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Global Pricing of Carbon-Transition Risk

PATRICK BOLTON and MARCIN KACPERCZYK*

ABSTRACT

The energy transition away from fossil fuels exposes companies to carbon-transition risk. Estimating the market-based premium associated with carbon-transition risk in a cross section of 14,400 firms in 77 countries, we find higher stock returns associated with higher levels and growth rates of carbon emissions in all sectors and most countries. Carbon premia related to emissions growth are greater for firms located in countries with lower economic development, larger energy sectors, and less inclusive political systems. Premia related to emission levels are higher in countries with stricter domestic climate policies. The latter have increased with investor awareness about climate change risk.

PUBLIC OPINION, GOVERNMENTS, BUSINESS LEADERS, and institutional investors all over the world are awakening to the urgency of combatting climate change.[1] This growing concern about climate change may crystalize into a faster and perhaps more disorderly transition away from fossil fuels to

*Patrick Bolton is with Columbia University; Imperial College; CEPR; and NBER. Marcin Kacperczyk is with Imperial College and CEPR. We thank Lucian Bebchuk; John Cochrane; Harrison Hong; Paul Hsu; Louis Kaplow; Paymon Khorrami; Christian Leuz; Pedro Matos; Stefan Nagel (the editor); Kunal Sachdeva; Zacharias Sautner; two referees; and the associate editor for many helpful suggestions. We are also grateful to seminar participants at the Bank for International Settlements, Bank of England, Bank of Italy, Bank of Japan, Blackrock, Danmarks Nationalbank Climate Conference, Florida State University, Harvard Law School, HEC Montreal, Imperial College, INSEAD, Mayo Finance Seminar, McGill, NBER LTAM Meetings, NBIM, Rice University, University of Alberta, University of Cyprus, University of Geneva Climate Conference, University of Miami, UNPRI, Virtual Seminar on Climate Economics, and the World Bank for their comments. We are grateful to Trucost for giving us access to their corporate carbon emissions data, and to Adrian Lam and Jingyu Zhang for their very helpful research assistance. Some of the ideas in this paper have been reported in the working draft, "Carbon Premium around the World." This project has received funding from the European Research Council (ERC) under the ERC Advanced Grant program (grant agreement No. 885552 Investors and Climate Change). We have read *The Journal of Finance's* disclosure policy and have no conflicts of interest to disclose.

Correspondence: Marcin Kacperczyk, Imperial College, London Business School, London, SW7 2AZ, UK, e-mail: m.kacperczyk@imperial.ac.uk

[1] Some of the most notable actions include the national and pan-national initiatives, such as Conference of the Parties (COP), Nationally Declared Contributions (NDCs) supported by the United Nations, or the G20 Taskforce for Climate-related Financial Disclosure (TCFD).

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renewable energy. By now, over 100 countries have committed to carbon net neutrality targets, representing nearly 50% of the world's gross domestic product (GDP). In addition, several multilateral agreements and other commitments to reduce carbon emissions have been reached.[2] This, in turn, means greater carbon-transition risk for companies, especially those that rely more on fossil fuel production or consumption. From an individual firm's perspective, transition risk reflects the uncertain rate of adjustment toward carbon neutrality. From investors' perspective, the risk also embodies evolving beliefs about the transition to cleaner energy. Hence, transition risk is the amalgamation of a wide range of shocks, including changes in climate policy, reputational impacts, shifts in market preferences and norms, and technological innovation. In this paper, we take a (forward-looking) global financial market perspective to evaluate the economic importance investors attach to this transition risk by looking at stock prices of a large set of global companies with different degrees of exposure to this risk.

The economics literature on climate change following Nordhaus (1991) has framed the issue of mitigation of climate change as a public goods problem that requires a global Pigouvian carbon tax to internalize the externality of carbon emissions. The tax should be set equal to the social cost of carbon (SCC) to achieve efficiency, where the SCC is given by the discounted, expected, and physical harm from a warming climate caused by the accumulation of carbon particles in the atmosphere. This literature does not address the transition risk that firms relying on fossil energy face as the economy adjusts to a renewable energy base. In contrast, the finance literature on climate change is more directly concerned with the pricing of climate change risk, in particular, transition risk. But this literature is still in its infancy, and we currently only have patchy evidence on the pricing of carbon-transition risk, and especially on the various sources of this risk. Accordingly, in this study we attempt a more systematic, a more wide-ranging analysis than has been done to date on the pricing of transition risk. We explore how corporate carbon emissions together with country characteristics that reflect the country's likely progress in the energy transition affect stock returns of over 14,400 listed companies in 77 countries over a period ranging from 2005 to 2018. This is essentially the universe of all listed companies globally for which it is possible to obtain carbon emissions data and represents 80% of the market value of all public firms.

As is well known, cross-country studies are beset by endogeneity and identification challenges, as country-level variation can be driven by many different sources. In this study, we can to some extent overcome these challenges by exploiting rich country-, industry-, and firm-level variation in carbon emissions and other characteristics to identify the different sources of transition risk relating to technological shifts, social norms, and energy policies. This granularity of firm-level observations can be combined with various fixed effects

[2] Some of the prominent examples include China's commitment to carbon net neutrality by 2060, and Japan's and the United Kingdom's commitments by 2050. See Bolton and Kacperczyk (2021b) for more details on net zero commitments.

to better understand what is driving transition risk. To our knowledge, this is the first study in economics on transition risk with such a large panel data structure.

The first contribution of our paper is to shed light on the distribution of corporate carbon emissions across all countries in our sample. In most studies on global carbon emissions, the unit of analysis is the country and little information is provided about the breakdown of emissions across companies within each country. According to *Fortune* magazine, in 2017 the 500 largest companies in the world generated $30 trillion in revenues.[3] This represents 37.5% of world GDP, which was around $80 trillion in 2017 according to the Central Intelligence Agency's CIA World Factbook. It is thus natural to view climate change mitigation not just through the lens of the largest emitting countries, but also through the lens of the largest emitting companies.

As a second contribution of our paper, we estimate the size of a global carbon-transition risk premium by relating lagged firm-level emissions to individual stock returns. Given the lack of concern about climate change until recently, a plausible null hypothesis is that we should not find higher stock returns for companies with higher carbon emissions over our sample period, with the exception perhaps of Europe (and to some extent the United States, Japan, and a few other OECD countries). A reasonable alternative hypothesis, however, is that investors do pay attention to climate risk and that a carbon premium is to be found in the parts of the world responsible for the highest fraction of carbon emissions, that is, in the largest and most developed economies. It is in these economies that emission reductions are most urgent and therefore where transition risk is highest.

A few general striking results emerge from our analysis. The first general finding is that the carbon premium is positively related to both the level of emissions and the year-to-year growth in emissions, controlling for characteristics that predict returns. Given that the carbon transition is in essence transitory, carbon transition risk a priori ought to be reflected in both the levels and rates of change in emissions. We also find that the premium is related to both direct emissions from production (scope 1) and indirect emissions from firms in the supply chain (scope 2 & scope 3). All the results are statistically and economically highly significant. As an example, a one-standard-deviation increase in cross-sectional scope 1 emissions is associated with a 1.1% increase in annualized stock returns. A comparable result for changes in emissions is 2.2%. In general, the magnitude of the effect is stronger when we account for underlying differences across industries, which underscores the importance of industry adjustment in any study of carbon-transition risk. It is also stronger for indirect scope 3 emissions.

Our findings bring out the fact that a firm's exposure to carbon-transition risk is proportional to the level of its emissions. This is a very robust finding, which goes against the near exclusive focus of attention on emission intensity (the ratio of carbon emissions over sales, assets, or kWh) by practitioners

[3] https://fortune.com/global500/2018/.

and other climate finance studies. There are two reasons why asset managers have focused on emission intensity. First, from a portfolio diversification perspective, the emission intensity measure allows for a portfolio construction approach that is independent of the size of the portfolio. Second, emission intensity treats firms of different sizes the same way. Firms are evaluated on their carbon efficiency per unit of sales. By that metric, a large firm can be seen as more environmentally friendly than a small firm, even though its climate impact in terms of the size of its carbon emissions is much larger.

To be sure, the *Financial Times*-Statista ranking of Europe's Climate Leaders ranks which companies performed best in terms of improving their carbon intensity. As the 2022 *Financial Times* article listing the best performers explains: "The 400 companies listed below are those that achieved the greatest reduction in their Scope 1 and 2 greenhouse gas (GHG) emissions intensity over a 5-year period (2015–20) this time."[4] Two problematic examples from this list (among others) are Fortum, with a reported 29.8% reduction in emission intensity, but an increase in total emissions of 157.2%; and Axereal, with a 23.8% reduction in emission intensity, but an increase in total emissions of 236.2%. The list of climate leaders also includes companies with huge GHG emissions, for example, Engie with 40.9 million tons of CO2e for 2020, or Holcim Group with 117 million tons of CO2e. These examples vividly illustrate the difficulty with carbon intensity as a measure of carbon-transition risk.

Given the limited and fast disappearing carbon budget (consistent with maintaining a temperature rise below 1.5° C with 83% probability),[5] any improvement in carbon efficiency is, of course, desirable. Yet, the overriding objective for the world is to achieve carbon neutrality and bring net emissions down to zero. The fact that all net zero pledges are in terms of absolute emission reduction targets is telling. What the world needs and aims for is first a reduction in carbon emission levels, and second only an improvement in carbon efficiency. It is therefore to be expected that investor exposure to carbon-transition risk would be proportional to the level of emissions. The size of emissions is also the core focus of institutional investor initiatives to reduce carbon emissions, such as Climate Action 100+, which aims "to ensure [that] the world's largest corporate GHG emitters take necessary action on climate change."[6]

Interestingly, the levels of and growth in emissions affect the carbon premium independently, which we interpret as reflecting both a long-run and short-run component in carbon transition. Given that emissions are highly persistent over time, the level of emissions picks up the long-run exposure to transition risk, whereas changes reflect a company's short-run drift away from (or into) greater future emissions. Changes in emissions could also reflect

[4] Neville Hawcock, "Special Report: Europe's Climate Leaders 2022," *Financial Times*, April 8, 2022, https://www.ft.com/climate-leaders-europe-2022.

[5] See Intergovernmental Panel on Climate Change (IPCC) "Climate Change 2021, The Physical Science Basis, Summary for Policy Makers," https://www.ipcc.ch/report/sixthassessment-report-working-group-i.

[6] See https://www.climateaction100.org/.

changes in earnings, but we control for this effect by adding the company's return on equity and sales growth to our independent variables.

To provide additional robustness to our estimation of the carbon premium, and to partially address the possibility that stock returns are noisy, we also relate carbon emissions to firms' book-to-market ratios. We find that a one-standard-deviation increase in cross-sectional direct emissions is associated with 13% higher book-to-market ratios, again controlling for a host of fixed effects and firm characteristics. These results corroborate our return-based findings. In particular, the economic magnitude of these findings is within the range of our return estimates. This adds further evidence against the interpretation that the carbon premium is driven by unexpected return components.

A second general finding is a positive and significant carbon premium in most areas of the world. It is present in North America, Europe, and Asia, but with different magnitudes. It is less present in the Southern Hemisphere region, but this is an economically and socially more diverse group of countries. Our cross-country results also suggest that financial markets are not fully integrated globally. A simple categorization of countries based on their level of economic development does not explain the variation in carbon premium across countries. However, at a more granular level, we find that the short-term carbon premium is generally higher among firms that are headquartered in countries with more modest economic development. It is higher in countries with lower GDP per capita, countries whose economic output relies more on the manufacturing sector, and in countries with less developed healthcare sectors. Yet, the same characteristics cannot explain the cross-country variation in the long-term carbon premium. These results stand in contrast to the common view that carbon transition is exclusively a problem for developed countries.

As a third general contribution of our paper, we study the different sources of this carbon-transition risk. The main premise of our tests is that in partially segmented markets, the local country environment can amplify or mitigate the average premium. Since country-level evidence is possibly subject to omitted variables bias, we exploit firm-level variation in carbon emissions in conjunction with a variety of firm-level controls and fixed effects to better identify each economic channel. Our identification approach is similar to the one effectively used by Rajan and Zingales (1998) in their study of the link between financial development and economic growth.

We identify several country-level characteristics that matter significantly. We group these characteristics into two broad categories, respectively, political or social factors, and energy factors. Regarding political factors, we find that both "voice" and "rule of law" significantly affect the short-run carbon premium associated with the growth in emissions. More democratic countries (with stronger rules of law) tend to have lower carbon premia, other things equal. Further, we find that the long-term carbon premium is larger in countries with tighter climate policies. This finding suggests that investors perceive climate policies to be permanent and unlikely to be reversed. Notably, when we separate domestic policies from international agreements, we find that only the former are economically significant, and the latter have a very small effect. This result underscores the importance of political coordination costs associated with climate policies, a problem that has beset the international community in recent years.

When we consider country-level variations in the energy mix, we find that the carbon premium is lower in countries with a higher share of renewable energy, and higher in countries with greater dependence on the energy sector. The energy mix effect is reflected in the short-term premium, which suggests that any technological shocks are perceived as transitory, or alternatively as a factor that is hard to estimate in the long run. Interestingly, we find that a country's energy consumption is not a significant predictor of the carbon premium, which underscores the importance of distinguishing between the production and consumption sides of energy.

Finally, we also find that in the countries that have been exposed to greater damages from climate disasters (such as floods, wild fires, and droughts) there is no significantly different carbon premium. This result suggests that the carbon premium does not reflect physical climate risks, nor that physical risk is positively correlated with transition risk, or that (consistent with the findings of Hong, Li, and Xu (2019)) transition risk may be more salient to investors in countries experiencing rising physical risk.

The sociopolitical and energy-related channels mostly reflect the cash flow effects related to transition risk. Of equal importance may be discount rate effects that reflect investors' perceptions about carbon-transition risk. To assess the importance of the latter, we consider natural time period breaks in our sample period. Given that climate change has become a major issue for investors only recently, we explore how the carbon premium has changed in recent years. We compare the estimated premia for the 2 years leading up to the Paris agreement in 2015 and following the agreement. Several striking results emerge from this analysis. First, when we pool all countries together, we find that there was no significant premium right before the Paris agreement, but a highly significant and large premium after the agreement. This result is consistent with the view that the Paris agreement has changed investors' awareness regarding the urgency of climate change. Second, the change in the carbon premium is mostly related to long-term risks, which, given our previous results, suggests that the Paris agreement led investors to update their beliefs about the long-term impact of climate policy tightness rather than on the short-term impact of technological shocks or changes in the political environment. Finally, when we break down the change in the carbon premium around the Paris agreement by continent, we find that the premium has sharply risen in Asia, and less so in North America and Europe. In effect, Asia is entirely responsible for the rise in the global carbon premium around the Paris agreement.

A difficult question to answer is how changes in carbon-transition risk get impounded into asset prices. From an equilibrium perspective, our results imply the existence of a transition stage during which prices of assets with low emissions are bid up while prices of assets with high emissions are bid down in response to changing investor beliefs. The different repricing phases are difficult to pin down since individual asset prices may transition at different times and at different speeds. Still, we provide some evidence that such repricing has indeed taken place. We show that the rise in the use of renewable technology coincides with the decrease in stock prices of oil majors. Similar findings can be observed for countries that rely more on natural resources. These repricing effects are economically large and underscore the importance of the energy transition to a new equilibrium.

I. Related Literature

We are obviously not the first to undertake a cross-country analysis in sustainable finance. The closest analysis to ours is by Görgen et al. (2021), who construct a carbon risk factor using stock return differences between a group of "brown" and "green" firms around the world. Their paper is mostly focused on the pricing properties of the factor and not on transition risk itself. It does not relate stock returns to any of the mechanisms that are central to our paper, such as short-term versus long-term risk, or technology, social, and policy risk. Also related in terms of general subject matter are the studies by Dyck et al. (2019) and Gibson et al. (2022), both of which explore how environmental, social, and governance (ESG)-motivated investing varies around the world. Notably, neither of these studies addresses the pricing of carbon-transition risk, which is the focus of our paper.

Next to this cross-country literature there is, of course, a growing country-level climate finance literature, mostly focused on the United States. In an early theoretical contribution, Heinkel, Kraus, and Zechner (2001) have shown how divestment from companies with high emissions can give rise to higher stock returns. An early study by Matsumura, Prakash, and Vera-Munoz (2014) finds that higher emissions are associated with lower firm values. Similarly, Chava (2014) finds that firms with higher carbon emissions have a higher cost of capital. More recently, Ilhan, Sautner, and Vilkov (2021) have found that carbon emission risk is reflected in out-of-the-money put option prices. Hsu, Li, and Tsou (2023) derive and test a model showing that highly polluting firms are more exposed to environmental regulation risk and command higher average returns. Engle et al. (2020) have constructed an index of climate news through textual analysis of the *Wall Street Journal* and other media and show how a dynamic portfolio strategy can be implemented that hedges risk with respect to climate change news. Monasterolo and De Angelis (2020) explore whether investors demand higher risk premia for carbon-intensive assets following the COP21 agreement. Garvey, Iyer, and Nash (2018) study the effect of changes in direct emissions on stock returns, and Bolton and Kacperczyk (2021a) find that there is a significantly positive effect of carbon emissions on U.S. firms' stock returns for both direct and indirect carbon emissions. Among all these studies, the last one is most closely related given its focus on carbon pricing and the use of similar data sources. Nevertheless, that paper is mostly focused on carbon pricing and the response of portfolio managers to transition risk. More fundamentally, because it is solely based on U.S. data, that paper is silent on the mechanisms driving transition risk, which is the central focus of this paper.

Other related studies have explored the asset pricing consequences of greater material risks linked to climate events and global warming. Bansal, Kiku, and Ochoa (2016) reveal the asset pricing implications of rising temperatures using an equilibrium framework with an endogenous temperature process embodied in a standard long-run risk model. Hong, Wang, and Yang (2023) propose an asset pricing model in which natural disaster mitigation costs are priced in the cross section of firms. Hong, Li, and Xu (2019) find that the rising drought risk caused by climate change is not efficiently priced by stock markets.

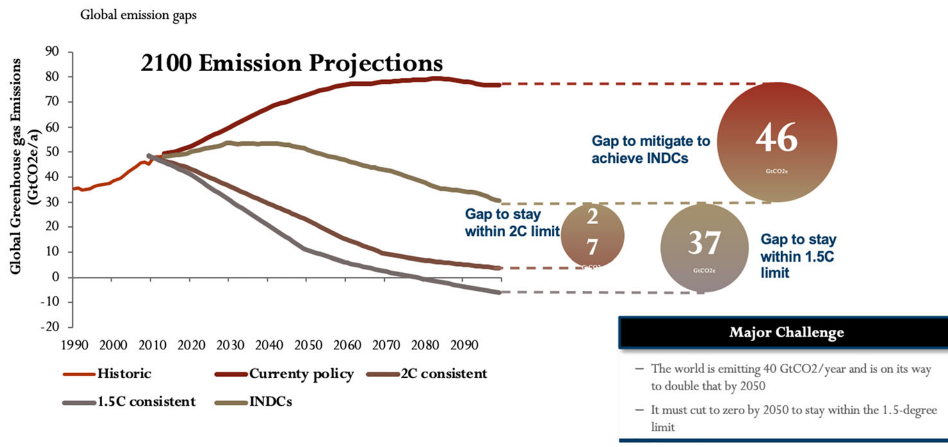
The remainder of the paper is organized as follows: Section II outlines the conceptual framework for our empirical tests, Section III describes the data and provides summary statistics, Section IV discusses the results, and Section V concludes.

II. Conceptual Framework

We begin by outlining a conceptual framework that could account for the presence of carbon-transition risk for investors in a global economy on the way to decarbonization in the next couple of decades. The basic concept of carbon-transition risk is meant to capture investor uncertainty with respect to all the changes companies will be faced with along the expected pathway to *carbon net neutrality*. The net zero targets that many countries and companies have embraced are anchored around the current scientific consensus on the need to eliminate global carbon emissions by 2050 to avoid increases in average temperatures of more than 1.5 C relative to preindustrial levels that would pose a threat to human existence.

We illustrate the formal link between global emissions and temperature changes in Figure 1. This Intergovernmental Panel on Climate Change (IPCC) graph provides simulations of various scenarios relating the changes in emissions and projected temperature outcomes. As is illustrated, to stay within a 1.5 C limit, global emissions would need to go down to zero by 2050, from the level of 420 Gt of CO_2 as of 2018. Since then, the problem has become even more dire, as the latest IPCC report warns that additional carbon emissions as of 2020 should not exceed a cumulative total of 300Gt of CO_2. Achieving this goal involves a complete *transition* of the corporate sector from brown to green energy. Such a radical transition will come with new risks, which we define as *carbon-transition risk*. Importantly, this risk will materialize irrespective of the physical damages due to future changes in climate.

This carbon-transition risk should be understood in the context of a nonstationary climate that is evolving in response to the accumulation of carbon emissions in the atmosphere. Because the underlying economy and climate are nonstationary, carbon-transition risk is also a nonstationary risk. Even if there is no unexpected change in a company's emissions, the carbon premium can change with time simply because the underlying economy is nonstationary.



Source: Climate Action Tracker Database, Global emissions time series, updated November 2017. Time series data for INDCs, 2C consistent, 1.5C consistent time series are computed as medians of highest and lowest potential global emission level results.

Figure 1. Global emissions and projected average annual global temperature. (Color figure can be viewed at wileyonlinelibrary.com)

Also, the marginal effect of emissions is different depending on how close we are to a potentially cataclysmic tipping point.

