Carbon Firm Devaluation and Green Actions*

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Abstract

Using global evidence, we show that high-emission firms have lower price valuation ratios than low-emission firms in the same country, especially in recent years. The price gap coincides with heightened climate awareness following local natural disasters. In the presence of equity price pressure, high-emission firms reduce carbon emission levels, increase green innovation, and downsize operations. An instrumental variable approach, in which high-emission firms' price valuation is instrumented by local natural disasters, suggests that the effect on firms' actions is causal. Our findings are not solely driven by stricter environmental regulations, as private high-emission firms do not show the same results.

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Keywords: Price Valuation, Carbon Emissions, Green Innovation, Climate Awareness, Equity Market

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1 Introduction

In recent years, public concerns over climate risks have risen and the urge to combat climate change has become stronger. The Paris Agreement, which aims to limit global temperature rise in this century, was drafted in 2015 and signed by 195 participating member states and the European Union. U.S. surveys run by the Yale Program on Climate Change Communication show that the percentage of adults who think global warming will harm future generations increased from 59% in 2011 to 72% in 2020. According to surveys conducted by the Pew Research Center, the proportion of participants who consider global climate change a major threat to their country has risen in 11 out of the 13 countries surveyed from 2013 to 2022.

Evidence suggests that climate awareness is reflected in stock prices. Using data from 26 major equity markets, we compare the average valuation ratio, measured by price-to-book, price-to-earnings, price-to-sales, or price-to-cashflow, of high-emission firms and that of low-emission firms.[1] We show that the price valuation gap between high- and low-emission stocks (emission-minus-clean, EMC price gap) was close to zero before 2011 but negative and growing in magnitude afterward (see Figure I for the value-weighted average price-to-book gap). The value-weighted average price-to-book ratio in our sample is 4.1, and the EMC price-to-book gap reached about −2 in 2018.

This change in stock valuation is consistent with a positive shock in the ESG (Environmental, Social, and Governance) factor in Pástor et al. (2021)'s theoretical framework. Their ESG factor captures investors' ESG concerns and tastes for green holdings. Pástor et al. (2021) show that, in equilibrium, strong investor ESG preferences create a valuation gap

[1] Following Choi et al. (2020a), we adopt the definition provided by the Intergovernmental Panel on Climate Change (IPCC), the leading international body for the assessment of climate change, which lists five major industry categories of carbon dioxide and other greenhouse gas emission sources: Energy; Transport; Buildings; Industry (such as chemicals and metals); and Agriculture, Forestry, and Other Land Use (AFOLU). Firms in these industries are labeled as high-emission firms; those in other industries are labeled as low-emission. A similar price pattern is observed if emission firms are defined based on firm-level emission intensities or news-based environmental ratings instead, or in a regression setting that controls for stock characteristics and firm fixed effects.

between green and brown firms. To empirically link the price valuation gap to climate concerns, we exploit plausible exogenous shocks to people's attention to climate change at the country level. People's awareness of climate risk increases after experiencing local extreme weather events and natural disasters (Alok et al., 2020; Choi et al., 2020a; Alekseev et al., 2021) (we verify this by examining Google search volume and Bloomberg news publications on the topic of "climate change" in the country). We show that the EMC price gap is larger when there are more major natural disasters (provided by Baker et al. (2023)) in a country during a quarter, suggesting that prices are at least partially driven by heightened climate concerns.[2]

The primary research question we ask is: do stock prices influence firms' green actions? In Pástor et al. (2021), the valuation gap between green and brown firms incentivizes firms to become greener, as managers maximize market value. Empirically, regressing a firm's actions on its own price valuation ratio would be inappropriate because of the endogenous relationship between stock prices and capital investment. We adopt two approaches to circumvent this problem. First, we use the country-level EMC price gap, which is not determined by an individual firm. Second, following our previous result, we utilize exogenous natural disaster shocks as an instrumental variable for emission firms' log price-to-book ratio.

Using firm-level data provided by Trucost, we show that a more negative EMC price gap in the country in the past is associated with relatively lower CO_2 emission levels by high-emission firms. Widening the EMC price gap by one standard deviation is associated with declines of 18.6%, 3.0%, and 6.0% in Scopes 1, 2, and 3 emissions respectively, compared with low-emission firms. Focusing on Scope 1 direct emissions, a one-standard-deviation change in the EMC price gap corresponds to a decrease of 0.813 gigatons of carbon dioxide equivalent emissions annually (as a reference, the IPCC estimates that global net anthropogenic

[2]We do not directly measure investors' climate awareness or attempt to differentiate it from overall climate awareness. It is possible that, for example, investors do not become more aware of climate risk, but they react because they believe that the climate awareness of other participants (such as regulators, managers, consumers, and other stakeholders of the firm) has increased.

greenhouse gas emissions were 59 ± 6.6 gigatons of carbon dioxide equivalent in 2019).[3] The United Nations Climate Change Conference (COP28) concludes that global greenhouse gas emissions need to be cut 43% by 2030, compared to 2019 levels, to limit global warming to 1.5°C. We offer a calculation of the potential contribution the public equity market can make towards this objective.

Following Cohen et al. (2020), we then identify green patents filed by firms. Green patents are those related to environmental management, water adoption, biodiversity protection, climate change mitigation, and greenhouse gas management. We find that high-emission firms tend to file more green patents than clean firms following a more negative EMC price gap in the country. A one standard deviation increase in the magnitude of the gap is associated with a 15.9% increase in the number of green patents filed by emission firms, relative to clean firms. This result suggests that high-emission firms invest in methods that make them more environmentally friendly.

To further improve our identification, we re-run these tests on *private* firms. We do not find that private emission firms become greener, relative to private clean firms, when the country-level EMC price gap widens. This is expected because private firms do not face the same price pressure. Although it is still possible that some omitted variables simultaneously drive stock prices and public firms' decisions, variables affecting both public and private high-emission firms (such as stricter environmental regulations) cannot explain our findings.

Our instrumental variable approach yields consistent results. In the first stage, we regress emission firms' log price-to-book ratio on the number of natural disaster shocks in the country. In the second stage, we again use private firms as a benchmark. For each public emission

[3]In 2021 (the end of our sample period), total Scopes 1, 2, and 3 emissions by our sample of public high-emission firms are 4,381 million tons, 765 million tons, and 4,466 million tons, respectively. Part of the decrease in emissions is attributable to firms' downsizing their operations, as we show later. Scope 1 emissions are direct emissions from firms' activities. Scope 2 captures indirect emissions from the consumption of purchased electricity, heat, or steam. Scope 3 emissions are all indirect emissions (not included in Scope 2) that occur in the value chain of the reporting company. Our result that high-emission firms become greener to a larger extent than low-emission firms is consistent with lower ESG adjustment costs among high-emission firms in Pástor et al. (2021)'s model and with the price differential between clean and dirty firms exceeding the cost of reforming a dirty firm in Heinkel et al. (2001)'s framework.

firm in the sample, we attempt to match it with private firms that are in the same country and the same industry and have similar sizes (measured by either total sales or total assets). Then we examine the difference between public emission firms and their matched private firms in terms of emission levels and the number of green patents filed. While natural disasters may also raise the awareness of firm managers' climate awareness and prompt them to become greener, the *difference* between public and private firms would not be directly affected by natural disasters. We show that the instrumented price-to-book ratio is associated with larger differences in emission levels (negative) and the number of green patents filed (positive), suggesting that public emission firms respond to the price pressure from the equity market.

Facing a higher cost of capital due to their lower price valuation in the equity market, do high-emission firms adjust their operations and financing? We show that high-emission firms downsize their operations, as evidenced by lower sales, total assets, and capital expenditures. They also significantly reduce their new stock issuance under a larger price gap; they do not increase cash dividend distributions or short/long-term debt financing. Therefore, high-emission firms are more likely to use internal rather than external financing.

Besides the change in stock price valuation, there also appears to be a recent shift in investors' capital allocation from high-emission firms to cleaner firms, which we term carbon divestment. The Principles for Responsible Investment (PRI) has over 5,000 signatories (with collective assets under management of US$121 trillion) as of 2022. Negative screening, the process of excluding certain sectors or companies from a portfolio, has been one of the most common sustainable investment strategies (Alliance, 2020). Investors allocate more money to funds rated high in terms of sustainability: Morningstar reports that sustainable funds in the U.S. attracted a record level of inflows in 2021. From our data, we estimate that institutional and retail investors reduce their ownership of high-emission firms by 1.17% from 2016 to 2020.

Several recent papers examine the effect of activist and other institutional investors through shareholder engagement and divestment (e.g., Chowdhry et al. (2019); Dyck et al. (2019); Krueger et al. (2020); Berk and Van Binsbergen (2021); Naaraayanan et al. (2021); Broccardo et al. (2022); Oehmke and Opp (2022); Rohleder et al. (2022); Atta-Darkua et al. (2023); Dasgupta et al. (2023)). While our tests on firms' actions control for proxies for these strategies, we do not mean to quantify the effectiveness of engagement and divestment in reducing emissions. Although we show that carbon divestment, like firm devaluation, has an increasing trend and is more prominent after natural disasters, we argue that carbon divestment and firm devaluation are closely linked as they both are functions of increased climate awareness. As a result, it is challenging to separate the specific impact of divestment alone. In our analysis, we primarily concentrate on firm valuation, which may reflect the effect of current as well as expected future divestment, as Cenedese et al. (2023) claim. Empirical results also suggest devaluation can better reflect the pressure from heightened climate awareness than divestment (more details in Section 4.5).

We are not the first paper that compares the stocks of emission and clean firms. Many papers study the relationship between emission levels and stock returns. For example, Bolton and Kacperczyk (2023) demonstrate higher returns globally for stocks with higher levels and growth rates of carbon emissions, while Hsu et al. (2023) show that U.S. firms with high toxic emission intensity earn higher stock returns. However, Zhang (2022) challenges this view and argues that emissions contain forward-looking firm performance information; after adjusting for the data release lag, the carbon returns turn negative in the U.S. and insignificant globally. Pástor et al. (2022) show that brown assets delivered lower returns in recent years despite having higher expected returns than green assets. Karolyi et al. (2023) find that green stocks earned higher returns than brown stocks globally from 2012 to 2015, but the green minus brown return became negative or statistically insignificant from 2016 to 2021.

Given the difficulty in measuring expected returns, we examine various price valuation ratios, which consistently point to lower valuation and higher costs of capital faced by brown firms. In line with our international evidence, Chava (2014) finds that U.S. firms with environmental concerns have higher costs of capital. Doidge et al. (2023) find that U.S. firms have higher valuations than firms in other developed countries in recent years, which can be partly attributed to the decreased valuation of brown firms in other developed countries relative to the U.S. Our unique contribution is that we emphasize the role of the equity market by linking price devaluation to public firms' emissions and green activities. Our findings are consistent with Gormsen et al. (2023), who estimate firms' perceived cost of capital from corporate conference calls and show that the perceived cost of capital and discount rates of green firms are lower than those of brown firms. In a model, they claim that the difference in discount rates between green and brown firms can reduce firm-level emissions.

Two recent studies also examine the sustainability responses of firms to investor demand, yet they reach divergent conclusions. Hartzmark and Shue (2023) show that the increase in financing costs for brown firms leads to an increase in brown firms' emission intensities. Noh et al. (2023) estimate the heterogeneity in investor demand for sustainable investing in an equilibrium framework. They find that investor pressure weakly predicts improvements in firm-level sustainability. Both papers' focus is U.S. public firms, and their measures of price pressure and environmental impact are different from ours. Our analysis of the emission levels and green innovation by public and private firms provides a more complete picture of firms' responses, and our international focus allows us to use local natural disasters as shocks to climate awareness in the country. We will further discuss the differences between the three papers in Section 4.4.

We contribute to the literature that studies the intersection of climate change and financial economics. Early work by Nordhaus (1977, 1991, 1992) points out that economic growth is a driver of climate change. Subsequent papers by, for example, Kelly and Kolstad (1999), Weitzman (2009), and Golosov et al. (2014), analyze the implications of risk and uncertainty about climate change on the economy. More recently, a growing field of climate finance examines the role of financial markets in mitigating and hedging climate risk (see, for example, survey articles by Hong et al. (2020), Giglio et al. (2021), and Stroebel and Wurgler (2021)). The contrasting outcomes we observe between public and private firms emphasize the impact of the equity market.

The remainder of the paper is structured as follows. Section 2 describes the data. Section 3 presents the results of the price gap and its changes during local natural disasters. Section 4 examines firms' real decisions. Section 5 concludes.

2 Data

In this paper, we combine several data sources to implement our analysis.

2.1 Stock and public company information

Stock price, market capitalization, industry information, and fundamentals are available from FactSet Fundamentals v3. The detailed construction of market capitalization and fundamentals can be found in the Internet Appendix IA.2.

Stock prices and shares outstanding are adjusted for company operations such as splits before calculating the market capitalization. Price-to-book (PB), price-to-sales (PS), price-to-earnings (PE), and price-to-cashflow (PCF) are calculated using the end-of-quarter market capitalization divided by book equity, total sales, earnings, and net cashflow in the previous year, respectively. All variables are transformed to USD using real-time exchange rates. We follow the procedure in Fama and French (1992) and assume a lag of six months before the fundamentals get public. We winsorize the fundamentals variables within country-year-month at the 1st and 99th percentiles.

To identify high-emission firms, we follow the procedure in Choi et al. (2020a). That is, we adopt the industry definitions provided by the Intergovernmental Panel on Climate Change (IPCC), the leading international body for the assessment of climate change. Five major industry sectors are identified as major emission sources: Energy; Transport; Buildings;

Industry (such as chemicals and metals); and Agriculture, Forestry, and Other Land Use (AFOLU). Each sector is further divided into subcategories. We hand-match the IPCC subcategories with FactSet industry codes. Since this IPCC measure is based on industries, it covers all the firms in our sample, a clear advantage for international studies. By comparison, other rating-based measures such as MSCI ESG ratings are only available for a subset of firms in our sample and may be subject to selection issues.[4] Firms that are matched with the IPCC emission industries are classified as high-emission firms, i.e., the indicator $Emission = 1$; the rest of the firms have $Emission = 0$ and are classified as clean firms. The full list of emission industries is in Table IA.II. We also use alternative definitions of high-emission firms: high-emission firms are determined either by their emission intensity (tons of CO_2 emission scaled by total sales) or by negative environmental news coverage (provided by RepRisk).

2.2 Carbon emission measures

The firm-level emission data are from Trucost. The dataset provides an estimation of companies' CO_2 equivalent emission (in tons) on an annual basis. Trucost categorizes emissions into three "Scopes" following the GHG Protocol Corporate Standard: Scope 1 emissions are direct emissions from owned or controlled sources; Scope 2 emissions are indirect emissions from the generation of purchased energy; and Scope 3 emissions are all indirect emissions (not included in Scope 2) that occur in the value chain of the reporting company, including both upstream and downstream emissions.[5] We use all three scopes of carbon emission from 2007 to 2021.

Trucost covers public firms and private firms. In our sample from 2007 to 2021, Trucost covers 17,273 unique public firms in 26 countries. The private firms that are covered are far more and have increased significantly in recent years. The private firms in Trucost do not come with information on other financials but sales. For public firms, we merge Trucost

[4] See page 1120 of Choi et al. (2020a).

[5] See https://ghgprotocol.org/sites/default/files/standards_supporting/FAQ.pdf.

with FactSet via ISIN. Our carbon emissions in use are of both absolute level and intensity. We follow Bolton and Kacperczyk (2023) to winsorize carbon emissions at the 2.5% level.

2.3 Company patent information

The patent information is from Bureau van Dijk's (BvD) Orbis IP database. The database covers both public and private firms around the world. We retrieve the patents' priority date and their International Patent Classification (IPC) code. Priority date specifies the earliest filing date of patent applications. We use IPC code to classify each patent into green patent or non-green patent based on the guidelines from the Organization for Economic Co-operation and Development (OECD) and the procedure in Cohen et al. (2020).[6] According to the OECD's guideline, patents that are environment-related belong to several types such as environmental management, water adoption, biodiversity protection, climate change mitigation, and greenhouse gas management. Haščič and Migotto (2015) offer a detailed description of how to identify environmental-related patents. We count green patents that a firm files during each quarter and merge them with other databases via firms' ISIN code. The patent data in our sample are from 2011 to 2018.

2.4 Stock ownership

Institutional and blockholder equity ownership is obtained from FactSet Ownership v5 (see also Koijen et al. (2023)).[7] The detailed construction of equity holdings can be found in the Internet Appendix IA.1.

[6]For OECD's identifications of environment-related technologies, see `https://www.oecd.org/environment/consumption-innovation/ENV-tech%20search%20strategies,%20version%20for%20OECDstat%20(2016).pdf`. A recent paper by Bolton et al. (2023) identifies brown efficiency patents, which improve the energy efficiency of fossil fuel-based technologies. They argue that some green patents within the OECD classification are brown efficiency patents.

