especially concerning its diverse sources.

At first glance, the carbon premium might appear paradoxical, yet closer scrutiny reveals its inherent logic. The Gordon growth model, introduced by Gordon & Shapiro (1956), provides a theoretical foundation for our research. In the Gordon growth model, the stock price equals the present discounted value of dividends. One of the three key inputs is the required rate of return, often determined with the assistance of the classic capital asset pricing model (CAPM), introduced by Sharpe (1964) & Lintner (1965). The Gordon growth model explains how higher required returns lead to lower stock prices. This impact is most directly seen in the discount rate applied to the future cash flows of the firm. In an equilibrium state, a carbon premium indicates reduced investor interest in stocks of companies linked to high emissions. This reduced demand results in a lower stock price and thus a reduction in its firm value. This, in turn, offers an enhanced entry point for investors, allowing them to obtain the higher required returns. Atilgan et al. (2023) explain how the pivotal aspect comes into focus when we shift our perspective to examine the carbon premium from the standpoint of corporate management. From a managerial standpoint, the reduced stock price translates into reduced executive compensation and an elevation in the cost of capital for the firm's expansion initiatives. In essence, the carbon premium serves as a financial incentive for transformative change.

The influential study by Bolton & Kacperczyk (2021) reveals that US companies with higher levels of and changes in carbon emissions earn higher stock returns. In a recent and subsequent study, Bolton & Kacperczyk (2023) document the existence of a carbon premium in various countries across the globe. These findings align with the concept that high-emitting firms encounter a higher cost of equity, indicating that financial markets incorporate carbon-transition risk into their pricing.

Conversely, the working paper of Atilgan et al. (2023) indicates that carbon-transition risk is not fully reflected in market pricing, implying a more skeptical view of financial markets’ ability to facilitate the transition to a low-carbon economy. The authors suggest that this discrepancy may arise from companies and investors perceiving carbon emissions as an external cost that primarily affects society rather than the polluting companies themselves, even over the long term. Consequently, firms primarily driven by a focus on shareholder value may opt not to invest in emissions reduction, thereby reaping higher profits and stock returns (Atilgan et al., 2023). Additionally, we recognize that better business opportunities might be linked to higher sales, resulting in both increased emissions and higher realized returns. Hence, it is crucial to investigate the relationship between carbon emissions and stock returns alongside firm value. When stock returns increase with higher emissions but firm value decreases (e.g. indicated by a higher book-to-market ratio), it suggests that firms with elevated carbon emissions are associated with lower stock prices rather than higher ones.

A growing number of influential studies indicate that firms with a weak environmental track record, characterized by higher carbon emissions or greater exposure to environmental risks, face higher capital costs (Sharfman & Fernando, 2008; Palea & Drogo, 2020; Bolton & Kacperczyk, 2021; Trinks et al., 2022; Ding et al., 2023) and exhibit inferior firm value (Iwata & Okada, 2011; Matsumura et al., 2014; Delmas et al., 2015; Busch & Lewandowski, 2018; Bolton & Kacperczyk, 2023). Furthermore, Benz et al. (2021) discover that all investor types have been consistently reducing their portfolio's carbon exposure since 2012. These findings underscore the strong incentives for companies to reduce their emissions, emphasizing the crucial role of pricing carbon-transition risk in financial markets for the likelihood and pace of transitioning to a low-carbon economy. The literature review summarized above leads to the following hypothesis.

Hypothesis 1. Carbon emissions are positively associated with stock returns and the book-to-market ratio.

There are at least three reasons why our hypothesis may not obtain. First, if the financial markets perceive voluntarily disclosed carbon emissions as unreliable, as observed by Chu et al. (2013) and Stanny (2013), they may neglect this information when making investment decisions (Matsumura et al., 2014). Second, there is considerable uncertainty regarding the extent to which firms will be obligated to internalize the costs of their carbon emissions in the future. Firms may have the ability to shift the burden of their carbon emissions' costs onto their consumers or supply chain partners. Consequently, the market is likely to incorporate this uncertainty (Matsumura et al., 2014). Third, considering the historical lack of concern about climate change, it is reasonable to hypothesize that we would not observe higher stock returns and lower firm valuations for companies with higher carbon emissions during our sample period (i.e. 2010−2020) (Bolton & Kacperczyk, 2023).

2.3. The Influence of Geographical and Industrial Carbon Dispersion

A heightened level of geographical or industrial carbon dispersion, reflecting the extent to which a firm operates across diverse geographical regions or industrial sectors, may increase a company's vulnerability to carbon-transition risk.

For example, several researchers document that global stakeholders increase firms' environmental awareness and prioritize sustainable development compared to stakeholders within a narrow geographical range (Marano et al., 2017; Park, 2018). Also, supervision from various international agencies and renowned environmental organizations, as well as media attention from different countries, forces geographically dispersed firms to address environmental concerns. This external pressure drives international firms to introduce environmentally friendly products and establish a reputation as eco-friendly businesses (Albort-Morant et al., 2016; Gómez-Bolaños et al., 2020). An early study by Denis et al. (2002) reports that both geographical and industrial sales dispersion are associated with a decrease in firm value. Although they neglect the influence of carbon-transition risk, they conjecture that geographically and industrially dispersed operations may lead to additional costs of the agency relationship between managers and investors, such as through inefficient investment policies. Hence, their study suggests that dispersed operations may amplify the complexity of navigating various challenges, such as those related to carbon. Furthermore, Bolton & Kacperczyk (2023) underscore the importance of the potential effect of increased geographical and industrial carbon dispersion on the pricing of carbon-transition risk. They argue that firms with geographically or industrially dispersed operations face varying social pressures, regulatory risks, and headline risks.

In sum, internationalization increases the complexity of firms' operating environment, prompting multinational corporations (MNCs) to implement global carbon reduction strategies to meet the environmental expectations of international stakeholders—such as investors, governments, customers, activists and other stakeholder groups. Similarly, one could argue that different industries face distinct challenges to meet the environmental expectations of all stakeholders. Hence, investors might perceive multi-divisional companies as facing a higher level of complexity in navigating sector-specific challenges, leading to an increase in the required rate of return and, consequently, to a decrease in firm value.

Furthermore, the study of Chu et al. (2013) reveals that high-emitting firms tend to provide more information on their emissions, consistent with legitimacy theory. Legitimacy theory posits that firms facing higher public pressure tend to provide more information about their carbon emissions or accounting methods to avoid scrutiny, maintain legitimacy, and protect their reputation (Chu et al., 2013). Pitrakkos and Maroun (2020) validate this line of argument, observing that as stakeholder scrutiny increases due to a heavier carbon footprint, firms not only enhance the quantity but also the quality of their carbon disclosure. They argue that the legitimacy benefits of high-quality reporting outweigh the associated costs, particularly for companies operating in sectors with a significant environmental impact, such as oil and gas. Matsumura et al. (2014) and Depoers et al. (2016) further note that the firms completing the CDP questionnaires are predominantly large firms with significant carbon emissions. In sum, firms that provide a geographical or industrial breakdown of their carbon emissions are likely to be those with an elevated exposure to carbon-transition risk, consistent with legitimacy theory.

In light of the above discussions, we have at least three arguments that lead us to predict that geographical and industrial carbon dispersion will positively moderate the hypothesized positive relationship between carbon emissions and stock returns, while also strengthening the hypothesized negative relationship between carbon emissions and firm value—indicated by a higher book-to-market ratio. First, geographical and industrial carbon dispersion leads to increased complexities which, in turn, may create heightened pressures and risks associated with the need to reduce carbon emissions. Second, investors may perceive detailed carbon disclosure as a signal for accurate carbon information, enabling them to incorporate carbon-transition risk into their pricing. Third, firms exposed to elevated levels of carbon-transition risk are possibly more likely to provide a breakdown of their carbon emissions across geographical regions and industrial sectors, consistent with legitimacy theory. The hypothesis testing this debate is as follows.

Hypothesis 2. Geographical and industrial carbon dispersion strengthen the expected positive associations of carbon emissions with stock returns and the book-to-market ratio.

Alternatively, geographical or industrial carbon dispersion can potentially decrease a firm's exposure to carbon-transition risk. Bolton & Kacperczyk (2021) draw attention to the ongoing debate regarding whether carbon emissions are considered a systematic risk factor and whether the carbon premium is tied to loadings on this risk factor. The classification of carbon emissions as a systematic risk factor relies on the assumption that expected developments aimed at reducing emissions (e.g. regulatory interventions, technology disruptions, changes in market preferences and norms) are uniformly applicable across all global emissions. However, the reality may be more nuanced.

Bolton & Kacperczyk (2021) argue, for instance, that technological disruptions related to renewable energy primarily impact specific operations or sectors. In addition, they argue that regulatory interventions are frequently directed at specific industries (or countries). Also, certain industrial sectors face heightened scrutiny and public concern regarding their carbon emissions, thereby increasing reputational risks for companies operating within those sectors. In such instances, carbon-transition risk varies across industries. As discussed earlier, this can increase the complexity for multi-divisional firms, leading to an increase in carbon-transition risk. On the other hand, industrial dispersion may result in diversification effects, mitigating the overall carbon-transition risk for the firm.

Further, the findings of Krueger et al. (2020) indicate that the financial implications of carbon-transition risk are primarily driven by regulatory risk. Moreover, the study by Hsu et al. (2023) reveals that regulatory risk is negatively priced, with high-emitting firms demonstrating a higher exposure to this risk, thereby earning higher risk premia. These findings suggest that regulatory risk is one of the most important factors influencing the pricing of carbon-transition risk. However, the lack of consensus on the most effective policy (e.g. Kyoto Protocol and Paris Agreement) has led to a highly fragmented climate policy landscape across jurisdictions (Bartram et al., 2022). On one hand, this may increase the complexity for geographically dispersed firms. On the other hand, geographical dispersion may result in diversification effects. Consequently, countries with weaker climate policies may attract foreign investment and shift economic activity to less-regulated areas, as observed by Bartram et al. (2022) and Dechezleprêtre et al. (2022).

Based on these arguments, carbon emissions may not be universally perceived as a systematic risk factor. Hence, geographical and industrial carbon dispersion have the potential to mitigate a firm's carbon-transition risk by altering its exposure to various factors, including social pressures, headline risks, and regulatory risks. This alternative mechanism explains a potential diversification effect.

3. Data and Sample

3.1. Sample Description

To examine the pricing of carbon-transition risk and the differential impacts of geographical and industrial carbon dispersion, we utilized a worldwide sample over a time span of eleven years (from 2010 to 2020). Carbon emissions data for firm-level variables are collected from the CDP. Other data for firm-level variables are collected from Thomson Reuters ESG/Eikon/DataStream databases, whereas the country-level data are from the World Bank and IMF databases. In contrast to Bolton & Kacperczyk (2023), we followed common practice in the finance literature and excluded financial firms and utility firms with standard industrial classification (SIC) codes 6000–6999 and 4900–4999. These companies are characterized by higher leverage and different business models. Additionally, financed emissions, a component of Scope 3 emissions, constitute the most important source of emissions for financial firms.[1] However, our dataset lacks a breakdown of Scope 3 emissions across geographical regions and industrial sectors. Utilities often have strong connections to the government and are affected by the state's decisions. We also excluded firms from countries with fewer than ten firm-year observations. The final sample contains unbalanced panel data with 11,710 firm-year observations from 39 countries.

3.2. Data on Corporate Carbon Emissions

The main reason why limited research exists is because of data availability and the fact that concerns over global warming linked to carbon emissions from human activity have only recently become salient (Bolton & Kacperczyk, 2021). First and of utmost importance, we use novel data on corporate carbon emissions from the CDP. The distinctive feature of the CDP data, as highlighted by Dechezleprêtre et al. (2022), is the breakdown of both Scope 1 and Scope 2 emissions for participating companies by geographical and industrial categories. Firms are encouraged to provide a breakdown across regions or countries and industrial sectors, and many choose to disclose this additional information.

There are two methods for calculating Scope 2 emissions. The location-based method relies on regional average emission factors, while the market-based method is based on

[1] Scope 1 emissions encompass the direct emissions originating from sources that are owned or under control of a company. These emissions are generated as a result of the company's operational activities. Scope 2 emissions are indirect emissions generated from purchased energy, including electricity, steam, heating, and cooling. Scope 3 emissions encompass the indirect emissions arising from various activities within the company's value chain. These emissions are a consequence of the company's business interactions with suppliers, customers, and other stakeholders throughout the value chain.

contractual agreements that validate the exclusive claim on electricity sourced from specific energy sources (Holzapfel et al., 2023). The market-based method was introduced in 2015 and has been strongly criticized for its fundamental flaws, as it potentially results in a misallocation of climate change mitigation efforts, according to leading experts (2015), Brander et al. (2018) and Bjørn et al. (2022). Hence, we use the location-based method for measuring Scope 2 emissions. Nonetheless, if a firm merely discloses its Scope 2 emissions via the market-based method, we use this value to maximize the sample size. The number of observations with only market-based Scope 2 emissions is fewer than five percent in our dataset.

In our study, we exclude Scope 3 emissions due to limited data availability during our sample period. This is attributed not only to the absence of a breakdown across geographical regions and industrial sectors but also to the significantly low quality and quantity of Scope 3 emissions data. Researchers also report that, until recently, companies had not reported Scope 3 emissions, despite their significance as the most crucial component of emissions in several industries (Brander et al., 2018; Bjørn et al., 2022; Holzapfel et al., 2023).

3.3. Variables

The main dependent variables are annual stock return (*RET*) and book-to-market ratio (*BEME*). The main independent variables are a firm's absolute level of total Scope 1 and Scope 2 carbon emissions (*LOGS12TOT*), a Gini-Simpson index to measure a firm's level of geographical or industrial carbon dispersion (*GEOCDS12* and *INDCDS12*, respectively) and an interaction term of these two. The Gini-Simpson index is equal to 1 minus the well-known concentration measure, the Herfindahl index, and is therefore considered the diversity twin of the Herfindahl index (Schäfer et al., 2023). Denis et al. (2002) outlined the effectiveness of the Herfindahl index in their study related to firm value and geographical and industrial diversification. Equation (1) presents the calculation of the Gini-Simpson index for a firm's level of geographical carbon dispersion in either Scope 1 or Scope 2 emissions.

$$GEOCDS1/2 = 1 - \sum_{c=1}^{N} s_c^2 \tag{1}$$

where s is the firms' percent carbon emissions in each country/region, c, —or in each business division for calculating industrial carbon dispersion. First, we calculated the Gini-Simpson index for Scope 1 and Scope 2 emissions separately. Subsequently, we combined these two indices into one, incorporating the weights of firms' Scope 1 and Scope 2 emissions.[2]

Further, we employ several control variables, comparable to those used by Bolton & Kacperczyk (2023), to account for well-recognized factors that predict returns and firm characteristics, such as market capitalization (*LOGSIZE*), the use of debt (*LEVERAGE*), asset tangibility (*PPEINT*), momentum (*MOM*), unsystematic risk (*VOLAT*) and earnings (*ROE*). To control for outliers in the data, we winsorize all firm-level continuous variables at 1% and 99%. Detailed definitions of all variables are given in Table 1.

There is currently disagreement among researchers about using absolute levels of carbon emissions or a ratio scaled to sales to measure a firm's carbon intensity. For instance, Aswani et al. (2023) argue that absolute emissions primarily stem from a firm's core operations, and consequently, unscaled emissions are mainly determined by the quantity of goods produced and sold. Hence, they argue that merely emissions intensity is an appropriate measurement choice to assess the carbon performance of individual firms and show that the carbon premium becomes insignificant when using carbon intensity as a proxy for carbon performance.

Busch & Lewandowski (2018) find a significant positive relationship with carbon intensity and financial performance—measured using both ROA and Tobin's q. However, they find no significant relationship with financial performance when carbon performance is based on absolute emissions. Conversely, Bolton & Kacperczyk (2021) find that the carbon premium in monthly stock returns is related to absolute emissions, but not to relative emissions. They find this result striking because companies with high carbon intensities may be among the first to face financial challenges if the carbon price rises. Bolton & Kacperczyk (2023) present a departure from their arguments in 2021 by criticizing the fact that researchers use carbon intensity as a proxy for carbon-transition risk. They argue that carbon intensity may portray a large firm as more environmentally friendly compared to a small firm, despite the fact that the larger firm has a significantly greater climate impact due to its larger emissions. Besides, they argue that scaling to sales introduces noise since the ratio is influenced by varying sales levels. They acknowledge that changes in emissions could also reflect changes in earnings, but argue that they control for this effect by adding the firm's return on equity among their independent variables.