The closer we get to exhausting the carbon budget, the worse any marginal emissions will be. The transition to a net zero economy involves a finite time frame. Thus, for the same level of emissions, coming closer to the end date (say, 2050) is going to be riskier for a given company because of the increasing pressure to eliminate emissions. That is why the premium is likely to be rising over time even if a company's level of emissions does not change. Of course, this does not necessarily mean that the carbon premium will rise steadily over time. A more plausible scenario could be an abrupt unexpected downward repricing of brown assets or upward repricing of green assets.

From an asset pricing perspective, we can split carbon-transition risk into two separate sources: risks tied to cash flows and risks associated with changes in discount rates. The cash flow channel concerns all the risks related to the cost of decarbonization, stranded assets, and technological shocks. Further, these adjustment costs and the speed at which they materialize are affected by the degree of climate policy tightness, which itself is uncertain. Another amplifying effect works through capital expenditures, which are required to refit the economy for renewable energy use. The rate at which these capital expenditures are made over the next decades is difficult to predict. Even if one can predict the relative vulnerabilities of certain industries, cash flow outcomes as well as investors' beliefs for individual firms are far from certain. Take the auto industry for example. All car manufacturers are now scrambling to switch to electric vehicles (EVs). Except for Tesla and new EV entrants, their market values have taken a beating (another way of saying that there is a carbon premium on their stocks). Which of these companies will successfully transition to 100% EVs is difficult to say.

There are no models for the energy transition that can be readily applied to capture carbon-transition risk. However, equilibrium models in which technological risk is priced, as in Kogan and Papanikolaou (2014) and Hsu, Li, and Tsou (2023), are helpful reference points to guide the analysis of carbon-transition risk. In addition, the asset pricing model of Hong, Wang, and Yang (2023), which links natural disaster mitigation costs to asset prices in the cross section of firms could be applied to determine the impact on firm valuation of expected future carbon-transition costs. Other helpful related frameworks are the equilibrium models with uncertainty about policy changes of Pastor and Veronesi (2013). The basic prediction from these models is that risk-averse investors require compensation for holding assets that are exposed to carbon-transition risk, so that the equilibrium firms with greater exposure to carbon-transition risk offer higher expected returns. Note that the same prediction would obtain if investors simply developed a distaste for brown companies. These investors would require compensation for holding their noses, so to speak, so that brown companies would also offer higher returns even if there is no divestment in equilibrium.

The carbon premium can also be affected by changes in discount rates and investor expectations about carbon-transition risk. An important aspect of investor preferences and expectations is how the prevailing socioeconomic environment shapes investors' attitudes and outlooks toward climate change. In a society that values protection of the environment and combatting climate change, one should expect that investors will demand greater premia for holding assets associated with high carbon emissions. The role of social preferences works in a way similar to specialized and incomplete information in the equilibrium models of Merton (1987), Pastor, Stambaugh, and Taylor (2021), or Pedersen, Fitzgibbons, and Pomorski (2021), which generate higher risk premia driven by limitations imposed on investors' effective investment opportunity sets. This discount rate channel is different from the categorical divestment channel, as in the "sin stock" literature (Hong and Kacperczyk (2009)). The main difference is that it involves an intensive margin adjustment, with investors demanding higher compensation for holding assets with greater exposure to carbon-transition risk, rather than an extensive margin adjustment by a fraction of categorical divestors. Of course, both discount rate channel and divestment channels could be present in practice. Our findings of a significant carbon premium in all sectors, not just in the coal, oil, and gas sector, suggest that the discount rate channel is an important factor and that carbon risk premia are not just caused by divestment.

Each of these different channels is a plausible driver of carbon-transition risk. Determining their relative importance is largely an empirical question. Also, determining the size of the premium associated with carbon-transition risk is an empirical matter. Our empirical analysis aims to provide a quantitative assessment of each channel. Following Bolton and Kacperczyk (2021a), we use firm-level carbon emissions as proxies for the relative exposure of a

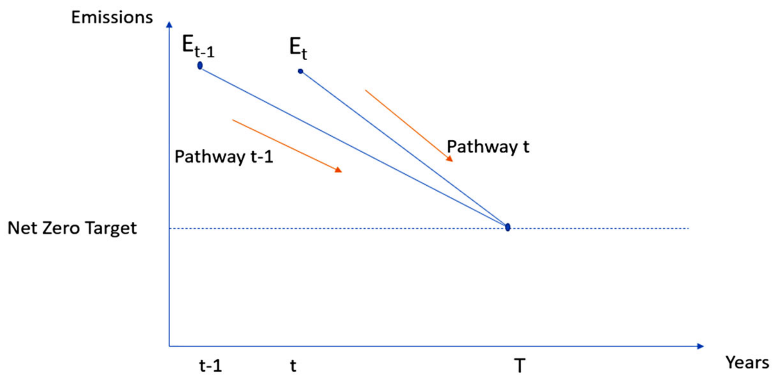


Figure 2. Decarbonization pathways conditional on period-specific emissions. (Color figure can be viewed at wileyonlinelibrary.com)

company to carbon-transition risk. We distinguish between the level of emissions, which indicates the firm's distance from a net zero emission target (a measure of long-term risk), and the growth rate of emissions, which indicates the rate at which a company is decarbonizing (a measure of short-term risk). Firms that keep increasing their emissions may be seen as riskier due to their growing future decarbonization challenge. In this respect, carbon emissions are a state variable that investors care about, and increasingly so, just as investors care about vulnerabilities such as supply bottlenecks and commodity price changes. In our empirical tests, we use the cross-sectional variation in both measures to characterize differences in corporate exposures to carbon-transition risk. Interestingly, we find that long-term and short-term carbon-transition risk are not highly correlated at the firm level.

Carbon emissions are plausibly a time-dependent state variable. The same level of emissions in year t does not reflect the same conditions as in year $t-1$ or year $t+1$. The reason is that any year that passes brings a firm closer to the net zero target deadline. If the level of emissions in year t remains the same as in year $t-1$, this means that the firm faces a steeper decarbonization challenge in year t than it did in year $t-1$, as Figure 2 below illustrates. Therefore, investors' perceptions of carbon transition risk evolve as they update their information about a firm's year-to-year decarbonization progress. The most recent carbon emissions data reflect investors' best assessment of the decarbonization effort their firm faces going forward. Given that the underlying context evolves over time, this means that the information contained in the emissions of year $t-1$ is superseded by those of year t as they are gradually revealed. We illustrate this logic in Figure 2 below.

The figure displays the level of emissions E in years $t-1$ and t. The level of emissions sets the pathway to net zero by year T. When investors observe the new level of emissions for year t, the information contained in the previous year's emissions E_{t-1} is obsolete because it no longer informs investors about the transition risk reflected in the new pathway starting in year t. This observation suggests that the news effect of the emissions in any given year should dissipate over time, as investors gradually learn about the likely new yearly emission numbers. Therefore, any carbon premium we may identify is likely to be linked to a transitory firm-level state variable. This firm-level state variable can be transitory even if yearly emissions are highly persistent. As the figure shows, the level E_t is almost the same as the level E_{t-1}, yet the pathway gets steeper as time passes. What investors care about is the transition risk embedded in the pathway to net zero going forward; the slope of this pathway changes even if the level of emissions remains unchanged. The level of emissions, of course, can itself change, but, as we show, this change is quite volatile and hard to predict. As a result, there is a lot of news content in the latest emission numbers.

The strength of our empirical analysis is its global reach. Given that firms in different countries may face different carbon transition paths, it is natural to explore whether such variation in geographic location matters for asset prices. From the perspective of investors pricing transition risk, what matters is the ability to share risk with other investors as well as across different assets. Under the hypothesis of fully integrated markets and a global representative investor, one should expect the pricing of transition risk not to vary much across different locations. On the other hand, under (partially) segmented markets, one would expect to see clear differences in pricing across different locations. This heterogeneity could result from different policy regimes, different technological progress, or different perceptions of the threat of climate change. Thus, our empirical tests should shed useful light on the degree of market integration in pricing carbon risk.

In the rest of the paper, we build on the broad notions above and test them empirically using a large cross section of publicly listed firms from around the world.

III. Data and Sample

Our primary database matches two data sets: Trucost, which provides annual information on firm-level carbon and other GHG emissions, and FactSet, which assembles data on stock returns and corporate balance sheets. We performed the matching using ISIN as a main identifier. In some instances, in which the ISIN was not available to create a perfect match, we relied on matching based on company names.[7] Finally, when there were multiple subsidiaries of a given company, we used the primary location as a matching entity. The ultimate matching produced 14,468 unique companies out of 16,222 companies available in Trucost. They represent 77 countries. Among the companies we were not able to match, more than twothirds are not listed, and the remaining ones are small and are not available through Factset. The top three countries in terms of missing data are China, Japan, and the United States. Our sample

[7] After standardizing the company names in FactSet and Trucost, we choose companies whose names have a similarity score of one, based on the standardized company names.

covers more than 98% of publicly listed companies (in terms of their market capitalization) for which we have emissions data, representing 80% to 85% of the market value of all publicly listed firms available in Factset. Since Trucost sample firms fairly uniformly across different industries, our sample ought to cover as a first approximation the value-weighted emissions of the Factset universe. We augment these data with country-level variables from the World Bank, Germanwatch (the provider of the global climate policy index and the climate risk index [CRI]), Morgan Stanley (for the MSCI world index data), and IBES (for analyst earnings growth forecasts).

A. Data on Corporate Carbon Emissions

The Trucost EDX firm-level carbon emissions database follows the Greenhouse Gas Protocol that sets the standards for measuring corporate emissions.[8] The Greenhouse Gas Protocol distinguishes between three different sources of emissions: Scope 1 emissions, which cover direct emissions over 1 year from establishments that are owned or controlled by the company; these include all emissions from fossil fuel used in production. Scope 2 emissions come from the generation of purchased heat, steam, and electricity consumed by the company. Scope 3 emissions are caused by the operations and products of the company but occur from sources not owned or controlled by the company; these include emissions from the production of purchased materials, product use, waste disposal, and outsourced activities. The Greenhouse Gas Protocol provides detailed guidance on how to identify a company's most important sources of scope 3 emissions and how to calculate them. For purchased goods and services, this basically involves measuring inputs, or "activity data," and applying emission factors to these purchased inputs that convert activity data into emissions data. Trucost upstream scope 3 data are constructed using an input-output model that provides the fraction of expenditures from one sector across all other sectors of the economy. This model is extended to include sector-level emission factors, so that an upstream scope 3 emission estimate can be determined from each firm's expenditures across all sectors from which it obtains its inputs.[9]

The Trucost database reports all three scopes of carbon emissions in units of tons of CO_2 emitted in a year. We first provide basic summary statistics on carbon emissions across our 77 countries aggregated up from the firm-level emissions reported by Trucost. Table I reports the country-level distribution of firms in our sample and various measures of emissions broken down into scope 1, scope 2, and scope 3. We consider the average total yearly emissions in tons of CO_2 equivalent per firm in each country (*S1TOT*, *S2TOT*, and *S3TOT*), the (winsorized at 2.5%) yearly percentage rate of change in emissions (*S1CHG*,

[8] See https://ghgprotocol.org.

[9] Downstream scope 3 emissions, caused by the use of sold products, can also be estimated and are increasingly reported by companies. Trucost has only recently started assembling these data; given its much shorter time span, we did not include these data in our study.

Table I

Carbon Emissions by Country: 2005 to 2018

S1TOT (S2TOT; S3TOT) measures the firm-level average (by country) of scope 1(scope 2; scope 3) carbon emissions measured in tons of CO2e. *S1CHG (S2CHG; S3CHG)* measures the percentage growth rate in carbon emissions of scope 1 (scope 2; scope 3) (winsorized at 2.5%). *TOTS1 (TOTS2; TOTS3)* is a sum of *S1TOT (S2TOT; S3TOT)* within a country in a given year (averaged across all years).

Code	Country	Frequency	Percentage.	# co.	*S1TOT*	*S2TOT*	*S3TOT*	*S1CHG*	*S2CHG*	*S3CHG*	*TOTS1*	*TOTS2*	*TOTS3*
AE	UAE	1,748	0.2	34	382,822	45,424	133,220	10.93%	16.32%	11.05%	13,000,000	1,106,904	3,338,979
AR	Argentina	550	0.06	6	1,977,235	259,067	1,032,782	11.18%	38.18%	10.24%	9,816,885	1,137,898	4,831,946
AT	Austria	3,741	0.42	42	1,543,117	175,280	1,478,427	10.00%	16.37%	7.56%	34,500,000	4,073,719	33,900,000
AU	Australia	37,405	4.21	471	580,313	225,151	390,624	14.38%	20.19%	11.88%	141,000,000	51,700,000	91,500,000
BD	Bangladesh	254	0.03	5	112,458	23,661	145,789	16.66%	25.97%	14.83%	490,572	106,452	624,504
BE	Belgium	3,883	0.44	52	1,611,505	398,625	1,586,838	5.88%	11.12%	6.28%	35,200,000	9,368,517	39,000,000
BG	Bulgaria	123	0.01	3	49,815	11,011	44,659	34.85%	6.04%	14.60%	1,010,125	85,163	303,958
BH	Bahrain	198	0.02	3	1,986	5,858	28,640	7.04%	8.84%	9.21%	5,696	16,924	83,299
BR	Brazil	10,249	1.15	126	1,846,871	200,604	2,147,921	11.05%	16.74%	9.09%	119,000,000	12,700,000	145,000,000
BW	Botswana	68	0.01	2	3,986	16,534	38,093	12.15%	21.45%	21.82%	6,650	28,041	64,964
CA	Canada	25,479	2.87	399	1,179,827	194,523	794,471	13.80%	18.99%	11.30%	226,000,000	35,700,000	147,000,000
CH	Switzerland	12,638	1.42	172	1,751,558	219,020	1,848,782	5.40%	9.95%	5.63%	142,000,000	18,500,000	144,000,000
CI	Côte d'ivoire	154	0.02	2	10,867	13,642	102,418	5.46%	6.50%	6.45%	18,779	25,697	181,503
CL	Chile	3,991	0.45	37	2,520,658	150,335	526,513	9.99%	17.85%	9.09%	61,800,000	3,816,032	13,500,000
CN	China	73,490	8.28	1,660	4,009,318	258,028	1,121,424	17.16%	24.86%	16.47%	2,910,000,000	232,000,000	841,000,000
CO	Colombia	1,141	0.13	13	2,638,497	153,165	1,602,004	16.65%	23.03%	13.89%	24,900,000	1,460,375	14,600,000
CZ	Czech Republic	446	0.05	5	80,966	84,133	106,096	3.29%	8.69%	−2.05%	298,304	276,486	311,847
DE	Germany	19,023	2.14	253	4,126,920	584,281	3,403,940	7.12%	13.69%	7.24%	458,000,000	70,800,000	397,000,000
DK	Denmark	4,310	0.49	48	1,830,641	81,427	715,844	6.29%	8.37%	5.98%	48,000,000	2,101,215	19,200,000
EE	Estonia	116	0.01	2	1,324,801	23,427	72,707	10.45%	18.91%	5.49%	2,649,601	46,855	145,415
EG	Egypt	2,855	0.32	30	1,300,763	71,534	347,754	4.98%	10.42%	5.58%	22,200,000	1,285,661	6,255,982
ES	Spain	7,140	0.8	84	3,733,641	254,727	2,095,625	9.14%	15.39%	6.55%	153,000,000	11,100,000	89,400,000
FI	Finland	4,049	0.46	42	1,401,658	320,239	1,548,562	2.96%	10.18%	3.74%	34,300,000	7,964,368	37,800,000
FR	France	20,256	2.28	248	3,537,015	457,697	2,902,571	7.12%	11.09%	6.26%	411,000,000	57,400,000	355,000,000
GB	UK	68,153	7.68	660	1,037,499	263,688	1,350,755	7.47%	8.86%	6.25%	436,000,000	110,000,000	560,000,000

(Continued)

Table I—*Continued*

Code	Country	Frequency	Percentage.	# co.	*S1TOT*	*S2TOT*	*S3TOT*	*S1CHG*	*S2CHG*	*S3CHG*	*TOTS1*	*TOTS2*	*TOTS3*
GH	Ghana	235	0.03	2	3,583	3,103	68,338	0.63%	3.23%	2.96%	6,882	5,945	133,928
GR	Greece	1,929	0.22	23	4,208,318	155,010	938,891	13.98%	18.93%	7.11%	47,800,000	2,284,545	11,200,000
HK	Hong Kong	28,827	3.25	830	1,963,473	177,584	524,083	14.95%	28.14%	14.69%	383,000,000	45,200,000	119,000,000
HR	Croatia	128	0.01	2	839,807	101,136	745,120	−6.99%	−1.29%	12.21%	1,503,091	194,606	1,321,002
HU	Hungary	474	0.05	3	2,033,690	348,850	2,292,191	8.91%	22.72%	0.16%	6,100,691	1,046,018	6,871,986
ID	Indonesia	8,865	1	130	982,778	88,318	416,476	12.58%	14.81%	10.12%	62,100,000	5,377,655	28,000,000
IE	Ireland	1,749	0.2	20	1,013,523	88,576	854,927	5.99%	9.48%	5.64%	12,700,000	1,108,046	10,300,000
IL	Israel	5,688	0.64	92	207,414	49,185	289,135	12.32%	15.74%	9.46%	9,144,490	1,943,727	10,900,000
IN	India	33,514	3.78	518	3,452,714	141,930	1,006,817	13.04%	19.06%	12.24%	831,000,000	34,700,000	248,000,000
IS	Iceland	81	0.01	3	1,257	1,412	26,849	32.91%	28.11%	28.32%	3,156	3,806	67,937
IT	Italy	6,656	0.75	107	4,129,000	307,340	2,549,945	6.26%	11.40%	5.64%	169,000,000	14,300,000	118,000,000
JM	Jamaica	68	0.01	2	335	1,422	11,711	1.05%	16.31%	12.74%	671	2,843	23,423
JO	Jordan	196	0.02	4	1,325	6,190	30,871	−7.52%	0.47%	6.09%	4,338	17,295	102,857
JP	Japan	124,903	14.07	2,258	1,312,299	231,427	1,511,355	4.90%	10.72%	5.22%	980,000,000	204,000,000	1,250,000,000
KE	Kenya	524	0.06	8	103,831	8,819	75,464	24.97%	27.08%	14.38%	799,872	58,883	458,581
KW	Korea	51,738	5.83	843	1,243,235	166,251	1,001,098	10.34%	14.19%	9.15%	397,000,000	60,700,000	344,000,000
KZ	Kazakhstan	45	0.01	1	1,153	1,005	21,863	19.74%	18.64%	13.32%	1,153	1,005	21,863
LB	Lebanon	85	0.01	2	3,788	11,484	34,112	10.68%	13.73%	19.42%	5,696	17,485	54,787
LK	Sri Lanka	452	0.05	4	11,715	29,408	42,644	10.17%	23.04%	6.94%	28,522	89,216	136,662
LT	Lithuania	58	0.01	1	1,590	4,595	18,366	23.73%	20.36%	21.61%	1,590	4,595	18,366
LU	Luxembourg	54	0.01	3	1,035	1,368	8,149	−33.03%	−36.01%	−24.82%	2,263	2,823	17,197
MA	Morocco	1,352	0.15	13	1,690,454	67,664	307,399	6.16%	8.18%	5.86%	15,400,000	582,425	2,563,349
MU	Mauritius	114	0.01	3	925	1,368	9,340	45.24%	67.68%	27.90%	2,115	3,259	22,106
MX	Mexico	4,157	0.47	65	630,508	322,220	1,146,013	10.20%	15.58%	9.50%	23,000,000	10,100,000	36,900,000
MY	Malaysia	12,596	1.42	188	1,289,048	58,716	364,614	12.85%	18.36%	9.32%	108,000,000	6,093,201	32,100,000
NG	Nigeria	1,182	0.13	16	1,556,752	68,555	299,827	1.31%	5.69%	0.65%	23,600,000	1,024,925	4,236,235
NL	Netherlands	5,579	0.63	63	5,563,867	702,550	2,898,875	5.06%	7.38%	4.50%	188,000,000	23,700,000	97,700,000
NO	Norway	5,680	0.64	97	1,269,294	294,583	1,627,966	10.02%	13.26%	9.33%	49,000,000	9,238,739	56,700,000

(*Continued*)

Table I—*Continued*

Code	Country	Frequency	Percentage.	# co.	*S1TOT*	*S2TOT*	*S3TOT*	*S1CHG*	*S2CHG*	*S3CHG*	*TOTS1*	*TOTS2*	*TOTS3*
NZ	New Zealand	3,011	0.34	50	393,267	32,502	239,998	5.67%	9.68%	8.79%	8,036,961	707,115	5,067,580
OM	Oman	488	0.05	8	369,577	60,682	106,543	6.60%	16.64%	8.10%	2,686,115	433,197	755,255
PE	Peru	544	0.06	5	1,023,906	213,257	201,341	15.87%	18.77%	10.71%	3,617,539	755,370	721,199
PH	Philippines	5,583	0.63	72	1,077,980	87,818	518,201	17.10%	26.63%	12.56%	49,100,000	4,010,504	23,100,000
PK	Pakistan	3,169	0.36	51	750,597	40,021	217,645	12.02%	14.41%	9.61%	25,900,000	1,223,456	6,959,005
PL	Poland	5,672	0.64	60	2,368,805	158,750	619,717	12.22%	18.37%	10.16%	94,300,000	6,032,271	22,200,000
PT	Portugal	1,351	0.15	17	3,179,836	233,808	1,365,071	2.71%	12.34%	3.92%	26,400,000	1,974,726	11,800,000
QA	Qatar	1,222	0.14	23	611,145	45,424	210,790	7.31%	12.18%	6.43%	10,900,000	812,774	3,752,829
RO	Romania	250	0.03	4	886,381	56,688	680,844	14.92%	9.79%	8.08%	3,381,664	202,319	2,430,224
RS	Serbia	168	0.02	3	272,240	23,975	196,896	23.17%	18.38%	19.48%	601,691	55,795	452,004
RU	Russia	1,925	0.22	26	10,100,000	816,962	6,098,643	16.11%	19.48%	9.72%	147,000,000	10,800,000	72,600,000
SA	Saudi Arabia	1,088	0.12	98	2,345,866	1,002,530	1,190,067	−10.47%	8.66%	4.26%	66,100,000	22,600,000	43,600,000
SE	Sweden	11,560	1.3	174	228,060	74,868	703,569	7.48%	11.15%	7.68%	17,000,000	6,014,555	53,200,000
SG	Singapore	9,881	1.11	145	864,602	122,194	1,143,235	12.55%	18.94%	10.64%	55,800,000	8,285,673	74,100,000
SI	Slovenia	220	0.02	3	13,270	26,995	71,210	1.05%	21.79%	5.40%	37,469	78,045	203,048
TH	Thailand	5,767	0.65	106	2,089,681	167,475	674,012	14.69%	23.17%	13.21%	88,800,000	6,770,391	31,000,000
TN	Tunisia	140	0.02	2	239	235	5,106	−6.55%	0.70%	−1.53%	477	469	10,212
TR	Turkey	4,706	0.53	58	1,697,617	130,762	768,350	15.98%	18.69%	8.58%	55,000,000	4,237,040	23,400,000
TW	Taiwan	41,061	4.63	684	530,858	134,310	531,483	10.24%	17.23%	7.74%	135,000,000	41,300,000	147,000,000
UG	Uganda	88	0.01	1	842	1,470	4,194	34.73%	71.91%	4.62%	842	1,470	4,194
US	USA	175,377	19.76	3,013	2,012,926	323,727	1,733,058	7.87%	13.84%	8.24%	2,330,000,000	403,000,000	2,100,000,000
VN	Vietnam	820	0.09	15	479,322	43,086	343,905	12.19%	18.35%	14.68%	6,087,639	552,733	4,260,247
ZA	South Africa	14,883	1.68	148	1,074,195	444,228	423,650	10.53%	17.41%	6.08%	95,900,000	41,400,000	40,100,000
ZW	Zimbabwe	56	0.01	2	15,480	14,546	138,070	−6.75%	1.28%	8.77%	48,346	45,915	457,559
Total		887,429	100	14,468	1,874,065	246,606	1,301,047	9.73%	15.35%	8.86%	11,813,099,883	1,615,895,170	7,990,066,031

S2CHG, and *S3CHG*), and the total yearly emissions by country (*TOTS1*, *TOTS2*, and *TOTS3*).