[7]FactSet Ownership v5 contains four main tables: 13F holdings (13F), fund level holdings (SOF), institutional stakes holdings (INST), and non-institutional stakes holdings (NINST). The first three tables are our source of institutional holdings while NINST is the source of blockholders' holdings. NINST reports holdings from non-institutional stakeholders and people that are identified as stakeholders. As explained in the Internet Appendix IA.1, some institutional holdings from 13F, SOF, and INST are included in NINST. We remove these holdings to construct the ownership of blockholders excluding institutions.

FactSet gathers its holdings data from a variety of sources, such as regulatory filings, corporate reports, and direct requests from fund managers. Although the frequency of updates varies by market, most institutional investors and companies update ownership data quarterly or even monthly. We interpolate holdings from the last available quarter prior to the perspective quarter for institutions that do not report holdings every quarter or who consistently report holdings longer than a quarter. Our analysis relies on quarterly ownership.

We restrict holdings to common equity and depositary receipts (DR). We categorize equity owners into three groups: institutions, blockholders excluding institutions, and retail investors. The ownership of stocks by institutional investors and blockholders is calculated directly from FactSet ownership data, as equity holdings over the market capitalization of the stock. Then, we define retail ownership as 100% minus institutional ownership minus blockholders' ownership excluding institutions. We exclude countries with less than 50 institutions or 50 stocks. Our sample contains 44,182 unique securities and 18,708 unique institutions in 26 countries from 2007Q1 to 2020Q4. At the end of 2020, the total market capitalization is 82.8 trillion USD, while the total holdings are 32.0 trillion USD by institutional investors and 10.7 trillion USD by blockholders excluding institutions. See Table IA.I for the list of markets in our sample.

2.5 Private firm information

We obtain the total assets for private firms from BvD Orbis Global database. The accounting data for private firms are available from 2011 to 2018. To match each public firm with comparable private firms and examine their patenting activities, we construct a propensity matching score based on country, industry, and total assets. The total assets for public firms are taken from BvD Orbis Global database and, if missing, from FactSet Fundamentals v3. The matched private firm must be in the same country and industry as the public firm and has total assets that are among the three closest to the public firm.

For public firms and the matched private firms, we require that they have filed at least one patent between 2011 and 2018. The matching is done with replacement.

To compare emission levels, we apply the same method to match each public firm with three closest private firms in Trucost. Here, we use total sales rather than total assets due to data availability. The matching is also done with replacement.

2.6 Natural disasters

The natural disaster data originate from the Center for Research on the Epidemiology of Disasters' EM-DAT database.[8] The EM-DAT data include information on disaster type, date, location, and impact. For a disaster to be entered into the database, at least one of the following conditions must be met: (1) ten or more people killed, (2) a hundred or more people impacted, (3) a state of emergency declared, and (4) a request for international help. Droughts, earthquakes, insect infestations, pandemics, floods, extreme temperatures, glacial outbursts, landslides, storms, volcanoes, wildfires, and hurricanes are among the disasters covered by the EM-DAT data. While not all of these disasters are scientifically proven to be driven by climate change, they are highly salient events that the media often mentions together with climate and they likely arouse public attention to climate risk, as we investigate in Section 3.[9]

We use the measure developed by Baker et al. (2023), *Natural Disasters*, which equals the number of major natural disasters in a country over the course of a quarter. A major natural disaster is one that kills 100 people or damages more than 0.1 percent of the country's GDP. If two or more incidents of the same type occur in a country-quarter, the measure *Natural Disasters* will be added by one to avoid double counting recurring but linked disasters. For example, *Natural Disasters* will obtain a value of two (= one earthquake plus one wildfire) if a country experiences two earthquakes and one wildfire in a quarter. We use disaster data

[8] For more information, see https://www.emdat.be/.

[9] For example, an article from the Public Broadcasting Service (PBS), "How Climate Change Impacts Each Type of Natural Disaster" (September 7, 2022), states that climate change affects floods, storms, earthquakes, extreme temperatures, landslides, droughts, wildfires, and volcanic activity.

from the first quarter of 2004 through the fourth quarter of 2020.

3 Devaluation of Carbon Stocks

3.1 The global trend

We examine the valuation gap between emission and clean firms at the country level and how it has evolved globally in recent years. In our main analysis, we categorize emission firms with the industry definitions provided by IPCC, while we use alternative measures as robustness checks in the Internet Appendix. The industry-based approach is more transparent and covers all firms over a longer period than firm-level environmental ratings provided by commercial vendors (such as MSCI ESG Ratings and Sustainalytics). Also, those ratings are usually industry-adjusted and do not capture the heterogeneity in the level of greenhouse gas emissions across different industries.[10]

For each country m at quarter t, *EMC Price Gap* equals the average price-to-book ratio (PB) of emission firms minus the average PB of clean firms in the country, value-weighted average by firm size (VW). We also use price-to-sales ratio (PS), price-to-earnings ratio (PE), and price-to-cashflow ratio (PCF), as well as the equal-weighted average ratios (EW) as alternative valuation measures in our analysis.[11] The country-level EMC price gap captures the aggregate devaluation level and implied financing costs for emission firms, and can be a function of the overall degree of climate concern in the country. Panel A of Table I presents summary statistics at the country level. Over our sample period of 2007 to 2020, the average *EMC Price Gap* of various versions appears to be negative: the mean of *EMC PB Gap (VW)* equals -0.78.

First, before conducting the country-level regressions, we plot the global trend of *EMC*

[10]See Choi et al. (2020a,b) and Pástor et al. (2022) for more discussion.

[11]Firm-year observations with negative earnings, book value, or cash flow are dropped. We consider value-weighted *EMC PB Gap* our primary measure, while our results, as shown later, are similar and robust to using the various versions of EMC price gap.

Price Gap in Figure I. The dashed (solid) line plots the quarterly value-weighted average of PB ratio of all clean (emission) firms in our global sample; the bar represents the gap between the two. One can see that the gap was not significant before 2011 but has become increasingly sizeable over time. In recent years after 2018, the gap of PB ratio between emission and clean firms reaches about −2.

Next, we run the regression of *EMC Price Gap* on a dummy variable, *Post2015*, which takes a value of 1 starting in 2015Q4. At that time, the drafting of the Paris Agreement was instrumental in reshaping investor beliefs regarding future climate-related policies. The regression specification is:

$$\text{EMC Price Gap}_{m,t} = \alpha + \beta \text{Post2015} + Control_{m,t} + \sigma_m + \epsilon_{m,t} \tag{1}$$

where σ_m refers to country fixed effects. $Control_{m,t}$ refers to a set of countries' demographic and economic characteristics, including log GDP per capita, female ratio, corruption, government effectiveness, political stability, regulatory quality, rule of law, and accountability (see the definitions in the Internet Appendix IA.2). We cluster standard errors by year-quarter.

Table II reports the results. In Panel A, we value-weight EMC price gap in columns (1)–(4) and equal-weight in columns (5)–(8). We consider four price-to-fundamental ratios: PB, PS, PE, and PCF. Across all specifications, the coefficients of the dummy variable *Post2015* are all negative, and they are statistically significant at the 1% level in 7 out of 8 regressions. The economic magnitude is also meaningful. Column (1), for example, suggests that the PB ratio of carbon-intensive firms decreases further by 0.455 after 2015Q4 relative to clean firms, whereas the mean of *EMC PB Gap (VW)* equals −0.781.[12]

We conduct several robustness tests using alternative emission measures and regression specifications; results are reported in the Internet Appendix. In Table IA.III's Panel A, we

[12] We do not expect this change in devaluation to continue at the same pace forever; the estimate applies to our sample period. It is possible for this change to slow down or even reverse in the future if climate awareness stops increasing. Zhang (2022) shows that in-sample sustainable flows and climate-concern shifts explain the stock returns earned by carbon firms and clean firms internationally.

acknowledge that different industries have different valuation ratios. We show that such devaluation pattern is not solely driven by the energy sector but also significant from other non-energy emission firms. In Table IA.III's Panel B, we find that the results are robust to using alternative categorizations of high emission firms based on firms' emission intensity (tons of CO_2 emission scaled by total sales) and news-based environmental ratings. Finally, in Table IA.IV, instead of using the dummy variable *Post2015*, we use year dummies and find that the EMC price gap becomes more negative and significant in around 2013–2015. While carbon devaluation is more pronounced after 2015, the year 2015 is not a structural breakpoint; there is a downward trend before that year.

Furthermore, we conduct an analogous analysis at the individual stock level, where we can better control for stock characteristics and firm fixed effects that could influence firms' valuation. Specifically, we run a pooled regression using the global sample of all firms to examine the difference in valuation between emission and clean firms and whether it is stronger over recent years. We adopt the specification of Hong and Kacperczyk (2009), that is, for firm i and quarter t,

$$\text{Log PB}_{i,t} = \alpha + \beta_1 \text{Emission}_i + \beta_2 \text{Emission}_i \times \text{Post2015} + X'_{i,t}\Gamma + \sigma_m + \delta_t + \epsilon_{i,t} \qquad (2)$$

where *Emission* is a dummy variable that equals one if the firm belongs to one of the emission industries defined by IPCC. σ_m and δ_t refer to the country and year-quarter fixed effects, respectively.[13] In two alternative specifications, we use firm fixed effects and further add country times year-quarter fixed effects, which can rule out the possibilities that certain firm invariant features or some country-specific events in a quarter drive firm valuation, respectively. $X_{i,t}$ represents our controls for firm characteristics that may be correlated with valuation, including log of total assets, book leverage, cash to total asset ratio, and return on equity (ROE). Standard errors are double clustered by firm and by year-quarter.

[13] We strictly follow Hong and Kacperczyk (2009) and use log(1+PB) as the dependent variable; our conclusion remains unchanged if we use log(PB) instead.

Panel B of Table II presents the results. In column (1), we only include *Emission*, control variables, and year-quarter and country fixed effects. It shows that the coefficient before *Emission* is -0.115 and statistically significant. This implies that during our sample period from 2007 to 2020, emission firms exhibit an 11.5% discount on their valuation relative to clean companies. This is comparable to the price of sin effect identified by Hong and Kacperczyk (2009), who show that the discount for sin stocks is about 15%.

Consistent with the price discount we document, Chava (2014), Bolton and Kacperczyk (2021, 2023), and Hsu et al. (2023) show that high-emission firms are like sin stocks and earn higher stock returns. We further examine whether the price gap between emission and clean firms is stronger after the Paris Agreement. We add an interaction term between *Emission* and *Post2015* and use firm fixed effects (thus the coefficient of *Emission* is subsumed) in column (2). The coefficient before the interaction term is significantly negative, implying that the pricing gap between carbon and clean firms has grown larger in magnitude after 2015. In terms of economic magnitude, the devaluation for emission firms increases by 4.5% percentage points after 2015. In column (3), we add country times year-quarter fixed effects, and the estimates are virtually the same. Last, we repeat the regressions in columns (1) to (3) but use *Log PS*, *Log PE* or *Log PCF* as the dependent variable. As shown in columns (4)–(12), the results are highly similar and significant with minor differences in magnitude.

3.2 Natural disasters as climate-awareness shocks

To identify the causal impact of devaluation on green actions by emission firms, we use the occurrence of local natural disasters as plausibly exogenous shocks to people's awareness of climate change in the affected country. Several studies find that residents tend to become aware of climate issues after experiencing local extreme weather events and natural disasters (e.g., Choi et al. (2020a), Anderson and Robinson (2019), and Boermans and Galema (2019)). The heightened climate awareness can potentially shift investors' preference for carbon-intensive firms and lead to an equilibrium pricing effect.

We use the measure developed by Baker et al. (2023), *Natural Disasters*, which equals the number of major natural disasters in a country during a quarter. Major natural disasters refer to those that cause either 100 deaths or real damages of more than 0.1% of national GDP. Those extreme events usually attract wide attention and media coverage and can potentially generate significant impacts on residents. Specifically, the data cover extreme weather events such as droughts, earthquakes, insect infestations, pandemics, floods, extreme temperatures, avalanches, landslides, storms, volcanoes, fires, and hurricanes. We also confirm the validity of using natural disasters as exogenous shocks to people's attention to climate change. In the Internet Appendix Table IA.V, we show that when a country experiences a disaster over a quarter, both Google search volume and news coverage on the topic of "climate change" increase significantly from the country.

Next, we examine whether the occurrence of local natural disasters causes the devaluation of carbon-intensive firms (i.e., EMC price gap decrease). Specifically, we replace the time dummy variable in Equation (2) with *Natural Disasters* and conduct the following firm-level regression,

$$\text{Log PB}_{i,t} = \alpha + \beta_1 \text{Natural Disasters}_{m,t} + \beta_2 \text{Emission}_i \times \text{Natural Disasters}_{m,t} + X'_{i,t}\Gamma + \gamma_i + \delta_t + \epsilon_{i,t} \quad (3)$$

where we control for firm fixed effects and year-quarter fixed effects. β_2 is expected to be negative, as upon the occurrence of a natural disaster, emission firms should exhibit a lower price ratio than clean stocks. The same set of stock characteristics, $X_{i,t}$, as in regressions of Equation (2) are used as control variables. This regression also serves as the first-stage regression for our IV tests in the next section.

Table III presents the results. In column (1), the left-hand side variable is *Log PB*. The coefficient before the interaction term between *Emission* and *Natural Disasters* equals -0.016 and is statistically significant. The coefficient before *Natural Disasters* is insignificant. In column (2), we add country times year-quarter fixed effects. This is to mitigate any possible country-quarter level events that impact the valuation of all public firms. Thus the variable *Natural Disasters* itself is subsumed in the regression. The coefficient before the interaction term between *Natural Disasters* and *Emission* remains significantly negative. In column (3), we further add *Emission* times year-quarter fixed effects, to rule out the possibility that in certain quarters the valuation gap between emission and clean firms may vary due to other reasons; the effect remains robust and becomes even stronger in magnitude. In columns (4) to (12), we use alternative price ratios (*Log PS*, *Log PE*, and *Log PCF*), and the results are similar and statistically significant in 7 out of 9 specifications. In terms of economic magnitude, upon the occurrence of a natural disaster, the valuation ratio of emission firms decreases by 0.7–2.1% relative to clean firms in the same country.

4 Firms' Green Actions

Does the price pressure push companies to lower emissions and upgrade to cleaner technology? The management of the companies that cares about their stock price should react and improve their carbon footprint, hoping to bring back up their firm's valuation. We, therefore, hypothesize that carbon-intensive firms with lower price valuation ratios are more likely to take these actions.

4.1 The impact on carbon emissions

4.1.1 Country-level Price Gap

We first examine firms' actions on carbon emissions. We investigate Scopes 1, 2, and 3 emissions, respectively, to understand the impact on both direct emissions and indirect emissions. Given the highly skewed distribution of non-negative carbon emissions, especially many zeros, we run Poisson regressions as suggested by Cohn et al. (2022) and Chen and

Roth (2023).

$$
\begin{aligned}
\text{SNtot}_{i,t} = & \exp(\beta_1 \text{EMC Price Gap}_{m,t-1} + \beta_2 \text{Emission}_i \times \text{EMC Price Gap}_{m,t-1} \\
& + \text{Emission}_i \times \text{IO}_{i,t-1} + \text{Emission}_i \times \text{ESG Disclosure}_{m,t} + X'_{i,t}\Gamma + \gamma_i + \delta_{m,t}) + \epsilon_{i,t},
\end{aligned}
\tag{4}
$$

where *SNtot* is the level of carbon emission, in which $N \in \{1, 2, 3\}$. *Emission* equals one when the firm belongs to high-emission industries and zero otherwise. *EMC Price Gap* is the difference between the value-weighted average valuation ratio of high-emission firms and the value-weighted average of low-emission firms in country m. We control for firm characteristics in $X_{i,t}$ including price ratios, the natural logarithm of one plus total assets, book leverage, total cash and equivalents divided by total assets, and ROE. γ_i denotes firm fixed effects. $\delta_{m,t}$ denotes country-year fixed effects. Standard errors are clustered by firm.

Inspired by Dyck et al. (2019), the independent variables include institutional ownership (IO), as well as its interaction with *Emission*, to control for possible institutional engagement with emission activities. We also include a dummy variable, *ESG Disclosure*, which takes a value of 1 if the country-year has mandatory ESG disclosure requirements for listed firms (absorbed by the country-year fixed effects), and its interaction with *Emission*. This is to control for the effect shown by Krueger et al. (2021): mandatory ESG disclosure regulation improves the corporate information environment and reduces negative ESG incidents.