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[2] E.g. weight of firms' Scope 1 emissions = WS1 = Scope 1 / (Scope 1 + Scope 2).
GEOCDS12 = WS1 × GEOCDS1 + WS2 × GEOCDS2

We align with the arguments of Bolton & Kacperczyk (2023), who advocate for prioritizing what the world needs: a reduction in carbon emission levels as the primary focus, followed by an improvement in carbon efficiency as the secondary goal. Therefore, our focus will be on using firms' absolute emission levels, with carbon intensity employed as a sensitivity test.

3.4. Methodology

We perform multivariate regressions with ordinary least squares (OLS) estimations, in which heteroskedasticity-robust standard errors are clustered at the firm-level to test our hypotheses. To test for the proposed hypotheses in an international environment, regarding how firms' carbon emissions influence annual stock returns and firm value (Hypothesis 1) and the influence of firms' geographical and industrial dispersion of carbon emissions on these relationships (Hypothesis 2), the equation below will be used. Equation 2 employs either annual stock return (*RET*) or book-to-market ratio (*BEME*) as the dependent variable. When using *RET* as dependent variable, we also include the book-to-market ratio (*BEME)* as an additional control variable.

$$DV_{i,t} = \beta_0 + \beta_1 LOGS12TOT_{i,t-1} + \beta_2 CDS12_{i,t-1} + \beta_3 (LOGS12TOT \times CDS12)_{i,t-1} + \beta_4 Controls_{i,t-1} + Year\ FE + Country\ FE + Industry\ FE + \varepsilon_{i,t} \qquad (2)$$

where i is the firm and t the year. $CDS12$ is a generic term alternately standing for geographical carbon dispersion (*GEOCDS12*) and industrial carbon dispersion (*INDCDS12*). To control for the effects of omitted-variable bias, we include year-, country-, and industry-fixed effects. These fixed effects control for differences across countries, industries, and years, in order to determine different stock returns and firm values that may be explained by unobservable variables. Additionally, we employ firm- and year-fixed effects as an alternative robustness test. All of the explanatory variables are lagged by one year to take endogeneity concerns into account. This prevents accidently relating stock returns to emission data in year t that might not have been available to investors (i.e. look-ahead bias). Besides, higher emissions could result from better business opportunities and higher returns (i.e. reversed causality). This endogeneity concern is the main reason why we also employ a two-stage least-squares (2SLS) approach.

In the context of this study, as emphasized by Wu et al. (2022), a valid instrument employed in the 2SLS regression must satisfy two criteria. Firstly, the instrumental variable should be correlated with the carbon-transition risk faced by individual firms. Secondly, the instrument should impact a firm's stock return and firm value merely due to its effect on the firm's specific carbon-transition risk exposure. To account for the fact that unobserved firm characteristics can simultaneously affect the dependent and explanatory variables, we utilize the average carbon emissions at the country- and industry-level, as well as at the country- and year-level, as two instrumental variables to compute estimated values of corporate carbon emissions.

Furthermore, we employ a propensity score matching (PSM) methodology. In studies examining the pricing of carbon-transition risk, self-selection bias is one of the main endogeneity concerns due to voluntarily disclosed carbon information (Matsumura et al., 2014). Via PSM, we address self-selection bias by utilizing a matched sample of UK firms and non-UK firms. We use UK firms as a benchmark sample since they are subject to the UK's Streamlined Energy and Carbon Reporting (SECR) policy, which mandates listed (or large) firms to disclose information about their carbon emissions. We identify similar non-UK firms to our benchmark sample of UK firms based on observable firm characteristics that may be associated with the dependent variables. The matched sample approach reduces the possibility that differences in firm characteristics confound our results.

3.5. Descriptive Statistics

Table 2 provides sample descriptive statistics for all the variables incorporated into the empirical analysis. The table reports the mean, median, minimum, maximum and standard deviation values of the variables. We normalized the firm-level carbon emissions in units of tons of CO_2 emitted in a year using the natural log scale. Thus, the log of total Scope 1 and Scope 2 emissions of the average firm in our sample (*LOGS12TOT*) is 12.75, with a standard deviation of 2.20. The mean of *GEOCDS12* indicates that, on average, a firm's level of geographical carbon dispersion is 36%, as measured by the Gini-Simpson index. Similarly, the mean of *INDCDS12* suggests that a firm is, on average, industrially dispersed in its emissions by 21%. *GEOCDS1* and *GEOCDS2* have mean values of 0.33 and 0.37, respectively. This suggests that the levels of geographical carbon dispersion for the average firm are comparable between direct and indirect carbon emissions. Likewise, the mean values of *INDCDS1* and *INDCDS2* are highly comparable. However, it is noteworthy that the medians for both industrial carbon dispersion variables are zero. This may suggest that many firms operate solely within one business division or are less willing to calculate/disclose their carbon emissions by business division compared to calculating/disclosing their carbon emissions by country or region.

Figure 1 shows the time trend of the average values of Scope 1 and Scope 2 emissions over time. It also presents the average values of geographical and industrial carbon dispersion. As anticipated, there is a decreasing trend in firm-level Scope 1 and Scope 2 emissions over time, driven by increasing awareness of climate change, improvements in energy efficiency, technological innovations, stricter regulations and a growing reliance on renewable energy sources (Bolton & Kacperczyk, 2021; Gonenc & Poleska, 2023). To be more specific, average Scope 1 emissions for firms decreased by 26.5%, and Scope 2 emissions decreased by 25.2% during the 2010–2020 period. In contrast, both geographical carbon dispersion (*GEOCDS12*) and industrial carbon dispersion (*INDCDS12*) show an increasing trend over time. This trend may suggest that, on average, companies are expanding their operations into new geographic regions and industrial sectors or, alternatively, are providing a more detailed breakdown of their carbon emissions.

We then provide basic summary statistics on carbon emissions across our 39 countries, aggregated from the firm-level emissions reported by the CDP. Table 3 displays the country-level distribution of firms in our sample, including measures of emissions broken down into Scope 1 and Scope 2. We consider the average total yearly emissions in tons of CO2 equivalent per firm in each country (*S1TOT*, and *S2TOT*) and the average yearly emissions scaled to sales per firm in each country (*S1INT* and *S2INT*). We also provide the total Scope 1 and Scope 2 carbon dispersion indices for both geographical (*GEOCDS12*) and industrial (*INDCDS12*) carbon dispersion. Additionally, we present the average yearly total GDP in USD millions (*GDP*) and GDP per capita (*GDPPC*) of each country.

The country with the highest number of observations is the United States, representing 21.3% of total observations, with Japan as second with 15.2% of observations, and the United Kingdom as third with 10.7% of observations. Important for our analysis, the majority of the listed firms in our sample are not concentrated in a few countries. The SECR policy in the UK may account for the relatively high concentration of UK-headquartered firms in our dataset, as large UK firms are required to include information about their carbon emissions in their annual reports. Consequently, they may be more inclined to also share the results of their calculations with the CDP. Remarkably, Chinese headquartered companies are reluctant to report their climate change information to the CDP, as also confirmed by the study of Khalid et al. (2022).

This is particularly striking considering that China is responsible for the largest energy production and consumption (Khalid et al., 2022). It is also remarkable that among the Chinese firms that reported their carbon emissions to the CDP, they exhibit the lowest average levels of geographical and industrial dispersion in their emissions.

The top three countries in terms of Scope 1 emissions per firm are Luxembourg, Russia and Mexico, with their respective emission levels of 23.7 million, 10.4 million, and 10.2 million tons of CO2 per year. The remarkably high average in Luxembourg is attributed to the elevated emissions of ArcelorMittal, significantly impacting Luxembourg's average due to its limited number of firm-year observations. Nevertheless, the average level of geographical carbon dispersion for ArcelorMittal is 85.5%, indicating that the majority of its total carbon emissions are, in fact, produced outside its headquarters in Luxembourg.

To test for potential multicollinearity, we employ Pearson’s pairwise correlation method and the results are found in Appendix A. As expected, the total of Scope 1 and Scope 2 emissions (*LOGS12TOT*) shows a positive correlation with both total market capitalization (*LOGSIZE*) and the ratio of tangible assets (*PPEINT*). However, the coefficients are relatively small. Similarly, the total of Scope 1 and Scope 2 emissions (*LOGS12TOT*) is, logically, positively correlated with Scope 1 and Scope 2 emission intensity (*S12INT*), but the size of the coefficient is only 0.45, reflecting the fact that two firms with the same intensity may have very different absolute emission levels. Further, the correlation between *FRGNSAL* and *GEOCDS12* is 0.50, indicating that the level of foreign sales is not highly correlated with the level of foreign emissions. This may be due to firms exporting domestically produced products or outsourcing their production to foreign countries. Given that the mean and median of *FRGNSAL* are higher compared to *GEOCDS12*, it may also indicate that foreign sales information is more readily available for the listed firms in our dataset compared to information on foreign pollution. Overall, the coefficients of the variables in the regression model are not high, implying that the analysis does not suffer from multicollinearity.

4. Results

In this section, we provide a comprehensive analysis of our regression estimations on the pricing of carbon-transition risk. We begin with an examination of the cross-section between firms’ annual carbon emissions alongside either their stock returns or book-to-market ratios. We then analyze the joint impact on the dependent variables of the level of carbon emissions and the extent to which a firm is either geographically or industrially dispersed in its carbon emissions.

4.1. Global Pricing of Carbon-Transition Risk

4.1.1. Annual Stock Return

Panel A of Table 4 reports the results of the relationship between corporate carbon emissions (*LOGS12TOT*) and annual stock returns (*RET*). We report the results of OLS estimations with five models that differ in terms of the composition of explanatory variables. All models include year-, country-, and industry-fixed effects.[3] The statistically significant estimated coefficient of *LOGS12TOT* in Model 1 indicates that, when the level of carbon emissions increases, firms' annual stock returns (*RET*) also increase. Thus, this finding presents the existence of a carbon premium. The other models include carbon dispersion variables and interactions between the main variables of interest. All models show consistent results, with the variable *LOGS12TOT* having positive and statistically significant coefficients at the 1% level. This outcome supports the stock returns part of Hypothesis 1, indicating that higher carbon emissions increase the firms' annual stock returns (*RET*). This effect is also economically significant and can be interpreted through Model (1) as follows: a one-standard-deviation increase in *LOGS12TOT* leads to a 3.3% [(0.015 × 2.20) = 0.033] increase in *RET*, which represents 31.1% [(0.033/0.106) = 0.311] of its mean.

Next, we separate our total Scope 1 and Scope 2 variable *LOGS12TOT* into two separate variables for direct emissions (Scope 1) and indirect emissions (Scope 2) and present the results in Appendix B. Models (1)–(2) in Panel A show that the coefficients of both *LOGS1* and *LOGS2* are positive and significant at the 1% level. The effect of Scope 2 emissions (*LOGS2*) on stock returns (*RET*) is slightly higher compared to the impact of Scope 1 emissions (*LOGS1*). Specifically, a one-standard-deviation increase in *LOGS1* leads to a 2.5% [(0.009 × 2.75) = 0.025] increase in *RET,* while a one-standard-deviation increase in *LOGS2* leads to a 2.8% [(0.013 × 2.16) = 0.028] increase in *RET*. These carbon premia are quantitatively highly comparable to the carbon premia identified by Bolton & Kacperczyk (2023), who only investigated the separate effects of Scope 1 and Scope 2 emissions. They report annualized carbon premia of 2.2% and 3.1%, respectively, within the 2005−2018 timeframe.

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[3] We performed separate F-tests to determine whether there existed significant year, country, and industry effects, in order to justify their inclusion into our models. The F-statistics were 185, 6 and 6 when we included dummies for year, country, and industry, respectively. These statistics indicated that there were unobserved heterogeneities that we need to control across those factors.

The effects of the control variables on *RET* are as follows: market capitalization (*LOGSIZE*), book-to-market ratio (*BEME*), ratio of debt to assets (*LEVERAGE*), and momentum (*MOM*) have negative and statistically significant effects, whereas volatility (*VOLAT*) and return on equity (*ROE*) influence *RET* positively and significantly. The effect of the intensity of tangible assets (*PPEINT*) on *RET* is negligible. Bolton & Kacperczyk (2023) report similar significant effects for *LOGSIZE*, *LEVERAGE*, and *ROE*, but observe effects with an opposite sign for *BEME* and *MOM*, and an insignificant effect for *VOLAT*. Their other included control variables are not found to be significant.[4]

4.1.2. Book-to-Market Ratio

A similar conclusion is reached by examining the pricing of carbon emissions from a different perspective and relate our firm-level carbon emissions (*LOGS12TOT*) to firm value—measured by the book-to-market ratio (*BEME*). This perspective provides important robustness to our estimation of the carbon premium, and addresses the possibility that stock returns are noisy and are driven by unexpected returns. As before, we cluster standard errors at the firm level and include year-, country-, and industry-fixed effects in all specifications. We present the results in Panel B of Table 4.

Again consistent with our hypothesis of the presence of carbon-transition risk, we find that companies with high emissions (*LOGS12TOT*) have higher book-to-market ratios (*BEME*)—which are associated with lower firm market value. Specifically, a one-standard-deviation increase in carbon emissions (*LOGS12TOT*) is associated with a 15.4% increase in the book-to-market ratio [(0.070 × 2.20) = 0.154], which represents 24.4% [0.154/0.63) = 0.244] of its mean.

The separation of Scope 1 and Scope 2 emissions, as presented in Panel B of Appendix B, documents an increase in the book-to-market ratio of 13.2% and 9.9%, respectively, for every one-standard-deviation increase in the corresponding carbon emissions. Again, these results closely align with those reported by Bolton & Kacperczyk (2023), who observed a 13.2% increase in the book-to-market ratio following a one-standard-deviation rise in either Scope 1 or Scope 2 emissions.

[4] *INVEST/A*, ratio of capital expenditures to assets; *HHI*, Herfindahl index of a firm's business divisions with weights proportional to sales; *LOGPPE*, natural logarithm of property, plant and equipment. We opted not to replicate these controls due to concerns about multicollinearity.

4.2. Moderating Role of Geographical and Industrial Carbon Dispersion

Next we analyze the potential moderating role of geographical and industrial carbon dispersion on the pricing of carbon-transition risk. Prior to examining this potential moderating role, we first present Model (2) in Table 4 to show that the stand-alone effects of geographical and industrial carbon dispersion do not influence the dependent variables *RET* or *BEME*, ceteris paribus. In addition, the interaction term *GEOCDS12xINDCDS12* in Model (3) shows that the combined effect of geographical and industrial carbon dispersion is also not significant.

Models (4)–(5) present our main specifications of interest. These models include the carbon dispersion variables and the joint impact on the dependent variables of the level of carbon emissions and the extent to which the firm is either geographically (Model 4) or industrially (Model 5) dispersed in its carbon emissions. We do not observe that the risk premium in annual stock returns (*RET*) significantly increases or decreases for different levels of geographical or industrial carbon dispersion. However, we observe significant positive effects on the book-to-market ratio (*BEME*), indicating that firm value decreases for firms with elevated carbon emissions and high levels of geographical or industrial carbon dispersion. These interaction effects are statistically significant at the 1% level, as presented in Models (4)–(5) of Panel B. The results indicate that the book-to-market ratios (*BEME*) of firms increase with higher carbon emissions (*LOGS12TOT*), but this impact is positively moderated by the level of a firm's geographical and industrial carbon dispersion (interaction variables *LOGS12TOTxGEOCDS12* and *LOGS12TOTxINDCDS12*, respectively).