The largest country by number of observations is obviously the United States, but remarkably it only represents around 19.8% of total observations, with Japan a close second with 14% of observations, and China as third with around 8.2% of observations. Importantly for our analysis, Table I highlights that the majority of the listed firms in our sample is not concentrated in these three large economies. In aggregate, the entire population of countries in our sample produces a staggering 11.81 billion tons of scope 1, 1.62 billion tons of scope 2, and 7.99 billion tons of scope 3 emissions per year. The three biggest contributors in terms of total carbon emissions produced are China producing 2.91 billion tons of scope 1 emissions per year, followed by the United States with 2.33 billion, and Japan contributing 980 million. The same three countries also dominate scope 2 and scope 3 emissions, except that the ranking changes, with the United States producing 2.1 billion of scope 3 emissions, followed by Japan with 1.25 billion, and China with 841 million tons of CO_2.

The global production of emissions does not necessarily reflect the contribution of each firm to the total, as the relative sizes of countries vary. In fact, the top three countries in terms of scope 1 emissions per firm are Russia, the Netherlands, and Greece, with their respective emission levels of 10.1 million, 5.6 million, and 4.2 million tons of CO_2 per year. An average Russian firm also leads the rankings in terms of scope 3 emissions with 6.1 million tons of CO_2, followed by Germany and France, with respective numbers of 3.4 and 2.9 million tons of CO_2. A slightly different picture can be painted when we compare firm-level emission intensities. The most intense countries in terms of scope 1 emissions include Estonia, Morocco, and Peru. Among the largest countries, Russia, India, and China score relatively high, while France, Japan, and the United Kingdom score relatively low.

Another striking observation is that carbon emissions are growing in most countries throughout our sample period. The country with the highest growth rate in scope 1 emissions is Mauritius, with an average yearly growth rate of 45%. The second largest is Bulgaria, with a 35% growth rate, and the third, fourth, and fifth largest are, respectively, Iceland, Kenya, and Lithuania. All these five countries have witnessed rapid GDP growth over our sample period. Among the largest economies, the ones with the highest growth rate in emissions are China with nearly 18%, the Russian Federation with 16%, the United States with 7.9%, and Germany with 7.1% growth rates. Among the countries with the lowest growth rates in scope 1 emissions are, remarkably, Saudi Arabia with a negative 10.5% growth rate (this may reflect the fact that a lot of companies have gone public over our sample period, lowering the average per-company scope 1 emissions), Luxembourg with a negative 33% growth rate, and Jordan with a minus 7.5% growth rate. When it comes to the growth rate in scope 3 emissions, some of these rankings are reversed, reflecting the fact that some countries increasingly rely on imports whose production generates high emissions. Thus, Saudi Arabia has a 4.3% growth rate in scope 3 emissions.

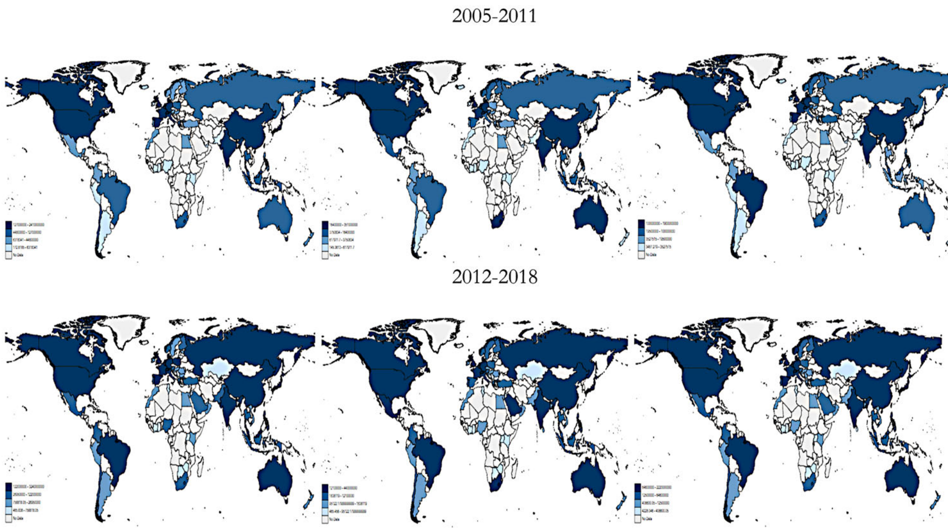


Figure 3. Total annual carbon emissions by country. (Color figure can be viewed at wileyonlinelibrary.com)

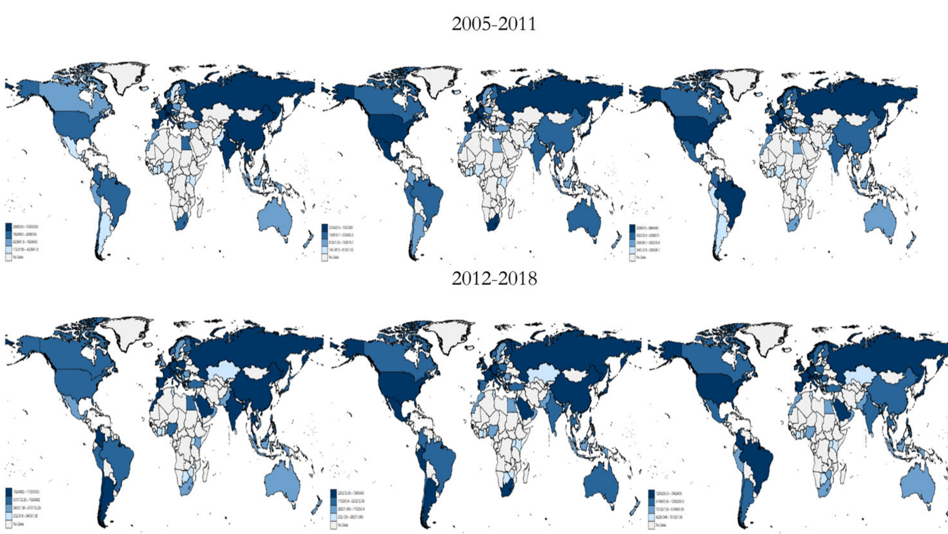


Figure 4. Average annual total carbon emissions per firm. (Color figure can be viewed at wileyonlinelibrary.com)

In Figures 3 and 4, we further represent the detailed cross-country variation in total emissions over two equal-length time periods, which classify countries into four categories by their performance in these metrics. The left panel of each figure represents scope 1 emissions, the middle panel scope 2 emissions, and the right panel scope 3 emissions. As can be seen in

Figure 3, the countries with the highest total average yearly emissions are first, the countries with the highest GDP, second the countries with the largest populations, and third the largest commodity exporting countries. Important exceptions are Sweden, which has the lowest emissions among developed countries, Iceland, and the Czech Republic. Importantly for our analysis, there is considerable cross-country variation in total emissions. To the extent that the carbon premium reflects concerns about the level of emissions, we expect to see considerable variation in the premium across countries.

We further show how the performance of countries has changed from the first half period of our sample from 2005 to 2011, to the second half period from 2012 to 2018. The most noteworthy changes are the deterioration in total emission performance of Latin America, the Russian Federation, Turkey, and Australia.

Interestingly, however, there is little correlation between a country's levels of total emissions and average per-firm emissions, as can be seen in Figure 4, which represents the cross-country variation in average per-firm emissions. Among the worst performers in the world in per-firm emissions are the United States, Saudi Arabia, Argentina, Colombia, China, the Russian Federation, India, Japan, and the European Union (excluding the United Kingdom).

In Table II, Panel A, we report summary statistics on per-firm carbon emissions in units of tons of CO_2 emitted in a year, normalized using the natural log scale. Thus, the log of total scope 1 emissions of the average firm in our sample (*LOGS1TOT*) is 10.32, with a standard deviation of 2.95. Note that the median number is the largest for scope 3 emissions (*LOGS3TOT*), indicating that most companies in our sample are significantly exposed to indirect emissions. To mitigate the impact of outliers, we have winsorized all growth measures at the 2.5% level. In Panel B, we report the correlations between the total emissions variable and the emission percentage change variable for the three different categories of emissions. Interestingly, the correlation coefficients are quite low, indicating that the emission change variable reflects a different type of variation in the data.

In Panel C, we study the autocorrelation patterns of both levels and rates of change of emissions. Formally, we estimate the regression model of annual emissions measures with their respective 1-year lags only (in columns (1) to (3)), and year-month- and firm-fixed effects (in columns (4) to (6)). We double the cluster standard errors by firm and year. The results indicate a significant persistence of emission levels, even after controlling for fixed effects, and almost no persistence in the rates of change measure. These results provide additional empirical support for emission levels as a metric of long-term transition risk and emission changes as a metric of short-term transition risk.

Finally, Panel D provides summary statistics on stock returns and several control variables we use in our subsequent tests. The dependent variable, $RET_{i,t}$, in our cross-sectional return regressions is the monthly return of an individual stock i in month t. We use the following control variables in our cross-sectional regressions: $LOGSIZE_{i,t}$, which is given by the natural logarithm of firm i's market capitalization (price times shares outstanding) at the

Table II

Summary Statistics

This tables reports summary statistics (averages, medians, and standard deviations) for the variables used in regressions. The sample period is from 2005 to 2018. Panels A and B report the emission variables and their pairwise correlations. Panel C shows the results from the autocorrelation results for the levels and changes in emissions measured at an annual frequency. Columns (1) to (3) include no fixed effects, while columns (4) to (6) include year- and firm-fixed effects. Standard errors (in parentheses) are double clustered by firm and year. Panel D reports summary statistics of the control variables. *RET* is the monthly stock return; *LOGSIZE* is the natural logarithm of market capitalization (in $ million); *B/M* is the book value of equity divided by market value of equity; *ROE* is the return on equity; *LEVERAGE* is the book value of leverage defined as the book value of debt divided by the book value of assets; *MOM* is the cumulative stock return over the 1 year period; *INVEST/A* is the CAPEX divided by book value of assets; *HHI* is the Herfindahl index of the business segments of a company with weights proportional to revenues; *LOGPPE* is the natural logarithm of plant, property, and equipment (in $ million); *VOLAT* is the monthly stock return volatility calculated over the 1 year period; $MSCI_{i,t}$ is an indicator variable equal to 1 if a stock i is part of MSCI World Index in year t, and 0 otherwise. *SALESGR* is the annual percentage change in firm revenues. *LTG* is the mean consensus forecast of long-term earnings growth. *GDPPC* is a country's GDP per capita. *MANUFPERC* is the percentage of a country's output that is attributed to the manufacturing sector. *HEALTHEXPPC* is the value of expenses on health per capita. *ELRENEW* is a country's percentage contribution of renewable energy to the total energy production. *ENINT* is a country's energy intensity. *ENUSEPC* is a country's energy consumption per capita. Rule of law, *RULELAW*, captures perceptions of the extent to which agents have confidence in and abide by the rules of society, and in particular the quality of contract enforcement, property rights, the police, and the courts, as well as the likelihood of crime and violence. The measure is standardized between −2.5 and 2.5. *VOICE* reflects perceptions of the extent to which a country's citizens are able to participate in selecting their government, as well as freedom of expression, freedom of association, and a free media. The measure is standardized between −2.5 and 2.5. *GINI* is a country's Gini inequality index as a percentage. *INTPOLICY* is a country's tightness of climate international policies. *DOMPOLICY* is a country's tightness of climate domestic policies. *CRI* is a country's index of physical climate risk. ***1% significance; **5% significance; *10% significance.

Panel A: Carbon Emissions

Variable	Mean	Median	Standard Deviation
Log (Carbon Emissions Scope 1 (tons CO2e)) (*LOGS1TOT*)	10.317	10.135	2.951
Log (Carbon Emissions Scope 2 (tons CO2e)) (*LOGS2TOT*)	10.173	10.233	2.265
Log (Carbon Emissions Scope 3 (tons CO2e)) (*LOGS3TOT*)	11.966	12.021	2.219
Growth Rate in Carbon Emissions Scope 1 (winsorized at 2.5%) (*S1CHG*)	9.73%	3.34%	41.34%
Growth Rate in Carbon Emissions Scope 2 (winsorized at 2.5%) (*S2CHG*)	15.35%	5.83%	49.01%
Growth Rate in Carbon Emissions Scope 3 (winsorized at 2.5%) (*S2CHG*)	8.86%	5.44%	25.74%

(*Continued*)

Table II—*Continued*

Panel B: Carbon Emissions: Cross-Correlations						
Variables	*S1CHG*	*S2CHG*	*S3CHG*	*LOGS1TOT*	*LOGS2TOT*	*LOGS3TOT*
S1CHG	1					
S2CHG	0.485	1				
S3CHG	0.555	0.503	1			
LOGS1TOT	0.040	−0.004	−0.045	1		
LOGS2TOT	−0.020	0.045	−0.061	0.736	1	
LOGS3TOT	−0.047	−0.046	−0.059	0.808	0.824	1

Panel C: Autocorrelations						
Variables	(1) *LOGS1TOT*	(2) *LOGS2TOT*	(3) *LOGS3TOT*	(4) *LOGS1TOT*	(5) *LOGS2TOT*	(6) *LOGS3TOT*
$LOGS1TOT_{t\text{-}12}$	0.981***			0.640***		
	(0.002)			(0.030)		
$LOGS2TOT_{t\text{-}12}$		0.962***			0.613***	
		(0.005)			(0.029)	
$LOGS3TOT_{t\text{-}12}$			0.973***			0.647***
			(0.005)			(0.027)
Constant	0.222***	0.462***	0.386***	3.809***	4.076***	4.349***
	(0.027)	(0.069)	(0.067)	(0.313)	(0.301)	(0.332)
Year-fixed effects	No	No	No	Yes	Yes	Yes
Firm-fixed effects	No	No	No	Yes	Yes	Yes
Observations	64,568	64,575	64,635	61,357	61,366	61,426
R-squared	0.962	0.936	0.973	0.975	0.956	0.983

(*Continued*)

Table II—*Continued*

Variables	(1) *S1CHG*	(2) *S2CHG*	(3) *S3CHG*	(4) *S1CHG*	(5) *S2CHG*	(6) *S3CHG*
$S1CHG_{t\text{-}12}$	0.016			−0.120***		
	(0.014)			(0.017)		
$S2CHG_{t\text{-}12}$		−0.009			−0.135***	
		(0.012)			(0.014)	
$S3CHG_{t\text{-}12}$			0.088**			−0.068**
			(0.029)			(0.029)
Constant	0.077***	0.127***	0.062***	0.086***	0.143***	0.074***
	(0.011)	(0.018)	(0.019)	(0.001)	(0.002)	(0.002)
Year-fixed effects	No	No	No	Yes	Yes	Yes
Firm-fixed effects	No	No	No	Yes	Yes	Yes
Observations	52,175	52,173	52,232	47,912	47,914	47,974
R-squared	0.000	0.000	0.009	0.162	0.164	0.241

(*Continued*)

Table II—*Continued*

Panel D: Regression Controls			
Variables	Mean	Median	Standard Deviation
RET (%)	1.076	0.054	10.229
LOGSIZE	11.105	9.644	5.212
B/M (winsorized at 2.5%)	0.572	0.440	0.510
LEVERAGE (winsorized at 2.5%)	0.227	0.209	0.175
MOM (winsorized at 2.5%)	0.136	0.089	0.383
INVEST/A (winsorized at 2.5%)	0.049	0.035	0.048
HHI	0.798	0.985	0.252
LOGPPE	7.748	7.684	3.313
ROE (winsorized at 2.5%)	11.094	10.870	16.076
VOLAT (winsorized at 2.5%)	0.090	0.079	0.051
MSCI	0.337	0	0.473
SALESGR (winsorized at 2.5%)	0.095	0.062	0.240
LTG (winsorized at 1%)	12.80	11.55	11.48
GDPPC	36,540.75	44,508	19,253
MANUFPERC (%)	15.93	12.99	7.43
HLTHEXPPC	4,235.74	4,099.47	3,025.87
ELRENEW (%)	5.33	3.83	5.71
ENINT	5.19	5.20	1.66
ENUSEPC	4,476.64	3,921.90	2,186.91
RULELAW	1.15	1.53	0.77
VOICE	0.73	1.03	0.85
GINI (%)	36.96	35.40	6.32
INTPOLICY	0.49	0.58	0.29
DOMPOLICY	0.53	0.51	0.27
CRI	46.84	44.83	25.86

end of year t; $B/M_{i,t}$, which is firm i's book value divided by its market cap at the end of year t; $LEVERAGE_{i,t}$, which is the ratio of debt to book value of assets; momentum, $MOM_{i,t}$, which is given by the average of the most recent 12 months' returns on stock i, leading up to and including month $t-1$; capital expenditures $INVEST/A_{i,t}$, which we measure as the firm's capital expenditures divided by the book value of its assets; a measure of the firm's specialization, $HHI_{i,t}$, which is the Herfindahl concentration index of the firm with respect to its different business segments, based on each segment's revenues; the firm's stock of physical capital, $LOGPPE_{i,t}$, which is given by the natural logarithm, of the firm's property, plant, and equipment; the firm's earnings performance $ROE_{i,t}$, which is given by the ratio of firm i's net yearly income divided by the value of its equity; the firm's idiosyncratic risk, $VOLAT_{i,t}$, which is the standard deviation of returns based on the past 12 month's returns; and, $MSCI_{i,t}$, which is an indicator variable equal to 1 if a stock i is part of the MSCI World index in year t, and 0 otherwise. $SALESGR_{i,t}$ is the annual growth rate in firm sales, $LTG_{i,t}$ is the analyst forecasts of the long-term earnings growth for firm i at time t, averaged across all analysts. To mitigate the impact of outliers, we have winsorized *B/M, LEVERAGE, INVEST/A*, *ROE*, *MOM*, and *VOLAT* at the 2.5% level, and *LTG* at the 1% level.

In Panel D, we also summarize all the relevant variables that we use in our cross-sectional analysis. These include measures related to technological progress, energy intensity, socioeconomic development, policy environment, and physical risk. We define each one explicitly in their respective tests in Section V. The average firm's monthly stock return equals 1.08%, with a standard deviation of 10.23%. The average firm has a market capitalization of $66 billion, significantly larger than the size of the median firm in our sample, which is $15 billion. The average book-to-market ratio is 0.57, and average book leverage is 23%. The average return on equity equals 11.1%, slightly more than the median of 10.87%.