Our focus lies in the interaction term *Emission*×*EMC Price Gap*, that is, whether high-emission firms tend to take more actions in countries facing higher price pressure on emissions industries. Columns (1) to (3) of Table IV report the results for all the public firms in our sample. We use average price gaps over the past year in the country. Since we expect firms under high price pressure to lower their CO_2 emission, β_2 should be positive.

We report the results using the price-to-book ratio for *EMC Price Gap*. Column (1) reports the impact on Scope 1 emissions. The result is both statistically and economically significant. A one standard deviation increase in the magnitude of *EMC Price Gap* (1.118) (making *EMC Price Gap* more negative) is associated with an 18.56% reduction in carbon emission of carbon firms, relative to clean firms.

We then turn to firms' Scopes 2 and 3 emissions in columns (2) and (3) by using *S2tot* and *S3tot* as the left-hand-side variable. The results are consistent. Economically, a one standard deviation increase in the magnitude *EMC Price Gap* (1.118) is associated with a 3.02% decrease in Scope 2 emission and a 6.04% decrease in Scope 3 emission of carbon firms, compared with clean firms. Carbon firms reduce their emissions substantially among all three scopes of the GHG Protocol Corporate Standard, suggesting the role of price pressure on both direct and indirect emissions of firms. The large magnitude of Scope 3 emissions implies that firms do not seem to outsource their emissions to upstream or downstream value chains in order to reduce their direct emissions.

To pin down the underlying mechanism, we conduct similar analyses on private firms. That is, if carbon stock devaluation is correlated with other country-level confounding events, such as more environmental regulatory policies or consumer pressure, we should find similar results for private firms in those countries. If this is not the case in the data, it will support our hypothesis that the price pressure from public stock markets incentivizes firms to reduce their carbon emissions.[14]

We match each public firm with three private firms with replacement based on firm sales, the only available financial variable for private firms in Trucost. We then run the Poisson regressions of emission levels for all three scopes for the sample of private firms with controls including firm revenue, ESG disclosure mandate, and its interaction term with *Emission*. We still use both firm and country-year fixed effects in regressions. As shown in Columns (4) to (6) of Table IV, the coefficients on the interaction term β_2 are insignificant or significantly negative, suggesting that private carbon firms do not reduce their emissions in the presence of price pressure, which supports our conjecture.[15]

[14] While regulatory policies should apply to both public and private firms, it is possible that exchanges around the world impose stricter disclosure requirements on public firms. This is controlled by the dummy variable of the mandatory ESG disclosure requirements (Krueger et al. (2021)).

[15] While the coefficient in Column (5) is large in magnitude, Scope 2 emissions are much lower than Scopes 1 and 3 emissions in our data, as mentioned in footnote 3. Therefore, even if there is an increase in emissions in the private sector as a response to *EMC Price Gap*, it does not entirely offset the decrease among public

We present robustness results in the Internet Appendix Table IA.VI using alternative price gap measures including the price-to-sales, price-to-earnings, and price-to-cashflows ratios. The results are all consistent with Table IV, where we use the price-to-book ratio: in Panel A, we find that public emission firms reduce their emissions under higher price pressure for different measures of price gaps; in Panel B, the results indicate that private firms do not decrease their emissions in the presence of higher stock price pressure.

4.1.2 Firm-level Valuation and IV Estimation

In this subsection, we further consider the effect of firm-level valuation on their green actions such as carbon emissions. To circumvent the endogeneity concern of regressing a firm's actions on its stock price, we introduce a new instrumental variable (IV) approach. We utilize the exogeneity of natural disaster shocks as our IV and use matched private firms as a benchmark to identify price pressure from the equity market.

As demonstrated in the previous section, natural disasters act as a wake-up call for individuals and institutions and draw their attention to climate change. Following this exogenous shock, we expect the devaluation of carbon-intensive firms as a consequence. However, natural disasters would not directly impact the differences in emissions between public emission firms and their matched private counterparts—the climate awareness of both public and private firm managers may rise, but the *difference* between public and private firms should not be affected. This satisfies the exclusion restriction conditions required by the IV approach. As such, we employ two-stage least squares (2SLS) regressions. In the first stage, we regress the price-to-book ratio on the number of natural disaster shocks for the

firms. Also note that our results here do not suggest that private firms fail to improve their carbon footprints in general, although the negative β_2 estimates may hint at a shift of emissions from the public to the private sector. Private firms may still improve due to higher climate awareness, regulations, and the presence of impact investors (for the impact of regulations and policies on firms, see, e.g., Greenstone (2002); Hanna (2010); Shapiro and Walker (2018); He et al. (2020); Reynaert (2021); Shapiro (2021); Biais and Landier (2022); for the effect of impact investing, see, e.g., Barber et al. (2021) and Kumar (2023)). Our overall results highlight another important channel that affects public firms—the public equity market.

sample of emission firms.

$$
\begin{aligned}
\text{Log PB}_{i,t-1} = &\beta_1 \text{Natural Disasters}_{m,t-1} + \text{Emission}_i \times \text{IO}_{i,t-1} \\
&+ \text{Emission}_i \times \text{ESG Disclosure}_{m,t} + X'_{i,t}\Gamma + \gamma_i + \delta_t + \epsilon_{i,t},
\end{aligned} \tag{5}
$$

Subsequently, in the second stage, we regress the differences in carbon emissions (Scopes 1, 2, and 3) between public firms and their matched private firms on the predicted price-to-book ratio obtained from the first stage. Specifically, our second stage for the sample of emission firms is as follows:

$$
\begin{aligned}
\Delta \text{SNtot}_{i,t} = &\beta_1 \widehat{\text{Log PB}}_{i,t-1} + \text{Emission}_i \times \text{IO}_{i,t-1} \\
&+ \text{Emission}_i \times \text{ESG Disclosure}_{m,t} + X'_{i,t}\Gamma + \gamma_i + \delta_t + \epsilon_{i,t},
\end{aligned} \tag{6}
$$

where *Log PB* is the log of one plus price-to-book. *Natural Disasters* is the number of natural disasters that happen in a country-year-quarter. Δ*S1tot*, Δ*S2tot*, and Δ*S3tot* are the differences between public firms and their matched private firms of *S1tot*, *S2tot* and *S3tot* respectively. Control variables consist of *Log Total Assets*, *Book Leverage*, *Cash/Total Assets*, and *ROE*. Institutional ownership, ESG disclosure mandates, and their interaction terms with *Emission* are also included. Standard errors are clustered by firm.

Table V reports the results of the IV estimation of CO_2 emission and price ratios for emission firms. Column (1) shows the first stage result, and columns (2) to (4) display the second stage. In column (1), it is evident that natural disaster shocks significantly decrease the price-to-book ratio for high-emission firms. The first-stage regression yields a Kleibergen-Paap F statistic of 10.671, indicating that the IV used is not weak.

Moving to the second stage, we observe that the coefficients on *Log PB* are all significantly positive for different scopes of carbon emissions. This suggests that the devaluation of emission firms induced by disasters leads to a reduction in their direct and indirect carbon emissions. Economically, a one standard deviation decrease in the predicted *Log PB* (0.760) is associated with reductions of 1.693, 0.558, and 1.516 million tons Scopes 1, 2, and 3 emissions, respectively, for each public-traded carbon firm relative to its private counterpart.

In the Internet Appendix, we apply the same strategy to the sample of non-emission firms and report the results in Table IA.VII. In column (1), the coefficient on *Natural Disasters* in the first-stage regression is statistically insignificant and the Kleibergen-Paap F statistic is only 1.812. These results indicate that the valuation of non-emission firms is not responsive to natural disaster shocks. Combining these results with Table V, we conclude that the occurrence of natural disasters mostly exerts price pressure on public emission firms. This further incentivizes these firms to reduce their carbon emissions. In contrast, non-emission firms and private firms do not face devaluation and do not take subsequent environmentally friendly actions accordingly.

In Table IA.VIII, we use alternative valuation measures including the price-to-sales, price-to-earnings, and price-to-cashflows ratios, as robustness checks for our IV approach. The results are highly consistent: in the first stage, the coefficients on *Natural Disasters* are all statistically significant and the Kleibergen-Paap F statistics are all above 10; in the second stage, the instrumented valuation measures consistently lead to the decrease in carbon emissions across all three scopes.

4.2 The impact on green innovation

Next, we examine firms' innovation activities using patent data. We compare green patents filed by publicly traded carbon and clean firms in countries with different valuation gaps and expect that public carbon firms tend to file more green patents under higher price pressure. Similarly, we also conduct the same tests on private firms to rule out alternative interpretations.[16]

[16]Other than environmental regulations, taxes, and subsidies can also induce firms to redirect technical change away from dirty innovation and toward clean innovation (see, e.g., Acemoglu (2002); Acemoglu et al. (2012); Aghion et al. (2016)). As long as these regulations, taxes, and subsidies are applied to both public and private firms, our comparison of public and private firms helps us identify the effect of stock price pressure.

4.2.1 Country-level Price Gap

For each firm, we count the total number of patents filed every quarter, and the number of patents classified as green patents based on the classification in Cohen et al. (2020). We run the following Poisson regression for green patents at year-quarter level,

$$\begin{aligned}\text{Green}_{i,t} = &\exp(\beta_1 \text{EMC Price Gap}_{m,t-1} + \beta_2 \text{Emission}_i \times \text{EMC Price Gap}_{m,t-1} \\ &+ \text{Log Total Patent}_{i,t} + \text{Emission}_i \times \text{IO}_{i,t-1} \\ &+ \text{Emission}_i \times \text{ESG Disclosure}_{m,t} + X'_{i,t}\Gamma + \gamma_i + \delta_{m,t}) + \epsilon_{i,t},\end{aligned} \tag{7}$$

Similar to other regressions, we focus on the interaction term, that is, whether high-emission firms tend to increase green patenting in countries facing higher price pressure on emissions industries. Based on our hypothesis, we expect β_2 to be negative. Table VI presents the results for both public and private firms. In columns (1)-(2) and (5)–(6), we use the value-weighted average price-to-book gap between emission and non-emission firms over the past year. In columns (3)-(4) and (7)-(8), we also consider the past three-year average price gaps for robustness, because it may take time for firms to relocate research resources and file patents. Column (1) reports the results for the regression with firm and year-quarter fixed effects after controlling for public firm-level characteristics, including total number of patents, the price-to-book ratio, the natural logarithm of one plus total assets, book leverage, total cash and equivalents divided by total assets, and ROE. Institutional ownership, ESG disclosure mandates, and their interaction terms with Emission are also included. The significant, negative coefficient on the interaction between *Emission* and *EMC Price Gap* indicates that publicly traded high-emission firms tend to file more green patents than clean firms when countries have wider pricing gaps.

In terms of economic magnitude, in column (1), a one standard deviation increase in the magnitude of *Price Gap* (0.782) is associated with 15.87% rise in *Green* for emission firms, or 0.242 increase in the number of green patents. The estimates from column (2) are similar after including firm fixed effects and county-year-quarter fixed effects (which absorb the past one-year average price gaps *Price Gap*). When we use the past three-year window to calculate price gaps, as shown in columns (3) and (4), the results are consistent and the economic magnitudes are even greater.

To test the effect of price pressure on green innovations, we conduct a placebo test using private firms. We match private firms with public firms based on country, industry, and total assets, and perform the same regressions in columns (5) to (8). However, due to the limited availability of private firm information from the BvD Orbis Global database, we can only control for the total number of patents, total assets, ESG disclosure mandate, and its interaction term with *Emission*. The insignificant coefficients on the interaction term suggest that private firms are not responsive to pricing gaps between high-emission and clean firms, thus isolating the price pressure mechanism.

We also construct an intensity measure *Green Ratio*, which is the ratio of the number of green patents to the total number of all patents. This measure can capture a firm's concentration of green innovations. Table IA.IX reports the panel regression results for the green patent ratio, both for public firms and the matched private firms. Similar to Table VI, the coefficients on the interaction term between *Emission* and *EMC Price Gap* are all negative and statistically significant for various specifications for public firms, while they are insignificant for private firms. These results suggest that public high-emission firms not only increase the number of green patents but also become more focused on green innovations when facing wider pricing gaps. In contrast, we find no significant results for comparable private firms under price pressure.

4.2.2 Firm-level Valuation and IV Estimation

In this subsection, we utilize the IV strategy to investigate the impact of devaluation on green innovations. Following the approach described in Subsection 4.1.2, we employ natural disaster shocks as the IV for the endogenous variable, namely the price-to-book ratio. Our objective is to assess how this instrumented variable affects the difference in the number of green patents between public emission firms and their matched private counterparts. Table VII reports the results of the 2SLS regressions. We consider the average log P/B in the past year in columns (1) and (2), and in the past three years in columns (3) and (4). In column (1), the statistically significant coefficient on *Natural Disasters* and the Kleibergen-Paap F static of 22.392 suggest that *Natural Disasters* serves as a strong IV in the first stage.

In the second stage, column (2) presents a significantly negative coefficient on *Log PB*, indicating that the devaluation of emission firms incentivizes their innovations in green technology. In terms of economic magnitude, a one standard deviation decrease in the predicted *Log PB* (0.091) is associated with an increase in the number of green patents of 0.353 of a public-traded carbon firm relative to its matched private counterpart. The results are similar when we consider the price-to-book ratio over the past three years, as reported in columns (3) and (4).

For the sample of non-emission firms, Table IA.X of the Internet Appendix presents the results of the 2SLS regressions. The Kleibergen-Paap F statics reported in columns (1) and (3) are much lower than 10, which fail to pass the weak-instrument test. Therefore, the IV of natural disaster shocks can be only applied to the valuation of public emission firms, and the resulting devaluation contributes to the advancement of green innovations.

Our paper establishes the causal link between past price pressure and firms' green actions. Note that the future price valuation of high-emission firms will likely go up when these firms have lower carbon emissions and more green innovation activities, as the theory by Pástor et al. (2021) predicts. We do not test this notion explicitly, but we cite two studies that adopt quasi-natural experiments to show the positive relationship between a firm's greenness and its future firm value. These findings also allay the potential concern that our documented link is driven by reverse causality (e.g., brown firms deviate from their optimal strategies and result in lower firm value), as brown firms likely have higher future value after they become greener.

Kumar and Purnanandam (2023) conduct a study on the implementation of the Regional Greenhouse Gas Initiative (RGGI), which introduced a cap-and-trade policy for carbon emissions on electric utilities in certain states in the Northeastern and Mid-Atlantic regions. The authors find that this regulation effectively reduced CO2 emissions from power plants located in the RGGI states, compared to unaffected plants. Publicly traded power utility companies in the affected states experienced an increase in their market-to-book ratio following the implementation of the initiative. This increase in value was attributed to the increased demand by institutional funds with a focus on environmental objectives. Hege et al. (2023b) utilize the quasi-random assignment of patent examiners with varying levels of leniency as a shock in patent approvals. Their findings reveal that companies with a greater number of climate-related patents experience greater positive abnormal stock returns and reduced costs of capital in the future, compared to similarly innovative firms with fewer climate-related patents.[17]

4.3 Operations and financing

Our findings imply that carbon public firms tend to reduce carbon emissions and increase green patenting activities, although they are confronted with higher costs of capital from equity markets due to lower price valuation ratios for high-emission industries. Then how do they adjust their operations and financing to become greener? To answer this question, we examine whether firms downsize their operations including sales, total assets, and capital expenditures in the presence of price pressure. We also investigate their financing channels in response. Specifically, we conduct the following panel regressions:

[17] While Bolton et al. (2023) find little evidence that green innovation reduces carbon emissions of innovating firms and other firms in the same sector, Hege et al. (2023a) argue that emission reductions happen in supply chain networks. Hege et al. (2023a) find that climate innovations help customer firms reduce carbon emissions, and that the effect is driven by innovations embedded in the supplier's products.

$$
\begin{aligned}
\text{Operation/Financing}_{i,t} =& \beta_1 \text{EMC Price Gap}_{m,t-1} + \beta_2 \text{Emission}_i \times \text{EMC Price Gap}_{m,t-1} \\
&+ \text{Emission}_i \times \text{IO}_{i,t-1} + \text{Emission}_i \times \text{ESG Disclosure}_{m,t} \\
&+ X'_{i,t}\Gamma + \gamma_i + \delta_{m,t} + \epsilon_{i,t},
\end{aligned} \tag{8}
$$

where the dependent variable represents the size of operations in various dimensions: the log of one plus sales, *Log Sales*, the log of one plus total assets, *Log Total Assets*, and total capital expenditures over lagged assets, *CapEx*. We also consider different financing channels including total payout (dividend plus repurchase) and stock repurchases, divided by total earnings, *Payout Ratio* and *Repur. Ratio*; new stock issuance, divided by lagged market capitalization, *Stock Sale Rate*; as well as net cashflows from short-term debt and long-term debt, divided by lagged total assets (*ST Debt/Total Assets* and *LT Debt/Total Assets*). For independent variables, *EMC Price Gap* is the difference between the value-weighted average price-to-book of high-emission firms and the value-weighted average of low-emission firms in country m over the past year and *Emission* is an indicator of high-emission industries based on IPCC's categorization. In addition, we add firms' institutional ownership and the ESG disclosure dummy (which is absorbed by country-year fixed effects), as well as their interactions with *Emission* as controls for institutional engagement and ESG disclosure regulations. We control for firm characteristics in $X_{i,t}$ including price-to-book ratio, total assets, lagged book leverage, cash-to-total assets ratio, and ROE. We also control for country-year fixed effects as well as firm fixed effects. Standard errors are clustered by firm.