Similarly, the negative impact of carbon emissions on firm value is higher for firms that have a high level of carbon dispersion (indicated by a Gini-Simpson index approaching 1) compared to firms with a low level of carbon dispersion (indicated by a Gini-Simpson index approaching 0). This finding holds true for both geographical carbon dispersion (*GEOCDS12*) and industrial carbon dispersion (*INDCDS12*), providing strong support for confirming the validity of Hypothesis 2 when employing the book-to-market ratio as the dependent variable instead of annual stock return. A separation of direct and indirect emissions reveals that the effects of Scope 1 emissions are comparable to the effects of Scope 2 emissions, as presented in Appendix B.

4.3. Subsample Periods and Continent-Level Differences

Next we perform our OLS regressions for two subsample periods to control for potential bias as a result of a general decrease in carbon emissions in the later portion of the sample period, driven by significant global developments such as the adoption of the Paris Agreement in 2015. We divide the sample into two periods: 2010–2014 and 2015–2020, and present the results in Table 5.

In both periods, we observe quantitatively highly comparable effects of *LOGS12TOT* on *RET* and *BEME*. Contrary to our main analysis, Panel A reveals a significant coefficient of the interaction between carbon emissions and geographical carbon dispersion (*LOGS12TOTxGEOCDS12*). This positive coefficient suggests that geographical carbon dispersion positively moderates the relationship between carbon emissions and stock returns if we limit the sample to the 2010–2014 period. The results in Panel B indicate that the moderating effects of geographical carbon dispersion exhibit similar characteristics in both periods. However, the positive moderating effect of industrial carbon dispersion (*INDCDS12*) on the relationship between *BEME* and *LOGS12TOT* is only significant in the most recent period.

We also evaluate the geographical distribution of the pricing of carbon-transition risk by comparing the largest three regions of our dataset: North America, Europe and Asia. Examining the geographical distribution of the carbon premium allows us to evaluate the influence of a specific region on our main results. This is relevant since different geographic areas experience diverse levels of climate change vulnerability and possess varying capabilities for the transition to a low-carbon economy (Bolton & Kacperczyk, 2023). Panels A and B of Appendix C present the results on *RET* and *BEME*, respectively. Interestingly, the interaction effect of *LOGS12TOTxGEOCDS12* on *RET* is positive and significant at the 10% level when the sample is limited to European headquartered firms. Panel B shows significant positive moderating effects of geographical and industrial carbon dispersion on the pricing of carbon-transition risk in *BEME* when we restrict the sample to firms headquartered in Europe or Asia.

In summary, we observe significant carbon premia and positive moderating effects of geographical carbon dispersion in both the 2010–2014 and 2015–2020 periods, as well as in Europe and Asia. The moderating effect of industrial carbon dispersion is merely significant in the most recent period or in the regions Europe and Asia. In contrast to our main analysis, where we merely report significant moderating effects of carbon dispersion on the pricing of carbon-transition risk by using the book-to-market ratio (*BEME*), we now also find significant moderating effects by using annual stock returns (*RET*). This is achieved by limiting the sample to a specific region or period.

4.4. Influence of Advanced Countries and Multinational Corporations

Next we turn to an investigation of whether carbon-transition risk is tied to a country's economic development. The level of a country's economic development is an important consideration when it comes to international climate policy. Developed countries are generally expected to make stronger commitments to combat climate change due to their substantial historical contributions to carbon emissions (Bolton & Kacperczyk, 2023). We classify our sample countries as advanced using the International Monetary Fund (IMF) World Economic Outlook Database, which classifies economies as advanced based on several factors, including GDP per capita (*GDPPC*).

We present the results in Panels A and B of Appendix D for the dependent variables *RET* and *BEME*, respectively. Panel A reveals significant carbon premia in *RET* for firms headquartered in both advanced and developing countries. The results do not show any significant moderating effects of carbon dispersion on these carbon premia. In contrast to what one might expect, firms headquartered in developing countries exhibit relatively higher carbon premia. Panel B reveals that *LOGS12TOT* is positively associated with *BEME* for both advanced and developing countries, indicating that an increase in carbon emissions leads to a decrease in firm value. We also observe that the moderating effect of geographical carbon dispersion on the relationship between *LOGS12TOT* and *BEME* is significant for firms headquartered both in advanced and developing countries. However, the moderating effect of industrial carbon dispersion is merely significant for firms headquartered in advanced countries.

Similar to the rationale for developed countries, one could argue that MNCs are expected to make stronger commitments to combat climate change due to their substantial contributions to carbon emissions. Bolton & Kacperczyk (2023) argue that the distinction between MNCs and domestic firms may be relevant since global firms are subject to different social pressures, policies, or headline risks. As an alternative of our Gini-Simpson index to measure geographical carbon dispersion, we explore the existence of a moderating effect of geographical dispersion on the pricing of carbon-transition risk using two indicator variables and one ratio variable. First, we follow Bolton & Kacperczyk (2023) and use an indicator variable equal to one for firms with any sales generated abroad and zero if all its sales are generated domestically (*FORDUM*). Second, we use an indicator variable equal to one for firms with a foreign sales ratio above 30% and zero if its sales generated abroad are below 30%

(*MNC*). This definition of an MNC aligns with common practice in the literature, as in Aabo et al., (2015). Lastly, we also include the ratio of foreign sales to sales (*FRGNSAL*).

We present the results in Appendix E. In contrast to the insignificant results of Bolton & Kacperczyk (2023), we observe a positive and significant result for the interaction coefficient of *LOGS12TOTxFORDUM* on the pricing of carbon-transition risk in *RET*, although the magnitude of the increased carbon premium is relatively small. We do not observe significant interaction coefficients of *LOGS12TOTxMNC* or *LOGS12TOTxFRGNSAL* on *RET*, as shown in Panel A. However, we do find significant results for all three variables (*FORDUM*, *MNC* and *FRGNSAL*) interacted with carbon emissions (*LOGS12TOT*) on the pricing of carbon-transition risk in the book-to-market ratio (*BEME*), as shown in Panel B. These findings enhance the robustness of our analysis, particularly by emphasizing the amplifying impact of geographical dispersion on the negative effect of carbon emissions on firm value.

4.5. Treatment of Endogeneity using Two-Stage Least-Squares

A common concern in studies investigating causal relationships is the potential issue of endogeneity. It is plausible that all our results could be influenced by a common factor that simultaneously affects both the dependent variables and firms' carbon emissions, raising questions about the observed positive relationship. For instance, higher emissions could result from better business opportunities and higher returns. To address this endogeneity concern, we employ an instrumental variable two-stage least-squares (2SLS) approach.

We specifically utilize the average values of *LOGS12TOT* at the country- and industry-level (*CIS12TOT)*, as well as at the country- and year-level (*CYS12TOT)*, as two instrumental variables to estimate the effect of carbon-transition risk on stock returns. Panel A of Table 6 shows that firms with higher average country- and year-level carbon emissions (*CYS12TOT*) are more likely to exhibit higher firm-specific carbon emissions (*LOGS12TOT*). A similar conclusion is reached by examining the coefficient of the average country- and industry-level carbon emissions (*CIS12TOT*). The reasonably high F-statistics suggest that the models do not suffer from the weak instrument issue. Noteworthy, Model (2) reveals that a firm's level of geographical and industrial carbon dispersion is positively and significantly associated with carbon emissions, even after controlling for several firm-characteristics. This indicates that firms choosing to disclose detailed carbon information across regions or sectors have, on average, a higher exposure to carbon-transition risk, aligning with our literature review related to legitimacy theory.

We use the predicted values for *LOGS12TOT* from the first-stage regression and use it as the main independent variable in the second stage regression. Panels B and C show the coefficients from the second-stage regressions with the dependent variables *RET* and *BEME*, respectively. Consistent with the baseline results, *LOGS12TOT* has a significant positive effect on firms' stock returns (*RET*) and the book-to-market ratio (*BEME*). In Models (4)–(5), we report the results of the interactions between *LOGS12TOT* and geographical and industrial carbon dispersion (*GEOCDS12* and *INDCDS12*, respectively). Again in line with the main analysis, Panel C shows that the coefficients of the interactions are positive and significant, indicating an increase in *BEME*, and thus a decrease in firm value, for firms with high levels of geographical or industrial carbon dispersion and elevated carbon emissions. Further, we again find some evidence that geographical carbon dispersion also positively influences the pricing of carbon-transition risk in *RET*, as shown in Model (4) of Panel B. In sum, the results of our OLS regressions also hold when we run 2SLS regressions to control for endogeneity issues.

4.6. Treatment of Endogeneity using Propensity Score Matching

Another endogeneity concern may emerge due to the substantial discretion firms possess in disclosing their climate risks, as noted by Wu et al. (2022). Similarly, Matsumura et al. (2014) argue that, in studies examining the pricing of carbon-transition risk, self-selection bias is one of the main endogeneity concerns due to voluntarily disclosed information. As discussed in the literature review, firms may merely disclose neutral or positive news. In addition, several researchers observe that high-emitting firms tend to provide more information on their emissions, consistent with legitimacy theory. Consequently, there is a possibility that our sample exhibits a certain degree of self-selection bias. In the UK, however, the Streamlined Energy and Carbon Reporting (SECR) policy mandates listed (or large) firms to disclose information about their energy use and carbon emissions in their annual reports. This mandatory disclosure framework is significant because it ensures standardized reporting of environmental performance across companies in the UK.

We hypothesize that the treatment group (non-UK firms) should exhibit a higher risk premium compared to the control group (UK firms), even with similar emission levels. If, in a sample of non-UK firms matched with UK firms based on firm-level characteristics, including emission levels, this holds true, we can conclude that voluntary disclosure creates a higher pricing of carbon-transition risk compared to mandatory disclosure. This expectation stems from the belief that mandatory emission reporting in the UK reduces uncertainty for investors. The SECR enhances information transparency, offering investors accurate data on firms' carbon emissions and lowering uncertainty about a firm's carbon-transition risk. This reduction in uncertainty may prompt investors to demand a lower risk premium for firms with mandatory reporting. Additionally, investors may perceive compliance with ESG reporting regulations as a commitment to addressing environmental risks, leading to a decrease in perceived risks associated with carbon emissions. To test this idea, we use PSM to identify similar non-UK firms to our benchmark sample of UK firms based on observable firm characteristics that may be associated with the dependent variables. The matched sample approach reduces the possibility that differences in firm characteristics confound our results.

In particular, we match UK and non-UK firms in the same two-digit industry categories using the firm-level carbon emissions (*LOGS12TOT*), market capitalization (*LOGSIZE*), ratio of debt to assets (*LEVERAGE*), ratio of tangible assets to assets (*PPEINT*), momentum (*MOM*), volatility (*VOLAT*) and return on equity (*ROE*). These variables may determine the variation in annual stock returns or book-to-market ratios between firms, as covariates in the propensity score regressions. In each year, we first run probit regressions to determine the propensity score. We use nearest-neighbor matching without replacement with common support and caliper (0.02) options. We check for differences in the covariates of the matched samples for each year (not reported) and find them insignificant, which suggests that our matching procedure is successful. Our sample consists of 970 firm-year observations of UK firms and 970 firm-year observations of matched non-UK firms, that is, a total of 1,940 firm-year observations, covering 35 countries.

Table 7 reveals that the differences in the means and medians of stock returns (*RET*) and book-to-market ratios (*BEME*) consistently favor non-UK firms, demonstrating higher values compared to their UK counterparts. Our specific focus is on investigating the factors contributing to these differences in *RET* and *BEME* between UK and non-UK firms. Therefore, we next focus on firm-level characteristics that may explain these differences. Panel A shows important differences in firm-level characteristics between UK and non-UK firms in the full sample. In particular, UK firms have lower mean and median values for carbon emissions, market capitalization, ratio of debt to assets and ratio of tangible assets to assets than non-UK firms. At the same time, the return on equity is higher for UK firms than non-UK firms.

Panel B provides summary statistics for the matched sample. We now find that the mean and median values of all firm-level characteristics are similar for UK and non-UK firms, with the exception of the median level of leverage and tangible assets. This suggests that the matching procedure we apply is successful in significantly reducing firm-level differences between UK firms and matched non-UK firms. In addition, we compared the pseudo R^2 of the matched and unmatched sample in each year. Our results (unreported) show that the pseudo R^2 of the matched sample is always lower than that of the full sample, suggesting that no significant differences exist in the distribution of covariates between the two groups.

Panels A and B of Table 8 present the results on *RET* and *BEME*, respectively. The specifications of Models (1)–(3) are equal to the main analysis, except for the fact that we use the matched sample instead of the full sample. The coefficients of Models (1)–(3) provide additional evidence supporting our prior results, as we reduce self-selection bias by limiting the sample to UK and matched non-UK firms. Specifically, Model (1), in both panels, provides support for Hypothesis 1. Models (2)–(3) in Panel A show that solely geographical carbon dispersion is significant at the 10% level in strengthening the positive relationship between carbon emissions and stock returns. Models (2)–(3) in Panel B show that both geographical and industrial carbon dispersion significantly strengthen the positive relationship between carbon emissions and the book-to-market ratio. These findings support the geographical carbon dispersion aspect of Hypothesis 2 and also the industrial carbon dispersion aspect when employing the book-to-market ratio as the dependent variable.

The interactions of interest in Model (4) in Panel A are as follows: (*LOGS12TOTxUKFIRM*) measures the difference in stock returns between UK firms and non-UK firms at high levels of carbon emissions and when geographical carbon dispersion is low; (*LOGS12TOTxGEOCDS12*) measures the difference in the relationship between carbon emissions and stock returns at high levels of geographical carbon dispersion; and (*LOGS12TOTxGEOCDS12xUKFIRM*) measures the difference in the role of UK firms with high carbon emissions and high geographical carbon dispersion in explaining the stock returns compared with those with a low level of geographical carbon dispersion.

In Model 4, first, the insignificant coefficient of *LOGS12TOT* indicates that matched non-UK firms do not experience a significant carbon premium when their level of geographical carbon dispersion is low. Second, the interaction variable (*LOGS12TOTxUKFIRM*) has a negative and significant coefficient. This indicates a reduction in stock returns for UK firms (relative to non-UK firms) with high carbon emissions (*LOGS12TOT*) and low geographical carbon dispersion (*GEOCDS12*). This result aligns with our expectations, indicating that investors require a lower carbon premium for UK firms compared to non-UK firms. This could be attributed to the influence of the SECR framework, which likely mitigates uncertainty in the assessment of carbon-transition risk for UK firms. Finally, the triple interaction variable

(*LOGS12TOTxGEOCDS12xUKFIRM*) has a positive and significant coefficient. The sum of the relevant coefficients shows that the stock returns of UK firms increase with 6.4% [((−0.018 + 0.047) × 2.20) = 0.064] for every one-standard-deviation increase in carbon emissions when they have high levels of geographical carbon dispersion. This contrasts with the relative decrease in stock returns of UK firms with high carbon emissions and low levels of geographical carbon dispersion (−0.018, as captured by the variable *LOGS12TOTxUKFIRM*).

Model (4) in Panel B presents a significant coefficient of *LOGS12TOT*, indicating that carbon emissions are negatively associated with firm value for matched non-UK firms, consistent with our baseline results. Further, the interaction variable (*LOGS12TOTxUKFIRM*) is not significant, indicating that the decrease in firm value as a result of higher carbon emissions is not significantly different for UK firms compared to matched non-UK firms when the level of geographical dispersion is low. However, and similar to Panel A, the triple interaction variable *LOGS12TOTxGEOCDS12xUKFIRM* exhibits a positive and significant coefficient. The sum of the relevant coefficients shows that the book-to-market ratio of UK firms increases with 8.4% [((−0.036 + 0.074) × 2.20) = 0.084] for every one-standard-deviation increase in *LOGS12TOT* when firms have a high level of geographical carbon dispersion. Therefore, the triple interaction term *LOGS12TOTxGEOCDS12xUKFIRM*, both in Panel A and Panel B, indicates that UK firms experience an increase in stock returns and a decrease in firm value when they have high levels of carbon emissions and geographical carbon dispersion. Interestingly, this effect is larger for UK firms compared to matched non-UK firms. This may result from increased uncertainty regarding carbon-transition risk for UK firms when they decide to expand their operations internationally, where no carbon reporting policies are active. Model (5) in both Panel A and Panel B support this argument, as the moderating effect of industrial carbon dispersion is not significantly different for UK firms compared to matched non-UK firms, indicated by the triple interaction term *LOGS12TOTxINDCDS12xUKFIRM*.