Table III provides summary statistics by year for the total number of firms in our sample in any given year, and the level and percentage change in emissions for all three *scope* categories. Note the large increase in coverage after 2015, when the number of firms jumps from 5,427 in 2015 to 11,961 in 2016. This is because Trucost has been able to substantially expand the set of firms for which it collects data on carbon emissions from 2016 onward. For most of our empirical tests, we rely on cross-sectional variation in the data, so that we are less exposed to a possible structural break in the data in 2016. Moreover, many of our results hold when we restrict our sample to legacy firms, that is, those present in the sample prior to 2016.

We also report the distribution of firms by industry in Table IA.I, using the six-digit Global Industry Classification (GIC6). Our global database should reflect a greater proportion of firms in manufacturing and agriculture than is the case in developed economies. This is indeed what is reflected in Table IV, with 580 companies in the machinery industry; 530 in the chemicals industry; 520 in the electronic equipment, instruments, and components industry; 506 in metals and mining; and 440 food products companies. In the services sector,

Table III

Carbon Emissions by Year

The table reports the annual averages across all countries of all emission variables over the period 2005 till 2018.

Year	Number of Firms	*S1TOT*	*S2TOT*	*S3TOT*	*S1CHG*	*S2CHG*	*S3CHG*	*TOTS1*	*TOTS2*	*TOTS3*
2005	3,232	2,391,417	246,612	1,822,093	–	–	–	917000000	106000000	828000000
2006	3,532	2,367,787	264,064	1,705,187	16.18%	18.59%	9.83%	894000000	115000000	749000000
2007	3,689	2,488,889	290,500	1,800,563	18.89%	22.94%	15.94%	934000000	125000000	766000000
2008	3,736	2,541,971	330,705	1,679,148	9.34%	18.13%	−0.16%	955000000	146000000	728000000
2009	3,949	2,285,281	311,700	1,643,489	3.24%	8.47%	10.02%	870000000	136000000	720000000
2010	4,098	2,407,166	308,070	1,633,414	14.26%	18.14%	8.34%	904000000	130000000	689000000
2011	4,221	2,563,380	322,518	1,825,353	9.51%	15.73%	14.51%	937000000	136000000	761000000
2012	4,253	2,402,493	317,779	1,791,769	8.71%	10.60%	3.31%	868000000	133000000	748000000
2013	4,912	2,211,603	297,793	1,619,450	7.06%	8.43%	4.06%	878000000	135000000	743000000
2014	5,323	2,118,666	292,460	1,432,881	6.88%	20.46%	4.90%	895000000	142000000	694000000
2015	5,427	2,009,876	276,453	1,228,497	3.87%	2.48%	−1.76%	860000000	137000000	604000000
2016	11,961	1,038,161	143,425	693,127	5.95%	11.13%	10.81%	1130000000	183000000	902000000
2017	12,817	1,046,853	167,407	759,076	13.60%	26.03%	19.03%	1230000000	221000000	1050000000
2018	8,781	1,136,396	148,745	729,199	10.53%	12.24%	6.21%	1050000000	142000000	663000000

Table IV
Predictors of Carbon Emissions

The sample period is from 2005 to 2018. The dependent variables are carbon emission levels (Panel A) and the growth in emissions (Panel B). All variables are defined in Tables I and II. We report the results of the pooled regression with standard errors (in parentheses) double clustered at the firm and year levels. All regressions include year-month-fixed effects and country-fixed effects. In columns (4) to (6), we additionally include Trucost industry-fixed effects. ***1% significance; **5% significance; *10% significance.

Panel A: Levels

Variables	(1) *LOGS1TOT*	(2) *LOGS2TOT*	(3) *LOGS3TOT*	(4) *LOGS1TOT*	(5) *LOGS2TOT*	(6) *LOGS3TOT*
LOGSIZE	−0.085**	0.265***	0.210***	0.329***	0.472***	0.453***
	(0.039)	(0.023)	(0.016)	(0.020)	(0.027)	(0.023)
B/M	−0.093	0.108**	−0.007	0.371***	0.451***	0.381***
	(0.061)	(0.040)	(0.037)	(0.044)	(0.051)	(0.047)
ROE	0.010***	0.011***	0.014***	0.008***	0.008***	0.009***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
LEVERAGE	0.533**	0.326	−0.363*	0.669***	0.671***	0.370***
	(0.221)	(0.226)	(0.170)	(0.099)	(0.127)	(0.097)
INVEST/A	5.021***	1.079**	−1.882***	−1.136***	−1.928***	−3.089***
	(0.698)	(0.396)	(0.300)	(0.371)	(0.322)	(0.287)
HHI	−2.038***	−0.763***	−1.232***	−1.216***	−0.660***	−0.722***
	(0.145)	(0.087)	(0.118)	(0.074)	(0.059)	(0.062)
LOGPPE	0.782***	0.469***	0.534***	0.428***	0.336***	0.346***
	(0.026)	(0.014)	(0.014)	(0.015)	(0.016)	(0.016)
MSCI	0.119*	0.226***	0.203***	0.176***	0.256***	0.218***
	(0.059)	(0.045)	(0.041)	(0.040)	(0.049)	(0.042)
Constant	6.359***	3.850***	6.456***	3.902***	2.415***	4.555***
	(0.383)	(0.263)	(0.240)	(0.215)	(0.260)	(0.212)
Year/month-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Country-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry-fixed effects	No	No	No	Yes	Yes	Yes
Observations	886,751	886,895	887,429	874,592	874,736	875,270
R-squared	0.544	0.531	0.621	0.779	0.715	0.793

(*Continued*)

Table IV—*Continued*

Panel B: Growth in Emissions						
Variables	(1) *S1CHG*	(2) *S2CHG*	(3) *S3CHG*	(4) *S1CHG*	(5) *S2CHG*	(6) *S3CHG*
LOGSIZE	0.025***	0.029***	0.025***	0.025***	0.027***	0.025***
	(0.002)	(0.005)	(0.002)	(0.002)	(0.005)	(0.003)
B/M	−0.060***	−0.061***	−0.066***	−0.067***	−0.069***	−0.070***
	(0.009)	(0.009)	(0.006)	(0.009)	(0.009)	(0.007)
ROE	−0.002***	−0.002***	−0.001***	−0.001***	−0.002***	−0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
LEVERAGE	0.060***	0.064***	0.049***	0.060***	0.063***	0.043***
	(0.015)	(0.012)	(0.011)	(0.012)	(0.012)	(0.008)
INVEST/A	0.594***	0.589***	0.372***	0.451***	0.525***	0.317***
	(0.073)	(0.098)	(0.069)	(0.085)	(0.063)	(0.052)
HHI	0.007	−0.022	0.019***	0.011*	−0.017	0.020***
	(0.008)	(0.012)	(0.005)	(0.005)	(0.014)	(0.004)
LOGPPE	−0.021***	−0.021***	−0.020***	−0.023***	−0.022***	−0.021***
	(0.003)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)
MSCI	−0.033***	−0.041***	−0.030***	−0.033***	−0.040***	−0.029***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.004)
Constant	0.004	0.037	−0.025	0.020	0.071	−0.015
	(0.024)	(0.059)	(0.026)	(0.024)	(0.062)	(0.031)
Year/month-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Country-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry-fixed effects	No	No	No	Yes	Yes	Yes
Observations	765,387	765,397	765,949	755,257	755,267	755,819
R-squared	0.036	0.044	0.119	0.047	0.055	0.131

the largest represented industries are banking, with 679 banks and real estate, with 619 companies (some of which are also engaged in construction and development).

Finally, we report summary statistics on the main determinants of carbon emissions in Table IV. We regress in turn the log of total firm-level emissions and the percentage change in total emissions on the following firm-level characteristics: *LOGSIZE, B/M, ROE, LEVERAGE, INVEST/A, HHI, LOGPPE*, and *MSCI*. To allow for systematic differences in correlations across countries and over time, we include year-month-fixed effects and country-fixed effects, so that our identification comes from within-country variation across firms. In columns (4) to (6), we further include industry-fixed effects (following the classification of Trucost[10]) to account for possible differences across industries. The results are also robust to using GIC6 codes, though these are less desirable because they may capture companies with different emission profiles.

In Panel A, we show considerable variation across industries in the effect of these variables on emissions (e.g., the R-square increases from 0.696 to 0.779 when we add industry-fixed effects to the regression for *LOGS1TOT*). Accordingly, we focus on the regressions with industry-fixed effects and note that total emissions significantly increase with the size of the firm (in particular, if it is a constituent of the MSCI world index), its book-to-market ratio, its leverage, and its tangible capital stock (*PPE*). This is altogether not surprising to the extent that emissions are generated by economic activity, which is proportional to the size of the firm. Somewhat surprising is the strong effect of leverage. One possible explanation is that firms with higher emissions may anticipate a future drop in profitability due to transition risk and, as a result, take more leverage. Interestingly, investment has a strong negative effect on emissions, suggesting that new capital vintages are more carbon efficient. Industry specialization (a high Herfindahl index [HHI]) also has a negative effect on emissions, perhaps because nonspecialized conglomerates tend to be larger. Alternatively, conglomeration can reflect a firm's response to potential costs of high emissions in a particular sector.

IV. Results

We organize our discussion into three subsections. The first subsection reports results on the pricing of carbon-transition risk throughout the world, the second reports results related to specific drivers of carbon-transition risk, and the third subsection briefly discusses how carbon-transition risk may be gradually priced in as the underlying economy is transitioning away from fossil fuels.

[10] These roughly correspond to a three-digit SIC classification.

A. Pricing Carbon-Transition Risk throughout the World

In this section, we present our main findings on the pricing of carbon-transition risk. We begin by reporting findings for the full sample of firms. We then proceed to show how the carbon premium is distributed across geographic locations.

A.1. Empirical Specification

Our analysis of carbon-transition risk centers on two different cross-sectional regression models relating individual companies' stock returns to carbon emissions. Rather than a factor-based model, we take a firm characteristic–based approach along the lines of Daniel and Titman (1997). This approach is particularly well suited given the rich cross-sectional variation in firm characteristics in our sample.[11] As shown in Bolton and Kacperczyk (2021a), the following characteristics are particularly relevant when using carbon emissions as the main sorting variable: firm size, book-to-market, leverage, capital expenditures over assets, property plant and equipment, return on equity, sales growth, sectoral diversification, and a measure of stock price momentum and volatility. This characteristic–based approach also allows us to take full advantage of fixed effects along time, country, and industry dimensions. Further, we can better account for potential dependence of residuals by using a clustering methodology. Finally, the advantage of taking a characteristic-based approach is that we do not need to take a stance on the underlying asset pricing model. One basic conceptual difficulty with the choice of asset pricing model in the context of a complex pricing problem such as climate change risk, is that such a model has not yet been formulated. However, since we do not take a risk-factor approach, we cannot explore the presence of a "carbon alpha" or of any mispricing of carbon-transition risk. Our aim is more limited: to provide a comprehensive picture of the cross-sectional variation in stock-level returns throughout the world. Stated differently, our approach is to identify a company's "carbon beta."

We begin by linking companies' monthly stock returns to their corresponding *total* emissions and other characteristics, all lagged by 1 month. This regression model reflects the long-run, structural, firm-level impact of emissions on stock returns. Taking absolute carbon neutrality as a benchmark, one can think of this measure as a rough proxy for the quantity of risk a firm is exposed to at a given point in time. Specifically, we estimate the following model:

$$RET_{i,t} = a_0 + a_1\big(TOT\ Emissions\big)_{i,t-1} + a_2 Controls_{i,t-1} + \mu_t + \varepsilon_{i,t}, \qquad (1)$$

where $RET_{i,t}$ measures the stock return of company i in month t and *TOT Emissions* is a generic term standing for *LOGS1TOT*, *LOGS2TOT*,

[11] The risk factor-based approach has been a popular method for measuring risk premia in a single country, but in a fully global study such as this one, this approach is problematic because of the difficulties in specifying appropriate factor-mimicking portfolios for a large number of countries with limited data, and because of cross-country comparability issues.

and *LOGS3TOT*. The vector of firm-level controls includes the firm-specific variables *LOGSIZE, B/M, LEVERAGE, MOM, INVEST/ASSETS, HHI, LOGPPE, ROE*, and *VOLAT*.

Second, we relate companies' *growth in* annual total emissions to their monthly stock returns by estimating the following cross-sectional regression model:

$$RET_{i,t} = a_0 \ + a_1 \left(Total\ Emissions\right)_{i,t-1} + a_2 Controls_{i,t-1} + _{\mu t} + \epsilon_{i,t}. \qquad (2)$$

The percentage change in total emissions (*S1CHG*, *S2CHG*, and *S3CHG*) captures the short-run impact of emissions on stock returns. In particular, changes in total emissions reflect the extent to which companies load up on, or decrease, their material risk with respect to carbon emissions. From a transition perspective, this measure captures the position of a firm on a long-term path toward carbon neutrality. In this respect, it is complementary to the long-term objective captured by the level of emissions.

We estimate these two cross-sectional regressions using pooled OLS. In both models, we also include country-fixed effects, as well as year-month-fixed effects. Hence, our identification is cross-sectional in nature. In some tests, we also include the same set of industry-fixed effects as in Table IV to capture within-industry variation across firms. In all the model specifications, we double cluster standard errors at the firm and year levels, which allows us to account for any cross-firm correlation in the residuals as well as capture the fact that some control variables, including emissions, are measured at an annual frequency. Our coefficient of interest is a_1.

A.2. Evidence from the United States and China

We begin our analysis by comparing the results for our regression models in the two economies with the largest emissions, China and the United States. We report the results in Table V. These two economies differ in fundamental ways, and one would expect the carbon premium to reflect basic differences in the level of economic and financial development and in the legal and political regimes. Yet, we find that the results for scope 1 emissions are surprisingly similar, which suggests that firm-level variation in emissions may be more relevant for transition risk than are the differences between the two countries. Specifically, once one controls for industry and time as well as a battery of firm characteristics, firm-level differences in *LOGS1TOT* generate a highly significant carbon premium of similar size both in China (.069) and in the United States (.071), or equivalently an annualized value of 1.18% and 0.95% per one-standard-deviation change in total emission levels in each country, respectively.[12] Using a slightly shorter period (from 2005 to 2017), Bolton and Kacperczyk (2021a) find that the premium for U.S. companies is slightly lower. Here

[12] Throughout the paper, whenever we refer to a one-standard-deviation movement, we calculate standard deviations of a given variable, taking into account the impact of all other controls in

Table V

Carbon Emissions and Stock Returns: United States and China

The sample period is from 2005 to 2018. The dependent variable is *RET*, measured monthly. The main independent variables are carbon emission levels (Panel A) and the growth in emissions (Panel B). All variables are defined in Tables I and II. We report the results of the pooled regression with standard errors (in parentheses) double clustered at the firm and year level. All regressions include year-month-fixed effects, country-fixed effects, and industry-fixed effects. ***1% significance; **5% significance; *10% significance.

Panel A: Levels

Dependent Variable: *RET*	(1)	(2) United States	(3)	(4)	(5) China	(6)
LOGS1TOT	0.071***			0.069**		
	(0.021)			(0.030)		
LOGS2TOT		0.075*			0.147*	
		(0.036)			(0.073)	
LOGS3TOT			0.126**			0.208*
			(0.044)			(0.106)
LOGSIZE	−0.115	−0.134	−0.159	−0.338***	−0.369***	−0.387***
	(0.129)	(0.135)	(0.138)	(0.096)	(0.111)	(0.114)
B/M	0.535	0.522	0.496	1.003**	0.963**	0.944**
	(0.347)	(0.340)	(0.345)	(0.395)	(0.373)	(0.363)
LEVERAGE	−0.453	−0.456	−0.467*	−0.113	−0.121	−0.194
	(0.266)	(0.257)	(0.261)	(0.198)	(0.186)	(0.172)
MOM	0.296	0.305	0.307	1.014*	1.005*	0.993*
	(0.328)	(0.327)	(0.328)	(0.517)	(0.511)	(0.501)
INVEST/A	0.407	0.507	0.734	−0.403	−0.150	−0.062
	(2.422)	(2.420)	(2.343)	(0.786)	(0.866)	(0.869)
HHI	0.013	−0.037	0.001	0.610	0.561	0.563
	(0.117)	(0.093)	(0.108)	(0.431)	(0.418)	(0.413)
LOGPPE	0.011	0.014	0.000	0.058	0.038	0.003
	(0.043)	(0.045)	(0.044)	(0.079)	(0.066)	(0.054)
ROE	0.005*	0.005*	0.005	0.026*	0.025*	0.023*
	(0.003)	(0.003)	(0.003)	(0.013)	(0.012)	(0.012)
VOLAT	3.793	3.635	3.715	−2.932	−2.983	−2.829
	(3.655)	(3.597)	(3.636)	(1.966)	(1.941)	(1.911)
Constant	0.548	0.704	0.195	2.882*	2.727	2.251
	(0.944)	(1.000)	(1.003)	(1.585)	(1.613)	(1.814)
Year/month-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	143,367	143,340	143,461	60,210	60,210	60,210
R-squared	0.224	0.224	0.224	0.301	0.301	0.301

(*Continued*)

Table V—*Continued*

Panel B: Growth in Emissions						
Dependent Variable: *RET*	(1)	(2) United States	(3)	(4)	(5) China	(6)
S1CHG	0.679***			0.759**		
	(0.159)			(0.256)		
S2CHG		0.294*			0.587**	
		(0.137)			(0.193)	
S3CHG			1.254**			1.899***
			(0.467)			(0.504)
LOGSIZE	−0.145	−0.130	−0.163	−0.315***	−0.307***	−0.337***
	(0.103)	(0.103)	(0.103)	(0.092)	(0.090)	(0.098)
B/M	0.560	0.538	0.603*	0.969**	0.903**	1.031**
	(0.343)	(0.343)	(0.320)	(0.386)	(0.361)	(0.382)
LEVERAGE	−0.593**	−0.567**	−0.598**	−0.047	−0.002	−0.104
	(0.250)	(0.251)	(0.253)	(0.226)	(0.218)	(0.237)
MOM	0.209	0.238	0.151	0.872	0.876	0.717
	(0.331)	(0.335)	(0.320)	(0.509)	(0.493)	(0.450)
INVEST/A	−0.283	−0.086	−0.556	−0.987	−1.312	−1.401
	(2.425)	(2.374)	(2.453)	(0.785)	(0.754)	(0.793)
HHI	−0.114	−0.081	−0.125	0.539	0.534	0.426
	(0.096)	(0.100)	(0.096)	(0.425)	(0.414)	(0.395)
LOGPPE	0.074	0.061	0.089	0.091	0.085	0.103
	(0.048)	(0.046)	(0.051)	(0.083)	(0.083)	(0.093)
ROE	0.007**	0.006**	0.007**	0.027*	0.026*	0.026*
	(0.003)	(0.003)	(0.003)	(0.013)	(0.013)	(0.013)
VOLAT	2.678	2.842	2.622	−2.699	−2.833	−2.934
	(3.904)	(3.895)	(3.998)	(1.964)	(2.031)	(2.018)
Constant	1.335	1.264	1.354	3.050*	3.031*	3.198*
	(0.753)	(0.765)	(0.777)	(1.604)	(1.586)	(1.608)
Year/month-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	141,035	140,974	141,106	58,980	58,980	58,980
R-squared	0.227	0.227	0.227	0.303	0.302	0.304

we find a higher premium estimated over the time interval between 2005 and 2018. This higher premium is in line with the findings of Bolton and Kacperczyk (2021a) that the carbon premium is rising over time, especially after the Paris agreement of 2015.

The finding of a firm-level carbon premium for listed Chinese companies is novel and surprising. Although China in many ways has been a pioneer in the promotion of renewable energy, it does not stand out for its ESG institutional investor constituency, nor for its institutional investors' focus on carbon emissions. Yet, financial markets in China do price in a carbon premium at the firm level, both when it comes to direct emissions as well as indirect emissions. The magnitude of the premium is slightly lower relative to that in the United States. The quantitative similarities in the results across the two economies are slightly weaker for the carbon premium associated with the growth in emissions, as can be seen in Panel B. Still, for both countries, the premium is highly statistically significant, though the magnitudes of the premium for China are 10% to 20% higher. The latter finding could be due to the fact that a smaller fraction of companies in China disclose their emissions and to the generally higher growth rate in emissions of Chinese companies.

A.3. Unconditional Results

We next turn to the estimation of the model for the full sample of 77 countries. Relative to our previous specification, we also include country-fixed effects to account for country-specific variation in the data. We report the results in Table VI. In columns (1) to (3), the estimates are for regressions without industry adjustment; in columns (4) to (6), we include industry-fixed effects. In Panel A, we report the results for the level of carbon emissions. Throughout all specifications, we find a positive and mostly statistically significant effect of total emissions on individual stock returns, consistent with the hypothesis that higher-emission firms are riskier. Interestingly, when we do not control for industry, the economic significance of the carbon premium at the firm level for total scope 1 emissions is much smaller. One possibility is that some firms (or industries) with high emissions have experienced unexpectedly low returns. One example could be the recent devaluation of the energy sector following the decline in commodity prices. For that reason, it seems natural to focus on within-industry variations in carbon emissions. Indeed, when we add an industry-fixed effect, the premium is large and highly significant. A one-standard-deviation increase in *LOGS1TOT* across firms, equal to 1.4, is associated with a return premium of 1.06% per year. These results indicate that variations in stock returns across industries swamp variations in firm-level emissions within a given industry. In our untabulated results, we have also included country-fixed effects interacted with year-month-fixed effects, and industry-fixed effects interacted with year-month-fixed effects, to account

the model, including fixed effects. This is equivalent to calculating the standard deviation of the residual from the predictive model of each emission measure in the model.