Table VIII presents the results. In columns (1) to (3), We find that carbon-intensive public firms tend to downsize their operations, as evidenced by lower sales, total assets, and capital expenditures under price pressure. Taking this downsizing effect into account, we further calculate emission intensities for three scopes, which are defined as emissions in each scope divided by sales. In the Internet Appendix, Table IA.XI provides the results of regressing CO_2 emission intensities of public and private firms on EMC price gaps. These gaps represent the value-weighted average of price-to-book, price-to-sales, price-to-earnings, and price-to-cashflows ratios for emission firms, net of the value-weighted average of non-emission firms in the respective country or area. As shown in Panel A, for public firms, the coefficients on the interaction between *Emission* and *EMC Price Gap* are either positively significant or insignificant, indicating that emission intensities decrease or remain unchanged for public carbon firms in the presence of price pressure. On the other hand, all specifications in Panel B indicate that private emission firms do not decrease their carbon intensities in the countries or areas with wider price gaps. These results imply that downsizing can partially account for the reduction in emissions observed among public carbon-intensive firms, as demonstrated in Table IV.

In terms of financing channels, as shown in columns (4) to (8), when facing higher price pressure on high-emission industries, carbon-intensive public firms tend to reduce their new stock issuance. The estimates for the net cash flows from both short- and long-term debts are insignificant. Interestingly, these firms increase their stock repurchases in the presence of price pressure, which aligns with the notion that companies act as the last resort for their own stocks, engaging in share buybacks when prices fall below their intrinsic value (Hong et al. (2008)). The estimates for total payouts, which include both repurchase and dividend, appear insignificant although carbon firms significantly increase their stock repurchases with wider pricing gaps. Our results suggest that carbon-intensive firms tend to downsize their operations and reduce their external financing (especially equity financing) in the presence of high price pressure from publicly traded markets.

4.4 Discussion

Overall, our findings support the positive role of price pressure on high-emission industries in incentivizing public firms to become greener. With larger valuation gaps between carbon and clean industries, publicly traded carbon firms tend to reduce carbon emission levels in all three scopes and redirect technical change from dirty innovation toward clean innovation, although they downsize their operations at the same time. The results in the sample of private firms ensure that the documented effect comes from the equity market rather than environmental regulations, which should apply to both public and private firms.

Our conclusion contradicts that of a recent paper by Hartzmark and Shue (2023), who argue that sustainable investing is counterproductive because it makes brown firms more brown without making green firms more green. They develop a new measure of impact elasticity, which is the change in a firm's environmental impact due to a change in its cost of capital. Using the change in Scopes 1 and 2 carbon emission intensity as the measure of environmental impact, their paper shows a negative impact elasticity among U.S. public brown firms.

We replicate their findings in Column (1) of Panel A in Table IA.XII, which uses only U.S. public firms. The dependent variable is the change in Scopes 1 and 2 emission intensity, where Scopes 1 and 2 emission intensity is defined as Scope 1 plus Scope 2 emission levels, divided by sales. Column (1) is consistent with their main result, despite we adopt different definitions of brown firms and the cost of capital (they define brown firms as those in the highest quintile based on the level of carbon emissions, and the cost of capital as firm or industry past annual stock returns; we use the IPCC industry classification and the *EMC Price Gap*). This result is similar if we extend it to our global sample in Panel B, albeit with a smaller economic magnitude.

However, Column (2) of Panel A shows that the coefficient before *Emission*×*EMC Price Gap* flips signs when the dependent variable is the level of Scopes 1 and 2 emission intensity instead of the change. This suggests that U.S. high-emission public firms reduce their emission intensities (relative to low-emission public firms) in the presence of price pressure, although the rate of reduction is lower, as Column (1) shows. Columns (3) and (4) of Panel A demonstrate similar results to Column (2) when we switch to our specification of Poisson regressions and include firm fixed effects. In our global sample, the relationship between the level of emission intensities and *Emission×EMC Price Gap* is statistically insignificant.[18]

A key difference in the methodologies of our paper and Hartzmark and Shue (2023) is how we define a firm's environmental impact. We define it as the levels of Scopes 1, 2, and 3 carbon emissions and the number of green patents. We believe that level measures are relevant because they ultimately represent the total activity of the high-emission industry, which can be translated into the total amount of greenhouse gas emitted into our atmosphere.[19] On the other hand, emission intensities capture the efficiency of the production process—a low emission intensity indicates that a firm can produce the same amount of output by emitting less. Our overall results imply a positive impact elasticity among high-emission public firms globally, and part of the positive impact is attributable to the fact that brown public firms scale down their operations, relative to green public firms.[20]

Consistent with our paper, Noh et al. (2023) find that investor pressure predicts improvements in firm-level sustainability among U.S. public firms. However, they conclude that the impact is weak in economic terms. Noh et al. (2023) use the framework proposed by Koijen and Yogo (2019) and estimate the heterogeneity in investor demand for sustainable investing

[18] A subset of high-emission firms that are near financial distress may choose to focus on short-term projects and become more brown, as Hartzmark and Shue (2023) show with U.S. firms. Similarly, Thomas et al. (2022) find that U.S. firms pollute more when they meet or just beat consensus earnings forecasts, suggesting that the short-term goal of meeting earnings targets is more important than the long-term environmental benefits of reduced pollution. We invite future research to investigate how managerial short-termism affects global high-emission firms' impact elasticities.

[19] Using our regression coefficient estimates and the levels of emissions by our sample of public firms in 2021, we calculate that the total annual reductions in Scopes 1, 2, and 3 emissions by high-emission public firms are 813.2 million tons, 23.1 million tons, and 269.72 million tons, respectively, relative to low-emission public firms, under a one-standard-deviation change in *EMC Price Gap*. Bolton and Kacperczyk (2023) also state that "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."

[20] Hartzmark and Shue (2023) also highlight that outputs produced by green and brown industries are not perfectly substitutable. Table IV hints that some emissions from the public brown sector may be shifted to the private brown sector, as the coefficients before *Emission×EMC Price Gap* are opposite for public and private firms (but the results are weaker for private firms). Such a shift would suggest a substitution between outputs produced by brown public and brown private firms. While this substitution may not be ideal for the environment, it still shows evidence that the equity market successfully applies pressure on brown public firms. Note that in our analysis in Table VI, the coefficients before *Emission×EMC Price Gap* are not always opposite for public and private firms, indicating that the increase in green innovation by brown public firms is not associated with a lower number of green patents filed by brown private firms. In that sense, brown industries as a whole do become greener.

in an equilibrium framework. While this approach allows them to separately estimate the sensitivities of institutional investor demand to various dimensions of sustainability, their investor pressure proxy is derived from current portfolio holdings. Cenedese et al. (2023) and Becht et al. (2023) argue that the effects of future divestment and the threat to exit are nontrivial, given the net-zero commitments of many investors that aim to reduce carbon footprint over time. Gantchev et al. (2022) claim that the divestment of a small number of sustainable investors is expected to raise concerns among firm managers. This is because other sustainable investors may revise downward their beliefs about the firms' sustainable standards and potentially sell their investments in the future. Our proxy of price valuation ratios reflects both the impact of current and expected *future* divestment. Our international analysis also makes it possible to use country-level price gaps and local natural disasters to enhance identification.

4.5 Carbon divestment

Carbon divestment has become a viral topic among the green investment community. Here, we formally examine the divestment of carbon-intensive firms under our setting and report two main findings. First, we find that there is a significant time trend of divestment from carbon-intensive firms. As shown in Figure II and Internet Appendix Table IA.XIII and discussed in detail in the Internet Appendix, we find that compared with the clean firms in the same country, both institutional and retail investors together reduce their ownership of emission firms, especially after 2015, when divestment campaigns went mainstream (Hirji (2015)). From Column (1) of Table IA.XIII, the gap of institutional and retail ownership between clean and emission firms becomes wider by 1.17% after 2015, which translates into the dollar amount of \$328 billion in divestment globally.[21] While several researchers (e.g., Gibson Brandon et al. (2022) and Liang et al. (2022)) point out that some institutional investors may be committing "greenwashing" and not lowering their carbon exposure, our

[21] This is equal to 1.17% $\times$ total market value of high-emission firms in 2020Q4 = 1.17% $\times$ 28.0 trillion USD = \$328 billion.

result shows that there is a recent shift in institutions' and retail investors' capital toward green firms.[22] Furthermore, retail investors and domestic institutions, rather than foreign institutions, divest from emission firms more aggressively after 2015. Our results suggest that blockholders and carbon firms themselves (shown in Table VIII) are buying stocks of high-emission firms when retail and institutional investors are selling.

Second, we examine the effect of natural disasters on investor ownership. In Internet Appendix Table IA.XIV, we find that upon the occurrence of a natural disaster, institutions and retail investors reduce their ownership of emission firms by 0.43–0.54% relative to that of clean firms in the same country. The effects are statistically significant. Institutions and retail investors contribute about equally. Also, it is mostly domestic institutions rather than foreign institutions that divest from carbon firms upon a natural disaster. This result is natural as domestic institutions are the ones that experience the event.

Note that, however, while carbon divestment appears to be strong in recent years and following the occurrence of natural disasters, it is difficult to argue that the carbon firm devaluation phenomenon is caused by such divestment campaigns. Rather, as suggested by several other papers (e.g., Pástor et al. (2021); Pedersen et al. (2021); Goldstein et al. (2022); Pástor et al. (2022); Bolton and Kacperczyk (2023)), the devaluation of emission firms could be a consequence of preference shifts, changes in climate policy, reputational impacts, and technological innovation; some of which also result in divestment.

To check if devaluation, or divestment itself, drives the adoption of green actions by carbon-intensive firms, we rerun our regressions (4) and (7) by introducing an additional interaction term between *Emission* and *EMC Ownership Gap*. *EMC Ownership Gap* is calculated as the value-weighted average institution and retail ownership of emission firms minus the average ownership of clean firms. The results for regression (4), presented in Columns (1) to (3) of Table IA.XV in the Internet Appendix, indicate that for public firms,

[22] Using holdings of U.S. stocks, Pástor et al. (2023) find that the largest institutional investors tilt their portfolios increasingly toward green stocks. However, other institutions and households tilt increasingly toward brown stocks.

the coefficients on the interaction between *Emission* and *EMC Price Gap* are close to those in Table IV for all three scopes. In contrast, the coefficients on the interaction between *Emission* and *EMC Ownership Gap* are either statistically insignificant or have the opposite sign. Private firms do not exhibit a decrease in emissions in response to either price or ownership gap, as illustrated in Columns (4) to (6).

The results for regression (7) are presented in Table IA.XVI in the Internet Appendix. Once again, the coefficients on the interaction between *Emission* and *EMC Price Gap* for public firms (columns (1) to (4)) are similar to those in Table VI, while the coefficients on the interaction between *Emission* and *EMC Ownership Gap* are statistically insignificant. For private firms, as demonstrated in columns (4) to (8), the coefficients on both interaction terms are statistically insignificant. These two tables highlight the role of devaluation pressure in pushing publicly listed high-emission firms to become greener, even after accounting for divestment in our analysis.

5 Conclusion

Limiting future global temperature increases requires international coordination among scientists, governments, companies, and the general public. How does the financial market help? The empirical evidence on the role of investors so far focuses mostly on shareholder engagement and divestment. A survey of institutional investors (Krueger et al., 2020) finds that 43% of the respondents held discussions with portfolio companies' management regarding climate risks in the past five years. Azar et al. (2021) show that the largest institutional investors focus their engagement effort on large firms with high emissions and that the engagement influence results in lower carbon emissions.

The effect of divestment is a subject of debate—while Shell plc acknowledges in its 2018 Annual Report that "[divestment] could have a material adverse effect on the price of our securities and our ability to access equity capital markets," firms do not necessarily respond if their stocks earn higher returns (as shown by Bolton and Kacperczyk (2021) and Hsu et al. (2023)) and are held by other investors who are not committed to divestment (Broccardo et al., 2022), if managers' wealth is unaffected (Davies and Van Wesep, 2018), or if the impact on firms' cost of capital is too small (Berk and Van Binsbergen, 2021).

In this paper, we focus on the heightened climate awareness and the role of the equity market. We examine the impact of stock prices rather than divestment or engagement itself. Following theoretical predictions, we establish the association between climate awareness and stock prices and examine high-emission firms' real decisions under lower price valuation. Consistent with the predictions made by Pástor et al. (2021), the positive shock in people's climate awareness in a country is associated with lower equity prices of high-emission firms in the same country. Using natural disasters, we show that stock prices of high-emission firms fall after an increase in climate awareness.

Under the price pressure, public high-emission firms lower CO_2 emission levels and increase green innovation activities. Our instrumental variable approach, in which local natural disasters are used as instruments for high-emission firms' log price-to-book ratio, suggests that the effect is causal. We also find that these firms are more likely to downsize their operations and rely on internal financing facing a higher cost of capital. The comparison between public and private firms identifies the importance of the equity market. While a general increase in climate awareness may also prompt all high-emission firms to become cleaner, our evidence suggests that the stock market can amplify its impact. Private high-emission firms do not face the price pressure directly, and we find that these firms do not show the same response in carbon footprint improvements.

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Table I. Summary Statistics

This table reports summary statistics of key variables. Panel A shows the summary statistics for country-level variables. *EMC Price Gap (VW)* is calculated as the value-weighted average price-to-book, price-to-sales, price-to-earnings, price-to-cashflow of emission firms net of the value-weighted average of non-emission firms in the country/area. *EMC Price Gap (EW)* is calculated as the equal-weighted average price-to-book, price-to-sales, price-to-earnings, price-to-cashflow of emission firms net of the equal-weighted average of non-emission firms in the country/area. *Natural Disasters* is the number of natural disasters occurring in a country-year-quarter. Panel B shows the summary statistics for firm-level variables. *S1tot*, *S2tot* and *S3tot* represent the scope 1, scope 2, and scope 3 carbon emissions (in million tons). *S1int*, *S2int*, and *S3int* are total scope 1, scope 2 and scope 3 CO_2 emissions over total revenues. Δ*S1tot*, Δ*S2tot*, and Δ*S3tot* are the differences between public firms and their matched private firms of *S1tot*, *S2tot* and *S3tot* respectively. *Green* is the number of green patents that the firm files in the year-quarter. Δ*Green* is the difference between public firms and their matched private firms of *Green*. *Log PB* to *Log PCF* are the log of one plus price-to-book, price-to-sales, price-to-earnings, and price-to-cashflow. *Log Sales* and *Log Total Assets* are the log of total revenue and total assets for the firm. *CapEx(%)* is the total capital expenditures over lagged total assets. *Payout Ratio(%)* and *Repur. Ratio(%)* are total payout (=dividend plus repurchase) and stock repurchases, divided by total earnings. *Stock Sales Rate(%)* is the new stock issuance divided by lagged market capitalization. *ST Debt(%)* and *LT Debt(%)* are net cashflows from short-term debt and long-term debt, divided by lagged total assets. The sample includes the 26 markets listed in Online Appendix Table IA.I from 2007Q1 to 2020Q4.