4.7. Robustness and Discussion

We acknowledge concerns about the fact that our study is not immune to empirical challenges. This paper tried to address the most common endogeneity concerns related to the pricing of carbon-transition risk (i.e. reversed causality and self-selection bias). For instance, we performed several alternative methodologies, such as 2SLS and PSM regressions. As an additional test of our results, we run firm-fixed effect regressions to cross-check the regression outcomes and address omitted-variable bias. The findings in Panel A of Appendix F reveal that the carbon premium in *RET* exhibits a magnitude closely comparable to our baseline results, albeit with a lower significance level. Moving to Panel B, the analysis demonstrates that the positive association between *LOGS12TOT* and *BEME* persists as statistically highly significant, albeit with a diminished magnitude. Similar to our main results, Models (4)–(5) in Panel A show no significant differences between firms with high and low levels of geographical and industrial carbon dispersion concerning the relationship between carbon emissions and annual stock returns. In Panel B, we observe that the joint impact on *BEME* of geographical carbon dispersion and carbon emissions (*LOGS12TOTxGEOCDS12*) becomes insignificant, whereas the joint positive impact on *BEME* of industrial carbon dispersion and carbon emissions (*LOGS12TOTxINDCDS12*) remains quantitatively highly comparable, when we include firm- and year-fixed effects instead of year-, country- and industry-fixed effects.

Further, we replace our absolute emissions level variable (*LOGS12TOT*) by the emission intensity variable (*S12INT*) and present the results in Panels A and B of Appendix G for the impact of *S12INT* on *RET* and *BEME*, respectively. In line with the findings of Bolton & Kacperczyk (2021, 2023), we do not observe any significant carbon premia in *RET* when we use carbon intensity. However, Panel B shows a significant increase in *BEME,* indicating lower firm value as a result of an increase in a firm's carbon intensity. The economic significance can be interpreted through Model (1) as follows: a one-standard-deviation increase in *S12INT* leads to a 4.3% [$(0.009 \times 4.75) = 0.043$] increase in *BEME*, which represents 6.8% [$(0.043/0.63) = 0.068$] of its mean. Next, we look at the moderating role of geographical and industrial carbon dispersion on the pricing of carbon-transition risk using firm-level emission intensities. Notably, Model (4) in Panel A shows a modest carbon premium in *RET* for firms with a high carbon intensity (*S12INT*) and a high level of geographical carbon dispersion (*S12INTxGEOCDS12*). This outcome is particularly noteworthy as it contributes to the relatively limited evidence supporting a positive moderating effect of carbon dispersion on the pricing of carbon-transition risk in stock returns (*RET*). In line with our main results, Panel B shows that both geographical carbon dispersion (*GEOCDS12*) and industrial carbon dispersion (*INDCDS12*) positively moderate the relationship between carbon intensity (*S12INT*) and the book-to-market ratio (*BEME*), both interactions are significant at the 1% level.

Aswani et al. (2023), Atilgan et al. (2023) and Bolton & Kacperczyk (2023) highlight the potential endogenous relationship between absolute emissions and stock returns, stemming from the firm's production process. For instance, new business opportunities might be linked to higher sales, resulting in both increased emissions and higher realized returns. To address this issue, we use carbon intensity as our main emission variable where the level of carbon emission scaled by total sales. Our results in appendix G are robust when using carbon intensity instead of absolute carbon emissions.

Moreover, the results of our main analysis remain consistent when we do not lag our carbon emission variables, when we double cluster standard errors at the firm- and year-level, or when we exclude the year-, country- or industry-fixed effects. It turns out, however, that controlling for firm characteristics matters. Without these controls, there is still a significant premium associated with the level of emissions and the book-to-market ratio, but not with stock returns or with the level of geographical and industrial carbon dispersion.

In addition to employing the variables *FORDUM*, *MNC* and *FRGNSAL* as presented in Appendix E, we employed two deviations from the calculation of the Gini-Simpson index. Firstly, we excluded domestic emissions for the calculation of geographical carbon dispersion and excluded emissions from a firm's primary business division for the calculation of industrial carbon dispersion. Secondly, we created a weighted index which corrects for the number of countries/regions or business divisions to which a firm allocates its carbon emissions. In sum, we find consistent results for the moderating effect of geographical and industrial carbon dispersion, except when using the non-primary business divisions index for measuring industrial carbon dispersion.

We used *BETA* as a dependent variable and find that the beta's are increasing for firms with higher carbon emissions, which confirms that financial-markets reflect a premium for carbon-transition risk. However, we did not observe significant moderating effects of geographical or industrial carbon dispersion on the relationship between carbon emissions and *BETA*.

Taken together, we conducted several sensitivity tests to assess the robustness of our results, and our inferences remain unchanged. We report robust evidence that corporate carbon emissions increase annual stock returns and decrease firm value, suggesting that investors are demanding a premium for taking on the risks involved with carbon emissions—the market is putting a price on carbon. Hence, we confirm the validity of Hypothesis 1. The moderating effect of carbon dispersion on the carbon premia in annual stock returns is not conclusive. We observe patchy evidence in alternative analyses that geographical carbon dispersion increases the observed carbon premia in annual stock returns. Specifically, we report positive moderating effects when we use the 2SLS or PSM methodology, when employing carbon intensity instead of absolute carbon emissions, or when restricting the sample to European headquartered firms or the 2010–2014 period. Hence, we cannot fully confirm the stock returns aspect of Hypothesis 2, but we have some evidence that geographical carbon dispersion is a driver of the carbon premium. In contrast, we find strong evidence in the entire analysis that both geographical and industrial carbon dispersion strengthen the negative relationship between carbon emissions and firm value, as indicated by a higher book-to-market ratio. Therefore, we have robust evidence to confirm the validity of the book-to-market ratio aspect of Hypothesis 2.

5. Conclusion

To address global warming, the global economy must transition away from fossil fuels and achieve carbon neutrality by a finite timeframe. This requires an annual reduction in emissions comparable to the decline observed in 2020 during the COVID-19 pandemic (Bolton & Kacperczyk, 2023).

The pricing of carbon-transition risk in financial markets is pivotal for the likelihood and pace of transitioning to a low-carbon economy, as it can create strong incentives for companies to reduce their emissions. This paper offers useful insights into the particular role of geographical and industrial carbon dispersion regarding the pricing of carbon-transition risk. We posit that geographical and industrial carbon dispersion are both associated with an increase in annual stock returns and a decrease in firm value. This expectation is rooted in the notion that geographical and industrial carbon dispersion introduces elevated complexity in meeting environmental expectations of diverse stakeholders. Furthermore, companies that voluntarily disclose detailed carbon information across geographic regions and industrial sectors may signal a higher likelihood of exposure to increased levels of carbon-transition risk, while also affirming the accuracy of their carbon data. Additionally, possessing more information enables investors to make well-informed investment decisions, allowing them to incorporate carbon-transition risk into their pricing.

First, we have found evidence that carbon-transition risk is priced in financial markets—higher stock returns and lower firm valuations for companies with higher carbon emissions. The pricing of carbon-transition risk is impacting firms across three continents: North America, Europe and Asia. Second and of utmost importance, we find robust evidence that elevated levels of geographical and industrial carbon dispersion significantly strengthen the negative relationship between carbon emissions and firm value of companies headquartered in Europe or Asia. This conclusion holds true for firms with either a high level of absolute carbon emissions or a high carbon intensity. We also observe several indications that geographical carbon dispersion increases the pricing of carbon-transition risk in annual stock returns. Furthermore, our findings suggest that mandatory carbon reporting policies reduce the uncertainty regarding firms' exposure to carbon-transition risk and, in turn, reduce the pricing of carbon-transition risk.

Our study indicates that financial markets may serve as a significant amplifying factor in addressing the environmental impact of firms. Specifically, the rising cost of equity and lower firm valuations for companies with elevated carbon emissions can be interpreted as a type of taxation facilitated by capital markets. This mechanism provides a financial incentive for transformative change, encouraging firms to adopt more sustainable practices and mitigate their carbon footprint. Furthermore, the diminished firm values associated with high levels of carbon emissions and geographical and industrial carbon dispersion, imply that it is costly for firms to spread their negative climate impact across regions and sectors.

Given the finite timeframe and the ongoing increase in carbon emissions, achieving net-zero commitments becomes more challenging. This implies a rise in carbon-transition risk and an expected increase in investors' concerns for high-polluting firms. Hence, we may be currently underestimating the magnitude of the carbon premium. Now, as it becomes evident that market forces possess the capability to drive the transition towards a low-carbon economy, it is crucial to identify potential challenges. These challenges include environmental awareness, carbon leakage, regulatory complexities, and concerns about the availability and quality of carbon data. Accurately measuring Scope 3 emissions is particularly crucial, as it represents the most significant source of carbon emissions in several industries. Noteworthy in this context is the statement by ExxonMobil's CEO, Woods (2020): *"Individual companies setting targets and then selling assets to another company so that their portfolio has a different carbon intensity has not solved the problem for the world. We are taking steps to solve the problem for society as a whole and not trying to engage in a beauty competition."* Thus, an important point for future research is to investigate the impact of Scope 3 emissions, as it is the most crucial component of emissions in several industries, including mining, oil & gas, real estate, finance, automobile manufacturing, and food & beverages. The CDP underscores the importance of companies being aware of and measuring all relevant sources of Scope 3 emissions in their value chain. Nevertheless, the CDP acknowledges the inherent difficulty in measuring Scope 3 emissions, which partly explains why companies did not accurately report Scope 3 emissions in our dataset.

We urge policymakers, investors, researchers, managers, customers and other stakeholders to continue collaborating and implementing measures that incentivize managers to proactively reduce their carbon emissions. An illustrative example is the recent COP28 summit in Dubai, where nearly every country in the world has committed to transition away from fossil fuels—the primary contributor to climate change. By fostering a supportive environment for sustainable practices, we can collectively contribute to mitigating climate change and fostering a greener, more environmentally responsible future.

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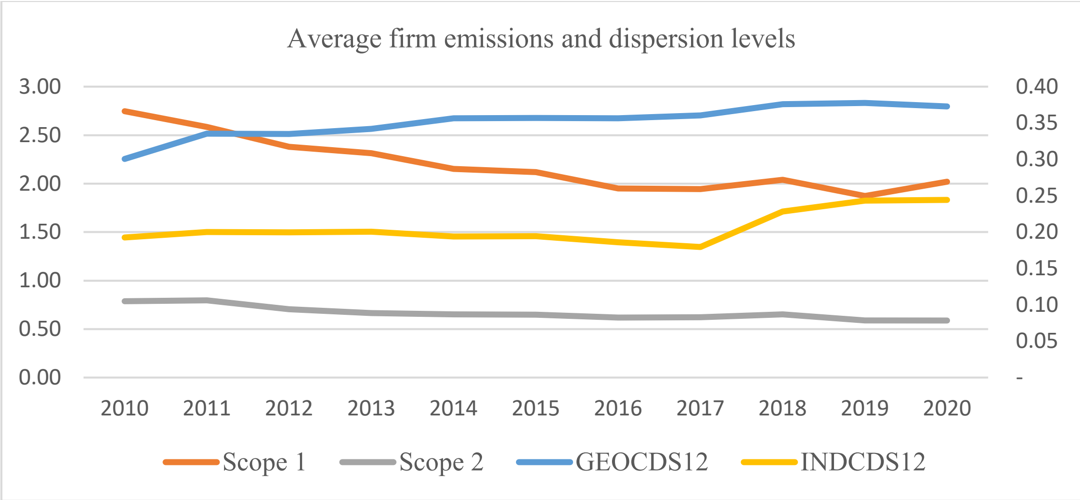

Figure 1: Carbon emissions and dispersion: time series summary

The data source is the CDP and the sample period is 2010–2020. The vertical axis on the left presents the average firm emissions in millions tons of CO2. The emissions are broken down into Scope 1 and Scope 2 emissions. The vertical axis on the right presents the average firm-levels of geographical carbon dispersion (*GEOCDS12)* and industrial carbon dispersion (*INDCDS12*), incorporating the weights of Scope 1 and Scope 2 emissions.

Table 1: Definitions of variables

This table provides definitions of firm- and country-level variables for the period 2010−2020. Carbon emissions data for firm-level variables are collected from the CDP. Other data for firm-level variables are collected from Thomson Reuters ESG/Eikon/DataStream databases, whereas the country-level data are from the World Bank and IMF databases.

Variables	Definitions
RET	Annual stock return
BEME	Ratio of common equity to market capitalization
S1TOT	Carbon emissions Scope 1 (tons CO2e)
S2TOT	Carbon emissions Scope 2 (tons CO2e)
LOGS12TOT	Natural logarithm of total Scope 1 and Scope 2 emissions [*S1TOT* + *S2TOT*]
S1INT	Carbon intensity Scope 1, ratio of emissions to sales (tons CO2e/USD m.)/100
S2INT	Carbon intensity Scope 2, ratio of emissions to sales (tons CO2e/USD m.)/100
S12INT	Weighted average of [*S1INT*] and [*S2INT*] with weights proportional to [*S1TOT*] and [*S2TOT*]
GEOCDS12	Weighted Gini-Simpson index of the carbon emissions per operating country of a company with weights proportional to [*S1TOT*] and [*S2TOT*] – see also Eq. (1)
INDCDS12	Weighted Gini-Simpson index of the carbon emissions per business division of a company with weights proportional to [*S1TOT*] and [*S2TOT*]
LOGSIZE	Natural logarithm of market capitalization (USD thousand)
LEVERAGE	Ratio of debt to book value of assets
PPEINT	Ratio of property, plant, and equipment to book value of assets
MOM	Average of historic 12-month returns
VOLAT	Standard deviation of historic 12-month returns
ROE	Ratio of net yearly income to common equity
GDP	A country's GDP (USD million)
GDPPC	A country's GDP per capita (in USD)
LOGGDPPC	Natural logarithm of [*GDPPC*]
FORDUM	Indicator variable equal to one if [*FRGNSAL*] > 1%, zero otherwise
MNC	Indicator variable equal to one if [*FRGNSAL*] > 30%, zero otherwise
FRGNSAL	Ratio of foreign sales to total sales
CYS12TOT	Country- and year-level average of [*LOGS12TOT*]
CIS12TOT	Country- and industry-level average of [*LOGS12TOT*]
UKFIRM	Indicator variable equal to one if a firm is headquartered in the UK, zero otherwise
BETA	The slope of the regression line, where the asset's historical (1Y) daily returns are regressed against the local market returns (CAPM OLS Beta)

Table 2: Summary statistics

This tables reports summary statistics (number of observations, averages, medians, mins, maxes and standard deviations) for the variables used for all sets of regressions. *LOGS1* is the natural logarithm of *S1TOT*; *LOGS2* is the natural logarithm of *S2TOT*. Definitions of all variables are given in Table 1. The sample period is 2010–2020. Carbon emissions data for firm-level variables are collected from the CDP. Other data for firm-level variables are collected from Thomson Reuters ESG/Eikon/DataStream databases, whereas the country-level data are from the World Bank and IMF databases. All firm-level continuous variables are winsorized at the 1st and 99th percentiles.