Table VI

Carbon Emissions and Stock Returns: Full Sample

The sample period is from 2005 to 2018. The dependent variable is *RET*. The main independent variables are carbon emission levels (Panel A) and the growth in emissions (Panel B). Panel C includes both levels and changes of respective emissions. In Panels D and E, we consider different (monthly) lag structures for the measures of emissions. All variables are defined in Tables I and II. We report the results of the pooled regression with standard errors (in parentheses) double clustered at the firm and year level. All regressions include year-month-fixed effects and country-fixed effects. In columns (4) to (6), we additionally include industry-fixed effects. Panels D and E only include specifications with the full set of fixed effects. ***1% significance; **5% significance; *10% significance.

Panel A: Levels

Dependent Variable: *RET*	(1)	(2)	(3)	(4)	(5)	(6)
LOGS1TOT	0.027			0.063***		
	(0.021)			(0.015)		
LOGS2TOT		0.093***			0.113***	
		(0.029)			(0.027)	
LOGS3TOT			0.112***			0.164***
			(0.031)			(0.035)
LOGSIZE	−0.149***	−0.180***	−0.180***	−0.185***	−0.222***	−0.244***
	(0.041)	(0.042)	(0.043)	(0.041)	(0.042)	(0.044)
B/M	0.519**	0.512**	0.522**	0.630**	0.608**	0.597**
	(0.217)	(0.215)	(0.216)	(0.218)	(0.212)	(0.213)
LEVERAGE	−0.426**	−0.431**	−0.362**	−0.373**	−0.402**	−0.386**
	(0.180)	(0.167)	(0.165)	(0.158)	(0.146)	(0.150)
MOM	1.028**	1.035**	1.035**	1.021**	1.030**	1.033**
	(0.365)	(0.366)	(0.364)	(0.370)	(0.370)	(0.369)
INVEST/A	−0.741	−0.693	−0.392	−0.435	−0.275	0.006
	(1.102)	(1.157)	(1.215)	(1.064)	(1.090)	(1.103)
HHI	0.010	0.028	0.097	0.055	0.056	0.102
	(0.119)	(0.117)	(0.114)	(0.125)	(0.121)	(0.127)
LOGPPE	−0.002	−0.024	−0.039	0.009	−0.001	−0.020
	(0.018)	(0.022)	(0.023)	(0.017)	(0.017)	(0.018)
ROE	0.014***	0.013***	0.012***	0.013***	0.013***	0.013***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)

(*Continued*)

Table VI—*Continued*

Panel A: Levels						
Dependent Variable: *RET*	(1)	(2)	(3)	(4)	(5)	(6)
VOLAT	0.129	−0.052	0.009	0.359	0.309	0.334
	(3.539)	(3.482)	(3.522)	(3.203)	(3.182)	(3.201)
Year/month-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Country-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry-fixed effects	No	No	No	Yes	Yes	Yes
Observations	746,499	746,642	747,139	736,711	736,854	737,351
R-squared	0.150	0.150	0.150	0.151	0.151	0.151

Panel B: Growth in Emissions						
Dependent Variable: *RET*	(1)	(2)	(3)	(4)	(5)	(6)
S1CHG	0.437***			0.453***		
	(0.086)			(0.088)		
S2CHG		0.250***			0.255***	
		(0.067)			(0.069)	
S3CHG			1.157***			1.175***
			(0.278)			(0.288)
LOGSIZE	−0.156***	−0.153***	−0.170***	−0.170***	−0.166***	−0.183***
	(0.041)	(0.040)	(0.041)	(0.039)	(0.039)	(0.040)
B/M	0.506**	0.500**	0.537**	0.640**	0.633**	0.672**
	(0.217)	(0.216)	(0.217)	(0.221)	(0.220)	(0.220)

(*Continued*)

Table VI—*Continued*

Panel B: Growth in Emissions						
Dependent Variable: *RET*	(1)	(2)	(3)	(4)	(5)	(6)
LEVERAGE	−0.459**	−0.444**	−0.492**	−0.393**	−0.379**	−0.421**
	(0.179)	(0.173)	(0.173)	(0.150)	(0.145)	(0.144)
MOM	0.958**	0.974**	0.880**	0.944**	0.961**	0.867**
	(0.362)	(0.363)	(0.350)	(0.368)	(0.369)	(0.356)
INVEST/A	−1.000	−0.870	−1.180	−0.785	−0.690	−0.963
	(1.180)	(1.194)	(1.204)	(1.059)	(1.058)	(1.058)
HHI	−0.046	−0.036	−0.064	−0.033	−0.022	−0.051
	(0.127)	(0.128)	(0.124)	(0.122)	(0.124)	(0.120)
LOGPPE	0.029	0.025	0.041*	0.047**	0.043**	0.060***
	(0.021)	(0.020)	(0.020)	(0.017)	(0.017)	(0.018)
ROE	0.014***	0.014***	0.014***	0.014***	0.014***	0.014***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
VOLAT	−0.146	−0.059	−0.175	0.182	0.252	0.169
	(3.602)	(3.619)	(3.670)	(3.258)	(3.274)	(3.308)
Year/month-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Country-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry-fixed effects	No	No	No	Yes	Yes	Yes
Observations	735,359	735,362	735,903	725,745	725,748	726,289
R-squared	0.151	0.151	0.152	0.153	0.153	0.153

(*Continued*)

Table VI—*Continued*

Panel C: Joint Regressions						
Dependent Variable: *RET*	(1)	(2)	(3)	(4)	(5)	(6)
LOGS1TOT	0.016			0.046***		
	(0.021)			(0.014)		
S1CHG	0.429***			0.430***		
	(0.086)			(0.087)		
LOGS2TOT		0.082**			0.099***	
		(0.029)			(0.025)	
S2CHG		0.221***			0.213***	
		(0.068)			(0.069)	
LOGS3TOT			0.104***			0.150***
			(0.029)			(0.033)
S3CHG			1.138***			1.135***
			(0.279)			(0.285)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year/month-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Country-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry-fixed effects	No	No	No	Yes	Yes	Yes
Observations	735,121	735,206	735,903	725,507	725,592	726,289
R-squared	0.151	0.151	0.152	0.153	0.153	0.153

(*Continued*)

Table VI—*Continued*

Panel D: Alternative Lags (Levels)									
Dependent Variable: *RET*	(1)	(2) Lag 3	(3)	(4)	(5) Lag 6	(6)	(7)	(8) Lag 12	(9)
LOGS1TOT	0.056***			0.042**			0.023		
	(0.016)			(0.015)			(0.015)		
LOGS2TOT		0.108***			0.095***			0.074**	
		(0.027)			(0.028)			(0.025)	
LOGS3TOT			0.149***			0.117***			0.080**
			(0.035)			(0.032)			(0.027)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year/month-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	736,433	736,552	737,057	736,023	736,106	736,623	735,197	735,208	735,749
R-squared	0.151	0.151	0.151	0.151	0.151	0.151	0.151	0.151	0.151
Panel E: Alternative Lags (Changes)									
Dependent Variable: *RET*	(1)	(2) Lag 3	(3)	(4)	(5) Lag 6	(6)	(7)	(8) Lag 12	(9)
S1CHG	0.377***			0.259***			−0.078		
	(0.078)			(0.074)			(0.075)		
S2CHG		0.214**			0.165**			−0.054	
		(0.070)			(0.074)			(0.058)	
S3CHG			1.009***			0.684**			−0.079
			(0.273)			(0.310)			(0.188)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year/month-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	703,278	703,267	703,806	669,337	669,305	669,841	600,010	599,938	600,466
R-squared	0.155	0.155	0.156	0.160	0.160	0.160	0.172	0.172	0.172

for any demand-side shocks affecting different countries and industries. The estimated risk premia from these models are only slightly smaller than those reported here, which suggests that our results are not affected by transitory, business-cycle shocks but are more reflective of permanent shocks, such as transition risk.

Note that the coefficient of *LOGS3TOT* is highly significant in the regressions without and with industry-fixed effects. It is also economically significant, as a one-standard-deviation increase in *LOGS3TOT* is associated with a return premium of 1.81% for the specification without industry-fixed effects, and 1.97% with the fixed effects.

The results with respect to the growth in carbon emissions are all highly significant and are not affected at all by the inclusion of industry fixed effects, as can be seen in Panel B. In the model with industry fixed effects, per one-standard-deviation change in scope 1 and scope 3, the corresponding return premia amount to 2.17% and 3.38% per year, slightly smaller in magnitude than the effects we observed for the levels of emissions. Of course, statistically speaking, taking differences in emissions is close to including firm-fixed effects in the model with levels of emissions.[13]

Our conceptual framework posits that the two different emission measures proxy for two types of transition risk: a short-term and a long-term risk component. A natural question is to what extent these two measures capture independent variation in stock returns. Evidence in Table II shows that they are largely independent of each other given the relatively small correlations. We test this relative independence using a return regression model that jointly includes both measures. We report the results in Panel C. In columns (1) to (3), we present the results with country- and time-fixed effects and in columns (4) to (6) we add industry-fixed effects. We find that in the joint model both measures of emissions retain their positive coefficients and economic significance, which further confirms our starting premise that they capture economically different sources of risk.

In another test, we assess the predictions of our model with respect to *carbon intensity*, a measure of firms' total emissions scaled by their revenues. This measure has been the focus of other research on investment strategies based on discriminating between green and brown firms, and on asset managers' exclusionary screening policies (e.g., Garvey, Iyer, and Nash (2018), and Cheema-Fox et al. (2021)), but when it comes to carbon-transition risk, carbon intensity does not directly capture the transition effort of a firm to attain net zero. As we have pointed out in the introduction, a reduction in emission intensity does not necessarily correspond to a reduction in total emissions. The level of

[13] We have also explored the robustness of our results to different cut-offs for our measure of emission changes. Specifically, we have considered measures that are winsorized at the 1% level. The results, reported in Table IA.II of the Internet Appendix, are broadly consistent with those we obtain in the baseline specification. (The Internet Appendix is available in the online version of the article on *The Journal of Finance* website). We note that the results for unwinsorized metrics, even though statistically significant, would be less desired because of significant outliers in the right tail of the empirical distribution.

emissions is a more direct proxy for carbon-transition risk exposure than emission intensity. Dividing by sales revenue introduces noise: when emission intensity changes it could be because of a change in sales revenue or because of a change in the level of emissions. One potential concern with linking emission levels to stock returns could be that, if variations in emissions are driven entirely by variations in the firm's operating activities, emission levels could be a proxy for sales revenues, so that the effect of emissions on stock returns could simply reflect the effect of sales revenue on stock returns. Note, however, that we do control for firm size so that the effect of size on emission levels is accounted for. With a noisier proxy for carbon-transition risk exposure, one should expect a less significant result. When we link carbon intensity to stock returns, we indeed find no statistically significant relation. These results are presented in Table IA.III of the Internet Appendix.

As an additional robustness check, we also associate carbon emissions with *annual* returns. The results are reported in Table IA.IV and corroborate our main findings relating carbon emissions to *monthly* returns.

The overarching conclusion from this part of our analysis is that firm-level global stock returns reflect firm-level variation in both *total emissions* and *growth in total emissions*, which indicates that investors price carbon-transition risk both from a short-term and long-term perspective.

A.4. Book-to-Market Ratios

It is well known that stock returns are noisy proxies for expected returns. It is sometimes possible to get more precise measures of expected returns based on analyst forecasts. However, a major challenge with this approach is that (i) analyst forecasts are only available for a relatively small subset of global stocks, (ii) analyst forecasts may be biased because of industry incentive structures, and (iii) the metric of implied cost of equity critically depends on the postulated valuation model.

As an alternative, we look at the pricing of carbon emissions from a different perspective and relate our firm-level carbon emission measures to book-to-market ratios, which tend to be more stable over time and are available for a large set of firms. Looking at book-to-market ratios helps us to better distinguish the explanation of our results as one based on required expected returns as opposed to one due to luck. Accordingly, we estimate the following regression model:

$$LNBM_{i,t} = a_0 + a_1\left(TOT\ Emissions\right)_{i,t} + a_2 Controls_{i,t-1} +_{\mu t} + \epsilon_{i,t}. \qquad (3)$$

Our dependent variable is the natural logarithm of the firm book-to-market ratio, *LNBM*. Our control variables include *MSCI*, *MOM*, *VOLAT*, and *SALESGR*. In addition, we use 1- and 2-year-ahead measures of *SALESGR* to proxy for future cash flow growth and *LTG* to proxy for long-term earnings growth forecasts. Finally, in all specifications, we include country- and year-month-fixed effects. Some variants of our tests also include industry-fixed effects. As before, we double cluster standard errors at the firm and year level. We present the results in Table VII.

In Panel A, the main independent variables of interest are *LOGS1TOT, LOGS2TOT*, and *LOGS3TOT*. Consistent with our hypothesis of the presence of carbon-transition risk, we find that companies with high emissions have higher book-to-market ratios. The effects are statistically significant in the model that does not account for industry-fixed effects, in columns (1) to (3). As before, the magnitudes become even stronger when we add industry-fixed effect. In terms of economic significance, a one-standard-deviation increase in cross-sectional scope 1 emissions is associated with a 13.2% increase in book-to-market ratios. The results for scope 2 and scope 3 emissions are comparable in magnitude.

A natural question is whether these magnitudes are comparable to those obtained from the return regressions. To answer this question, we take a simple Gordon growth model with an expected growth rate of 4% and expected return of 12% (these numbers roughly correspond to an average stock) and ask how much of an increase in expected returns is required to get a 13% lower valuation for high carbon emission stocks. For these parameters, this would imply a number that is slightly less than a 1.4% excess return. This value is slightly higher in magnitude than that estimated using our return regressions, but in general it falls within a one-standard-error bound of the return coefficient. Hence, statistically speaking, the two numbers are not very different from each other.

In Panel B, we consider the specification with the growth in emissions as the main independent variable. We estimate the same empirical model as before and find a strong positive effect of changes in emissions on the log-book-to-market variable. The effect is statistically and economically highly significant both in the model without and with industry-fixed effects.

We note that in the above tests our sample size is naturally restricted due to data limitations imposed by the computation of *LTG*. To ensure that our results are not spuriously driven by the smaller sample, we repeat our analysis using the model without *LTG*, but with a sample size that is comparable to that used in our return models. We report the results in Table IA.V of the Internet Appendix. In these large data, we find the effects that are statistically more significant but broadly consistent in terms of their magnitudes with our baseline results.

Overall, we conclude that our baseline results on stock returns are unlikely to be explained by unexpected returns (or noise therein). They are more consistent with a systematic repricing of assets with different levels of emissions and changes thereof. Hence, in the remaining parts of the paper we continue with the specifications with stock returns as a main dependent variable.

Table VII

Carbon Emissions and Stock Book-to-Market Ratios: Full Sample

The sample period is from 2005 to 2018. The dependent variable is *LNBM*. The main independent variables are carbon emission levels (Panel A) and the growth in emissions (Panel B). All variables are defined in Tables I and II. We report the results of the pooled regression with standard errors (in parentheses) double clustered at the firm and year level. All regressions include year-month-fixed effects and country-fixed effects. In columns (4) to (6), we additionally include industry-fixed effects. ***1% significance; **5% significance; *10% significance.

Panel A: Levels

Dependent Variable: *LNBM*	(1)	(2)	(3)	(4)	(5)	(6)
LOGS1TOT	0.021**			0.056***		
	(0.007)			(0.009)		
LOGS2TOT		−0.005			0.057***	
		(0.010)			(0.009)	
LOGS3TOT			0.016			0.079***
			(0.014)			(0.012)
MSCI	−0.208***	−0.173***	−0.203***	−0.235***	−0.255***	−0.274***
	(0.034)	(0.036)	(0.035)	(0.031)	(0.033)	(0.033)
MOM	−0.634***	−0.623***	−0.631***	−0.596***	−0.591***	−0.597***
	(0.070)	(0.069)	(0.069)	(0.057)	(0.055)	(0.056)
VOLAT	1.982**	1.928**	1.965***	2.151***	2.028***	2.197***
	(0.629)	(0.623)	(0.618)	(0.426)	(0.410)	(0.399)
SALESGR	−0.496***	−0.513***	−0.504***	−0.487***	−0.498***	−0.498***
	(0.058)	(0.056)	(0.057)	(0.058)	(0.058)	(0.058)
$SALESGR_{t+12}$	−0.376***	−0.411***	−0.389***	−0.307***	−0.311***	−0.290***
	(0.037)	(0.046)	(0.044)	(0.038)	(0.038)	(0.037)
$SALESGR_{t+24}$	−0.351***	−0.384***	−0.361***	−0.282***	−0.282***	−0.269***
	(0.069)	(0.075)	(0.074)	(0.046)	(0.049)	(0.046)
LTG	−0.012***	−0.013***	−0.013***	−0.008***	−0.008***	−0.008***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)
Year/month-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Country-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry-fixed effects	No	No	No	Yes	Yes	Yes
Observations	88,390	88,349	88,426	87,093	87,052	87,129
R-squared	0.263	0.259	0.260	0.475	0.474	0.477

(*Continued*)

Table VII—*Continued*

Panel B: Growth in Emissions						
Dependent Variable: *LNBM*	(1)	(2)	(3)	(4)	(5)	(6)
S1CHG	0.066***			0.029		
	(0.020)			(0.021)		
S2CHG		0.045***			0.022*	
		(0.013)			(0.012)	
S3CHG			0.030			−0.027
			(0.123)			(0.037)
MSCI	−0.180***	−0.181***	−0.180***	−0.165***	−0.165***	−0.165***
	(0.033)	(0.033)	(0.033)	(0.029)	(0.029)	(0.029)
MOM	−0.624***	−0.624***	−0.624***	−0.587***	−0.587***	−0.587***
	(0.069)	(0.069)	(0.069)	(0.056)	(0.056)	(0.056)
VOLAT	1.909**	1.917**	1.916**	1.884***	1.882***	1.884***
	(0.623)	(0.623)	(0.628)	(0.457)	(0.457)	(0.456)
SALESGR	−0.566***	−0.552***	−0.541***	−0.524***	−0.521***	−0.473***
	(0.063)	(0.052)	(0.134)	(0.072)	(0.060)	(0.076)
$SALESGR_{t+12}$	−0.411***	−0.412***	−0.406***	−0.349***	−0.350***	−0.347***
	(0.044)	(0.044)	(0.044)	(0.041)	(0.040)	(0.039)
$SALESGR_{t+24}$	−0.379***	−0.379***	−0.379***	−0.327***	−0.325***	−0.327***
	(0.071)	(0.071)	(0.071)	(0.053)	(0.054)	(0.052)
LTG	−0.013***	−0.013***	−0.013***	−0.009***	−0.009***	−0.009***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Year/month-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Country-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry-fixed effects	No	No	No	Yes	Yes	Yes
Observations	88,414	88,338	88,426	87,117	87,041	87,129
R-squared	0.260	0.260	0.259	0.466	0.466	0.466

A.5. Information Observability and Carbon Premium

An important aspect of any risk premium analysis concerns the measurability of information on which investors condition their investment choices. While some elements of our analysis are typical of any standard approach in the literature, others are unique in the context of carbon-transition risk. As we have noted, progress in the transition is reflected in the rate of change in emissions, which is why we should expect a priori transition risk to be tied to both the level and rate of change in emissions. Such horizon effects should be present even over shorter time spans. Hence, one should not expect the risk premium to be independent of when we observe emissions relative to stock prices. This is an important difference with respect to classical asset pricing, which essentially presumes a stationary world and stochastic general equilibrium.

To ensure that all the conditioning information is in investors' information sets at the time of the realization of returns, we have performed several robustness checks with different lags of emission information, since investors' information sets are not perfectly observable. We have considered lags of 3 months, 6 months, and 12 months between the end of the year for which emissions are reported and the month when returns are realized. Using the different lags, we estimate the models in equations (1) and (2). We report the results in Panels D and E of Table VI for the levels and changes of emissions. In most specifications, the premium for the level of emissions remains large and significant for the different lags. In turn, the premium based on emission changes is positive and significant for up to 6 months but becomes insignificant after 12 months.

These results raise two questions. First, why does the premium persist for such a long period? And second, why does it disappear after 12 months? Our answer to the first question is that investors have limited attention and do not immediately absorb all the new information about carbon emissions at the firm level (Kacperczyk, van Nieuwerburgh, and Veldkamp (2016)). The information about carbon emissions for year t is gradually reflected in returns over the year. A related way to micro-found the friction would be with a model of slow-moving capital (Duffie (2010)). Our answer to the second question is that carbon emission numbers become stale after a while, and after a year the information in these numbers is subsumed in the new numbers. Interestingly, when we compare the effect of lagging emissions on returns for respectively levels and changes, we find that the former retains information longer than the latter. The rate of change in emissions is naturally less persistent and conveys more transitory information. In other words, the news component is larger for the rate of change in emissions numbers than for the emission levels numbers.