Panel A: Country Level

Variable	**N**	**Mean**	**SD**	**P5**	**P25**	**P50**	**P75**	**P95**
EMC PB Gap (VW)	1456	-0.781	1.798	-3.448	-1.371	-0.596	0.144	1.285
EMC PS Gap (VW)	1456	-0.821	3.264	-4.907	-1.738	-0.804	0.321	2.676
EMC PE Gap (VW)	1456	-1.044	16.411	-20.302	-7.586	-1.526	4.581	18.526
EMC PCF Gap (VW)	1456	-1.506	11.176	-16.599	-5.319	-0.749	3.697	11.187
EMC PB Gap (EW)	1456	-0.648	0.717	-1.851	-1.083	-0.599	-0.258	0.441
EMC PS Gap (EW)	1456	-1.600	2.341	-5.581	-2.852	-1.446	-0.356	2.099
EMC PE Gap (EW)	1456	-3.312	10.287	-20.099	-9.376	-3.530	2.665	13.268
EMC PCF Gap (EW)	1456	-2.183	6.210	-12.039	-6.028	-2.507	1.309	9.185
Natural Disasters	1456	0.424	0.906	0.000	0.000	0.000	0.000	3.000

Panel B: Firm Level

Variable	**N**	**Mean**	**SD**	**P5**	**P25**	**P50**	**P75**	**P95**
Log PB	1192213	1.061	0.664	0.260	0.570	0.909	1.409	2.393
Log PS	1126664	1.055	0.908	0.121	0.379	0.792	1.472	2.863
Log PE	861703	3.060	1.004	1.627	2.403	2.939	3.590	4.974
Log PCF	857916	2.577	1.025	1.055	1.885	2.482	3.138	4.503
S1tot	87460	0.664	2.984	0.000	0.003	0.016	0.101	3.016
S2tot	87550	0.124	0.329	0.000	0.004	0.019	0.081	0.649
S3tot	87581	0.617	1.478	0.002	0.022	0.105	0.465	3.241
S1int	87456	192.497	743.768	0.652	7.492	17.435	49.286	971.601
S2int	87550	43.952	81.369	1.920	9.648	21.019	47.612	163.037
S3int	87581	173.244	169.947	26.433	49.273	109.556	244.634	514.683
ΔS1tot	27431	0.128	1.889	-0.091	-0.002	0.002	0.038	1.304
ΔS2tot	27429	0.014	0.231	-0.090	-0.002	0.001	0.012	0.164
ΔS3tot	27437	0.029	1.033	-0.459	-0.006	0.005	0.057	0.645
Green	50874	1.525	9.915	0	0	0	0	6
ΔGreen	90069	-0.105	3.649	-0.667	0	0	0	0
Log Sales	278793	4.761	2.327	0.029	3.354	4.929	6.363	8.460
Log Total Assets	281234	5.522	2.183	1.880	4.015	5.495	6.988	9.298
CapEx (%)	276218	5.086	6.945	0.003	0.774	2.765	6.469	18.744
Payout Ratio (%)	224104	20.107	24.637	0.000	0.000	10.753	33.321	73.024
Repur. Ratio (%)	250951	1.111	6.240	0.000	0.000	0.000	0.000	4.225
Stock Sales Rate (%)	267712	3.696	12.223	0.000	0.000	0.000	0.331	24.389
ST Debt (%)	209787	0.288	3.752	-4.727	0.000	0.000	0.000	6.534
LT Debt (%)	277149	1.132	6.549	-5.925	-0.429	0.000	0.519	13.076

Table II. Trend of EMC Price Gaps and Firm Price Ratios

This table presents the time trend of country-level price gaps and firm-level price ratios. Panel A shows the results of regressions of *EMC Price Gap* on the dummy variable *Post2015*. *Post2015* equals one starting in 2015Q4 and equals zero before. *EMC Price Gap* is calculated as the value-weighted or equal-weighted average price-to-book, price-to-sales, price-to-earnings, price-to-cashflow of emission firms net of the value-weighted or equal-weighted average of non-emission firms in the country/area. Columns (1)–(4) in Panel A report results for value-weighted *EMC Price Gap*. Columns (5)–(8) in Panel A report results for equal-weighted *EMC Price Gap*. Panel A controls for country level variables, including log GDP per capita, female ratio, corruption, government effectiveness, political stability, regulatory quality, rule of law, and accountability. Panel B shows the regression results of price ratios for emission vs. clean firms. The price ratios are *Log PB* in columns (1)–(3), *Log PS* in columns (4)–(6), *Log PE* in columns (7)–(9), and *Log PCF* in columns (10)–(12). *Emission* is an indicator of high-emission industries based on IPCC's categorization. Control variables in Panel B consist of firm-level *Log Total Assets*, *Book Leverage*, *Cash/Total Assets*, and *ROE*. The sample includes the 26 markets listed in Online Appendix Table IA.I from 2007Q1 to 2020Q4. Standard errors are clustered by year-quarter in Panel A, by firm and by year-quarter in Panel B, and reported in parentheses. $^{*}p < .1$;$^{**}p < .05$;$^{***}p < .01$.

Panel A: Country-level regression

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Value-weighted				Equal-weighted			
	PB	PS	PE	PCF	PB	PS	PE	PCF
Post2015	-0.455***	-1.020***	-1.408	-3.274***	-0.299***	-0.350**	-2.396***	-1.202***
	(0.104)	(0.250)	(1.262)	(0.831)	(0.074)	(0.174)	(0.850)	(0.406)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	1456	1456	1456	1456	1456	1456	1456	1456
Adj. R^2	0.610	0.311	0.138	0.314	0.468	0.406	0.261	0.395

Panel B: Firm-level regression

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Log PB			Log PS			Log PE			Log PCF		
Emission	-0.115***			-0.152***			-0.123***			-0.132***		
	(0.009)			(0.012)			(0.011)			(0.012)		
Emission×Post2015		-0.045***	-0.046***		-0.036***	-0.036***		-0.021	-0.039***		-0.076***	-0.078***
		(0.013)	(0.013)		(0.012)	(0.012)		(0.017)	(0.014)		(0.015)	(0.015)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes		Yes	Yes		Yes	Yes		Yes	Yes	
Country FE	Yes			Yes			Yes			Yes		
Firm FE		Yes	Yes		Yes	Yes		Yes	Yes		Yes	Yes
Country×Year-Quarter FE			Yes			Yes			Yes			Yes
Obs.	1192970	1192213	1192213	1158743	1158001	1158001	873471	872701	872701	874959	874169	874169
Adj. R^2	0.217	0.674	0.696	0.212	0.762	0.773	0.231	0.563	0.580	0.179	0.527	0.541

Table III. Prices and Natural Disasters

This table presents the results of regressing price ratios on *Natural Disasters*. Price ratios are logs of one plus price-to-book, price-to-sales, price-to-earnings, and pricing-to-cashflows. *Emission* is an indicator of high-emission industries based on IPCC's categorization. *Natural Disasters* is the number of natural disasters that happen in a country-year-quarter. Control variables consist of *Log Total Assets*, *Book Leverage*, *Cash/Total Assets*, and *ROE*. The sample includes the 26 markets listed in Online Appendix Table IA.I from 2007Q1 to 2020Q4. Standard errors are clustered by firm and by year-quarter, and reported in parentheses. $^{*}p < .1$;** $p < .05$;*** $p < .01$.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Log PB			Log PS			Log PE			Log PCF		
Natural Disasters	0.013			0.014			-0.001			0.021		
	(0.012)			(0.012)			(0.013)			(0.013)		
Emission×Natural Disasters	-0.016***	-0.010***	-0.018***	-0.015***	-0.007*	-0.012***	-0.021***	-0.012**	-0.013	-0.012**	-0.008	-0.012**
	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)	(0.008)	(0.006)	(0.008)	(0.005)	(0.005)	(0.006)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes			Yes			Yes			Yes		
Country×Year-Quarter FE		Yes	Yes		Yes	Yes		Yes	Yes		Yes	Yes
Emission×Year-Quarter FE			Yes			Yes			Yes			Yes
Obs.	1192213	1192213	1192213	1158001	1158001	1158001	872701	872701	872701	874169	874169	874169
Adj. R^2	0.674	0.696	0.697	0.762	0.773	0.773	0.563	0.580	0.580	0.527	0.541	0.541

Table IV. CO_2 Emission and Price Gap

This table presents the Poisson regression results of total CO_2 emission on price gaps. Columns (1)–(3) are for public firms and columns (4)–(6) are for matched private firms. *EMC Price Gap* is value-weighted average price-to-book gap between emission and non-emission firms over the past year in the country/area. *S1tot*, *S2tot*, and *S3tot* are the scope 1, scope 2, and scope 3 CO_2 emissions (in million tons). *Emission* is an indicator of high-emission industries based on IPCC's categorization. Control variables for public firms consist of firm-level price-to-book ratio, *Log Total Assets*, *Book Leverage*, *Cash/Total Assets*, and *ROE*. Institutional ownership, ESG disclosure mandates, and their interaction terms with *Emission* are also included. Control variables for private firms are firm revenue, ESG disclosure mandate and its interaction term with *Emission*. The sample includes the 26 markets listed in Online Appendix Table IA.I from 2007 to 2021. Standard errors are clustered by firm, and reported in parentheses. $^{*}p < .1$;$^{**}p < .05$;$^{***}p < .01$.

	(1)	(2)	(3)	(4)	(5)	(6)
	Public Firms			Private Firms		
	S1tot	S2tot	S3tot	S1tot	S2tot	S3tot
Emission×EMC Price Gap	0.166***	0.027	0.054***	-0.073	-0.183**	-0.040
	(0.038)	(0.018)	(0.013)	(0.062)	(0.077)	(0.055)
Controls	Full	Full	Full	Revenue	Revenue	Revenue
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Country×Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	87457	87548	87581	62442	62442	62442
Pseudo R^2	0.823	0.448	0.616	0.624	0.435	0.669

Table V. CO_2 Emission and Firm-level Valuation Shock: Emission Firms

This table presents the IV estimation of CO_2 emission on price ratios for emission firms. Column (1) shows the first stage result; Columns (2)–(5) show the second stage results of the IV estimation. *Log PB* is the log of one plus price-to-book. *Natural Disasters* is the number of natural disasters occurring in a country-year-quarter. Δ*S1tot*, Δ*S2tot*, and Δ*S3tot* are the differences between public firms and their matched private firms of *S1tot*, *S2tot* and *S3tot* respectively. Control variables consist of *Log Total Assets*, *Book Leverage*, *Cash/Total Assets*, and *ROE*. Institutional ownership, ESG disclosure mandates, and their interaction terms with *Emission* are also included. The sample includes the 26 markets listed in Online Appendix Table IA.I from 2007Q1 to 2021Q4. The Kleibergen-Paap F statistic for the first stage is reported in column (1). Standard errors are clustered by firm, and reported in parentheses. $^{*}p < .1;^{**}p < .05;^{***}p < .01$.

	(1)	(2)	(3)	(4)
	1st Stage	2nd Stage		
	Log PB	ΔS1tot	ΔS2tot	ΔS3tot
Natural Disasters	-0.018***			
	(0.005)			
Log PB		2.228**	0.734***	1.995***
		(1.005)	(0.251)	(0.735)
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
Obs.	29840	29834	29832	29840
Kleibergen-Paap F	10.671			

Table VI. Green Patents and Price Gap

This table reports the Poisson regression results of green patents on price gaps. Columns (1)–(4) are for public firms and columns (5)–(8) are for matched private firms. *EMC Price Gap* is the value-weighted average price-to-book gap between emission and non-emission firms over the past four quarters (in columns (1)–(2) and (5)–(6)) or twelve quarters (in columns (3)–(4) and (7)–(8)). The dependent variables are *Green*, the number of green patents that the firm files in the year-quarter. Control variables for public firms consist of *Log Total Patents*, firm-level *PB*, *Log Total Assets*, *Book Leverage*, *Cash/Total Assets*, and *ROE*. Institutional ownership, ESG disclosure mandates, and their interaction terms with *Emission* are also included. Control variables for private firms are *Log Total Patents*, *Log Total Assets*, ESG disclosure mandate and its interaction term with *Emission*. The sample includes the 26 markets listed in Online Appendix Table IA.I from 2011Q1 to 2018Q4. Standard errors are clustered by firm, and reported in parentheses. $^{*}p < .1;^{**}p < .05;^{***}p < .01$.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Public Firms				Private Firms			
	One Year		Three Years		One Year		Three Years	
EMC Price Gap	0.058		0.099		-0.174**		-0.204**	
	(0.082)		(0.156)		(0.069)		(0.092)	
Emission×EMC Price Gap	-0.203**	-0.171***	-0.260	-0.308***	0.065	0.000	-0.010	-0.022
	(0.091)	(0.064)	(0.164)	(0.118)	(0.082)	(0.077)	(0.107)	(0.113)
Controls	Full	Full	Full	Full	AT	AT	AT	AT
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes		Yes		Yes		Yes	
Country×Year-Quarter FE		Yes		Yes		Yes		Yes
Obs.	52267	50874	52267	50874	90208	88063	90208	88063
Pseudo R^2	0.814	0.819	0.814	0.819	0.817	0.823	0.817	0.823

Table VII. Green Patents and Firm-level Valuation Shock: Emission Firms

This table reports the IV estimations of green patents on price ratios for emission firms. Columns (1) and (3) show the first stage results; Columns (2) and (4) show the second stage results of IV estimations. *Natural Disasters* is the average number of natural disasters that happen in a country in the past four quarters (in columns (1)–(2)) or twelve quarters (in columns (3)–(4)). *Log PB* is the average log P/B in the past four or twelve quarters accordingly. $\Delta Green$ is the difference between public firms and their matched private firms of the number of green patents. Control variables consist of *Log Total Patents*, *Log Total Assets*, *Book Leverage*, *Cash/Total Assets*, and *ROE*. Institutional ownership, ESG disclosure mandates, and their interaction terms with *Emission* are also included. The sample includes the 26 markets listed in Online Appendix Table IA.I from 2011Q1 to 2018Q4. The Kleibergen-Paap F statistic for the first stage is reported in columns (1) and (3). Standard errors are clustered by firm, and reported in parentheses. $^{*}p < .1;^{**}p < .05;^{***}p < .01$.

	(1)	(2)	(3)	(4)
	One Year		Three Years	
	1st Stage	2nd Stage	1st Stage	2nd Stage
	Log PB	ΔGreen	Log PB	ΔGreen
Natural Disasters	-0.022***		-0.086***	
	(0.005)		(0.009)	
Log PB		-3.874***		-1.687***
		(1.497)		(0.493)
Controls	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Obs.	100230	100230	90069	90069
Kleibergen-Paap F	22.392		96.536	

Table VIII. Firm Sizes and Price Gap

This table reports the regression results of the firm's sales, total assets, capital expenditure, payout, external financing on price gaps for public firms. *EMC Price Gap* is the value-weighted average price-to-book gap between emission and non-emission firms in the country/area. *Log Sales* and *Log Total Assets* are the log of total revenue and total assets for the firm. *CapEx(%)* is the total capital expenditures over lagged total assets. *Payout Ratio(%)* and *Repur. Ratio(%)* are total payout(=dividend plus repurchase) and stock repurchases, divided by total earnings. *Stock Sales Rate(%)* is the new stock issuance divided by lagged market capitalization. *ST Debt(%)* and *LT Debt(%)* are net cashflows from short-term debt and long-term debt, divided by lagged total assets. *Emission* is an indicator of high-emission industries based on IPCC's categorization. Control variables include firm-level *PB*, *Log Total Assets*, *Book Leverage*, *Cash/Total Assets*, and *ROE*. Institutional ownership, ESG disclosure mandates, and their interaction terms with *Emission* are also included. Columns (1) and (2) do not control *Log Total Assets*. The sample includes the 26 markets listed in Online Appendix Table IA.I from 2007 to 2020. Standard errors are clustered by firm, and reported in parentheses. $^{*}p < .1;^{**}p < .05;^{***}p < .01$.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Log Sales	Log Total Assets	CapEx(%)	Payout Ratio(%)	Repur. Ratio(%)	Stock Sales Rate(%)	ST Debt(%)	LT Debt(%)
Emission×EMC Price Gap	0.025***	0.041***	0.157***	0.044	-0.108***	0.189***	0.004	-0.023
	(0.005)	(0.004)	(0.042)	(0.122)	(0.033)	(0.069)	(0.024)	(0.039)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country×Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	280605	281234	276041	222710	250295	267376	208229	277301
Adj. R^2	0.945	0.961	0.442	0.627	0.246	0.251	0.043	0.122

Figure I. Time Trend of P/B Ratio

This figure plots the average price-to-book ratio and gap between emission vs. non-emission firms of the 26 markets listed in Online Appendix Table IA.I from 2007 to 2020. For each month, the value-weighted average of price-to-book of emission firms and non-emission firms are plotted. *EMC PB Gap* is calculated as the value-weighted average of price-to-book of emission firms net of the value-weighted average of non-emission firms.