Variable	N	Mean	Median	Min	Max	St. Dev.
RET (%)	11710	10.58	8.86	−38.28	68.35	28.50
BEME	11710	0.63	0.49	0.04	2.85	0.50
LOGS1	11710	11.57	11.57	0.00	17.71	2.75
LOGS2	11710	11.74	11.95	3.93	16.11	2.16
LOGS12TOT	11710	12.75	12.74	4.02	17.90	2.20
S12INT	11710	1.90	0.30	0.00	35.40	4.75
GEOCDS1	11710	0.33	0.33	0.00	0.96	0.30
GEOCDS2	11710	0.37	0.40	0.00	0.95	0.31
GEOCDS12	11710	0.36	0.37	0.00	0.95	0.30
INDCDS1	11710	0.20	0.00	0.00	0.95	0.27
INDCDS2	11710	0.22	0.00	0.00	0.96	0.28
INDCDS12	11710	0.21	0.00	0.00	0.96	0.27
LOGSIZE	11710	15.64	15.65	12.06	19.16	1.50
LEVERAGE	11710	0.25	0.24	0.00	0.96	0.15
PPEINT	11710	0.30	0.26	0.01	1.00	0.21
MOM	11710	0.01	0.01	−0.06	0.10	0.03
VOLAT	11710	0.09	0.08	0.03	0.24	0.04
ROE (%)	11710	11.47	11.01	−91.57	91.09	20.81
LOGGDPPC	11710	10.52	10.69	7.21	11.73	0.75
FORDUM	11710	0.85	1.00	0.00	1.00	0.36
MNC	11710	0.68	1.00	0.00	1.00	0.47
FRGNSAL	11710	0.50	0.52	0.00	1.00	0.34
CYS12TOT	11710	12.75	12.95	11.18	14.89	0.68
CIS12TOT	11710	12.75	12.83	8.62	16.97	1.66
UKFIRM	11710	0.11	0.00	0.00	1.00	0.31
BETA	11710	1.00	0.97	0.06	2.29	0.43

Table 3: Carbon emissions by country

S1TOT (*S2TOT*) measures the firm-level average (by headquarter country) of Scope 1 (Scope 2) carbon emissions measured in tons of CO2e. *S1INT* (*S2INT*) measures the firm-level average carbon intensity (by country) of Scope 1 (Scope 2) carbon emissions measured in tons of CO2e scaled to sales measured in USD millions divided by 100 [(tons CO2e/USD m.)/100]. Definitions of all variables are given in Table 1. The sample period is 2010–2020. Carbon emissions data for firm-level variables are collected from the CDP. Other data for firm-level variables are collected from Thomson Reuters ESG/Eikon/DataStream databases, whereas the country-level data are from the World Bank and IMF databases. All firm-level continuous variables are winsorized at the 1st and 99th percentiles. We excluded firms from countries with fewer than ten firm-year observations.

Country	*N*	*S1TOT*	*S2TOT*	*S1INT*	*S2INT*	*GEOCDS12*	*INDCDS12*	*GDP*	*GDPPC*
Australia	352	2,131,319	978,504	3.55	1.15	0.21	0.22	1,388,160	58,752
Austria	46	4,792,768	509,896	2.73	1.08	0.46	0.30	425,217	48,679
Belgium	66	2,159,349	885,680	1.75	0.51	0.51	0.23	513,336	45,365
Brazil	186	5,059,109	373,110	2.24	0.25	0.18	0.28	2,058,863	10,046
Canada	559	1,996,905	373,055	3.84	0.88	0.31	0.19	1,700,528	47,271
Chile	18	1,120,386	174,668	2.75	0.49	0.21	0.23	267,803	14,596
China	26	4,226,799	1,274,405	1.10	0.91	0.02	0.06	13,400,000	9,543
Colombia	19	6,140,119	230,916	13.46	0.59	0.19	0.44	316,245	6,608
Denmark	149	3,188,905	137,274	1.63	0.35	0.48	0.14	335,707	59,106
Finland	268	595,517	337,012	1.07	0.61	0.45	0.18	261,733	47,803
France	535	3,033,967	935,625	1.06	0.50	0.61	0.26	2,682,540	40,311
Germany	468	3,437,894	1,146,707	1.46	0.59	0.44	0.18	3,701,724	45,202
Hong Kong	113	3,621,496	842,977	4.42	0.95	0.18	0.09	320,332	43,526
India	307	5,509,731	339,720	8.31	0.95	0.07	0.13	2,275,236	1,704
Ireland	35	6,554,889	799,530	3.12	0.48	0.54	0.28	320,261	66,676
Israel	20	1,111,097	771,731	1.75	1.02	0.59	0.10	331,733	38,943
Italy	154	5,339,170	469,555	4.15	0.90	0.44	0.24	2,006,061	33,354
Japan	1777	1,150,070	600,113	0.90	0.46	0.35	0.21	5,167,576	40,672
Korea	423	2,494,663	980,380	1.18	0.68	0.18	0.24	1,478,928	29,005
Luxembourg	23	23,700,000	4,826,323	3.50	0.85	0.78	0.33	64,670	115,013
Malaysia	10	831,348	389,274	2.88	0.84	0.24	0.20	329,851	10,396

Mexico	48	10,200,000	1,313,784	7.57	1.28	0.28	0.20	1,177,686	9,702
Netherlands	171	593,637	283,703	1.15	0.38	0.56	0.24	862,903	50,739
New Zealand	69	379,523	72,997	1.10	0.19	0.12	0.17	193,528	41,095
Norway	228	1,643,405	309,674	2.90	0.41	0.41	0.20	432,825	83,419
Philippines	15	180,831	604,736	0.39	1.77	0.08	0.30	319,169	3,030
Poland	10	443,499	310,621	1.45	0.82	0.07	0.27	532,728	14,035
Portugal	51	713,293	224,176	0.65	0.22	0.14	0.19	225,861	21,758
Russia	26	10,400,000	2,082,765	4.26	1.08	0.11	0.19	1,628,196	11,158
Singapore	50	717,354	204,211	0.40	0.21	0.30	0.22	334,454	60,009
South Africa	467	1,733,575	960,605	3.14	2.59	0.14	0.27	386,815	7,006
Spain	205	2,548,463	294,791	1.28	0.47	0.44	0.28	1,332,707	28,504
Sweden	349	556,225	193,748	0.78	0.32	0.55	0.24	544,493	55,147
Switzerland	298	2,097,755	580,383	1.06	0.39	0.53	0.15	703,274	84,681
Taiwan	273	1,154,322	828,687	1.44	1.06	0.13	0.11	563,923	24,011
Thailand	47	7,279,696	664,337	3.95	0.56	0.11	0.38	454,115	6,426
Turkey	107	426,045	97,776	3.68	0.77	0.03	0.06	831,069	10,314
UK	1249	1,256,715	433,775	0.88	0.47	0.40	0.25	2,781,524	42,723
USA	2493	2,122,843	812,663	1.30	0.49	0.38	0.18	18,600,000	57,605
Total/Mean	11,710	3,401,094	708,971	2.67	0.73	0.31	0.22	1,826,969	36,511

Table 4: Pricing of carbon-transition risk and carbon dispersion

We report the results of the pooled OLS regression with standard errors clustered at the firm level (in parentheses). All regressions include year-, country- and industry-fixed effects. **Panel A** reports the regression results for annual stock return (*RET*) as dependent variable; **Panel B** reports the regression results for the book-to-market ratio (*BEME*) as dependent variable. All independent variables are lagged by one year. Definitions of all variables are given in Table 1. The sample period is 2010–2020. Carbon emissions data for firm-level variables are collected from the CDP, whereas the firm-level data are collected from Thomson Reuters ESG/Eikon/DataStream databases. All firm-level continuous variables are winsorized at the 1st and 99th percentiles. ***1% significance; **5% significance; *10% significance.

Panel A: Annual stock returns

	(1)	(2)	(3)	(4)	(5)
Variables	*RET*	*RET*	*RET*	*RET*	*RET*
LOGS12TOT	0.015***	0.015***	0.015***	0.014***	0.016***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
GEOCDS12		−0.001	0.005	−0.046	
		(0.011)	(0.012)	(0.054)	
INDCDS12		0.002	0.014		0.061
		(0.009)	(0.017)		(0.063)
GEOCDS12xINDCDS12			−0.027		
			(0.030)		
LOGS12TOTxGEOCDS12				0.004	
				(0.004)	
LOGS12TOTxINDCDS12					−0.004
					(0.005)
LOGSIZE	−0.032***	−0.032***	−0.032***	−0.033***	−0.032***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
BEME	−0.179***	−0.179***	−0.179***	−0.179***	−0.179***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
LEVERAGE	−0.082***	−0.082***	−0.082***	−0.083***	−0.083***
	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)
PPEINT	−0.004	−0.004	−0.003	−0.004	−0.003
	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)
MOM	−0.966***	−0.966***	−0.966***	−0.966***	−0.966***
	(0.126)	(0.126)	(0.126)	(0.126)	(0.126)
VOLAT	0.499***	0.499***	0.499***	0.498***	0.500***
	(0.093)	(0.093)	(0.093)	(0.093)	(0.093)
ROE	0.196***	0.196***	0.195***	0.196***	0.196***
	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)
Constant	0.459***	0.459***	0.455***	0.476***	0.447***
	(0.058)	(0.059)	(0.059)	(0.063)	(0.060)
Year F.E.	YES	YES	YES	YES	YES
Country F.E.	YES	YES	YES	YES	YES
Industry F.E.	YES	YES	YES	YES	YES
Observations	11,710	11,710	11,710	11,710	11,710
Adjusted R-squared	0.273	0.273	0.273	0.273	0.273

(Continued)

Table 4−*Continued*

Panel B: Book-to-market ratio					
	(1)	(2)	(3)	(4)	(5)
Variables	*BEME*	*BEME*	*BEME*	*BEME*	*BEME*
LOGS12TOT	0.070***	0.071***	0.070***	0.059***	0.066***
	(0.006)	(0.006)	(0.006)	(0.007)	(0.006)
GEOCDS12		−0.027	−0.013	−0.514***	
		(0.029)	(0.033)	(0.146)	
INDCDS12		−0.006	0.022		−0.379***
		(0.022)	(0.040)		(0.142)
GEOCDS12xINDCDS12			−0.067		
			(0.070)		
LOGS12TOTxGEOCDS12				0.038***	
				(0.011)	
LOGS12TOTxINDCDS12					0.028***
					(0.011)
LOGSIZE	−0.113***	−0.112***	−0.112***	−0.115***	−0.114***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
LEVERAGE	−0.131**	−0.128**	−0.128**	−0.137**	−0.129**
	(0.057)	(0.057)	(0.057)	(0.056)	(0.057)
PPEINT	0.059	0.052	0.054	0.049	0.057
	(0.060)	(0.061)	(0.061)	(0.062)	(0.061)
MOM	−3.344***	−3.350***	−3.350***	−3.335***	−3.337***
	(0.192)	(0.193)	(0.193)	(0.191)	(0.192)
VOLAT	1.109***	1.108***	1.108***	1.095***	1.102***
	(0.208)	(0.208)	(0.208)	(0.207)	(0.208)
ROE	−0.466***	−0.468***	−0.468***	−0.465***	−0.467***
	(0.041)	(0.041)	(0.041)	(0.041)	(0.041)
Constant	1.785***	1.769***	1.759***	1.948***	1.861***
	(0.252)	(0.252)	(0.252)	(0.260)	(0.253)
Year F.E.	YES	YES	YES	YES	YES
Country F.E.	YES	YES	YES	YES	YES
Industry F.E.	YES	YES	YES	YES	YES
Observations	11,710	11,710	11,710	11,710	11,710
Adjusted R-squared	0.434	0.434	0.434	0.436	0.435

Table 5: Subperiod analysis for the pricing of carbon-transition risk and dispersion

We report the results of the pooled OLS regression with standard errors clustered at the firm level (in parentheses). All regressions include year-, country- and industry-fixed effects. **Panel A** reports the regression results for annual stock return (*RET*) as dependent variable; **Panel B** reports the regression results for the book-to-market ratio (*BEME*) as dependent variable. All independent variables are lagged by one year. Definitions of all variables are given in Table 1. The full sample period is 2010–2020. Carbon emissions data for firm-level variables are collected from the CDP, whereas the firm-level data are collected from Thomson Reuters ESG/Eikon/DataStream databases. All firm-level continuous variables are winsorized at the 1st and 99th percentiles. ***1% significance; **5% significance; *10% significance.

Panel A: Annual stock returns

	2010−2014		2015−2020	
	(1)	(2)	(3)	(4)
Variables	*RET*	*RET*	*RET*	*RET*
LOGS12TOT	0.021***	0.025***	0.014***	0.014***
	(0.004)	(0.004)	(0.004)	(0.003)
GEOCDS12	−0.169*		0.008	
	(0.098)		(0.077)	
INDCDS12		0.066		0.023
		(0.127)		(0.085)
LOGS12TOTxGEOCDS12	0.012*		−0.000	
	(0.007)		(0.006)	
LOGS12TOTxINDCDS12		−0.005		−0.001
		(0.009)		(0.006)
LOGSIZE	−0.052***	−0.050***	−0.030***	−0.029***
	(0.006)	(0.005)	(0.005)	(0.005)
BEME	−0.230***	−0.228***	−0.210***	−0.210***
	(0.016)	(0.016)	(0.011)	(0.011)
LEVERAGE	−0.130***	−0.130***	−0.095***	−0.094***
	(0.038)	(0.038)	(0.030)	(0.030)
PPEINT	−0.006	−0.002	−0.010	−0.011
	(0.034)	(0.034)	(0.029)	(0.029)
MOM	−0.810***	−0.810***	−1.799***	−1.800***
	(0.220)	(0.220)	(0.208)	(0.208)
VOLAT	0.755***	0.761***	0.729***	0.729***
	(0.166)	(0.165)	(0.156)	(0.156)
ROE	0.214***	0.214***	0.239***	0.238***
	(0.042)	(0.042)	(0.025)	(0.025)
Constant	0.618***	0.554***	0.373***	0.366***
	(0.202)	(0.200)	(0.101)	(0.097)
Year F.E.	YES	YES	YES	YES
Country F.E.	YES	YES	YES	YES
Industry F.E.	YES	YES	YES	YES
Observations	4,511	4511	7199	7,199
Adjusted R-squared	0.316	0.315	0.269	0.269

(Continued)

Table 5−*Continued*

Panel B: Book-to-market ratio				
	2010−2014		2015−2020	
	(1)	(2)	(3)	(4)
Variables	*BEME*	*BEME*	*BEME*	*BEME*
LOGS12TOT	0.053***	0.062***	0.060***	0.065***
	(0.009)	(0.008)	(0.009)	(0.007)
GEOCDS12	−0.571***		−0.411**	
	(0.180)		(0.165)	
INDCDS12		−0.194		−0.430***
		(0.195)		(0.156)
LOGS12TOTxGEOCDS12	0.040***		0.032**	
	(0.014)		(0.013)	
LOGS12TOTxINDCDS12		0.013		0.034***
		(0.015)		(0.012)
LOGSIZE	−0.097***	−0.096***	−0.121***	−0.121***
	(0.011)	(0.011)	(0.009)	(0.009)
LEVERAGE	−0.208***	−0.207***	−0.111	−0.103
	(0.070)	(0.071)	(0.070)	(0.071)
PPEINT	0.153**	0.172**	−0.000	−0.000
	(0.077)	(0.075)	(0.069)	(0.069)
MOM	−3.484***	−3.502***	−3.106***	−3.100***
	(0.269)	(0.271)	(0.251)	(0.251)
VOLAT	1.454***	1.463***	0.623**	0.628**
	(0.263)	(0.266)	(0.279)	(0.278)
ROE	−0.520***	−0.522***	−0.423***	−0.425***
	(0.064)	(0.064)	(0.048)	(0.048)
Constant	2.069***	1.985***	1.886***	1.819***
	(0.514)	(0.508)	(0.198)	(0.185)
Year F.E.	YES	YES	YES	YES
Country F.E.	YES	YES	YES	YES
Industry F.E.	YES	YES	YES	YES
Observations	4,511	4,511	7,199	7,199
Adjusted R-squared	0.454	0.451	0.449	0.449

Table 6: IV regressions−Pricing of carbon-transition risk and dispersion

We report the first- and second-stage results of an instrumental variable regression with standard errors clustered at the firm level (in parentheses). The instrumented variable is *LOGS12TOT.* **Panel A** reports the first-stage results where we employ two instrumental variables; *CYS12TOT* is the country- and year-level average of Scope 1 and Scope 2 emissions; *CIS12TOT* is the country- and industry-level average of Scope 1 and Scope 2 emissions; **Panel B** reports the second-stage results for annual stock return (*RET*) as dependent variable; **Panel C** reports the second-stage results for book-to-market ratio (*BEME*) as dependent variable. All independent variables are lagged by one year. Definitions of all variables are given in Table 1. All regressions include year-, country- and industry-fixed effects. The sample period is 2010–2020. Carbon emissions data for firm-level variables are collected from the CDP, whereas the firm-level data are collected from Thomson Reuters ESG/Eikon/DataStream databases. All variables are winsorized at the 1st and 99th percentiles. ***1% significance; **5% significance; *10% significance.