In our benchmark specification, we measure carbon emissions 1 month before the returns are realized. The reason for this choice is largely dictated by the horizon effects and information staleness discussed above. We also note that investors can obtain more accurate forecasts of future cash flow risk related to carbon emissions from industry and firm characteristics. The more up to date their information about firm characteristics is, the more accurate are their forecasts of emissions and returns, which is why basing returns predictions on too long lags for the firm characteristics would underestimate the true return premium. As an example, if we lag emissions by 12 months, that would be saying that investors do not condition their forecasts on any updates in firm characteristics for an entire year. This does not seem plausible. Therefore, we believe that shorter lags, of 1 or 3 months, are more natural than a 12-month lag.

We have also explored the extent to which emissions are a persistent characteristic. We ask how different is the effect of emissions on stock returns when we abstract from any news effect contained in the latest emission numbers? To do this, we replace the actual emission numbers in years $\tau < t = 2018$ in our sample with emission estimates based on a backward imputation of the emissions in year 2018, the last year of the sample. We can then determine how different the carbon premium is when we relate it to emissions that are imputed back in time versus the actual year-by-year emission numbers. If the premia are similar, this would suggest that emissions in year t are a good statistic for emissions in years $t-\tau$ for all $\tau < t$ in our sample. This is indeed what we find and report in Table IA.VI, which suggests that carbon-transition risk, as proxied by the level of emissions, is a persistent characteristic when you take out any news effects.

Another important issue is with respect to the delayed availability of emissions numbers from Trucost. First, the fact that our analysis is based on data from Trucost does not mean that Trucost is the only source of information on carbon emissions for investors. Investors can acquire information about corporate carbon emissions from other sources. Indeed, large asset managers like BlackRock or Amundi rely on multiple data sources for carbon emissions that are not all available at the same time. For example, a lot of firms disclose their emissions first to the Carbon Disclosure Project organization, data that then are merged into and combined with other sources by Trucost. Different information that is likely to be highly correlated with Trucost information (given that all providers use the same data collection protocols) becomes available at different times. Furthermore, investors are likely to be heterogeneous with respect to access to information about carbon emissions. Therefore, the information set of investors is likely to be updated earlier than the information set of the econometrician. In fact, in an additional (untabulated) test, we explore whether there are announcement returns around the date when Trucost enters the data on emissions into its database and we find no effect. Stated differently, our analysis is not meant to identify a trading strategy based on Trucost data; we use these data only as a proxy for carbon-transition risk.

A related concern is about how Trucost gathers and aggregates the data on corporate carbon emissions: Could the methodology that Trucost uses directly affect the size of the carbon premium? Trucost reports two types of data, one that is directly taken from corporate reports and another that is estimated using its own prediction model. Could it be that the estimated emission numbers are noisy or biased because of the methodology used by Trucost? We find the possibility of a systematic bias that is correlated with future stock returns unlikely, given the weak evidence of autocorrelation in stock returns typically found in empirical studies. To evaluate the differences in carbon-transition risk, as they relate to whether the carbon emissions are based on corporate disclosures or are estimated, we take advantage of information provided by Trucost on how particular emissions data have been sourced. We define an indicator variable *Disclosure* if emissions for firm i at time t are based on directly disclosed information, and zero if they come from an estimate based on a model-based approach. We amend our return regression by adding this variable and its interactions with our measures of carbon emissions. We report the results in Table IA.VII. The results show two effects. First, the level of the carbon premium is lower for emissions based on directly disclosed data, a finding that is inconsistent with the uncertainty reduction hypothesis. Second, the premium remains positive and significant for both types of data, especially in the model with industry-fixed effects. Hence, we conclude that the source of emission data does not alter the qualitative aspects of our results.[14]

While our analysis considers different information sets based on monthly frequency, it is important to note that corporate emissions data from Trucost are provided at an annual frequency. However, the annual measurement of corporate emissions should not imply that our empirical tests should be cast at an annual frequency for stock returns. Even if data for corporate carbon emissions are released at an annual frequency, investors' information sets get updated at a greater than annual frequency. It is more plausible that investors' learning process is continuous, and that more information gets processed over time. This process can further rationalize the fact that the impact of emissions gets progressively smaller with an increasing lag between when emissions are available and when returns are measured.

Finally, a common concern could be that emissions and stock returns are endogenously related through the company's production channel. For example, better business opportunities could be associated with higher sales and could generate both higher emissions and higher realized returns. We note that this prediction is not borne out in our data. Market value does not increase with higher emissions (consistent with business opportunities getting better). We find the exact opposite result, that the book-to-market ratio is positively related to carbon emissions. Stock prices are lower rather than higher for firms

[14] In a related paper, Aswani, Raghunandan, and Rajgopal (2023) find that the carbon premium associated with the level of emissions goes to zero for companies that directly disclose their emissions and suggest that investors may not be pricing carbon risk at all. Our results differ in that we find a positive premium for both types of emission sources in a sample that includes roughly five times more firms than in their sample. More importantly, we note that the smaller magnitude of the carbon premium for directly disclosed emissions is consistent with a model in which firms endogenously decide whether to disclose their emissions. In this model, a benefit for the firm of disclosing emissions is a lower risk premium achieved by lowering the perceived uncertainty investors face with respect to carbon-transition risk. Hence, our evidence is fully consistent with the hypothesis that investors do price carbon-transition risk, but differently for different levels of perceived uncertainty. We provide an extensive analysis of this economic mechanism in Bolton and Kacperczyk (2021c).

with higher levels and higher growth in emissions. Thus, to the extent that production endogeneity is a concern, the estimates we provide constitute a lower bound on the true effect of carbon emissions on the risk premium.

A.6. Geographic Distribution

By looking at the geographic distribution of the carbon premium, we can assess how our unconditional results are driven by a particular region. The economics literature on climate change has emphasized the importance of the spatial distribution of climate policies (Nordhaus and Yang (1996)) and physical impacts (Cruz and Rossi-Hansberg (2023)). Different regions have different exposures to climate change as well as different capacities to adapt. With respect to transition risk, one might expect that a country's economic development, social norms, or headline risk may be equally important. At the same time, financial market integration may erase some of the country-level heterogeneity.

We evaluate the geographic distribution of carbon-transition risk pricing by comparing four different regions: North America, Europe, Asia, and Southern Hemisphere countries (defined as "Others"). We define the respective indicator variables: (i) *Namerica* for firms that are located in North America, (ii) *Europe* for firms located in Europe, and (iii) *Asia* for firms located in Asia. The omitted category is firms located in the Southern Hemisphere. We test two hypotheses simultaneously: whether risk premia are positive and statistically significant, and whether they differ from each other.

We report the results in Table VIII, Panel A, for the level of emissions, and in Panel B for the growth in emissions. For brevity, we focus on scope 1 and scope 3 emissions. We find that the carbon premium is generally larger in North America, Europe, and Asia than in the residual Southern Hemisphere group of countries. However, the only statistically significant result, at the 10% level, is for firms located in North America. Importantly, all premia, especially those that absorb industry-fixed effects, are positive and statistically significant. When it comes to the growth in emissions, the magnitudes of the effects for Europe are visibly smaller than those in North America and Asia. Still, they are all positive and statistically significant. The regions of the world that stand out are Africa, Australia, and South America, where the coefficient of *S1CHG* is borderline significant in the baseline model and insignificant when we add industry-fixed effects. This result is quite interesting, as these countries are least aligned with the principle of carbon neutrality.

An important robustness question is what matters more? Where the company is headquartered (which is the determinant of classification in our data), or where emissions are generated? This distinction may be particularly relevant for firms with global operations, which are subject to different social pressures, policies, or headline risk. While the granularity of our data does not allow us to attribute total firm emissions to individual plants, we can evaluate whether the impact of firm emissions differs in a sample of multinational companies versus those operated in a single country. Empirically, we define an

Table VIII

Carbon Emissions and Stock Returns: Regional

The sample period is from 2005 to 2018. The dependent variable is *RET*. The main independent variables are carbon emission levels (Panel A) and the growth in firm-level total emissions (Panel B). All variables are defined in Tables I and II. We report the results of the pooled regression with standard errors (in parentheses) double clustered at the firm and year level. All regressions include year-month-fixed effects and country-fixed effects. All regression models include the controls of Table VI (unreported for brevity). In columns (4) to (6), we additionally include Trucost industry-fixed effects. ***1% significance; **5% significance; *10% significance.

Panel A: Levels

Dependent Variable: *RET*	(1)	(2)	(3)	(4)	(5)	(6)
LOGS1TOT	−0.001			0.041		
	(0.031)			(0.024)		
LOGS2TOT		0.065			0.092**	
		(0.038)			(0.036)	
LOGS3TOT			0.075			0.132***
			(0.043)			(0.042)
*Namerica*LOGS1TOT*	0.042*			0.043*		
	(0.020)			(0.020)		
*Namerica*LOGS2TOT*		0.051			0.044	
		(0.039)			(0.037)	
*Namerica*LOGS3TOT*			0.065			0.059
			(0.042)			(0.043)
*Europe*LOGS1TOT*	0.028			0.019		
	(0.019)			(0.020)		
*Europe*LOGS2TOT*		0.022			0.014	
		(0.029)			(0.031)	
*Europe*LOGS3TOT*			0.042			0.040
			(0.031)			(0.033)
*Asia*LOGS1TOT*	0.029			0.020		
	(0.022)			(0.021)		
*Asia*LOGS2TOT*		0.027			0.020	
		(0.036)			(0.036)	
*Asia*LOGS3TOT*			0.028			0.022
			(0.039)			(0.041)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year/month-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Country-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry-fixed effects	No	No	No	Yes	Yes	Yes
Observations	746,499	746,642	747,139	736,711	736,854	737,351
R-squared	0.150	0.150	0.150	0.151	0.151	0.152

(*Continued*)

Table VIII—*Continued*

Panel B: Growth in Emissions						
Dependent Variable: *RET*	(1)	(2)	(3)	(4)	(5)	(6)
S1CHG	0.230**			0.275**		
	(0.098)			(0.112)		
S2CHG		0.054			0.078	
		(0.090)			(0.098)	
S3CHG			0.780**			0.843**
			(0.349)			(0.383)
*Namerica*S1CHG*	0.362**			0.341**		
	(0.138)			(0.136)		
*Namerica*S2CHG*		0.211*			0.193	
		(0.114)			(0.112)	
*Namerica*S3CHG*			0.499			0.464
			(0.337)			(0.345)
*Europe*S1CHG*	−0.010			−0.050		
	(0.091)			(0.099)		
*Europe*S2CHG*		0.039			0.020	
		(0.115)			(0.120)	
*Europe*S3CHG*			0.007			−0.028
			(0.457)			(0.464)
*Asia*S1CHG*	0.322**			0.287*		
	(0.142)			(0.142)		
*Asia*S2CHG*		0.340***			0.314**	
		(0.104)			(0.105)	
*Asia*S3CHG*			0.607			0.541
			(0.420)			(0.430)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year/month-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Country-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry-fixed effects	No	No	No	Yes	Yes	Yes
Observations	735,359	735,362	735,903	725,745	725,748	726,289
R-squared	0.151	0.151	0.152	0.153	0.153	0.153

indicator variable, *FORDUM*, equal to 1 for firms that have at least some sales generated abroad and 0 for firms whose sales are entirely from a single country. Next, we estimate the models in equations (1) and (2) with an additional interaction term between measures of emissions and *FORDUM*.

We present the results in Table IA.VIII. Across all empirical specifications, we find only weak evidence that firms with multinational operations exhibit different sensitivities of their stock returns with respect to total firm emissions. For the specifications with the level of emissions, the interaction terms are small and statistically insignificant and for the specifications with the growth in emissions, the interaction term is significant at the 10% level for scope 3 emissions. Overall, it does not seem that the geographic source of firm-level emissions is a primary driver of the carbon premium in our data.

In sum, our continent-level results reveal that carbon-transition risk is economically relevant in most geographic regions and that there is some geographic variation in the carbon premium throughout the world, even though it is mostly related to short-term measures of carbon-transition risk. In the final part of this section, we turn to an investigation of whether carbon-transition risk is tied to a country's economic development, one of the main issues that frames discussions of international climate mitigation agreements.

A.7. Economic Development

The level of a country's economic development is an important consideration when it comes to climate policy. Typically, richer countries are expected to, and have for the most part, made stronger commitments to combat climate change. Rich countries have a greater responsibility to combat climate change as they are the source of the largest cumulative emissions over the past two centuries by far. Another reason to expect a lower carbon premium in developing countries is simply that currently these countries have low levels of emissions. In addition, these countries' economies are not as deeply founded on fossil fuel energy consumption and may therefore be able to transition more easily to a renewable energy development path. On the other hand, if these countries depend a lot on fossil fuels, they may be less willing to adjust in the short-run.

In this section, we explore the empirical relevance of these arguments. A remarkable general finding, as we show in Table IA.IX, is that the carbon premium does not seem to be related to countries' overall level of development. We first broadly categorize developed countries as the G20 countries and the remaining group of countries as developing countries.[15] When we add industry-fixed effects, we observe from Table IA.IX (Panel A) that the G20 group of countries have highly significant carbon premia related to the level of emissions for all three scope categories. But this is also the case for the most part for the group of developing countries (scope 2 emissions are only significant at the 10% level for this group). Moreover, the size of the coefficients is similar. As

[15] The results are qualitatively very similar, reported in Panel B, if we define developed countries based on the Organisation for Economic Co-operation and Development (OECD) membership.

for the short-run effects of carbon emissions on stock returns, we observe that they are again highly significant for both the G20 countries (controlling for industry) and the group of developing countries. Also, the size of the coefficients is again broadly similar.

Admittedly, the above classification of countries into two groups, developing and developed, is rather coarse, and there is substantial heterogeneity in country characteristics within each group. Accordingly, we also investigate the effect of interacting GDP per capita, and other development variables such as the share of the manufacturing sector in GDP and health expenditure per capita, with the level and changes in emissions. As we show in Panel A of Table IX, the interaction of per capita GDP and the level of emissions is insignificant. The same is true for the interaction of the share of manufacturing and the level of emissions, and for the interaction of per capita health expenditures and the level of emissions. Overall, these results indicate that differences in development do not appear to explain much of the variation in long-run carbon premia across countries. On the other hand, when we interact the same variables with the percentage change in emission, as a measure of short-term risk, a slightly different picture emerges. Now, firms located in countries with higher GDP per capita and a more developed health system have statistically smaller stock returns. Further, firms located in countries with a higher dependence on the manufacturing sector in their output creation have higher stock returns. These results are consistent with the view that firms in developed countries face lower challenges in conforming to their country's carbon neutrality objective. The growth in the emissions variable tells us the sustainability of a country's development path. If, for example, the growth in emissions in a developing country is large because of high reliance on coal, then, in effect, the companies in that developing country are exposed to greater future transition risk when pressure grows to phase out coal.

Altogether, both regional and economic variation in carbon-transition risk likely nest several specific factors that contribute to the observed results. Investigating the origins of these factors is the subject of our next section.

B. Carbon-Transition Risk Drivers

Even though the notion of carbon-transition risk has been commonly referred to in policy discussions, surprisingly little is known about the different sources of this risk. Part of the reason is that most of the studies on carbon-transition risk are either highly aggregated or focus on a single country or industry (e.g., Bolton and Kacperczyk (2021a), Hsu, Li, and Tsou (2023)). Also, many commentators often reduce carbon-transition risk purely to policy uncertainty, whereas other dimensions (for example, technological innovation or the prevailing belief system) are clearly relevant.

We explore several channels through which carbon-transition risk could manifest itself: technological, socioeconomic, regulatory policy, and reputation risk, all of which affect future cash flows and changing investor attention to climate change as a source of variation for the discount-rate channel. The main

Table IX
Carbon Emissions and Stock Returns: Economic Development

The sample period is from 2005 to 2018. The dependent variable is *RET*. The main independent variables are carbon emission levels (Panel A) and the growth in emissions (Panel B). *GDPPC* measures a country's GDP per capita in current dollars in a given year, *MANUFPERC* is the percentage of a country's GDP that is produced in a given year in the manufacturing sector, and *HLTHEXPPC* is a country's health expenditures per capita in current dollars in a given year. All other variables are defined in Tables I and II. We report the results of the pooled regression with standard errors (in parentheses) double clustered at the firm and year level. All regression models include the controls of Table VI (unreported for brevity), year-month-fixed effects, and country-fixed effects. In selected columns, we additionally include Trucost industry-fixed effects. ***1% significance; **5% significance; *10% significance.

Panel A: Levels												
Dependent Variable: *RET*	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
GDPPC	−106.966**	−107.168**	−102.286**	−102.108**								
	(50.082)	(50.443)	(50.288)	(50.647)								
MANUFPERC					13.721	15.378*	14.549*	16.083*				
					(8.422)	(8.635)	(8.418)	(8.586)				
HLTHEXPPC									−0.048	−0.130	−0.040	−0.106
									(0.195)	(0.202)	(0.193)	(0.196)
LOGS1TOT	0.030		0.064***		0.030		0.072***		0.009		0.047**	
	(0.021)		(0.018)		(0.023)		(0.019)		(0.022)		(0.018)	
LOGS3TOT		0.118***		0.170***		0.136***		0.191***		0.079**		0.131***
		(0.032)		(0.033)		(0.032)		(0.033)		(0.031)		(0.034)
*GDPPC*LOGS1TOT*	−0.113		−0.101									
	(0.418)		(0.402)									
*GDPPC*LOGS3TOT*		−0.210		−0.272								
		(0.655)		(0.612)								
*MANUFPERC*LOGS1TOT*					−0.028		−0.068					
					(0.112)		(0.106)					
*MANUFPERC*LOGS3TOT*						−0.139		−0.161				
						(0.173)		(0.164)				
*HLTHEXPPC*LOGS1TOT*									0.003		0.003	
									(0.003)		(0.003)	
*HLTHEXPPC*LOGS3TOT*										0.008*		0.007
										(0.005)		(0.005)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year/month-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-fixed effects	No	No	Yes	Yes	No	No	Yes	Yes	No	No	Yes	Yes
Observations	712,325	712,965	702,742	703,382	679,747	680,362	671,251	671,866	484,562	485,071	478,735	479,244
R-squared	0.150	0.150	0.152	0.152	0.152	0.152	0.153	0.153	0.175	0.175	0.177	0.177

(*Continued*)

Table IX—*Continued*

Panel B: Growth in Emissions												
Dependent Variable: *RET*	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
GDPPC	−112.536**	−115.011**	−107.466**	−109.815**								
	(50.414)	(50.457)	(50.642)	(50.689)								
MANUFPERC					11.674	10.472	12.035	10.880				
					(8.243)	(8.228)	(8.256)	(8.244)				
HLTHEXPPC									−0.044	−0.072	−0.034	−0.064
									(0.194)	(0.196)	(0.193)	(0.195)
S1CHG	0.587***		0.600***		0.088		0.112		0.654***		0.688***	
	(0.112)		(0.112)		(0.101)		(0.102)		(0.131)		(0.131)	
S3CHG		1.485***		1.505***		0.492*		0.543**		1.439***		1.501***
		(0.263)		(0.266)		(0.266)		(0.264)		(0.287)		(0.291)
*GDPPC*S1CHG*	−4.601*		−4.510*									
	(2.466)		(2.461)									
*GDPPC*S3CHG*		−11.536*		−11.598*								
		(6.250)		(6.250)								
*MANUFPERC*S1CHG*					2.230***		2.163***					
					(0.621)		(0.625)					
*MANUFPERC*S3CHG*						3.863***		3.650**				
						(1.453)		(1.454)				
*HLTHEXPPC*S1CHG*									−0.045*		−0.047**	
									(0.024)		(0.024)	
*HLTHEXPPC*S3CHG*										−0.093		−0.098*
										(0.058)		(0.057)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year/month-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-fixed effects	No	No	Yes	Yes	No	No	Yes	Yes	No	No	Yes	Yes
Observations	701,797	702,341	692,387	692,931	669,831	670,340	661,480	661,989	479,950	480,373	474,176	474,599
R-squared	0.151	0.152	0.153	0.153	0.153	0.153	0.154	0.155	0.175	0.176	0.177	0.177

challenge in identifying each of the channels empirically is that to a large extent we can only measure transition risk drivers at the country level. As is well known, regression specifications that relate stock returns to country-level characteristics, could yield biased estimates due to omitted country-level variables. To mitigate this concern, we rely on firm-level variation in carbon emissions and estimate the role of the different mechanisms by interacting the country variables with firm-level emissions. This approach follows closely the identification strategy of Rajan and Zignales (1998), which also interacts country-level financial development variables with industry-level financial constraints. In our tests, we are also able to sharpen our empirical identification by absorbing additional firm-level, industry-level, and country-level variation through a mix of observable characteristics and fixed effects.

B.1. Technological Mix

An important source of carbon-transition risk is technological change in energy production and carbon capture. As they transition to carbon neutrality, firms may find themselves at different points in their energy mix, carbon intensity, and outside demand for energy. The more distant the firms are from their target technology profile in a new green equilibrium, the more they are exposed to potential aggregate technology shocks. The resulting risk may come from unexpectedly high costs of green energy production as well as uncertainty about such costs.[16]

In this section, we explore the importance of these factors for the pricing of carbon-transition risk. We classify technology factors into three categories; the first two relate to the production side of carbon emissions and the third relates to the consumption side. First, we investigate whether firms located in countries with a higher share of renewable energy have lower carbon premia. Second, we explore whether the size of the fossil fuel production sector affects the carbon premium. We hypothesize that firms located in countries in which the share of the energy sector is large would have a larger carbon premium. Third, consumption of energy per capita may indicate how far the transition to a low-emission economy has progressed. It may also indicate the expected demand for fossil fuel energy going forward. We expect that firms in countries with high energy consumption are exposed to higher transition risk.