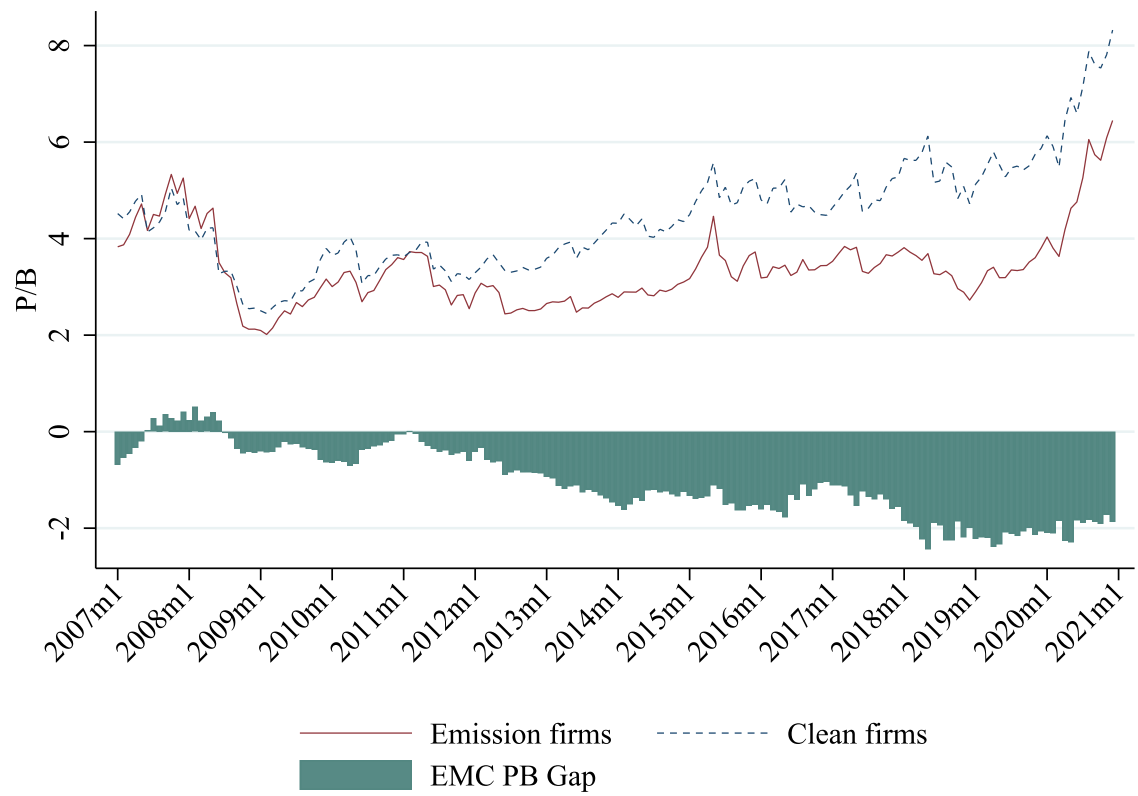
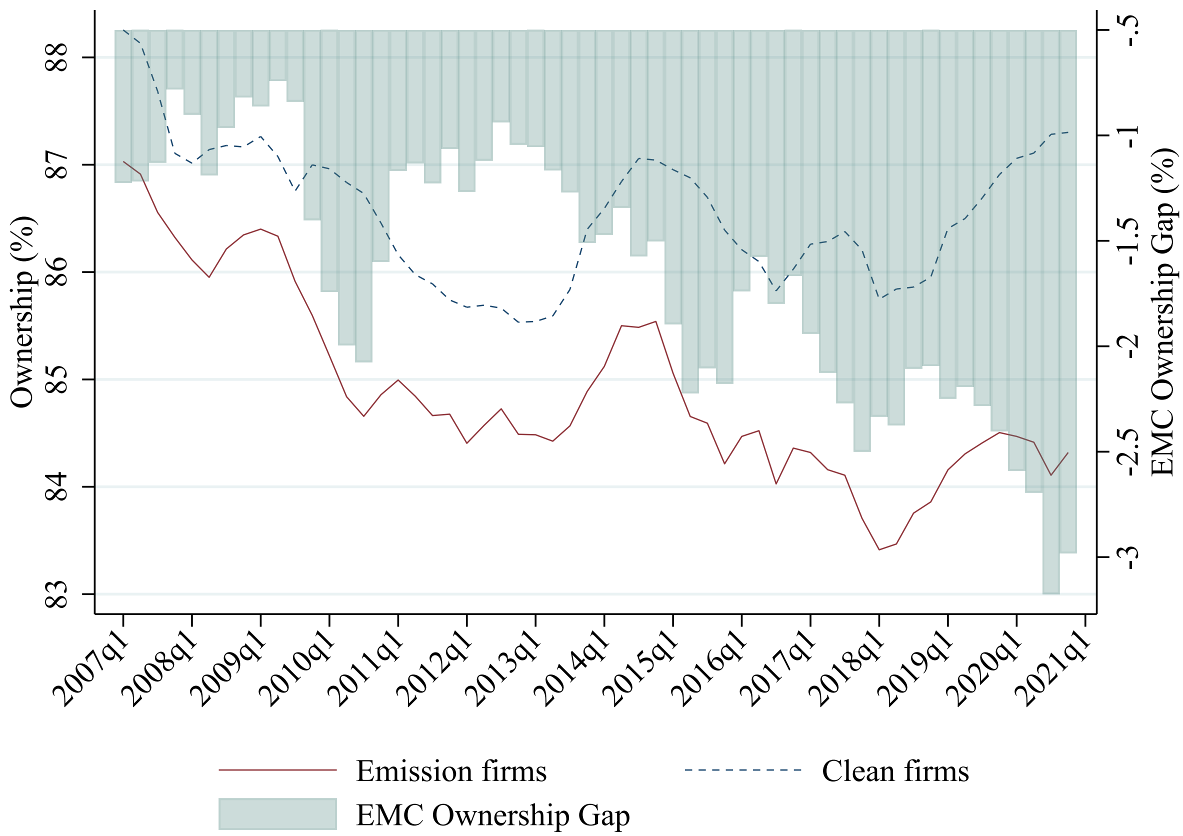


Figure II. Time Trend of Institution and Retail Ownership

This figure plots the average ownership by institution and retail investors, as well as gap between emission vs. non-emission firms of the 26 markets listed in Online Appendix Table IA.I from 2007Q1 to 2020Q4. For each quarter, the value weighted average of institution and retail ownership of emission firms and non-emission firms are plotted. *EMC Ownership Gap* is calculated as the value weighted average institution and retail ownership on emission firms net of the average ownership on non-emission firms. The moving average of four quarters are plotted to adjust for seasonality.



Internet Appendix for
"Carbon Firm Devaluation and Green Actions"

Darwin Choi, Zhenyu Gao, Wenxi Jiang, and Hulai Zhang

We provide additional information on portfolio holdings and fundamental variable constructions, as well as robustness tests in this internet appendix.

Section IA.1 describes the construction of portfolio holdings by institutions and blockholders from FactSet Ownership v5.

Section IA.2 illustrates additional variable definitions and data sources.

Section IA.3 gives the list of countries in our analysis, emission industry maps, and robustness regression results.

IA.1 Global equity holdings

We construct a panel of quarterly equity holdings of public companies for institutional investors and blockholders. Holdings data are from FactSet Ownership v5, which includes four main tables: 13F holdings (13F: own_inst_13f_detail_eq), fund level holdings (SOF: own_fund_detail_eq), institutional stakes holdings (INST: own_inst_stakes_detail_eq), and non-institutional stakes holdings (NINST: own_stakes_detail_eq). Some countries have very few public firms (e.g., less than 50 stocks) or have very few institutions holding these stocks (e.g., less than 50 institutions). We thus restrict our sample to 26 main markets that have ample public firms and institutions holding their stocks. These main countries are Australia, Austria, Belgium, Canada, China, Denmark, Egypt, Finland, France, Germany, Greece, Hong Kong, India, Israel, Italy, Japan, Korea, Netherlands, New Zealand, Poland, Singapore, South Africa, Spain, Sweden, United Kingdom, and United States.

We source institutional equity holdings from 13F, SOF, and INST, and non-institutional holdings from NINST.

1. 13F. These data are from mandatory 13F reports on US-traded equities held by institutions that manage more than $100 million in 13F securities.

2. SOF. These fund-level data are from SEC mandatory reports in the US and from FactSet direct collections from fund managers in other countries. We aggregate fund-level holdings to the institution level by mapping factset_fund_id to factset_inst_entity_id in own_ent_funds.

3. INST. These institutional stakes data are from several sources such as regulatory filings, company reports, etc. Institutional stakes holding for the UK are from share registers (UKSR) and regulatory news service filings (RNS). Institutional stakes holding for the US are from 13D, 13G, 13K, and proxies. For other countries, FactSet collects data from various regulatory filings. INST could be regarded as data from alternative sources other than 13F and SOF.

4. NINST. This table reports holdings from non-institutional stakeholders, and people that are identified as stakeholders. It contains duplicating institutional holdings from the previous three datasets. Thus in this table, we drop holdings of institutions in the previous three datasets.

Since institutions may not report their holdings every quarter, we interpolate their holdings using positions from the last available quarter prior to the perspective quarter. For example, if the institution reports holdings in quarter t and quarter $t+2$ but missing reports in quarter $t+1$, we will interpolate their positions in quarter $t+1$ using the holdings in quarter t.

We combine institutional holdings and non-institutional stake holdings using the following rules.

1. UK securities. For UK securities (fds_uksr_flag=1), select UKSR and RNS positions (source_code="W" or "Q") from INST. Duplicates are removed within each institution-security-year-quarter.

2. 13F securities in US/Canada&13F institutions. For 13F securities (fds_13f_flag=1 or fds_13f_ca_flag=1) and 13F institutions (fds_13f_flag=1), select holdings from 13F. Unless there are no records in 13F, use INST and SOF. Duplicates are removed within each institution-security-year-quarter.

3. 13F securities in US/Canada&non-13F institutions. For 13F securities (fds_13f_flag=1 or fds_13f_ca_flag=1) and non-13F institutions (fds_13f_flag=0), select holdings from INST. Unless there are no records in INST, use 13F and SOF. Duplicates are removed within each institution-security-year-quarter.

4. non-13F securities&non-UK securities. For non-13F securities and non-UK securities (fds_13f_flag=0 and fds_13f_ca_flag=0 and fds_uksr_flag=0), select holdings from INST, SOF, and 13F. Duplicates are removed within each institution-security-year-quarter.

5. Select non-institutional stake holdings from NINST. Remove duplicating holdings of institutions in 13F, SOF, and INST.

We merge on security prices from own_sec_prices_eq in FactSet Ownership v5 and calculate the dollar value of holdings. Prices are adjusted for company operations such as splits. Occasionally, the dollar holding of a given security by one entity is greater than the market cap of the security. We drop the holding in this case.

We restrict holdings to common equity and depositary receipts: sym_coverage.fref_security_type are among “SHARE”, “ADR”, “DR”, “GDR”, and “NVDR”.

IA.2 Variable Definitions and Data Sources

Data on market capitalization and fundamentals are from FactSet Fundamentals North America v3 and Fundamentals International v3. We select one security for each company which is uniquely identified: ff_sec_coverage.ff_iscomp=1.

Market capitalization. We get the monthly security prices and shares outstanding from cs3_monthly_prices_final_usc and cs3_monthly_prices_final_int. Prices and shares outstanding are adjusted for company operations such as splits before calculating the market capitalization. We convert market capitalization to USD using the point-in-time exchange rates in fx_rates_usd.

Fundamentals. We combine 12 files from FactSet Fundamentals v3: basic_X, basic_der_X, advanced_X, advanced_der_X, where X stands for three regions "am", "ap", and "eu." We convert fundamentals to USD using the point-in-time exchange rates in fx_rates_usd. We construct firm-level fundamentals following the procedure in Fama and French (1992). We assume the lag of six months before the fundamentals get public.

- Log Total Assets. This is defined as the log of one plus total assets (=log(ff_assets+1)).
- Log Sales. This is the log of total revenue of the firm (=log(ff_sales+1)).
- Book Equity. Book equity is shareholder equity plus deferred taxes and investment tax credit, minus preferred stock (=ff_shldrs_eq+ff_dfd_tax_itc-ff_pfd_stk). We regard deferred taxes and investment tax credit, and preferred stock as zero if they are missing.
- PB. Price-to-book is defined as market cap divided by book equity.
- PS. Price-to-sales is calculated by market cap divided by total sales (=MktCap/ff_sales).
- PE. Price-to-earnings is calculated by market cap divided by total income before extraordinary items (=MktCap/ff_net_inc_basic_beft_xord).
- PCF. Price-to-cashflow is calculated by market cap divided by net cashflow. Net cashflow equals funds from operations plus extraordinary item, plus changes in working capital (=ff_funds_oper_gross+ff_xord_cf+ff_wkcap_chg). We regard extraordinary item and changes in working capital as zero if they are missing.

- Book Leverage. It is defined as total debt over total assets (=ff_debt/ff_assets).
- Cash/Total Assets. It is calculated as total cash and equivalents divided by total assets (=ff_cash_generic/ff_assets).
- ROE. ROE is calculated as net income minus discontinued operations, divided by shareholder equity (=(ff_net_income-ff_disc_oper)/[(ff_shldrs_eq+L.ff_shldrs_eq)/2]).
- CapEx(%). It is the total capital expenditures over lagged total assets.
- Payout Ratio(%). It represent total dividend(=ff_div_cf) and repurchase(=ff_stk_purch_cf) payouts, divided by total earnings(=ff_shldrs_eq×ff_eps).
- Repurchase Ratio(%). It represents the payment for stock repurchases (=ff_stk_purch_cf), divided by total earnings(=ff_shldrs_eq×ff_eps).
- Stock Sales Rate(%). This gives the cash flow from selling stocks (ff_stk_sale_cf), divided by lagged market cap.
- LT Debt CF. It represents the net cashflow from long-term debt. It is calculated as the long-term borrowings (ff_debt_lt_iss_cf) minus reduction in long-term debt (ff_debt_lt_reduct_cf).
- ST Debt CF. It represents the net cashflow from short-term debt. It is calculated as the short-term borrowings (ff_debt_st_iss_cf) minus reduction in short-term debt (ff_debt_st_reduct_cf).
- LT Debt(%). It is defined as LT Debt CF over lagged total assets.
- ST Debt(%). It is defined as ST Debt CF over lagged total assets.

We get firm's industry information from sym_entity_sector.industry_code in FactSet and NACE Rev. 2 in BvD Orbis.

We collect climate news from RepRisk. RepRisk provides detailed information about each piece of news, including its novelty, severity, and influence. RepRisk also has information about which company each incidence is linked to. In our paper, we keep all environment related incidences (environment = "T") with medium or high severity (severity = 2 or 3) and with novelty (novelty = 2).

We collect country-level demographic and economic data from World Bank.

- GDP per capita. GDP per capita is gross domestic product over midyear population.
- Female ratio. It measures the share of female population in each country.
- Corruption. Control of corruption measures the degree of country power that prevents the abuse of public office for private gain. Coded from -2.5 (weak) to +2.5 (strong).
- Government effectiveness. It measures the extent of the quality of public services and civil service, independence from political pressures, the quality of policy formulation and implementation, and the credibility of the government's commitment to policies. Coded from -2.5 (weak) to +2.5 (strong).
- Political stability. This measures the likelihood of political instability and politically motivated violence such as terrorism. Coded from -2.5 (weak) to +2.5 (strong).
- Regulatory quality. This measures the government's ability to formulate and implement strong policies and regulations that promote private-sector development. Coded from -2.5 (weak) to +2.5 (strong).
- Rule of law. This measures the extent to which agents have confidence in the rules of society, especially the quality of contract enforcement, property rights, the police, and the courts, as well as the likelihood of crime and violence. Coded from -2.5 (weak) to +2.5 (strong).

- Accountability. Voice and accountability measure the degree to which citizens can participate in selecting their government, also the free expression, free association, and free media. Coded from -2.5 (weak) to +2.5 (strong).

We use Google Trends' internet search activity, which provides a Search Volume Index (SVI) for the topic "climate change", to measure the attention to and awareness of climate change by retail investors.[23] We download the SVI for all countries in the world every quarter between 2004Q1 and 2021Q4. Google Trends returns an SVI in the range of 0 to 100 every quarter. As a result, the country with the most searches obtains an SVI of 100 each quarter. SVI for other nations is calculated as a percentage of the most searched country's volume. A SVI of zero indicates that there are no or very few search volumes.

Bloomberg provides global news publications on the topic of "climate change", which is proxy for the attention to and awareness of climate change by institutional investors. The news is collected from a variety of sources, such as newspapers, social media, and Bloomberg itself. Our Bloomberg news count reflects the total number of "climate change" news related to a specific country each month since March 2012.[24]

IA.3 Additional Tables

Table IA.I lists the 26 countries or areas that we use in analysis and reports the average number of public firms, average number of institutions that hold the country's stocks, average institutional and retail ownership, and average price gaps (defined as the value-weighted average price-to-book, price-to-sales, price-to-earnings, price-to-cashflow of emission firms net of the value-weighted average of non-emission firms) in each country during the sample period from 2007Q1 to 2020Q4.

[23] Google Trends provides SVI for "topics" and "search terms." Topics address misspellings and searches in different languages, because Google groups different searches that have the same meaning under a single topic. For details, see the official Google Search blog: https://search.googleblog.com/2013/12/an-easier-way-to-explore-topics-and.html.

[24] We search "climate change" with country names in Bloomberg "NT" function. We use news publications from all sources.