Panel A: First-stage regressions					
	(1)	(2)	(3)	(4)	(5)
Variables	*LOGS12T.*	*LOGS12T.*	*LOGS12T.*	*LOGS12T.*	*LOGS12T.*
CYS12TOT	0.390***	0.385***	0.386***	0.423***	0.467***
	(0.052)	(0.051)	(0.051)	(0.069)	(0.058)
CIS12TOT	0.652***	0.640***	0.641***	0.651***	0.653***
	(0.031)	(0.031)	(0.031)	(0.036)	(0.034)
GEOCDS12		0.598***	0.701***	2.829**	
		(0.102)	(0.118)	(1.437)	
INDCDS12		0.463***	0.678***		4.832***
		(0.084)	(0.149)		(1.286)
GEOCDS12xINDCDS12			−0.507*		
			(0.263)		
CYS12TOTxGEOCDS12				−0.141	
				(0.119)	
CIS12TOTxGEOCDS12				−0.029	
				(0.053)	
CYS12TOTxINDCDS12					−0.321***
					(0.109)
CIS12TOTxINDCDS12					−0.015
					(0.050)
LOGSIZE	0.644***	0.602***	0.602***	0.612***	0.625***
	(0.026)	(0.026)	(0.026)	(0.026)	(0.026)
LEVERAGE	1.085***	0.962***	0.963***	1.006***	1.006***
	(0.196)	(0.193)	(0.193)	(0.193)	(0.195)
PPEINT	2.450***	2.573***	2.582***	2.563***	2.492***
	(0.232)	(0.233)	(0.234)	(0.233)	(0.231)
MOM	−4.624***	−4.299***	−4.290***	−4.414***	−4.443***
	(0.483)	(0.476)	(0.476)	(0.477)	(0.481)
VOLAT	2.226***	2.200***	2.194***	2.221***	2.256***
	(0.563)	(0.554)	(0.553)	(0.560)	(0.557)
ROE	−0.720***	−0.653***	−0.655***	−0.663***	−0.697***
	(0.095)	(0.092)	(0.092)	(0.094)	(0.093)
Constant	−10.854***	−10.321***	−10.424***	−10.899***	−11.827***
	(0.777)	(0.777)	(0.777)	(0.941)	(0.840)
Year F.E.	YES	YES	YES	YES	YES
Country F.E.	YES	YES	YES	YES	YES
Industry F.E.	YES	YES	YES	YES	YES
Observations	11,710	11,710	11,710	11,710	11,710
Adjusted R-squared	0.710	0.718	0.719	0.716	0.715
F-statistic	112.1	113.6	110.9	77.02	171.1

Panel B: Second-stage regressions for annual stock returns					
	(1)	(2)	(3)	(4)	(5)
Variables	*RET*	*RET*	*RET*	*RET*	*RET*
LOGS12TOT	0.021***	0.021***	0.021***	0.018***	0.020***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
GEOCDS12		−0.005	0.000	−0.133*	
		(0.011)	(0.013)	(0.069)	
INDCDS12		−0.000	0.010		−0.032
		(0.010)	(0.017)		(0.078)
GEOCDS12xINDCDS12			−0.026		
			(0.030)		
LOGS12TOTxGEOCDS.				0.010*	
				(0.005)	
LOGS12TOTxINDCDS.					0.002
					(0.006)
LOGSIZE	−0.038***	−0.037***	−0.038***	−0.038***	−0.037***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
BEME	−0.183***	−0.184***	−0.184***	−0.184***	−0.183***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
LEVERAGE	−0.090***	−0.089***	−0.089***	−0.091***	−0.089***
	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)
PPEINT	−0.022	−0.023	−0.023	−0.022	−0.021
	(0.025)	(0.026)	(0.026)	(0.025)	(0.025)
MOM	−0.951***	−0.952***	−0.952***	−0.953***	−0.952***
	(0.126)	(0.126)	(0.126)	(0.126)	(0.126)
VOLAT	0.483***	0.483***	0.483***	0.482***	0.484***
	(0.094)	(0.094)	(0.094)	(0.094)	(0.094)
ROE	0.198***	0.198***	0.198***	0.198***	0.198***
	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)
Constant	0.471***	0.469***	0.465***	0.517***	0.477***
	(0.058)	(0.058)	(0.058)	(0.064)	(0.061)
Year F.E.	YES	YES	YES	YES	YES
Country F.E.	YES	YES	YES	YES	YES
Industry F.E.	YES	YES	YES	YES	YES
Observations	11,710	11,710	11,710	11,710	11,710
Adjusted R-squared	0.272	0.272	0.272	0.272	0.272

Panel C: Second-stage regressions for the book-to-market ratio					
	(1)	(2)	(3)	(4)	(5)
Variables	*BEME*	*BEME*	*BEME*	*BEME*	*BEME*
LOGS12TOT	0.073***	0.074***	0.074***	0.057***	0.064***
	(0.012)	(0.012)	(0.012)	(0.013)	(0.012)
GEOCDS12		−0.029	−0.016	−0.732***	
		(0.030)	(0.034)	(0.190)	
INDCDS12		−0.008	0.019		−0.531***
		(0.023)	(0.041)		(0.182)
GEOCDS12xINDCDS12			−0.065		
			(0.070)		
LOGS12TOTxGEOCDS.				0.056***	
				(0.015)	
LOGS12TOTxINDCDS.					0.040***
					(0.014)
LOGSIZE	−0.116***	−0.115***	−0.115***	−0.118***	−0.114***
	(0.012)	(0.011)	(0.011)	(0.011)	(0.011)
LEVERAGE	−0.136**	−0.133**	−0.133**	−0.145***	−0.130**
	(0.057)	(0.057)	(0.057)	(0.056)	(0.056)
PPEINT	0.047	0.040	0.040	0.038	0.055
	(0.069)	(0.071)	(0.071)	(0.071)	(0.069)
MOM	−3.327***	−3.335***	−3.333***	−3.317***	−3.334***
	(0.201)	(0.200)	(0.200)	(0.199)	(0.200)
VOLAT	1.095***	1.095***	1.094***	1.078***	1.098***
	(0.212)	(0.212)	(0.212)	(0.211)	(0.212)
ROE	−0.462***	−0.464***	−0.465***	−0.461***	−0.466***
	(0.042)	(0.042)	(0.042)	(0.042)	(0.042)
Constant	1.790***	1.772***	1.762***	2.031***	1.894***
	(0.251)	(0.252)	(0.252)	(0.264)	(0.252)
Year F.E.	YES	YES	YES	YES	YES
Country F.E.	YES	YES	YES	YES	YES
Industry F.E.	YES	YES	YES	YES	YES
Observations	11,710	11,710	11,710	11,710	11,710
Adjusted R-squared	0.434	0.434	0.434	0.436	0.435

Table 7: Summary statistics of UK and matched non-UK firms

We report mean and median differences of all firm-level variables using the full sample (**Panel A**) and the matched sample (**Panel B**), which is based on propensity score matching. For the match, each year, UK firms are matched with non-UK firms using probit regression and nearest-neighbor matching without replacement with common support and caliper (0.02) options. Definitions of all variables are given in Table 1. The sample period is 2010–2020. Carbon emissions data for firm-level variables are collected from the CDP, whereas the firm-level data are collected from Thomson Reuters ESG/Eikon/DataStream databases. All firm-level continuous variables are winsorized at the 1st and 99th percentiles. We used a t-test to compare the means of all variables between Non-UK and UK firms. We used a Wilcoxon rank sum test to compare the medians of all variables between Non-UK and UK firms. The significance levels of these tests are shown in the UK columns. ***1% significance; **5% significance; *10% significance.

	Mean		Median	
Variables	Non−UK	UK	Non−UK	UK
Panel A: Full sample (N = 11,710)				
RET	0.106	0.103	0.088	0.092
BEME	0.636	0.575***	0.497	0.426***
LOGS12TOT	12.881	11.692***	12.863	11.619***
LOGSIZE	15.714	15.060***	15.726	14.907***
LEVERAGE	0.250	0.215***	0.239	0.210***
PPEINT	0.305	0.256***	0.261	0.183***
MOM	0.011	0.012	0.010	0.011
VOLAT	0.087	0.088	0.079	0.080
ROE	0.113	0.129**	0.108	0.126***
Panel B: Matched sample (N = 1,940)				
RET	0.118	0.085**	0.102	0.072**
BEME	0.616	0.562**	0.486	0.412***
LOGS12TOT	12.036	12.045	11.870	11.842
LOGSIZE	15.291	15.299	15.140	15.220
LEVERAGE	0.223	0.229	0.204	0.223*
PPEINT	0.277	0.261	0.221	0.188***
MOM	0.011	0.010	0.010	0.010
VOLAT	0.088	0.087	0.079	0.079
ROE	0.131	0.120	0.113	0.124

Table 8: Matched sample−Pricing of carbon-transition risk, dispersion and UK firms

We used propensity score matching to select a matched sample and report the results of the pooled OLS regression. Standard errors are clustered at the firm level (in parentheses). The matched sample contains 1,940 observations. All regressions include year-, country- and industry-fixed effects. **Panel A** reports the regression results for annual stock return (*RET*) as dependent variable; **Panel B** reports the regression results for the book-to-market ratio (*BEME*) as dependent variable. All independent variables are lagged by one year. Definitions of all variables are given in Table 1. The sample period is 2010–2020. Carbon emissions data for firm-level variables are collected from the CDP, whereas the firm-level data are collected from Thomson Reuters ESG/Eikon/DataStream databases. All firm-level continuous variables are winsorized at the 1st and 99th percentiles. ***1% significance; **5% significance; *10% significance.

Panel A: Annual stock returns

	(1)	(2)	(3)	(4)	(5)
Variables	*RET*	*RET*	*RET*	*RET*	*RET*
LOGS12TOT	0.009*	0.002	0.006	0.010	0.005
	(0.005)	(0.006)	(0.006)	(0.007)	(0.006)
GEOCDS12		−0.206		0.122	
		(0.125)		(0.179)	
LOGS12TOTxGEOCDS12		0.018*		−0.007	
		(0.010)		(0.015)	
INDCDS12			−0.076		−0.046
			(0.130)		(0.181)
LOGS12TOTxINDCDS12			0.008		0.006
			(0.010)		(0.014)
UKFIRM				0.283**	0.043
				(0.125)	(0.100)
LOGS12TOTxUKFIRM				−0.018*	0.001
				(0.010)	(0.008)
UKFIRMxGEOCDS12				−0.612***	
				(0.234)	
LOGS12T.xGEOCDS12xUKF.				0.047**	
				(0.019)	
UKFIRMxINDS12					−0.037
					(0.237)
LOGS12T.xINDCDS12xUKF.					0.002
					(0.019)
LOGSIZE	−0.022***	−0.025***	−0.023***	−0.026***	−0.023***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
BEME	−0.153***	−0.156***	−0.154***	−0.159***	−0.154***
	(0.017)	(0.018)	(0.017)	(0.018)	(0.017)
LEVERAGE	−0.071	−0.078*	−0.075	−0.071	−0.075
	(0.046)	(0.047)	(0.046)	(0.048)	(0.047)
PPEINT	0.035	0.036	0.037	0.037	0.037
	(0.039)	(0.039)	(0.039)	(0.038)	(0.039)
MOM	−0.327	−0.352	−0.334	−0.367	−0.334
	(0.282)	(0.284)	(0.282)	(0.286)	(0.283)
VOLAT	0.597***	0.600***	0.600***	0.608***	0.598***
	(0.222)	(0.223)	(0.222)	(0.225)	(0.222)
ROE	0.135***	0.136***	0.136***	0.134***	0.136***
	(0.038)	(0.038)	(0.038)	(0.038)	(0.038)
Constant	0.356***	0.482***	0.393***	0.400***	0.399***
	(0.119)	(0.136)	(0.122)	(0.140)	(0.126)
Year F.E.	YES	YES	YES	YES	YES
Country F.E.	YES	YES	YES	YES	YES

Industry F.E.	YES	YES	YES	YES	YES
Observations	1,940	1,940	1,940	1,940	1,940
Adjusted R-squared	0.253	0.254	0.253	0.256	0.252

Panel B: Book-to-market ratio					
	(1)	(2)	(3)	(4)	(5)
Variables	*BEME*	*BEME*	*BEME*	*BEME*	*BEME*
LOGS12TOT	0.057***	0.035**	0.049***	0.049***	0.049***
	(0.013)	(0.014)	(0.014)	(0.017)	(0.015)
GEOCDS12		−0.813***		−0.328	
		(0.283)		(0.298)	
LOGS12TOTxGEOCDS12		0.064***		0.028	
		(0.023)		(0.025)	
INDCDS12			−0.497**		−0.339
			(0.245)		(0.313)
LOGS12TOTxINDCDS12			0.039*		0.032
			(0.020)		(0.025)
UKFIRM				0.382	−0.052
				(0.304)	(0.246)
LOGS12TOTxUKFIRM				−0.036	0.002
				(0.025)	(0.021)
UKFIRMxGEOCDS12				−0.964*	
				(0.495)	
LOGS12T.xGEOCDS12xUKF.				0.074*	
				(0.041)	
UKFIRMxINDS12					−0.206
					(0.495)
LOGS12T.xINDCDS12xUKF.					0.007
					(0.041)
LOGSIZE	−0.099***	−0.104***	−0.101***	−0.103***	−0.101***
	(0.016)	(0.016)	(0.017)	(0.016)	(0.016)
LEVERAGE	−0.386***	−0.398***	−0.380***	−0.381***	−0.376***
	(0.119)	(0.114)	(0.116)	(0.113)	(0.116)
PPEINT	0.214*	0.199*	0.205*	0.195*	0.199*
	(0.110)	(0.116)	(0.112)	(0.116)	(0.112)
MOM	−3.087***	−3.166***	−3.058***	−3.181***	−3.060***
	(0.450)	(0.452)	(0.450)	(0.450)	(0.450)
VOLAT	1.638***	1.637***	1.631***	1.638***	1.607***
	(0.514)	(0.507)	(0.514)	(0.496)	(0.511)
ROE	−0.568***	−0.563***	−0.568***	−0.563***	−0.567***
	(0.083)	(0.082)	(0.083)	(0.082)	(0.083)
Constant	1.436***	1.778***	1.552***	1.618***	1.540***
	(0.242)	(0.267)	(0.262)	(0.281)	(0.266)
Year F.E.	YES	YES	YES	YES	YES
Country F.E.	YES	YES	YES	YES	YES
Industry F.E.	YES	YES	YES	YES	YES
Observations	1,940	1,940	1,940	1,940	1,940
Adjusted R-squared	0.443	0.449	0.444	0.451	0.444

Appendix A – Correlation matrix

The correlation matrix presents the pairwise correlations. Definitions of all variables are given in Table 1. The sample period is 2010–2020. Carbon emissions data for firm-level variables are collected from the CDP, whereas the firm-level data are collected from Thomson Reuters ESG/Eikon/DataStream databases. All firm-level continuous variables are winsorized at the 1st and 99th percentiles.