The results of this analysis are reported in Table X. We uncover a few interesting patterns. First, we find that green and brown energy variables do not matter much for how stock returns react to emission levels. Across all specifications, the coefficients of the interaction terms are small and statistically insignificant. The exception is the interaction term between scope 3 emissions and the reliance on renewable energy. This effect, however, is only marginally significant. Second, the hypothesis that a more renewable energy–based

[16] A separate issue that we do not explore formally in the paper is the uncertainty about the depreciation of any stranded assets and their impact on firm value. Atanasova and Schwartz (2020) analyze the empirical importance of this issue in the oil and gas industry.

Table X

Carbon Emissions and Stock Returns: Energy Structure

The sample period is from 2005 to 2018. The dependent variable is *RET*. The main independent variables are carbon emission levels (Panel A) and the growth in emissions (Panel B). *ELRENEW* measures a country's share of electricity generated by renewable power plants in total electricity generated by all types of plants in a given year; *ENINT* is the ratio between energy supply and gross domestic product measured at purchasing power parity in a given country. Energy intensity is an indication of how much energy is used to produce one unit of economic output in a given year; *ENUSEPC* is a country's energy consumption (in kg of oil equivalent per capita) in a given year. All other variables are defined in Tables I and II. We report the results of the pooled regression with standard errors (in parentheses) double clustered at the firm and year level. All regression models include the controls of Table VI (unreported for brevity), year-month-fixed effects, and country-fixed effects. In selected columns, we additionally include industry-fixed effects. ***1% significance; **5% significance; *10% significance.

	Panel A: Levels											
Dependent Variable: *RET*	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
ELRENEW	7.809*	2.588	8.161*	2.322								
	(4.150)	(5.042)	(4.164)	(5.059)								
ENINT					−7.864	2.400	−9.565	5.223				
					(60.851)	(61.263)	(60.818)	(61.358)				
ENUSEPC									−1.386**	−1.427**	−1.442***	−1.411**
									(0.545)	(0.550)	(0.546)	(0.554)
LOGS1TOT	0.006		0.059***		0.030		0.069**		−0.005		0.038*	
	(0.024)		(0.020)		(0.028)		(0.027)		(0.024)		(0.021)	
LOGS3TOT		0.077**		0.132***		0.162***		0.222***		0.085**		0.153***
		(0.030)		(0.034)		(0.052)		(0.053)		(0.039)		(0.041)
*ELRENEW*LOGS1TOT*	0.028		0.010									
	(0.175)		(0.176)									
*ELRENEW*LOGS3TOT*		0.480*		0.518*								
		(0.288)		(0.289)								
*ENINT*LOGS1TOT*					−0.443		−0.209					
					(0.551)		(0.525)					
*ENINT*LOGS3TOT*						−1.198		−1.299				
						(0.844)		(0.840)				
*ENUSEPC*LOGS1TOT*									0.004		0.005	
									(0.005)		(0.005)	
*ENUSEPC*LOGS3TOT*										0.006		0.002
										(0.007)		(0.007)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year/month-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-fixed effects	No	No	Yes	Yes	No	No	Yes	Yes	No	No	Yes	Yes
Observations	438,446	438,918	433,249	433,721	438,488	438,960	433,291	433,763	423,298	423,770	418,233	418,705
R-squared	0.185	0.186	0.187	0.187	0.185	0.185	0.187	0.187	0.190	0.190	0.192	0.192

(*Continued*)

Table X—*Continued*

Dependent Variable: *RET*	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Panel B: Growth in Emissions											
ELRENEW	8.254**	8.221**	8.434**	8.389**								
	(3.387)	(3.381)	(3.401)	(3.395)								
ENINT					−25.255	−29.735	−24.552	−29.244				
					(60.766)	(60.556)	(60.724)	(60.459)				
ENUSEPC									−1.397**	−1.385**	−1.446**	−1.431**
									(0.553)	(0.552)	(0.553)	(0.553)
S1CHG	0.597***		0.644***		0.021		0.039		0.313**		0.316**	
	(0.113)		(0.114)		(0.199)		(0.199)		(0.155)		(0.153)	
S3CHG		1.201***		1.294***		0.113		0.158		0.728*		0.760**
		(0.289)		(0.289)		(0.400)		(0.395)		(0.373)		(0.372)
*ELRENEW*S1CHG*	−1.839*		−2.068*									
	(1.087)		(1.089)									
*ELRENEW*S3CHG*		0.005		−0.502								
		(2.671)		(2.675)								
*ENINT*S1CHG*					9.254**		9.562**					
					(4.009)		(4.037)					
*ENINT*S3CHG*						20.786***		21.199***				
						(7.830)		(7.854)				
*ENUSEPC*S1CHG*									0.036		0.044	
									(0.033)		(0.033)	
*ENUSEPC*S3CHG*										0.097		0.107
										(0.083)		(0.082)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year/month-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-fixed effects	No	No	Yes	Yes	No	No	Yes	Yes	No	No	Yes	Yes
Observations	433,851	434,226	428,710	429,085	433,893	434,268	428,752	429,127	418,791	419,166	413,782	414,157
R-squared	0.186	0.186	0.188	0.188	0.186	0.186	0.188	0.188	0.190	0.191	0.192	0.193

economy is associated with lower carbon premia is broadly borne out in the data when it comes to firm-level growth in emissions. Firms located in countries with a larger fraction of renewable energy production have lower carbon premia with respect to their year-to-year emissions growth, as indicated by the negative highly significant coefficients for the interaction terms. Similarly, we find that the coefficients of the interaction terms between the share of the energy sector and the growth in emissions are highly significant and positive, indicating that investors perceive the risk with respect to carbon emissions to be greater in countries with large fossil fuel energy sectors. Interestingly, the countries with higher reliance on renewables and lower reliance on fossil fuels are typically developed countries, which could partly explain why we found that short-term transition risk is priced more for developing countries. At the same time, we find that energy use is not significantly related to stock returns irrespective of the risk measure on which we focus. One reason could be that the energy source being consumed may be green. Also, the place of consumed energy need not be the same as the country in which it is sourced. In sum, the distinction between short-term and long-term reactions to technological mix suggests that this variable is transitory in nature, at least when assessed from the capital markets perspective. The energy mix cannot inform the long-term costs of the transition, as any potential product or process innovation in this market is likely to modify future expectations.

Overall, we find strong evidence that a country's energy production mix is an important predictor of how investors price risk with respect to short-term changes in emissions, but not with respect to the level of emissions. The gist of these results is broadly consistent with our hypothesis that uncertainty about technological change increases transition risk. Our decomposition further reveals that production side factors are more relevant for investors than energy consumption factors.

B.2. Sociopolitical Environment

Uncertainty about future carbon emission policies depends on the institutional and sociopolitical environment that shapes government action. We should expect lower policy uncertainty in politically stable and socially harmonious societies, and in countries with more democratic institutions that tend to reduce the risk of arbitrary policy swings. In contrast, less equal societies are more likely to waver in their policy commitments and make less predictable progress toward carbon neutrality. This greater climate policy uncertainty, in turn, is likely to be reflected in a higher carbon premium. We explore this channel by looking at whether a country's "rule of law" and "voice" affects the carbon premium of its companies. The rule of law captures perceptions of the extent to which agents have confidence in and abide by the rules of society, and in particular the quality of contract enforcement, property rights, the police, and the courts, as well as the likelihood of crime and violence. The measure *RULELAW*, is standardized between -2.5 and 2.5. Voice reflects perceptions of the extent to which a country's citizens are able to participate in selecting their government, as well as freedom of expression, freedom of association, and a free media. The standardized value, defined as *VOICE*, lies between 2.5 and −2.5. The 2.5 indicates the situation in which there is no obstacle to expressing voice and −2.5 number reflects situations in which people have no way of expressing their voices. Another indirect measure of social and political stability we look at is the country's income inequality, as measured by the Gini coefficient. All three country measures are obtained at an annual frequency from the World Bank. As before, we interact each of these variables with the level and growth of emissions to distinguish between long-term and short-term effects. We report the results in Table XI.

We do not find a significant effect of any of these variables on the premium associated with the level of emissions and conclude from these results that social factors do not appear to affect the long-run risk associated with carbon emissions. All coefficients of the interaction terms in Panel A are small and statistically insignificant. In contrast, we find that sociopolitical factors do matter for investors' carbon-transition risk perceptions in the short-run. As reported in Panel B, the coefficients of the interaction terms between "rule of law" and changes in emissions, and between "voice" and changes in emissions, are both highly significant and negative, indicating that the carbon premium is lower in countries with better rule of law and more democratic political institutions. Similarly, the coefficient of the interaction term between the Gini coefficient and changes in emissions is significant and positive, meaning that in countries with higher inequality, the carbon premium is likely to be larger. Overall, these results on the effect of sociopolitical factors are consistent with the view that greater social harmony produces less climate policy uncertainty. But these effects manifest themselves in the short-run, presumably because the socioeconomic environment can evolve, so that current conditions are seen as having a transitory impact on policy uncertainty by investors. For example, the political environment and social norms can change in the medium- and long-term; hence, any constraints imposed in the short-run may no longer bind in the long-run. From a different angle, one can link our prior findings on the heterogeneity in short-term risk premia between developed and developing countries to the different states of socioeconomic capital across countries.

B.3. Climate Policy Tightness

Transition risk is often associated with expected regulatory changes dictating the adjustment to a green economy. Investor expectations of future climate-related policies can be an important risk component. Firms located in countries in which the government has made the most ambitious pledges to reduce carbon emissions may therefore be associated with a higher carbon premium. This is particularly true when local regulations are reinforced by pan-governmental policy actions, such as the United Nations-led COP initiative.

Climate change mitigation policies may originate from two sources: domestic regulators or international pan-governmental agreements. In this section, we evaluate the importance of each of the channels separately using unique

Table XI

Carbon Emissions and Stock Returns: Sociopolitical Environment

The sample period is from 2005 to 2018. The dependent variable is *RET*. The main independent variables are carbon emission levels (Panel A) and the growth in emissions (Panel B). *RULELAW* measures a country's perceptions in a given year of the extent to which agents have confidence in and abide by the rules of society, and in particular the quality of contract enforcement, property rights, the police, and the courts, as well as the likelihood of crime and violence. Estimate gives the country's score on the aggregate indicator, in units of a standard normal distribution. *VOICE* captures perceptions in a given year of the extent to which a country's citizens are able to participate in selecting their government, as well as freedom of expression, freedom of association, and a free media. Estimate gives the country's score on the aggregate indicator, in units of a standard normal distribution. *GINI* is a country's GINI index in a given year. All other variables are defined in Tables I and II. We report the results of the pooled regression with standard errors (in parentheses) double clustered at the firm and year level. All regression models include the controls of Table VI (unreported for brevity), year-month-fixed effects, and country-fixed effects. In selected columns, we additionally include industry-fixed effects. ***1% significance; **5% significance; *10% significance.

Panel A: Levels												
Dependent Variable: *RET*	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
RULELAW	−0.677	−0.721	−0.660	−0.705								
	(0.752)	(0.766)	(0.755)	(0.776)								
VOICE					−0.700	−0.676	−0.723	−0.697				
					(0.805)	(0.822)	(0.803)	(0.828)				
GINI									−6.619	−7.181	−6.753	−7.776
									(12.017)	(11.998)	(12.000)	(11.998)
LOGS1TOT	0.026		0.061***		0.031*		0.067***		0.020		0.023	
	(0.017)		(0.015)		(0.017)		(0.014)		(0.081)		(0.081)	
LOGS3TOT		0.108***		0.162***		0.120***		0.173***		0.085		0.081
		(0.025)		(0.028)		(0.024)		(0.027)		(0.115)		(0.115)
*RULELAW*LOGS1TOT*	0.002		0.002									
	(0.009)		(0.009)									
*RULELAW*LOGS3TOT*		0.004		0.003								
		(0.015)		(0.015)								
*VOICE*LOGS1TOT*					−0.005		−0.006					
					(0.011)		(0.011)					
*VOICE*LOGS3TOT*						−0.009		−0.010				
						(0.018)		(0.018)				

(*Continued*)

Table XI—*Continued*

Panel A: Levels												
Dependent Variable: *RET*	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
*GINI*LOGS1TOT*									0.027		0.124	
									(0.219)		(0.219)	
*GINI*LOGS3TOT*										0.069		0.195
										(0.296)		(0.302)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year/month-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-fixed effects	No	No	Yes	Yes	No	No	Yes	Yes	No	No	Yes	Yes
Observations	746,289	746,929	736,501	737,141	746,289	746,929	736,501	737,141	238,048	238,236	235,027	235,215
R-squared	0.150	0.150	0.151	0.152	0.150	0.150	0.151	0.152	0.195	0.195	0.198	0.198

Panel B: Growth in Emissions												
Dependent Variable: *RET*	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
RULELAW	−0.627	−0.606	−0.610	−0.587								
	(0.743)	(0.744)	(0.743)	(0.745)								
VOICE					−0.778	−0.782	−0.806	−0.804				
					(0.811)	(0.815)	(0.811)	(0.816)				
GINI									−7.074	−8.585	−6.232	−7.788
									(12.484)	(12.489)	(12.425)	(12.419)
S1CHG	0.599***		0.613***		0.535***		0.547***		−0.469		−0.402	
	(0.097)		(0.097)		(0.075)		(0.075)		(0.396)		(0.399)	
S3CHG		1.512***		1.524***		1.327***		1.339***		−1.072		−0.887
		(0.226)		(0.228)		(0.179)		(0.180)		(1.024)		(1.020)
*RULELAW*S1CHG*	−0.145**		−0.144**									
	(0.060)		(0.060)									
*RULELAW*S3CHG*		−0.331**		−0.326**								
		(0.151)		(0.150)								
*VOICE*S1CHG*					−0.145***		−0.140***					
					(0.051)		(0.051)					
*VOICE*S3CHG*						−0.275**		−0.266**				
						(0.130)		(0.130)				

(*Continued*)

Table XI—*Continued*

Panel B: Growth in Emissions												
Dependent Variable: *RET*	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
*GINI*S1CHG*									2.521**		2.378**	
									(1.075)		(1.084)	
*GINI*S3CHG*										6.030**		5.687**
										(2.677)		(2.675)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year/month-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-fixed effects	No	No	Yes	Yes	No	No	Yes	Yes	No	No	Yes	Yes
Observations	735,150	735,694	725,536	726,080	735,150	735,694	725,536	726,080	236,017	236,159	233,026	233,168
R-squared	0.151	0.152	0.153	0.153	0.151	0.152	0.153	0.153	0.196	0.196	0.199	0.199

data on country-specific regulatory tightness. Our policy data come from Germanwatch. To our knowledge, ours is the first large-sample study that evaluates the direct importance of both types of policies for global stock returns. Each year, Germanwatch collects information on all climate-related policies and converts this information into a numerical score, where a higher number means a stricter regulatory regime. We define two variables that we interact with firm-level carbon emissions. *INTPOLICY* is a normalized measure of international policy tightness; *DOMPOLICY* is a normalized measure of domestic policy tightness.[17] We interact each of the two variables with the level and growth in firm emissions.

We report the results in Table XII. Two interesting findings emerge. First, in Panel A, we show that the effects of climate policy operate on the carbon premium associated with carbon emission levels. The effect is positive and economically significant for both scope 1 and scope 3 emissions, and statistically significant for scope 3 emissions. On the other hand, neither type of climate policy tightness affects the carbon premium associated with the year-by-year growth in emissions, as shown in Panel B. These results support the view that carbon policies are seen by investors as permanent shocks to carbon-transition risk. That is, investors' perspective appears to be that climate policies that are already in place are largely irreversible. Second, and perhaps more unexpectedly, we find that between the two types of climate policies, domestic ones have a bigger effect on the carbon premium. This result sheds light on many analysts' concerns that the commitments made by countries in Paris or Glasgow could be empty promises, that is, that commitments made through international agreements lack credibility unless they are translated into domestic policy. It is only when these commitments are followed up by domestic policy implementation that investors start paying attention.

B.4. Brown Reputation Risk

An important component of transition risk is reputation risk. A few fossil fuel-intensive industries that we define as "salient" are known to attract negative media coverage, which could further amplify transition risk. Hence, the question of whether the carbon premium is mostly concentrated in the oil and gas, utilities, and motor sectors that are the focus of much negative press. Could it be that the reason behind much cross-sector variation in the carbon premium lies in the negative reputation earned by brown sectors? Given that the media focus is largely on the salient brown industries, one would expect that the investors in companies in these sectors price-in an additional risk compensation for their exposure to the negative stigma of holding these stocks.

To explore this hypothesis, we estimate a modified regression specification from that in Table VI, conditional on whether a company belongs to one of the salient industries mentioned above, or not. We define an indicator variable,

[17] Further details on the methodology behind the policy measures can be obtained from the Germanwatch website, at https://www.germanwatch.org/en/21110.

Table XII

Carbon Emissions and Stock Returns: Climate Policy Tightness

The sample period is from 2005 to 2018. The dependent variable is *RET*. The main independent variables are carbon emission levels (Panel A) and the growth in emissions (Panel B). *INTPOLICY* measures the strictness of a country's international climate policy in a given year. *DOMPOLICY* measures the strictness of a country's domestic climate policy in a given year. All other variables are defined in Tables I and II. We report the results of the pooled regression with standard errors (in parentheses) double clustered at the firm and year level. All regression models include the controls of Table VI (unreported for brevity), year-month-fixed effects, and country-fixed effects. In selected columns, we additionally include Trucost industry-fixed effects. ***1% significance; **5% significance; *10% significance.

Panel A: Levels								
Dependent Variable: *RET*	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
INTPOLICY	−0.684	−1.171	−0.624	−1.272				
	(0.387)	(1.009)	(0.384)	(0.983)				
DOMPOLICY					−1.087*	−2.634**	−1.094*	−2.723**
					(0.566)	(1.014)	(0.535)	(0.971)
LOGS1TOT	0.044*		0.083***		0.001		0.037	
	(0.023)		(0.022)		(0.024)		(0.027)	
LOGS3TOT		0.123***		0.171***		0.041		0.088**
		(0.038)		(0.040)		(0.027)		(0.030)
*INTPOLICY*LOGS1TOT*	−0.015		−0.020					
	(0.040)		(0.041)					
*INTPOLICY*LOGS3TOT*		0.027		0.035				
		(0.086)		(0.084)				
*DOMPOLICY*LOGS1TOT*					0.064		0.065	
					(0.050)		(0.048)	
*DOMPOLICY*LOGS3TOT*						0.181**		0.188**
						(0.076)		(0.072)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year/month-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-fixed effects	No	No	Yes	Yes	No	No	Yes	Yes
Observations	551,075	551,642	544,127	544,694	551,075	551,642	544,127	544,694
R-squared	0.153	0.153	0.155	0.155	0.153	0.153	0.154	0.155

(*Continued*)

Table XII—*Continued*

Panel B: Growth in Emissions

Dependent Variable: *RET*	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
INTPOLICY	−0.852**	−0.892**	−0.842**	−0.891**				
	(0.314)	(0.302)	(0.316)	(0.306)				
DOMPOLICY					−0.386	−0.430	−0.383	−0.430
					(0.272)	(0.280)	(0.280)	(0.289)
S1CHG	0.570***		0.593***		0.475***		0.492***	
	(0.125)		(0.109)		(0.121)		(0.105)	
S3CHG		1.264**		1.252**		0.984		0.998*
		(0.534)		(0.513)		(0.573)		(0.542)
*INTPOLICY*S1CHG*	−0.175		−0.176					
	(0.186)		(0.170)					
*INTPOLICY*S3CHG*		−0.119		−0.038				
		(0.574)		(0.555)				
*DOMPOLICY*S1CHG*					−0.001		0.011	
					(0.201)		(0.194)	
*DOMPOLICY*S3CHG*						0.364		0.395
						(0.711)		(0.679)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year/month-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-fixed effects	No	No	Yes	Yes	No	No	Yes	Yes
Observations	544,610	545,073	537,766	538,229	544,610	545,073	537,766	538,229
R-squared	0.155	0.155	0.156	0.157	0.154	0.155	0.156	0.157

SALIENT, equal to 1 if the company belongs to one of the salient industries, and 0 otherwise. Our coefficients of interest are those of the interaction effect between *SALIENT* and respective emission measures. If these salient brown industries are indeed more stigmatized, one would expect the carbon premium to be smaller in the other sectors. In terms of our conditional regression specification, this would mean that the coefficient of the interaction term is positive and statistically significant.

We report the results in Table XIII. By and large, we find that the premium associated with the level of emissions is not statistically different for salient and nonsalient industries, and, if anything, the direction of the effect goes against the hypotheses of a premium being present mostly in salient industries. The results are slightly different for the premium associated with the growth in emissions. Here, we find a slightly stronger effect for changes in scope 3 emissions on returns for companies that operate in salient industries.

This finding could also mean that a stigma has mostly already been "baked in" in these brown sectors but is yet to materialize in the other sectors that have faced less analyst scrutiny. These findings are also consistent with the results in Table VI that variations in stock returns associated with carbon emissions across industries swamp within-industry variations. Another possibility is that the stigma could extend to an entire country when the country is disproportionately dependent on brown sectors, as is the case for many countries in the "Others" category. By this interpretation, the weaker results we found for this category could be due to this baked-in stigma associated with an overdependence on brown sectors. Note, however, that our regressions include country-fixed effects, which to some extent absorb any such country-level effects.