Table IA.II provides a map between FactSet industry groups, NAVE Rev. 2 industry categories, and industries identified as major emission sources by the Inter-governmental Panel on Climate Change (IPCC). The full list of IPCC Category Codes can be found in Annex II of the IPCC's Fifth Assessment Report, issued in 2014 (Krey and Masera (2015), p.1302–1304). We obtain industry information on firms from FactSet and BvD Orbis and classify firms as high-emissions if they belong to industries in this table.

Table IA.III presents the time trend of country-level price gaps. Panel A separates emission firms into non-energy and energy firms, and shows the trend of price gaps between non-energy emission firms and clean firms as well as price gaps between energy firms and clean firms. *EMC Price Gap* is defined by value weighted average PB, PS, PE and PCF among each group of firms. Panel B determines emission firms by their CO_2 intensities in columns (1)–(2): the sum of scope 1, 2, and 3 emissions over sales. When a firm's CO_2 intensity is among the top 30% in the country-year-quarter, the firm is regarded as an emission firm. When a firm's CO_2 intensity is among the bottom 30%, the firm is regarded as a non-emission firm. The value-weighted and equal-weighted average PB gaps between emission and non-emission firms show strong downward pattern. Panel B's columns (3)–(4) define emission firms by negative environmental news coverage. A firm is regarded as an emission firm if it has been covered by negative environmental news in the past twelve months and as a non-emission firm otherwise. The value-weighted and equal-weighted average PB gaps between emission and non-emission firms show strong downward pattern.

Table IA.IV presents the trends of price ratios for emission vs. non-emission firms. Instead of using the dummy variable *Post2015*, this table uses year dummies and compares price ratios each year with the base $Year == 2007$. This table shows a clear downward pattern of price ratios of emission firms relative to non-emission firms.

Table IA.V shows whether the Google search volume index and Bloomberg news of "Climate Change" change on local natural disasters. The occurrence of local extreme natural disasters induces increased attention to and awareness of climate change. We use two measures of attention to climate change. The first one is the Google search volume on the topic of "climate change" at the country-quarter level. When it is downloaded, the Google search volume index (SVI) data is normalized by quarter; that is, the country with the highest search volume on climate change among all countries during the quarter will be assigned 100 for SVI. Therefore, in the panel regression, we control for year-quarter fixed effects to address this. Specifically, for country m and quarter t, we run the regression $\text{Log SVI}_{m,t} = \alpha + \beta \text{Natural Disaster}_{m,t} + \delta_t + \epsilon_{m,t}$. The second measure is the number of news reports on Bloomberg using the keywords "climate change" and the country name in that quarter. We take the log of the variable, labeled as Log News. Google searches are mostly done by ordinary households and thus presumably better capture the attention of retail investors. As a complement, Bloomberg news is likely read by financial professionals and thus can be a valid proxy for institutional attention. This table shows that natural disasters increase attention to climate change among both retail and institutional investors.

Table IA.VI presents Poisson regression results of total CO_2 emissions by public and private firms on EMC price gaps defined by price-to-sales, price-to-earnings and price-to-cashflows. Panel A shows the emissions of public firms when faced with country-level carbon price pressures. Panel B shows the emissions of private firms when faced with country-level carbon price pressures. EMC Price Gaps are defined as the value-weighted average price-to-sales (Columns (1)–(3)), price-to-earnings (Columns (4)–(6)), and price-to-cashflows (Columns (7)–(9)) of emission firms net of the value-weighted average of non-emission firms in the country/area.

Table IA.VII presents the instrumental variable estimation of CO_2 emission on price ratios for non-emission firms. Natural disaster acts as an exogenous shock to the firm-level price-to-book ratio and thus can work for an instrument. We employ two-stage least squares regressions for non-emission firms. In the first stage, we regress the price-to-book ratio on the number of natural disasters for the sample of non-emission firms. Subsequently, in the second stage, we regress the differences in carbon emissions between public firms and their matched private firms on the predicted price ratio obtained from the first stage. The Kleibergen-Paap F statistic in the first stage shows a weak prediction of natural disasters for the price ratio of non-emission firms. Non-emission firms do not exhibit decreasing CO_2 emissions in response to firm-level price pressures.

Table IA.VIII presents the instrumental variable estimation of CO_2 emission on emission firms' price ratios defined by price-to-sales, price-to-earnings, and price-to-cashflows. We employ two-stage least squares regressions for emission firms similarly. In the first stage, we regress the price ratio on the number of natural disasters for the sample of non-emission firms. Subsequently, in the second stage, we regress the differences in carbon emissions between public firms and their matched private firms on the predicted price ratio obtained from the first stage. The Kleibergen-Paap F statistics in the first stage show strong predictions of natural disasters for the price ratio of emission firms. Emission firms exhibit decreasing CO_2 emissions in response to firm-level price pressures.

Table IA.IX presents OLS regression results of green patent ratios by public and private firms on country-level EMC price gaps. The green patent ratio is the number of green patents filed by the firm over its total patents filed in the quarter. EMC Price Gap is the difference between the value-weighted average price-to-book ratio of high-emission firms and the value-weighted average of low-emission firms in each country. This table emphasizes that public firms shift their resource to green patents in response to price pressures. Similar to Table VI, private firms do not shift resources to green patents in response to price pressures.

Table IA.X presents the instrumental variable estimation of green patents on price ratios for non-emission firms. The dependent variable is $\Delta Green$, defined as the difference in the number of green patents between public emission firms and their matched private counterparts. Natural disaster acts as an exogenous shock to the firm-level price-to-book ratio and thus can work for an instrument. We employ two-stage least squares regressions for non-emission firms. In the first stage, we regress the price-to-book ratio on the number of natural disasters for the sample of non-emission firms. Subsequently, in the second stage, we regress the differences in green patents between public firms and their matched private firms on the predicted price ratio obtained from the first stage. The Kleibergen-Paap F statistics in the first stage show weak predictions of natural disasters for the price ratio of non-emission firms. Non-emission firms do not exhibit increasing green patents in response to firm-level price pressures.

Table IA.XI presents Poisson regression results of CO_2 emission intensity by public and private firms on EMC price gaps, which are defined as the value-weighted average price-to-book (Columns (1)–(3)), price-to-sales (Columns (4)–(6)), price-to-earnings (Columns (7)–(9)), and price-to-cashflows (Columns (10)–(12)) of emission firms net of the value-weighted average of non-emission firms in the country/area. The scope 1, 2 and 3 CO_2 emission intensities are defined as firms' scope 1, 2 and 3 CO_2 emissions over sales. Panel A shows the emissions of public firms when faced with country-level carbon price pressures. Panel B shows the emissions of private firms when faced with country-level carbon price pressures.

Table IA.XII present regression results that replicate and extend Hartzmark and Shue (2023). Panel A shows linear and Poisson regressions of CO_2 emission intensity on EMC price gaps for US public firms. Panel B shows linear and Poisson regressions of CO_2 emission intensity on EMC price gaps for global public firms. Column (1) replicates Hartzmark and Shue (2023) and uses the change in *S12int* as the dependent variable. Column (2) changes the dependent variable to *S12int*. Both columns (1) and (2) use simple linear model. Column (3) is similar to column (2) except that column (3) uses Poisson regression. Column (4) add firm fixed effects to the model in column (3). EMC price gaps are defined as the value-weighted average price-to-book of emission firms net of the value-weighted average of non-emission firms in the country/area. *S12int* is the sum of scopes 1 and 2 CO_2 emissions over sales.

Table IA.XIII presents the trends of institutional and retail ownership for emission vs. non-emission firms. As more and more investors are aware of climate change, they may start to be concerned about potential risks (both physical and regulatory) for emission firms' future business, or they may adopt environmental-friendly investment preferences or green portfolio mandates. Those can lead to systematic carbon divestment or under-weight emission stocks in investors' portfolios. Using equity positions of institutions and blockholders reported in FactSet Ownership v5, we calculate quarterly Institutional Ownership for each stock as the fraction of shares outstanding held by financial institutions. Retail Ownership equals one minus Institutional Ownership and the fraction of shares owned by blockholders (excluding institutions). The regression here is $Ownership_{i,t} = \alpha + \beta Emission_i \times Post2015_t + X'_{i,t}\Gamma + \gamma_i + \delta_t + \epsilon_{i,t}$, where we control for firm fixed effects, as the investment composition (e.g., institutional vs retail) varies dramatically across countries and among firms with different size and so on, and for year-quarter fixed effects, because over the period institutional ownership increases significantly for most countries. Further, we also add country times year-quarter fixed effects to allow such a trend, if any, to vary across countries. β captures the trend of retail or institutional ownership, where negative value means carbon divestment: investors keep selling emission firms relative to non-emission firms.

Table IA.XIV presents ownership changes on the occurrence of natural disasters. We first examine the summation of institutional and retail ownership; we control for firm and year-quarter fixed effects in column (1), add country times year-quarter fixed effects in column (2), and *Emission* times year-quarter fixed effects in column (3). Columns (4)–(5) examines retail and institutional ownership separately. Column (6) shows the results for domestic institutional ownership, where domestic institutions are defined as institutions that come from the same listed country as the holding firm. Column (7) shows the results for foreign institutional ownership, where foreign institutions are defined as institutions that come from different listed country as the holding firm.

Table IA.XV shows Poisson regression results of CO_2 emissions by public and private firms on country-level EMC price gaps and EMC ownership gaps. EMC Price Gap is the difference between the value-weighted average valuation ratio of high-emission firms and the value-weighted average of low-emission firms in each country. EMC Ownership Gap is the value-weighted average institution and retail ownership of emission firms minus the average ownership of clean firms. This table highlights the role of devaluation pressure in reducing carbon emissions for publicly listed firms, even after accounting for the carbon divestment trend. Similar to Table IV, private firms do not exhibit decreasing emissions in response to price pressures.

Table IA.XVI presents Poisson regression results of the number of green patents by public and private firms on country-level EMC price gaps and EMC ownership gaps. EMC Price Gap is the difference between the value-weighted average price-to-book ratio of high-emission firms and the value-weighted average of low-emission firms in each country. EMC Ownership Gap is the value-weighted average institution and retail ownership of emission firms minus the average ownership of clean firms. This table highlights the role of devaluation pressure in incentivizing green patents for publicly listed firms, even after accounting for the carbon divestment trend. Similar to Table VI, private firms do not exhibit increasing green patents in response to price pressures.

Table IA.I. List of Countries

This table lists 26 countries/areas that we use in analysis and reports the average number of public firms, average number of institutions that hold the country's stocks, average institutional and retail ownership, and average *EMC Price Gaps* (defined as the value-weighted average price-to-book, price-to-sales, price-to-earnings, price-to-cashflow of emission firms net of the value-weighted average of non-emission firms) in each country during the sample period, from 2007Q1 to 2020Q4.

					EMC Price Gap			
Country/Area	#Public firms	#Institutions	IO(%)	Retail Ownership(%)	PB	PS	PE	PCF
Australia	1636.4	1246.1	17.2	75.3	-0.776	0.599	4.405	-3.541
Austria	67.8	873.8	16.3	46.5	0.413	0.834	0.341	6.977
Belgium	121.3	1123.5	16.4	45.6	0.067	-1.200	-6.109	-0.021
Canada	896.4	3121.0	39.0	52.0	-0.386	1.807	5.908	-0.237
China	2412.6	591.9	9.6	64.3	-1.671	-3.357	-2.338	-7.703
Denmark	160.3	1018.7	30.5	47.3	-6.165	-4.203	-7.993	-8.926
Egypt	196.9	177.4	7.4	64.1	1.125	3.387	15.035	7.029
Finland	123.2	867.8	32.3	50.6	-0.809	-0.715	-3.383	-13.224
France	711.5	1901.3	24.1	53.2	-0.127	-1.344	-4.742	-3.804
Germany	320.1	996.9	14.2	49.4	0.438	-0.228	-7.527	9.611
Greece	205.3	482.1	12.0	60.0	-1.118	-0.874	5.765	1.857
Hong Kong	1579.4	1427.3	15.0	53.7	-1.315	-0.354	-3.471	1.261
India	2810.1	680.3	21.7	38.7	-2.147	-0.239	-9.058	-3.891
Israel	385.6	509.5	8.1	65.5	0.821	1.162	-2.740	6.624
Italy	271.2	1472.0	19.3	53.0	-0.257	-1.569	2.142	-7.131
Japan	2817.3	1389.4	16.4	64.4	-0.684	-0.936	-3.414	-4.250
Netherlands	102.4	1493.9	29.6	54.0	0.687	-0.003	4.900	5.174
New Zealand	117.5	381.1	16.0	64.2	-1.292	-2.392	3.280	2.078
Poland	503.4	425.8	27.1	48.2	-0.401	0.046	-1.658	0.762
Singapore	651.9	913.0	11.5	58.4	-0.616	-1.654	1.510	2.653
South Africa	295.7	689.7	24.8	56.4	-1.231	-2.338	1.448	-14.309
South Korea	1722.6	854.7	18.7	46.3	-1.253	-3.211	-10.538	-7.928
Spain	154.9	1326.3	18.6	59.4	-1.335	0.052	-2.105	0.458
Sweden	533.1	1211.3	37.1	48.0	0.020	-2.121	4.286	-1.137
United Kingdom	1551.8	3364.3	43.5	49.9	-1.157	-0.894	-0.892	-3.380
United States	3964.0	5894.9	60.1	35.2	-1.129	-1.596	-10.208	-4.157
Average	935.1	1324.4	22.6	54.0	-0.781	-0.821	-1.044	-1.506
#Country/Area	26							

Table IA.II. Summary of industry information

This table maps emission industries in FactSet and NACE Rev. 2 to IPCC's categorization.

FactSet code	NACE	IPCC category code	IPCC industry name
Energy			
2125	05	1A2f4	Mining and quarrying
1235		1A1a	Power and Heat Generation
2105, 3105	06	1B2	Flaring and fugitive emissions from oil and Natural Gas
3130, 4735		1A3e, 1B2	Non-road transport (fossil), Flaring and fugitive emissions from oil and Natural Gas
2110, 2120, 3110		1A1bc	Other Energy Industries
Transport			
1330, 4605, 4610	51	1A3a, 1C1	Domestic air transport, International aviation
4625	49, 50	1A3d, 1C2	Inland shipping (fossil), International navigation
4620		1A3c	Rail transport
4630	52	1A2f2, 1A3b	Transport equipment, Road transport (includes evaporation) (fossil)
4615		1A3b	Road transport (includes evaporation) (fossil)
Buildings			
1135, 1230	43	1A4a, 2A1	Commercial and public services (fossil), Cement production
1220, 3115	41	1A2f6	Construction
1415, 4885	42	1A4b	Residential (fossil)
Industry			
1115		1A2b, 2C3	Non-ferrous metals, Aluminum production (primary),
1225, 1405	29, 30	1A2f2	Transport equipment
2205, 2210, 2215	19, 20, 22, 23	1A2c	Chemicals
1310, 1315, 1320, 1340, 1355	27	2F7a, 2F8a	Semiconductor Manufacture, Electrical Equipment Manufacture
1125	07, 08, 09	1A2f4	Mining and quarrying
1210	28, 33	1A2f3	Machinery
1105		1A2a	Iron and steel
1425, 1430, 2220, 1130, 4705, 4755	02, 13, 16, 35, 36	1A1a, 1A2f	Power and Heat Generation, Other industries (stationary) (fossil)
1120	24	1A2b	Non-ferrous metals
2230	17	1A2d	Pulp and paper
1205	25	2Cr	Non-ferrous metals production
1305	26	2F7a	Semiconductor Manufacture
2405, 2410, 2415, 2430	10, 12	1A2e	Food and tobacco
	37, 38, 39	6A	Solid waste disposal on land
AFOLU			
2225	01, 03	1A4c3, 4A, 4B, 4C, 4Dr	Fishing (fossil), Enteric Fermentation, Manure management, Rice cultivation, Agricultural soils (direct)

Table IA.III. Country-level EMC Price Gap

This table presents the time trend of country-level price gaps with different definitions of emission vs. non-emission firms. Panel A shows the results of regressions of *EMC Price Gap* on the dummy variable *Post2015* for non-energy emission firms and energy emission firms. *Post2015* equals one starting in 2015Q4 and equals zero before. *EMC Price Gap* in columns (1)–(4) and columns (5)–(8) of Panel A are calculated as the value-weighted average price-to-book, price-to-sales, price-to-earnings, price-to-cashflow of non-energy emission firms, energy emission firms net of the value-weighted average of non-emission firms in the country/area. Panel B shows the results of regressing *EMC Price Gap* on the dummy variable *Post2015*. *EMC Price Gap* in columns (1)–(2) are calculated as the value-weighted or equal-weighted average price-to-book of high CO_2 intensity firms net of the value-weighted or equal-weighted average of low CO_2 intensity firms in the country/area. When a firm's CO_2 intensity is among the top 30% in the country-year-quarter, the firm is regarded as a high emission firm. When a firm's CO_2 intensity is among the bottom 30% in the country-year-quarter, the firm is regarded as a low emission firm. CO_2 intensity is defined as the sum of scope 1, 2 and 3 emissions over sales. *EMC Price Gap* in columns (3)–(4) are calculated as the value-weighted or equal-weighted average price-to-book of firms with negative environmental news net of the value-weighted or equal-weighted average of firms without negative environmental news in the country/area. When a firm has been covered by negative environmental news in the past twelve months, the firm is regarded as an emission firm. When a firm has not been covered by negative environmental news in the past twelve months, the firm is regarded as a non-emission firm. The control variables are the log GDP per capita, female ratio, corruption, government effectiveness, political stability, regulatory quality, rule of law, and accountability. The sample includes the 26 markets listed in Table IA.I from 2007Q1 to 2020Q4. Standard errors are clustered by year-quarter and reported in parentheses. $^{*}p < .1$;$^{**}p < .05$;$^{***}p < .01$.