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1)	RET	1									
(2)	LOGS12TOT	−0.052	1								
(3)	S12INT	−0.062	0.454	1							
(4)	GEOCDS12	0.015	0.075	−0.106	1						
(5)	INDCDS12	−0.022	0.149	−0.050	0.185	1					
(6)	LOGSIZE	−0.011	0.480	−0.054	0.210	0.098	1				
(7)	BEME	−0.284	0.173	0.197	−0.103	0.019	−0.309	1			
(8)	LEVERAGE	−0.026	0.183	0.078	0.002	0.063	0.025	0.010	1		
(9)	PPEINT	−0.079	0.441	0.354	−0.218	−0.025	−0.044	0.239	0.187	1	
(10)	MOM	−0.013	−0.039	−0.056	−0.011	−0.033	0.096	−0.239	−0.058	−0.059	1
(11)	VOLAT	0.037	−0.021	0.128	−0.112	−0.041	−0.332	0.219	0.039	0.134	0.188
(12)	ROE	0.186	−0.063	−0.142	0.000	−0.011	0.254	−0.410	−0.002	−0.149	0.221
(13)	LOGGDPPC	0.005	−0.077	−0.220	0.299	−0.005	0.157	−0.079	−0.005	−0.080	0.023
(14)	FORDUM	0.009	0.080	−0.055	0.360	0.054	0.106	−0.048	−0.038	−0.162	0.005
(15)	MNC	0.014	0.047	−0.067	0.493	0.041	0.114	−0.043	−0.056	−0.179	0.008
(16)	FRGNSAL	0.022	0.021	−0.061	0.496	0.030	0.098	−0.066	−0.092	−0.162	0.014
(17)	CYS12TOT	−0.016	0.323	0.138	−0.130	−0.025	0.242	0.038	0.062	0.113	0.048
(18)	CIS12TOT	−0.049	0.768	0.433	−0.042	0.062	0.334	0.160	0.169	0.478	−0.024
(19)	UKFIRM	−0.003	−0.167	−0.064	0.047	0.056	−0.135	−0.038	−0.070	−0.070	0.007
(20)	BETA	−0.071	0.197	0.155	0.003	0.034	0.049	0.152	0.038	0.142	0.041

(Continued)

Appendix A−*Continued*

		(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
(11)	VOLAT	1									
(12)	ROE	−0.219	1								
(13)	LOGGDPPC	−0.140	0.016	1							
(14)	FORDUM	0.004	0.011	0.093	1						
(15)	MNC	0.023	−0.018	0.139	0.607	1					
(16)	FRGNSAL	0.033	−0.004	0.147	0.620	0.840	1				
(17)	CYS12TOT	0.047	0.014	−0.240	−0.000	−0.080	−0.178	1			
(18)	CIS12TOT	0.035	−0.076	−0.103	0.013	−0.036	−0.059	0.390	1		
(19)	UKFIRM	0.005	0.023	0.066	−0.049	0.006	0.061	−0.537	−0.221	1	
(20)	BETA	0.368	−0.138	−0.048	0.089	0.107	0.108	0.140	0.188	−0.083	1

Appendix B – Separation of direct and indirect carbon emissions

We report the results of the pooled OLS regression with standard errors clustered at the firm level (in parentheses). All regressions include year-, country- and industry-fixed effects. **Panel A** reports the regression results for annual stock return (*RET*) as dependent variable; **Panel B** reports the regression results for the book-to-market ratio (*BEME*) as dependent variable. All independent variables are lagged by one year. *LOGS1* is the natural logarithm of Scope 1 emissions (*S1TOT)*; *LOGS2* is the natural logarithm of Scope 2 emissions (*S2TOT); GEOCDS1* is a Gini-Simpson index for geographical dispersion in Scope 1 emissions; *GEOCDS2* is a Gini-Simpson index for geographical dispersion in Scope 2 emissions; *INDCDS1* is a Gini-Simpson index for industrial dispersion in Scope 1 emissions; *INDCDS2* is a Gini-Simpson index for industrial dispersion in Scope 2 emissions. Definitions of all other variables are given in Table 1. The sample period is 2010–2020. Carbon emissions data for firm-level variables are collected from the CDP, whereas the firm-level data are collected from Thomson Reuters ESG/Eikon/DataStream databases. All firm-level continuous variables are winsorized at the 1st and 99th percentiles. ***1% significance; **5% significance; *10% significance.

Panel A: Annual stock returns						
	(1)	(2)	(3)	(4)	(5)	(6)
Variables	*RET*	*RET*	*RET*	*RET*	*RET*	*RET*
LOGS1	0.009***		0.008***		0.010***	
	(0.002)		(0.002)		(0.002)	
LOGS2		0.013***		0.012***		0.014***
		(0.002)		(0.002)		(0.002)
GEOCDS1			−0.029			
			(0.039)			
GEOCDS2				−0.064		
				(0.052)		
INDCDS1					0.065	
					(0.047)	
INDCDS2						0.029
						(0.058)
LOGS1xGEOCDS1			0.003			
			(0.003)			
LOGS2xGEOCDS2				0.005		
				(0.004)		
LOGS1xINDCDS1					−0.005	
					(0.004)	
LOGS2xINDCDS2						−0.003
						(0.005)

LOGSIZE	−0.027***	−0.031***	−0.028***	−0.031***	−0.027***	−0.031***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
BEME	−0.175***	−0.175***	−0.175***	−0.176***	−0.174***	−0.175***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
LEVERAGE	−0.078***	−0.075***	−0.079***	−0.076***	−0.079***	−0.074***
	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)
PPEINT	0.013	0.012	0.013	0.010	0.014	0.012
	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)
MOM	−0.982***	−0.966***	−0.981***	−0.966***	−0.982***	−0.967***
	(0.126)	(0.126)	(0.126)	(0.126)	(0.126)	(0.126)
VOLAT	0.518***	0.515***	0.517***	0.514***	0.520***	0.515***
	(0.094)	(0.094)	(0.094)	(0.094)	(0.093)	(0.094)
ROE	0.193***	0.194***	0.193***	0.194***	0.194***	0.194***
	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)
Constant	0.460***	0.473***	0.473***	0.497***	0.449***	0.466***
	(0.060)	(0.058)	(0.064)	(0.063)	(0.061)	(0.060)
Year F.E.	YES	YES	YES	YES	YES	YES
Country F.E.	YES	YES	YES	YES	YES	YES
Industry F.E.	YES	YES	YES	YES	YES	YES
Observations	11,710	11,710	11,710	11,710	11,710	11,710
Adjusted R-squared	0.271	0.273	0.271	0.273	0.271	0.273

Panel B: Book-to-market ratio

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	*BEME*	*BEME*	*BEME*	*BEME*	*BEME*	*BEME*
LOGS1	0.048***		0.040***		0.045***	
	(0.005)		(0.005)		(0.005)	
LOGS2		0.046***		0.039***		0.044***
		(0.005)		(0.007)		(0.006)
GEOCDS1			−0.399***			
			(0.102)			
GEOCDS2				−0.337**		
				(0.145)		

INDCDS1					−0.277***	
					(0.106)	
INDCDS2						−0.261*
						(0.139)
LOGS1xGEOCDS1			0.033***			
			(0.009)			
LOGS2xGEOCDS2				0.028**		
				(0.012)		
LOGS1xINDCDS1					0.024***	
					(0.009)	
LOGS2xINDCDS2						0.021*
						(0.011)
LOGSIZE	−0.097***	−0.094***	−0.100***	−0.096***	−0.099***	−0.094***
	(0.007)	(0.008)	(0.007)	(0.008)	(0.007)	(0.008)
LEVERAGE	−0.127**	−0.084	−0.133**	−0.092	−0.127**	−0.085
	(0.057)	(0.058)	(0.056)	(0.058)	(0.057)	(0.058)
PPEINT	0.113*	0.172***	0.107*	0.163***	0.112*	0.168***
	(0.060)	(0.058)	(0.061)	(0.059)	(0.060)	(0.058)
MOM	−3.445***	−3.486***	−3.428***	−3.481***	−3.425***	−3.479***
	(0.193)	(0.196)	(0.191)	(0.196)	(0.193)	(0.196)
VOLAT	1.195***	1.245***	1.179***	1.240***	1.188***	1.242***
	(0.212)	(0.213)	(0.211)	(0.212)	(0.212)	(0.212)
ROE	−0.479***	−0.492***	−0.476***	−0.490***	−0.479***	−0.492***
	(0.042)	(0.042)	(0.042)	(0.042)	(0.042)	(0.042)
Constant	1.839***	1.845***	1.976***	1.967***	1.898***	1.903***
	(0.241)	(0.253)	(0.246)	(0.258)	(0.241)	(0.257)
Year F.E.	YES	YES	YES	YES	YES	YES
Country F.E.	YES	YES	YES	YES	YES	YES
Industry F.E.	YES	YES	YES	YES	YES	YES
Observations	11,710	11,710	11,710	11,710	11,710	11,710
Adjusted R-squared	0.427	0.418	0.429	0.419	0.428	0.419

Appendix C – Continent-level differences

We report the results of the pooled OLS regression with standard errors clustered at the firm level (in parentheses). All regressions include year-, country- and industry-fixed effects. **Panel A** reports the regression results for annual stock return (*RET*) as dependent variable; **Panel B** reports the regression results for the book-to-market ratio (*BEME*) as dependent variable. All independent variables are lagged by one year. Definitions of all variables are given in Table 1. The sample period is 2010–2020. Carbon emissions data for firm-level variables are collected from the CDP, whereas the firm-level data are collected from Thomson Reuters ESG/Eikon/DataStream databases. All firm-level continuous variables are winsorized at the 1st and 99th percentiles. ***1% significance; **5% significance; *10% significance.

Panel A: Annual stock returns

	North America		Europe		Asia	
	(1)	(2)	(3)	(4)	(5)	(6)
Variables	*RET*	*RET*	*RET*	*RET*	*RET*	*RET*
LOGS12TOT	0.032***	0.024***	0.010**	0.014***	0.024***	0.027***
	(0.007)	(0.006)	(0.005)	(0.004)	(0.005)	(0.005)
GEOCDS12	0.353*		−0.183*		−0.065	
	(0.180)		(0.095)		(0.151)	
LOGS12TOTxGEOCDS12	−0.024*		0.013*		0.007	
	(0.013)		(0.008)		(0.011)	
INDCDS12		−0.022		−0.060		0.124
		(0.189)		(0.102)		(0.171)
LOGS12TOTxINDCDS12		0.003		0.005		−0.010
		(0.014)		(0.008)		(0.013)
LOGSIZE	−0.047***	−0.047***	−0.035***	−0.034***	−0.055***	−0.054***
	(0.008)	(0.008)	(0.006)	(0.006)	(0.008)	(0.008)
BEME	−0.340***	−0.339***	−0.219***	−0.216***	−0.183***	−0.181***
	(0.022)	(0.022)	(0.015)	(0.015)	(0.017)	(0.017)
LEVERAGE	−0.164***	−0.168***	−0.072*	−0.076*	−0.089*	−0.082*
	(0.052)	(0.052)	(0.041)	(0.041)	(0.049)	(0.048)
PPEINT	−0.070	−0.077	0.047	0.057	−0.046	−0.057
	(0.047)	(0.048)	(0.036)	(0.035)	(0.055)	(0.055)
MOM	−1.124***	−1.088***	−0.840***	−0.820***	−1.984***	−1.972***
	(0.342)	(0.345)	(0.247)	(0.246)	(0.330)	(0.331)
VOLAT	1.016***	1.011***	1.267***	1.271***	−0.020	−0.025
	(0.221)	(0.221)	(0.199)	(0.199)	(0.224)	(0.224)

ROE	0.145***	0.143***	0.268***	0.270***	0.368***	0.367***
	(0.032)	(0.032)	(0.036)	(0.036)	(0.075)	(0.074)
Constant	0.580***	0.678***	0.514***	0.454***	0.810***	0.743***
	(0.125)	(0.112)	(0.162)	(0.151)	(0.156)	(0.150)
Year F.E.	YES	YES	YES	YES	YES	YES
Country F.E.	YES	YES	YES	YES	YES	YES
Industry F.E.	YES	YES	YES	YES	YES	YES
Observations	3,100	3,100	4,412	4,412	3,041	3,041
Adjusted R-squared	0.347	0.345	0.312	0.311	0.254	0.254

Panel B: Book-to-market ratio

	North America		Europe		Asia	
	(1)	(2)	(3)	(4)	(5)	(6)
Variables	*BEME*	*BEME*	*BEME*	*BEME*	*BEME*	*BEME*
LOGS12TOT	0.067***	0.064***	0.032**	0.047***	0.092***	0.093***
	(0.010)	(0.010)	(0.013)	(0.010)	(0.015)	(0.014)
GEOCDS12	0.174		−0.765***		−0.812**	
	(0.207)		(0.223)		(0.378)	
LOGS12TOTxGEOCDS12	−0.015		0.058***		0.064**	
	(0.016)		(0.019)		(0.029)	
INDCDS12		0.213		−0.472**		−0.863***
		(0.200)		(0.197)		(0.314)
LOGS12TOTxINDCDS12		−0.017		0.035**		0.068***
		(0.015)		(0.016)		(0.024)
LOGSIZE	−0.087***	−0.087***	−0.090***	−0.088***	−0.169***	−0.161***
	(0.011)	(0.011)	(0.013)	(0.013)	(0.014)	(0.015)
LEVERAGE	−0.450***	−0.463***	−0.059	−0.066	0.030	0.062
	(0.083)	(0.084)	(0.097)	(0.100)	(0.129)	(0.133)
PPEINT	0.012	0.012	0.273***	0.303***	−0.239*	−0.228*
	(0.094)	(0.094)	(0.097)	(0.093)	(0.137)	(0.136)
MOM	−2.829***	−2.838***	−3.317***	−3.290***	−3.052***	−3.059***
	(0.343)	(0.344)	(0.328)	(0.331)	(0.330)	(0.328)
VOLAT	1.842***	1.855***	1.821***	1.851***	−0.695*	−0.737*

	(0.341)	(0.345)	(0.346)	(0.354)	(0.378)	(0.384)
ROE	−0.251***	−0.248***	−0.583***	−0.583***	−0.476***	−0.480***
	(0.041)	(0.041)	(0.077)	(0.077)	(0.157)	(0.156)
Constant	1.068***	1.095***	2.122***	1.897***	2.565***	2.433***
	(0.266)	(0.260)	(0.362)	(0.369)	(0.313)	(0.297)
Year F.E.	YES	YES	YES	YES	YES	YES
Country F.E.	YES	YES	YES	YES	YES	YES
Industry F.E.	YES	YES	YES	YES	YES	YES
Observations	3,100	3,100	4,412	4,412	3,041	3,041
Adjusted R-squared	0.490	0.490	0.431	0.426	0.442	0.442

Appendix D – Subsample analysis country development

We report the results of the pooled OLS regression with standard errors clustered at the firm level (in parentheses). We classify our sample countries as advanced based on the International Monetary Fund (IMF) World Economic Outlook Database. All regressions include year-, country- and industry-fixed effects. **Panel A** reports the regression results for annual stock return (*RET*) as dependent variable; **Panel B** reports the regression results for the book-to-market ratio (*BEME*) as dependent variable. All independent variables are lagged by one year. Definitions of all variables are given in Table 1. The sample period is 2010–2020. Carbon emissions data for firm-level variables are collected from the CDP, whereas the firm-level data are collected from Thomson Reuters ESG/Eikon/DataStream databases. All firm-level continuous variables are winsorized at the 1st and 99th percentiles. ***1% significance; **5% significance; *10% significance.