B.5. Physical Risk

Much of the economics literature on climate risk has sought to estimate the expected physical damages due to climate change. A natural hypothesis is that transition risk is positively correlated with physical risk. As countries are exposed to more severe weather events caused by climate change, one would expect that there will be greater support for policies combatting climate change in these countries. In other words, the extent to which a country has been exposed to climate disasters may shape investors' beliefs about the cost of long-term damage due to climate change. To test this hypothesis, we use a country-level, year-by-year index measuring physical risk (CRI) from Germanwatch. This index is based on the frequency of climate-related damages. Countries with higher values of the CRI index are considered to have higher physical risk. We estimate the coefficients of the interaction terms between CRI and firm-level emission measures, both their levels and growth rates. The results are reported in Table IA.X. Columns (1) to (4) show the results based on total emissions, and columns (5) to (8) show the results based on growth rates. Consistent with the hypothesis that physical risk amplifies the carbon premium associated with transition risk, we find that positive values for the interaction

Table XIII

Carbon Emissions and Stock Returns: Reputational Risk

The sample period is from 2005 to 2018. *SALIENT* is an indicator variable equal to 1 for all companies in the oil and gas (GICS = 2), utilities (GICS = 65-69), and motor (GICS = 18, 19, 23) industries, and 0 for companies in all other industries. The dependent variable is *RET*. The main independent variables are carbon emission levels (columns (1) to (4)) and the growth in emissions (columns (5) to (8)), all interacted with *SALIENT*. All variables are defined in Tables I and II. We report the results of the pooled regression with standard errors (in parentheses) double clustered at the firm and year level. All regressions include year-month-fixed effects and country-fixed effects. All regression models include the controls of Table VI (unreported for brevity). In even-numbered columns, we additionally include Trucost industry-fixed effects. ***1% significance; **5% significance; *10% significance.

Dependent Variable: *RET*	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
LOGS1TOT	0.047		0.073**					
	(0.032)		(0.024)					
SALIENT	0.417	0.945	0.331	0.350	0.247	0.202	0.142	0.095
	(0.530)	(0.651)	(0.328)	(0.403)	(0.156)	(0.155)	(0.119)	(0.113)
*SALIENT*LOGS1TOT*	−0.006		−0.006					
	(0.040)		(0.028)					
LOGS3TOT		0.159***		0.176***				
		(0.034)		(0.036)				
*SALIENT*LOGS3TOT*		−0.053		−0.013				
		(0.045)		(0.033)				
S1CHG					0.433**		0.472**	
					(0.191)		(0.200)	
*SALIENT*S1CHG*					0.010		−0.020	
					(0.205)		(0.209)	
S3CHG						0.555		0.601
						(0.404)		(0.412)
*SALIENT*S3CHG*						0.710*		0.671*
						(0.369)		(0.367)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year/month-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-fixed effects	No	Yes	No	Yes	No	Yes	No	Yes
Observations	744,864	745,504	735,109	735,749	733,724	734,268	724,143	724,687
R-squared	0.150	0.150	0.151	0.151	0.151	0.152	0.153	0.153

terms with emission changes. However, all these coefficients are statistically insignificant. Also, contrary to our prediction, the coefficients of the interaction terms with emission levels are negative (again, however, these coefficients are statistically and economically small). Hence, greater physical risk exposure for a country because of climate change, and greater incidence of physical climate shocks, does not result in greater carbon transition risk.

Overall, we conclude that transition risk does not appear to be significantly linked to different exposures to physical risk, perhaps because physical risk is a localized risk, and is unlikely to affect all regions with the same intensity, whereas the carbon transition is a global issue, which is largely independent of whether physical risks materialize in a specific country or not. It is simply a reflection of the shift away from fossil fuels. Indeed, countries like Australia, Brazil, and Russia, or U.S. states like Texas, Florida, or West Virginia, that have experienced massive climate disasters, have not seen a political movement emerge to shut down coal mines and other fossil fuel-dependent economic activity. Somehow the political process in these countries (and U.S. states) does not seem to commingle physical and transition risk.

B.6. Changes in Investor Awareness

Our analysis so far has explored the carbon premium through the cash flow uncertainty channel. Another force that could affect the carbon premium is the discount rate channel related to changing investor perceptions about climate change and carbon-transition risk. Bolton and Kacperczyk (2021a) find evidence of a discount rate channel, with investor perceptions of carbon-transition risk changing over time, but their evidence is based purely on U.S. companies, which naturally raises the question of external validity. More importantly, this evidence has little to say about what aspects of transition risk are altered by the changed beliefs. Although our analysis here includes 77 countries, we cannot clearly isolate the effects of this channel given that we are pooling all observations from 2005 to 2018 together. However, we can explore how the carbon premium reacts to salient events that could reshape public perceptions of climate change. One such defining event is the landmark Paris climate agreement at the COP21 in December 2015. This event has enhanced the salience of the climate debate worldwide and raised the importance of possible transition risk going forward. It is therefore to be expected that the event has likely changed investors' perception of risk along multiple dimensions, including future energy costs, social preferences, or policy changes. Our empirical analysis around this event captures the aggregate effect, encompassing all the above possibilities, of investors' responses to this event.

Specifically, we define an indicator variable *Paris* that is equal to 0 for the 2 years (from 2014 to 2015) preceding the Paris agreement and equal to 1 for the 2 years (from 2016 to 2017) following the agreement. Next, we regress stock returns on carbon emissions interacted with *Paris*. We report the results in Table XIV, which provides the estimates for the differences in levels and changes in emissions for our aggregate sample of 77 countries. Notably, there

Table XIV

Carbon Emissions and Stock Returns: The Role of Investor Awareness

The dependent variable is *RET*. The main independent variables are carbon emission levels (columns (1) to (4)) and the growth in emissions (columns (5) to (8)). All variables are defined in Tables I and II. We report the results of the pooled regression with standard errors (in parentheses) double clustered at the firm and year level. *Paris* is an indicator variable equal to 0 for the period January 2014–November 2015 (2 years before Paris COP21 conference) and equal to 1 for the period January 2016–December 2017 (2 years after Paris COP21 conference). All regression models include the controls of Table VI (unreported for brevity), year-month-fixed effects, and country-fixed effects. In selected columns, we additionally include Trucost industry-fixed effects. ***1% significance; **5% significance; *10% significance.

Dependent Variable: *RET*	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
LOGS1TOT	−0.045		−0.017					
	(0.031)		(0.031)					
LOGS3TOT		0.060		0.119**				
		(0.047)		(0.050)				
S1CHG					0.658***		0.662***	
					(0.158)		(0.157)	
S3CHG						1.864***		1.856***
						(0.344)		(0.350)
*Paris***LOGS1TOT*	0.132***		0.133***					
	(0.048)		(0.048)					
*Paris***LOGS3TOT*		0.098*		0.101*				
		(0.053)		(0.054)				
*Paris***S1CHG*					−0.207		−0.198	
					(0.210)		(0.211)	
*Paris***S3CHG*						−0.716		−0.757
						(0.528)		(0.550)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year/month-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-fixed effects	No	No	Yes	Yes	No	No	Yes	Yes
Observations	301,993	302,309	298,113	298,429	295,469	295,780	291,686	291,997
R-squared	0.061	0.061	0.064	0.064	0.062	0.062	0.065	0.065

is no significant premium associated with the level of scope 1 emissions right before Paris (even with industry-fixed effects), whereas there is a significantly larger positive premium after Paris. We also find a significant increase in the premium for the level of scope 3 emissions. In turn, the results for changes in emissions are significant in the pre-Paris period and show no significant difference with the post-Paris period. One way to interpret these contrasting results is that, because of COP21, investors significantly updated their beliefs about long-term transition risk. Consistent with our previous findings, these results also suggest that the Paris agreement has been particularly important in reshaping investor beliefs about forthcoming climate-related policies. Indeed, this has been a popular narrative among practitioners and policy makers.

In which parts of the world did the Paris agreement have the biggest effect? To explore this question, we estimate the same model as in Table XIV for each continent. We report the results for the level of carbon emissions in Table XV. Remarkably, there is no apparent change for North America. Both before and after the Paris agreement, there is no significant carbon premium associated with the level of emissions. In Europe, both before and after Paris, there is a significant carbon premium (except that the premium for scope 1 emissions becomes insignificant after Paris). As a result, there is no significant change in the value of the premium around the Paris event for Europe. The biggest and most statistically significant change is in Asia, where the carbon premium was insignificant before Paris, but became highly significant after Paris. This is true whether we exclude China or not. Finally, in the other continents (Africa, Australia, and South America) there is also a significant positive change before and after Paris, even though this change is based on a smaller sample size.

Another relevant breakdown is between the group of G20 countries and the group of other countries. The results are reported in Table IA.XI. Again, the difference in the carbon premium before and after Paris is dramatic for the group of G20 countries. Before the agreement there was no significant carbon premium, but after the agreement there is a highly significant positive premium, whether we include industry-fixed effects or not. In contrast, the changes in the other group of countries are much smaller. While there is a shift toward a significant premium, it is mostly for scope 3 emissions.

We also undertake this analysis after excluding the salient industries associated with fossil fuels. Recall that our cross-sectional analysis when we pool all years together established that the carbon premium is present even beyond these industries. The results reported in Table IA.XII reveal similar robustness in the carbon premium around the Paris shock. Indeed, there is a highly significant and positive premium associated with the level of emissions in other industries as well after Paris.[18]

[18] We have also tested whether the changing awareness results are driven by the sample of new companies that Trucost has added to its database. The results, in Table IA.XIII, show similar effects for the "legacy sample," so it is unlikely that the addition of the new companies is driving the results.

Table XV

Carbon Total Firm Emissions and Stock Returns: Awareness (Regional)

The dependent variable is monthly *RET*. The main independent variable is carbon emission level. All variables are defined in Tables I and II. We report the results of the pooled regression with standard errors (in parentheses) double clustered at the firm and year level. *Paris* is an indicator variable equal to 0 for the period January 2014–November 2015 (2 years before the Paris COP21 conference) and equal to 1 for the period January 2016–December 2017 (2 years after the Paris COP21 conference). All regression models include the controls of Table VI (unreported for brevity), year-month-fixed effects, and country-fixed effects. In selected columns, we additionally include Trucost industry-fixed effects. Panel A samples firms from North America, Panel B from Europe, Panel C from Asia, and Panel D from all the remaining countries. ***1% significance; **5% significance; *10% significance.

Panel A: North America

Dependent Variable: *RET*	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	North America				North America (excl. USA)			
LOGS1TOT	−0.035		−0.013		−0.078		0.009	
	(0.059)		(0.060)		(0.078)		(0.089)	
LOGS3TOT		0.106		0.071		0.209		0.196
		(0.093)		(0.104)		(0.125)		(0.159)
*Paris*LOGS1TOT*	0.083		0.079		0.072		0.090	
	(0.081)		(0.077)		(0.115)		(0.122)	
*Paris*LOGS3TOT*		−0.052		−0.044		−0.211		−0.190
		(0.109)		(0.102)		(0.163)		(0.170)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year/month-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-fixed effects	No	No	Yes	Yes	No	No	Yes	Yes
Observations	74,410	74,503	73,442	73,535	12,978	13,025	12,876	12,923
R-squared	0.090	0.090	0.098	0.098	0.105	0.106	0.119	0.120

(*Continued*)

Table XV—*Continued*

Panel B: Europe								
Dependent Variable: *RET*	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Europe				EU			
LOGS1TOT	−0.022		−0.011		−0.022		−0.011	
	(0.041)		(0.043)		(0.041)		(0.043)	
LOGS3TOT		0.099		0.176**		0.099		0.176**
		(0.069)		(0.079)		(0.069)		(0.079)
*Paris*LOGS1TOT*	0.089		0.091		0.089		0.091	
	(0.061)		(0.061)		(0.061)		(0.061)	
*Paris*LOGS3TOT*		0.065		0.062		0.065		0.062
		(0.083)		(0.082)		(0.083)		(0.082)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year/month-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-fixed effects	No	No	Yes	Yes	No	No	Yes	Yes
Observations	63,965	64,034	62,911	62,980	63,965	64,034	62,911	62,980
R-squared	0.097	0.097	0.105	0.105	0.097	0.097	0.105	0.105

(*Continued*)

Table XV—*Continued*

Panel C: Asia								
Dependent Variable: *RET*	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Asia				Asia (excl. China)			
LOGS1TOT	−0.055		−0.034		−0.031		−0.025	
	(0.033)		(0.036)		(0.029)		(0.030)	
LOGS3TOT		0.007		0.097		0.077		0.147*
		(0.057)		(0.067)		(0.073)		(0.078)
*Paris*LOGS1TOT*	0.161***		0.166***		0.128***		0.132***	
	(0.052)		(0.051)		(0.041)		(0.041)	
*Paris*LOGS3TOT*		0.208***		0.216***		0.089		0.092
		(0.071)		(0.074)		(0.081)		(0.083)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year/month-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-fixed effects	No	No	Yes	Yes	No	No	Yes	Yes
Observations	134,732	134,814	133,201	133,283	105,375	105,457	103,988	104,070
R-squared	0.078	0.078	0.082	0.083	0.062	0.062	0.067	0.067

(*Continued*)

Table XV—*Continued*

Panel D: Others				
Dependent Variable: *RET*	(1)	(2)	(3)	(4)
	Others			
LOGS1TOT	−0.163***		−0.055	
	(0.057)		(0.084)	
LOGS3TOT		−0.129		−0.000
		(0.081)		(0.112)
*Paris*LOGS1TOT*	0.271***		0.267***	
	(0.083)		(0.087)	
*Paris*LOGS3TOT*		0.268**		0.253**
		(0.109)		(0.109)
Controls	Yes	Yes	Yes	Yes
Year/month-fixed effects	Yes	Yes	Yes	Yes
Country-fixed effects	Yes	Yes	Yes	Yes
Industry-fixed effects	No	No	Yes	Yes
Observations	28,251	28,323	27,924	27,996
R-squared	0.067	0.067	0.078	0.077

All in all, these results paint a rather striking picture of the pricing of transition risk across countries. The expectation of a significant long-term change in the carbon premium seems to be reflected in salient events, such as the Paris agreement. The striking and surprising finding here is that awareness about carbon risk, as reflected in the carbon premium, has changed the most in Asia, where investor awareness has jumped after the Paris agreements, whereas it has remained basically unchanged in Europe and North America, either because these regions already had greater awareness of climate change (Europe), or because they had less awareness and did not revise their beliefs (North America). To further explore this conjecture, we look at the predictability of national reforms (measured by *DOMPOLICY*) from the previous year's international policy framework (measured by *INTPOLICY*), before and after Paris, for the three different regions, Asia, Europe, and North America. In the regression model, we also include country-fixed effects. Consistent with our narrative, we find that there is predictive power of national policies in past international commitments following the Paris agreement. It is the highest for Asia, much lower for Europe, and the opposite for North America, the last result being consistent with the fact that the U.S. administration around Paris has mostly moved in the opposite direction from the international framework. We report these results in Table IA.XIV.

One potential concern with the risk premium interpretation is that we have measured changes in the risk premium over relatively short periods, even if a period of a decade and a half is not that short. Could it be that our findings are just a random draw? Although it is not possible to test this luck hypothesis, one should bear in mind that the Paris agreement is a particularly salient event and its important consequences have been established in other contexts. Also, the last decade has witnessed a significant increase in climate-related events, and a sharp increase in media coverage of these events, so that our interpretation based on changing risk (perceptions) has a solid grounding in these trends.[19]

C. Transitioning to a Green Equilibrium

Our results are broadly consistent with the existence of a return premium compensating investors for the carbon-transition risk they face. But at what point did investors begin to demand compensation for this risk? Basic logic suggests that the period in which carbon-transition risk is compensated should be preceded by a period during which assets are repriced to reflect the new risk. This repricing can in principle be a protracted process that parallels the economic shift from a brown to a green equilibrium. Moreover, the repricing is driven by changes in investor awareness about climate change risk. During this transition phase, one would expect to see increased demand (and there-

[19] In untabulated tests, we have also tested the change in the risk premium by using the long period from 2005 to 2015 as the pre-period. The results for the interactions terms are qualitatively similar.

fore higher prices) for assets with low levels of emissions, and decreased demand (and lower prices) for assets with high levels of emissions. Although this adjustment mechanism is straightforward, testing for such asset price adjustments is challenging, especially in the context of heterogenous global financial markets, in which individual assets may transition at different times and at different speeds.

In the absence of a clear large-scale empirical setting, we fall back on suggestive evidence from one individual sector, the tobacco industry, in which such a repricing process accompanied the rebranding of tobacco companies as "sin stocks." As Hong and Kacperczyk (2009) show, the reclassification of the tobacco industry as a sin asset class meant that tobacco companies were added to the divestment lists of many investors. This divestment movement resulted in higher expected returns (Merton (1987)). Prior to the 1950s, the negative health effects of tobacco consumption were not known; in fact, many considered tobacco a cure. This perception changed following the reports of the U.S. Surgeon General, which resulted in a massive change in beliefs about the industry. Consequently, the 1950–1970 period saw a massive revaluation of the industry, with tobacco companies being valued at much lower multiples. Following this repricing, however, tobacco companies over the subsequent four decades delivered very large returns.

We believe that a similar process is underway in the energy industry, with green energy companies being valued at much higher multiples and some brown companies already being valued at lower multiples. We can infer some of these repricing effects from some of our tests. As highlighted in Table XIII, when we exclude salient industries from our sample the effect of scope 1 emission levels on stock returns increases relative to the unconditional value in Table VI, which means that the salient industries, on an average, underperformed other sectors (with lower emissions) over our sample period. Interestingly, however, this difference only appears in regressions without industry-fixed effects, which suggests that the repricing has been a broad categorical repricing of the whole industry rather than individual firms in these industries. Of course, this repricing need not be a once-and-for-all revaluation as it appears to have been for the tobacco industry. In fact, it seems to us that investors' attitudes toward carbon emissions are much more dynamic, and thus it is quite possible that one could witness multiple waves of repricing followed by periods with high returns. This is in fact what we think our data capture. Because the carbon transition process is ongoing, this can only be a speculative inference, which we expect future out-of-sample tests of the carbon transition will confirm.

V. Conclusion

If global warming is to be checked, the global economy will have to wean itself off fossil fuels and reduce carbon emissions to zero by 2050 or 2060 at the latest. This translates into a year-to-year rate in emissions reductions equal to the drop we have witnessed in 2020 as a result of the COVID-19 pandemic.

Whether the global economy will be able to stick to such a rate of reduction in the use of fossil fuels, whether the reduction in emissions will be smooth or highly nonlinear and abrupt, is impossible to say. But what is certain is that in the coming years and decades investors will be exposed to substantial transition risk. Given that stock markets are fundamentally forward looking, it is natural to ask whether and to what extent this transition risk is reflected in stock returns.

We have taken the broadest possible look at this question by analyzing the pricing of carbon-transition risk at the firm level in a cross section of over 14,400 listed companies in 77 countries. To date, very little is known about how carbon emissions affect stock returns around the world. Our wide-ranging exploratory study provides a first glimpse into this question. We have found evidence of a widespread, significant, and rising carbon premium—higher stock returns for companies with higher carbon emissions. This premium is not just present in a few countries (the United States and the European Union) or in a few sectors tied to fossil fuels. It is ubiquitous, affecting firms in all sectors over three continents: Asia, Europe, and North America. Moreover, stock returns are related not just to firms' direct emissions but also to their indirect emissions through the supply chain and the carbon premium is associated both with the year-to-year growth in emissions (a short-run carbon-transition risk exposure) and the level of emissions (a long-run exposure).

Finally, we find that carbon-transition risk is not just a reflection of climate policy uncertainty but is also tied to uncertainty with respect to technological progress in renewable energy and the sociopolitical environment that could support or undermine climate policies. In turn, time-series patterns point to a time-varying carbon premium, with the premium rising significantly following the COP21 meeting.

At a broad level, our study is relevant for the discussions centered on carbon taxation as a means to achieve reductions in emissions. While the idea of a carbon tax is appealing based on economic first principles, it clearly faces practical obstacles. A major impediment to the introduction of a global carbon tax is coordination among political parties with diverse interests and financial capacities. Our study suggests that financial markets could play an important amplifying role. The increasing cost of equity for companies with higher emissions can be seen as a form of taxation through capital markets.

Our study is obviously not free of empirical challenges. One particular concern is that the shifting beliefs about climate change during our sample period are unusual and unlikely to be representative of the climate shocks that will unfold in the foreseeable future. It could be that investors have overreacted to the Paris agreement and all the attention devoted to climate change issues over our sample period. If that were the case, we would not really be picking up a persistent expected return difference. Rather, we would be finding return premia driven by nonpersistent shocks to investor beliefs. This is a possibility that we cannot rule out. But, given the climate science, this seems highly unlikely. If anything, evidence of an overheating planet is building day by day and alarm about climate change is rising. Given that carbon emissions continue to rise, the net zero commitments will be harder to achieve, which means that carbon-transition risk is rising. It is therefore far more likely that investor concerns about carbon-transition risk will grow. This, of course, means that we are potentially underestimating the size of the carbon premium.

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Supporting Information

Additional Supporting Information may be found in the online version of this article at the publisher's website:

Appendix S1: Internet Appendix.
Replication Code.