Panel A: Annual stock returns				
	Advanced		Developing	
	(1)	(2)	(3)	(4)
Variables	*RET*	*RET*	*RET*	*RET*
LOGS12TOT	0.017***	0.017***	0.040***	0.044***
	(0.003)	(0.003)	(0.009)	(0.009)
GEOCDS12	−0.038		−0.161	
	(0.067)		(0.342)	
LOGS12TOTxGEOCDS12	0.002		0.014	
	(0.005)		(0.024)	
INDCDS12		0.001		0.184
		(0.078)		(0.250)
LOGS12TOTxINDCDS12		−0.000		−0.013
		(0.006)		(0.019)
LOGSIZE	−0.037***	−0.037***	−0.096***	−0.094***
	(0.004)	(0.004)	(0.014)	(0.014)
BEME	−0.212***	−0.212***	−0.234***	−0.232***
	(0.010)	(0.010)	(0.030)	(0.030)
LEVERAGE	−0.090***	−0.090***	−0.171*	−0.160*
	(0.025)	(0.025)	(0.090)	(0.090)
PPEINT	0.005	0.007	−0.060	−0.065
	(0.024)	(0.024)	(0.088)	(0.089)
MOM	−1.129***	−1.127***	−1.310***	−1.304***
	(0.169)	(0.169)	(0.425)	(0.423)
VOLAT	0.762***	0.763***	0.899***	0.902***
	(0.126)	(0.126)	(0.319)	(0.323)
ROE	0.234***	0.234***	0.217***	0.217***
	(0.023)	(0.023)	(0.063)	(0.062)
Constant	0.418***	0.410***	1.273***	1.176***
	(0.099)	(0.095)	(0.216)	(0.219)
Year F.E.	YES	YES	YES	YES
Country F.E.	YES	YES	YES	YES
Industry F.E.	YES	YES	YES	YES
Observations	10,424	10,424	1,286	1,286
Adjusted R-squared	0.279	0.279	0.239	0.238

(Continued)

Appendix D−*Continued*

Panel B: Book-to-market ratio				
	Advanced		Developing	
	(1)	(2)	(3)	(4)
Variables	*BEME*	*BEME*	*BEME*	*BEME*
LOGS12TOT	0.063***	0.068***	0.042**	0.048***
	(0.008)	(0.007)	(0.019)	(0.018)
GEOCDS12	−0.413***		−1.174*	
	(0.152)		(0.651)	
LOGS12TOTxGEOCDS12	0.030**		0.088*	
	(0.012)		(0.048)	
INDCDS12		−0.349**		−0.732
		(0.141)		(0.553)
LOGS12TOTxINDCDS12		0.025**		0.054
		(0.011)		(0.041)
LOGSIZE	−0.112***	−0.111***	−0.137***	−0.143***
	(0.008)	(0.008)	(0.026)	(0.027)
LEVERAGE	−0.096	−0.090	−0.704***	−0.674***
	(0.060)	(0.061)	(0.155)	(0.153)
PPEINT	0.036	0.048	−0.069	−0.119
	(0.066)	(0.065)	(0.189)	(0.201)
MOM	−3.141***	−3.141***	−4.569***	−4.555***
	(0.196)	(0.197)	(0.550)	(0.549)
VOLAT	1.157***	1.168***	1.312**	1.274**
	(0.223)	(0.224)	(0.513)	(0.513)
ROE	−0.441***	−0.441***	−0.528***	−0.537***
	(0.042)	(0.042)	(0.126)	(0.126)
Constant	1.894***	1.835***	2.777***	2.796***
	(0.372)	(0.365)	(0.483)	(0.532)
Year F.E.	YES	YES	YES	YES
Country F.E.	YES	YES	YES	YES
Industry F.E.	YES	YES	YES	YES
Observations	10,424	10,424	1,286	1,286
Adjusted R-squared	0.455	0.454	0.439	0.437

Appendix E – Alternative proxies for geographical dispersion

We report the results of the pooled OLS regression with standard errors clustered at the firm level (in parentheses). *FORDUM* is an indicator variable equal to one for firms with any foreign sales. *MNC* is an indicator variable equal to one for firms with a foreign sales ratio of at least 30%. *FRGNSAL* is the ratio of foreign sales to total sales. All regressions include year-, country- and industry-fixed effects. **Panel A** reports the regression results for annual stock return (*RET*) as dependent variable; **Panel B** reports the regression results for the book-to-market ratio (*BEME*) as dependent variable. All independent variables are lagged by one year. Definitions of all variables are given in Table 1. The sample period is 2010–2020. Carbon emissions data for firm-level variables are collected from the CDP, whereas the firm-level data are collected from Thomson Reuters ESG/Eikon/DataStream databases. All firm-level continuous variables are winsorized at the 1st and 99th percentiles. ***1% significance; **5% significance; *10% significance.

Panel A: Annual stock returns			
	(1)	(2)	(3)
Variables	*RET*	*RET*	*RET*
LOGS12TOT	0.010***	0.013***	0.013***
	(0.004)	(0.003)	(0.003)
FORDUM	−0.090**		
	(0.045)		
LOGS12TOTxFORDUM	0.006*		
	(0.003)		
MNC		−0.047	
		(0.036)	
LOGS12TOTxMNC		0.004	
		(0.003)	
FRGNSAL			−0.054
			(0.049)
LOGS12TOTxFRGNSAL			0.004
			(0.004)
LOGSIZE	−0.032***	−0.032***	−0.032***
	(0.003)	(0.003)	(0.003)
BEME	−0.180***	−0.179***	−0.179***
	(0.007)	(0.007)	(0.007)
LEVERAGE	−0.085***	−0.084***	−0.084***
	(0.020)	(0.020)	(0.020)
PPEINT	−0.006	−0.005	−0.005
	(0.020)	(0.020)	(0.020)
MOM	−0.975***	−0.969***	−0.969***
	(0.126)	(0.126)	(0.126)
VOLAT	0.509***	0.503***	0.503***
	(0.093)	(0.093)	(0.093)
ROE	0.195***	0.195***	0.195***
	(0.017)	(0.017)	(0.017)
Constant	0.533***	0.492***	0.488***
	(0.071)	(0.064)	(0.065)
Year F.E.	YES	YES	YES
Country F.E.	YES	YES	YES
Industry F.E.	YES	YES	YES
Observations	11,710	11,710	11,710
Adjusted R-squared	0.273	0.273	0.273

Panel B: Book-to-market ratio			
	(1)	(2)	(3)
Variables	*BEME*	*BEME*	*BEME*
LOGS12TOT	0.037***	0.057***	0.057***
	(0.012)	(0.008)	(0.009)
FORDUM	−0.547***		
	(0.148)		
LOGS12TOTxFORDUM	0.040***		
	(0.011)		
MNC		−0.265***	
		(0.102)	
LOGS12TOTxMNC		0.020**	
		(0.008)	
FRGNSAL			−0.416***
			(0.142)
LOGS12TOTxFRGNSAL			0.028**
			(0.011)
LOGSIZE	−0.113***	−0.113***	−0.112***
	(0.008)	(0.008)	(0.008)
LEVERAGE	−0.148***	−0.140**	−0.144**
	(0.055)	(0.056)	(0.056)
PPEINT	0.049	0.053	0.047
	(0.061)	(0.061)	(0.061)
MOM	−3.363***	−3.356***	−3.360***
	(0.192)	(0.192)	(0.192)
VOLAT	1.152***	1.130***	1.152***
	(0.207)	(0.209)	(0.209)
ROE	−0.464***	−0.466***	−0.465***
	(0.041)	(0.041)	(0.041)
Constant	2.233***	1.962***	1.973***
	(0.281)	(0.263)	(0.266)
Year F.E.	YES	YES	YES
Country F.E.	YES	YES	YES
Industry F.E.	YES	YES	YES
Observations	11,710	11,710	11,710
Adjusted R-squared	0.438	0.435	0.436

Appendix F – Firm- and year-fixed effects

We report the results of the pooled OLS regression with standard errors clustered at the firm level (in parentheses). All regressions include firm- and year-fixed effects. **Panel A** reports the regression results for annual stock return (*RET*) as dependent variable; **Panel B** reports the regression results for the book-to-market ratio (*BEME*) as dependent variable. All independent variables are lagged by one year. Definitions of all variables are given in Table 1. The sample period is 2010–2020. Carbon emissions data for firm-level variables are collected from the CDP, whereas the firm-level data are collected from Thomson Reuters ESG/Eikon/DataStream databases. All firm-level continuous variables are winsorized at the 1st and 99th percentiles. ***1% significance; **5% significance; *10% significance.

Panel A: Annual stock returns					
	(1)	(2)	(3)	(4)	(5)
Variables	*RET*	*RET*	*RET*	*RET*	*RET*
LOGS12TOT	0.015*	0.014*	0.014*	0.013	0.017**
	(0.009)	(0.009)	(0.009)	(0.009)	(0.008)
GEOCDS12		0.035	0.047*	−0.048	
		(0.027)	(0.028)	(0.149)	
INDCDS12		−0.009	0.017		0.152
		(0.018)	(0.033)		(0.135)
GEOCDS12xINDCDS12			−0.062		
			(0.057)		
LOGS12TOTxGEOCDS12				0.007	
				(0.011)	
LOGS12TOTxINDCDS12					−0.012
					(0.010)
LOGSIZE	−0.322***	−0.322***	−0.322***	−0.322***	−0.322***
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
BEME	−0.428***	−0.428***	−0.428***	−0.428***	−0.427***
	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)
LEVERAGE	−0.193***	−0.195***	−0.195***	−0.195***	−0.191***
	(0.063)	(0.063)	(0.063)	(0.063)	(0.063)
PPEINT	−0.037	−0.035	−0.034	−0.035	−0.036
	(0.074)	(0.074)	(0.074)	(0.075)	(0.074)
MOM	−1.934***	−1.934***	−1.933***	−1.932***	−1.935***
	(0.177)	(0.177)	(0.177)	(0.177)	(0.177)
VOLAT	0.681***	0.683***	0.681***	0.683***	0.680***
	(0.150)	(0.150)	(0.150)	(0.150)	(0.150)
ROE	0.280***	0.280***	0.279***	0.280***	0.280***
	(0.031)	(0.031)	(0.031)	(0.031)	(0.031)
Constant	5.218***	5.221***	5.220***	5.245***	5.192***
	(0.256)	(0.257)	(0.257)	(0.265)	(0.254)
Firm F.E.	YES	YES	YES	YES	YES
Year F.E.	YES	YES	YES	YES	YES
Country F.E.	NO	NO	NO	NO	NO
Industry F.E.	NO	NO	NO	NO	NO
Observations	11,710	11,710	11,710	11,710	11,710
Adjusted R-squared	0.419	0.419	0.419	0.419	0.419

(Continued)

Appendix F−*Continued*

Panel B: Book-to-market ratio					
	(1)	(2)	(3)	(4)	(5)
Variables	*BEME*	*BEME*	*BEME*	*BEME*	*BEME*
LOGS12TOT	0.023***	0.023**	0.023**	0.019*	0.019**
	(0.009)	(0.009)	(0.009)	(0.010)	(0.009)
GEOCDS12		−0.001	0.015	−0.190	
		(0.029)	(0.030)	(0.142)	
INDCDS12		−0.001	0.034		−0.388***
		(0.021)	(0.043)		(0.119)
GEOCDS12xINDCDS12			−0.082		
			(0.071)		
LOGS12TOTxGEOCDS12				0.015	
				(0.012)	
LOGS12TOTxINDCDS12					0.030***
					(0.009)
LOGSIZE	−0.163***	−0.163***	−0.163***	−0.163***	−0.163***
	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)
LEVERAGE	−0.197***	−0.197***	−0.197***	−0.196***	−0.201***
	(0.067)	(0.067)	(0.067)	(0.067)	(0.067)
PPEINT	−0.027	−0.027	−0.026	−0.029	−0.031
	(0.109)	(0.109)	(0.109)	(0.109)	(0.108)
MOM	−2.135***	−2.136***	−2.135***	−2.137***	−2.136***
	(0.176)	(0.175)	(0.175)	(0.176)	(0.175)
VOLAT	0.409**	0.410**	0.407**	0.412**	0.414**
	(0.167)	(0.167)	(0.167)	(0.167)	(0.167)
ROE	−0.213***	−0.213***	−0.213***	−0.213***	−0.213***
	(0.040)	(0.040)	(0.040)	(0.040)	(0.039)
Constant	2.927***	2.927***	2.926***	2.977***	2.982***
	(0.255)	(0.256)	(0.255)	(0.258)	(0.254)
Firm F.E.	YES	YES	YES	YES	YES
Year F.E.	YES	YES	YES	YES	YES
Country F.E.	NO	NO	NO	NO	NO
Industry F.E.	NO	NO	NO	NO	NO
Observations	11,710	11,710	11,710	11,710	11,710
Adjusted R-squared	0.744	0.744	0.744	0.744	0.745

Appendix G – Carbon intensity

We report the results of the pooled OLS regression with standard errors clustered at the firm level (in parentheses). *S12INT* measures the firm-level carbon intensity, which is ratio of carbon emissions to sales. All regressions include year-, country- and industry-fixed effects. **Panel A** reports the regression results for annual stock return (*RET*) as dependent variable; **Panel B** reports the regression results for the book-to-market ratio (*BEME*) as dependent variable. All independent variables are lagged by one year. Definitions of all variables are given in Table 1. The sample period is 2010–2020. Carbon emissions data for firm-level variables are collected from the CDP, whereas the firm-level data are collected from Thomson Reuters ESG/Eikon/DataStream databases. All firm-level continuous variables are winsorized at the 1st and 99th percentiles. ***1% significance; **5% significance; *10% significance.

Panel A: Annual stock returns

	(1)	(2)	(3)	(4)	(5)
Variables	*RET*	*RET*	*RET*	*RET*	*RET*
S12INT	0.000	0.000	0.000	−0.001	−0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
GEOCDS12		0.011	0.017	0.005	
		(0.012)	(0.014)	(0.012)	
INDCDS12		0.010	0.024		0.007
		(0.011)	(0.019)		(0.011)
GEOCDS12xINDCDS12			−0.031		
			(0.035)		
S12INTxGEOCDS12				0.004**	
				(0.002)	
S12INTxINDCDS12					0.003
					(0.003)
LOGSIZE	−0.023***	−0.024***	−0.024***	−0.024***	−0.024***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
BEME	−0.195***	−0.195***	−0.195***	−0.196***	−0.195***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
LEVERAGE	−0.075***	−0.077***	−0.077***	−0.077***	−0.077***
	(0.023)	(0.024)	(0.024)	(0.024)	(0.024)
PPEINT	0.052**	0.053**	0.054***	0.052**	0.052**
	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)
MOM	−1.216***	−1.210***	−1.210***	−1.214***	−1.212***
	(0.155)	(0.155)	(0.155)	(0.155)	(0.155)
VOLAT	0.780***	0.780***	0.780***	0.779***	0.779***
	(0.116)	(0.116)	(0.117)	(0.117)	(0.117)
ROE	0.225***	0.227***	0.226***	0.227***	0.226***
	(0.021)	(0.022)	(0.022)	(0.021)	(0.021)
Constant	0.485***	0.493***	0.488***	0.496***	0.488***
	(0.092)	(0.092)	(0.092)	(0.091)	(0.092)
Year F.E.	YES	YES	YES	YES	YES
Country F.E.	YES	YES	YES	YES	YES
Industry F.E.	YES	YES	YES	YES	YES
Observations	11,710	11,710	11,710	11,710	11,710
Adjusted R-squared	0.256	0.256	0.256	0.256	0.256

(Continued)

Appendix G−*Continued*

Panel B: Book-to-market ratio					
	(1)	(2)	(3)	(4)	(5)
Variables	*BEME*	*BEME*	*BEME*	*BEME*	*BEME*
S12INT	0.009***	0.009***	0.009***	0.005**	0.007***
	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)
GEOCDS12		0.027	0.045	0.005	
		(0.029)	(0.033)	(0.029)	
INDCDS12		0.034	0.070*		0.008
		(0.023)	(0.042)		(0.023)
GEOCDS12xINDCDS12			−0.087		
			(0.072)		
S12INTxGEOCDS12				0.016***	
				(0.005)	
S12INTxINDCDS12					0.018***
					(0.005)
LOGSIZE	−0.054***	−0.057***	−0.057***	−0.056***	−0.056***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
LEVERAGE	−0.048	−0.056	−0.055	−0.055	−0.054
	(0.057)	(0.057)	(0.057)	(0.056)	(0.057)
PPEINT	0.246***	0.250***	0.252***	0.243***	0.244***
	(0.057)	(0.057)	(0.057)	(0.057)	(0.057)
MOM	−3.693***	−3.672***	−3.671***	−3.674***	−3.663***
	(0.196)	(0.196)	(0.196)	(0.195)	(0.196)
VOLAT	1.330***	1.326***	1.326***	1.319***	1.318***
	(0.216)	(0.217)	(0.217)	(0.216)	(0.216)
ROE	−0.515***	−0.511***	−0.512***	−0.509***	−0.513***
	(0.043)	(0.043)	(0.043)	(0.043)	(0.043)
Constant	1.764***	1.783***	1.770***	1.787***	1.778***
	(0.231)	(0.230)	(0.231)	(0.231)	(0.229)
Year F.E.	YES	YES	YES	YES	YES
Country F.E.	YES	YES	YES	YES	YES
Industry F.E.	YES	YES	YES	YES	YES
Observations	11,710	11,710	11,710	11,710	11,710
Adjusted R-squared	0.405	0.405	0.405	0.407	0.407