Panel A: Price Gaps between Non-energy Emission, Energy and Non-emission Firms

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Non-energy Emission vs. Clean Firms				Energy vs. Clean Firms			
	PB	PS	PE	PCF	PB	PS	PE	PCF
Post2015	-0.426***	-0.977***	-3.111**	-3.061***	-0.654***	-1.791***	2.617	-5.434***
	(0.104)	(0.265)	(1.259)	(0.811)	(0.141)	(0.299)	(2.140)	(1.105)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	1456	1456	1456	1456	1456	1456	1456	1456
Adj. R^2	0.618	0.319	0.158	0.322	0.418	0.307	0.096	0.257

Panel B: Price Gaps between Firms with High and Low CO_2 Intensity or Negative Environmental News

	(1)	(2)	(3)	(4)
	CO_2 Intensity		Negative Environmental News	
Dep. Var.: EMC Price Gap	VW	EW	VW	EW
Post2015	-0.296*	-0.408***	-0.314*	-0.452***
	(0.169)	(0.119)	(0.182)	(0.134)
Controls	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
Obs.	1407	1407	547	547
Adj. R^2	0.453	0.371	0.314	0.483

Table IA.IV. Yearly Trends of Firm-level Prices

This table presents the trends of price ratios for emission vs. non-emission firms. The price ratios are *Log PB* in columns (1)–(3), *Log PS* in columns (4)–(6), *Log PE* in columns (7)–(9), and *Log PCF* in columns (10)–(12). *Emission* is an indicator of high-emission industries based on IPCC's categorization. Control variables consist of *Log Total Assets*, *Book Leverage*, *Cash/Total Assets*, and *ROE*. The sample includes the 26 markets listed in Table IA.I from 2007Q1 to 2020Q4. Standard errors are clustered by firm and by year-quarter, and reported in parentheses. $^{*}p < .1;^{**} p < .05;^{***} p < .01$.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Log PB		Log PS		Log PE		Log PCF	
Year2008×Emission	-0.006*	0.000	0.034***	0.038***	-0.013***	0.005	-0.012**	-0.010**
	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)	(0.004)	(0.004)	(0.004)
Year2009×Emission	-0.006***	-0.021***	0.053***	0.025***	0.014**	-0.012*	0.032***	-0.008
	(0.002)	(0.002)	(0.002)	(0.001)	(0.006)	(0.006)	(0.005)	(0.005)
Year2010×Emission	0.024***	0.001	0.076***	0.045***	0.057***	0.047***	0.046***	0.003
	(0.003)	(0.003)	(0.004)	(0.003)	(0.009)	(0.009)	(0.007)	(0.007)
Year2011×Emission	0.016***	0.003	0.058***	0.045***	-0.007	0.020*	0.061***	0.031***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.009)	(0.009)	(0.008)	(0.008)
Year2012×Emission	-0.035***	-0.031***	0.010	0.013**	-0.067***	-0.031***	0.029***	0.009
	(0.006)	(0.006)	(0.006)	(0.006)	(0.010)	(0.010)	(0.009)	(0.009)
Year2013×Emission	-0.105***	-0.083***	-0.031***	-0.018**	-0.089***	-0.048***	-0.066***	-0.063***
	(0.007)	(0.006)	(0.007)	(0.007)	(0.011)	(0.011)	(0.010)	(0.010)
Year2014×Emission	-0.114***	-0.102***	-0.041***	-0.038***	-0.047***	-0.033**	-0.062***	-0.074***
	(0.007)	(0.007)	(0.008)	(0.007)	(0.012)	(0.011)	(0.010)	(0.010)
Year2015×Emission	-0.122***	-0.150***	-0.048***	-0.091***	-0.042***	-0.091***	-0.099***	-0.153***
	(0.008)	(0.008)	(0.009)	(0.008)	(0.012)	(0.012)	(0.011)	(0.011)
Year2016×Emission	-0.087***	-0.118***	-0.012	-0.056***	-0.003	-0.050***	-0.088***	-0.138***
	(0.008)	(0.008)	(0.009)	(0.009)	(0.013)	(0.012)	(0.011)	(0.011)
Year2017×Emission	-0.069***	-0.076***	0.005	-0.015	0.002	-0.015	-0.072***	-0.100***
	(0.008)	(0.008)	(0.009)	(0.009)	(0.015)	(0.013)	(0.011)	(0.011)
Year2018×Emission	-0.105***	-0.086***	-0.043***	-0.030***	-0.085***	-0.062***	-0.093***	-0.098***
	(0.008)	(0.008)	(0.010)	(0.009)	(0.016)	(0.013)	(0.012)	(0.011)
Year2019×Emission	-0.100***	-0.082***	-0.045***	-0.028**	-0.102***	-0.081***	-0.093***	-0.093***
	(0.008)	(0.008)	(0.010)	(0.009)	(0.015)	(0.013)	(0.012)	(0.012)
Year2020×Emission	-0.095***	-0.086***	-0.044***	-0.038***	-0.066***	-0.070***	-0.093***	-0.102***
	(0.008)	(0.008)	(0.010)	(0.009)	(0.014)	(0.012)	(0.012)	(0.011)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes		Yes		Yes		Yes	
Country×Year FE		Yes		Yes		Yes		Yes
Obs.	1192213	1192213	1158001	1158001	872701	872701	874169	874169
Adj. R^2	0.665	0.684	0.759	0.768	0.553	0.565	0.521	0.533

Table IA.V. Google Search and Bloomberg News of "Climate Change" and Natural Disasters

This table presents the results of regressing the Google search volume index and Bloomberg news of "Climate Change" on the number of natural disasters. *Log SVI* is the log of one plus the Google search volume index of "Climate Change" in a country-year-quarter. *Log News* is the log of one plus the number of Bloomberg news of "Climate Change" in a country-year-quarter. *Natural Disasters* is the number of natural disasters that happen in a country-year-quarter. The sample in columns (1)–(2) includes the 26 markets except China listed in Table IA.I from 2004Q1 to 2021Q4. The sample in columns (3)–(4) includes the 26 markets listed in Table IA.I from 2012Q2 to 2021Q4. Standard errors are clustered by year-quarter, and reported in parentheses. $^{*}p < .1$;$^{**}p < .05$;$^{***}p < .01$.

	(1)	(2)	(3)	(4)
	Log SVI		Log News	
Natural Disasters	0.206^{***}	0.063^{**}	0.395^{***}	0.041^{*}
	(0.031)	(0.025)	(0.054)	(0.022)
Year-Quarter FE	Yes	Yes	Yes	Yes
Country FE		Yes		Yes
Obs.	1800	1800	1014	1014
Adj. R^2	0.20	0.77	0.08	0.90

Table IA.VI. CO_2 Emission on EMC PS, PE, and PCF Gap

This table presents the Poisson regression results of total CO_2 emission on price gaps defined by price-to-sales, price-to-earnings and price-to-cashflow. Panel A reports results for public firms and Panel B for matched private firms. *EMC Price Gap* is the average price gap over the past year in the country/area. Columns (1) to (3), (4) to (6), and (7) to (9) define *EMC Price Gap* as the value-weighted average price-to-sales, price-to-earnings, and price-to-cashflows of emission firms net of the value-weighted average of non-emission firms in the country/area, respectively. *S1tot*, *S2tot*, and *S3tot* are the scope 1, scope 2, and scope 3 CO_2 emissions (in million tons). *Emission* is an indicator of high-emission industries based on IPCC's categorization. Control variables in Panel A consist of firm-level price ratios, *Log Total Assets*, *Book Leverage*, *Cash/Total Assets*, and *ROE*. Institutional ownership, ESG disclosure mandates, and their interaction terms with *Emission* are also included. Control variables in Panel B are firm revenue, ESG disclosure mandate and its interaction term with *Emission*. The sample includes the 26 markets listed in Table IA.I from 2007 to 2021. Standard errors are clustered by firm, and reported in parentheses. $^{*}p < .1;^{**}p < .05;^{***}p < .01$.

Panel A: Public Firms

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
		PS			PE			PCF	
	S1tot	S2tot	S3tot	S1tot	S2tot	S3tot	S1tot	S2tot	S3tot
Emission×EMC Price Gap	0.067***	0.027***	0.033***	0.010***	0.002	0.003*	0.031***	0.007***	0.007***
	(0.018)	(0.010)	(0.007)	(0.003)	(0.002)	(0.002)	(0.005)	(0.002)	(0.002)
Controls	Full	Full	Full	Full	Full	Full	Full	Full	Full
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country×Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	88572	88666	88697	74044	74114	74142	75840	75918	75949
Pseudo R^2	0.822	0.446	0.614	0.821	0.438	0.608	0.820	0.440	0.607

Panel B: Private Firms

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	PS			PE			PCF		
	S1tot	S2tot	S3tot	S1tot	S2tot	S3tot	S1tot	S2tot	S3tot
Emission×EMC Price Gap	-0.048*	-0.103***	-0.056**	-0.008**	-0.015**	-0.004	-0.004	-0.046***	-0.018**
	(0.029)	(0.035)	(0.028)	(0.004)	(0.006)	(0.004)	(0.018)	(0.016)	(0.009)
Controls	Revenue	Revenue	Revenue	Revenue	Revenue	Revenue	Revenue	Revenue	Revenue
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country×Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	62442	62442	62442	62442	62442	62442	62442	62442	62442
Pseudo R^2	0.624	0.435	0.669	0.624	0.435	0.669	0.624	0.435	0.669

Table IA.VII. CO_2 Emission and Firm-level Valuation Shock: Non-emission Firms

This table presents the IV estimation of CO_2 emission on price ratios for non-emission firms. Column (1) shows the first stage result; Columns (2)–(5) show the second stage results of the IV estimation. *Log PB* is the log of one plus price-to-book. *Natural Disasters* is the number of natural disasters occurring in a country-year-quarter. Δ*S1tot*, Δ*S2tot*, and Δ*S3tot* are the differences between public firms and their matched private firms of *S1tot*, *S2tot* and *S3tot* respectively. Control variables consist of *Log Total Assets*, *Book Leverage*, *Cash/Total Assets*, and *ROE*. Institutional ownership, ESG disclosure mandates, and their interaction terms with *Emission* are also included. The sample includes the 26 markets listed in Online Appendix Table IA.I from 2007Q1 to 2021Q4. The Kleibergen-Paap F statistic for the first stage is reported in column (1). Standard errors are clustered by firm, and reported in parentheses. $^{*}p < .1;^{**}p < .05;^{***}p < .01$.

	(1)	(2)	(3)	(4)
	1st Stage	2nd Stage		
	Log PB	ΔS1tot	ΔS2tot	ΔS3tot
Natural Disasters	-0.004			
	(0.005)			
Log PB		2.809	1.661	6.467
		(3.151)	(1.774)	(6.929)
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
Obs.	55280	55091	55278	55280
Kleibergen-Paap F	0.891			

Table IA.VIII. CO_2 Emission and Firm-level PS, PE and PCF Shocks: Emission Firms

This table presents the IV estimation of CO_2 emission on price ratios (defined by PS, PE and PCF) for emission firms. Columns (1), (5) and (9) show the first stage results; Columns (2)–(4), (6)–(8) and (10)–(12) show the second stage results of IV estimations. *Log PS*, *Log PE* and *Log PCF* are the log of one plus price-to-book, price-to-sales, price-to-earnings, and price-to-cashflow. *Natural Disasters* is the number of natural disasters that happen in a country-year-quarter. Δ*S1tot*, Δ*S2tot*, and Δ*S3tot* are the differences between public firms and their matched private firms of *S1tot*, *S2tot* and *S3tot* respectively. Control variables consist of *Log Total Assets*, *Book Leverage*, *Cash/Total Assets*, and *ROE*. Institutional ownership, ESG disclosure mandates, and their interaction terms with *Emission* are also included. The sample includes the 26 markets listed in Table IA.I from 2007Q1 to 2021Q4. The Kleibergen-Paap F statistics for the first stage are reported. Standard errors are clustered by firm, and reported in parentheses. $^{*}p < .1;^{**}p < .05;^{***}p < .01$.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	PS				PE				PCF			
Natural Disasters	-0.017***				-0.051***				-0.042***			
	(0.006)				(0.010)				(0.010)			
Log Price Ratio		2.280**	0.758***	2.057**		0.837**	0.267***	0.728***		1.068**	0.298***	0.814***
		(1.090)	(0.287)	(0.828)		(0.329)	(0.071)	(0.204)		(0.466)	(0.095)	(0.262)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	29986	29980	29978	29986	24168	24162	24160	24168	25819	25813	25813	25819
Kleibergen-Paap F	8.523				25.347				17.580			

Table IA.IX. Green Patent Ratios and Price Gap

This table reports the regression results of green patent ratios on price gap. The dependent variable, *Green Ratio (%)*, is the proportion of green patents that the firm files in the year-quarter. Columns (1)–(4) are for public firms and columns (5)–(8) are for matched private firms. *EMC Price Gap* is the value-weighted average price-to-book gap between emission and non-emission firms over the past four quarters (in columns (1)–(2) and (5)–(6)) or twelve quarters (in columns (3)–(4) and (7)–(8)). Control variables for public firms consist of firm-level *PB*, *Log Total Assets*, *Book Leverage*, *Cash/Total Assets*, and *ROE*. Institutional ownership, ESG disclosure mandates, and their interaction terms with *Emission* are also included. Control variables for private firms are *Log Total Assets*, ESG disclosure mandate and its interaction term with *Emission*. The sample includes the 26 markets listed in Table IA.I from 2011Q1 to 2018Q4. Standard errors are clustered by firm, and reported in parentheses. $^{*}p < .1$;$^{**}p < .05$;$^{***}p < .01$.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Public Firms				Private Firms			
	One Year		Three Years		One Year		Three Years	
EMC Price Gap	0.118		0.068		-0.112		0.138	
	(0.099)		(0.135)		(0.167)		(0.214)	
Emission×EMC Price Gap	-0.235**	-0.239*	-0.440***	-0.431**	-0.077	-0.047	-0.237	-0.191
	(0.119)	(0.123)	(0.169)	(0.175)	(0.210)	(0.210)	(0.296)	(0.296)
Controls	Full	Full	Full	Full	AT	AT	AT	AT
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes		Yes		Yes		Yes	
Country×Year-Quarter FE		Yes		Yes		Yes		Yes
Obs.	98849	98803	98849	98803	180835	180800	180835	180800
Adj. R^2	0.319	0.319	0.319	0.319	0.470	0.472	0.470	0.472

Table IA.X. Green Patents and Firm-level Valuation Shock: Non-emission Firms

This table reports the IV estimations of green patents on price ratios for non-emission firms. Columns (1) and (3) show the first stage results; Columns (2) and (4) show the second stage results of IV estimations. *Natural Disasters* is the number of natural disasters that happen in a country in the past four quarters (in columns (1)–(2)) or twelve quarters (in columns (3)–(4)). *Log PB* is the average log P/B in the past four or twelve quarters accordingly. $\Delta Green$ is the difference between public firms and their matched private firms of the number of green patents. Control variables consist of *Log Total Patents*, *Log Total Assets*, *Book Leverage*, *Cash/Total Assets*, and *ROE*. Institutional ownership, ESG disclosure mandates, and their interaction terms with *Emission* are also included. The sample includes the 26 markets listed in Online Appendix Table IA.I from 2011Q1 to 2018Q4. The Kleibergen-Paap F statistics for the first stage are reported in columns (1) and (3). Standard errors are clustered by firm, and reported in parentheses. $^{*}p < .1;^{**}p < .05;^{***}p < .01$.

	(1)	(2)	(3)	(4)
	One Year		Three Years	
	1st Stage	2nd Stage	1st Stage	2nd Stage
	Log PB	ΔGreen	Log PB	ΔGreen
Natural Disasters	0.017**		-0.014	
	(0.007)		(0.015)	
Log PB		0.792		-0.241
		(0.606)		(2.413)
Controls	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Obs.	52806	52806	45050	45050
Kleibergen-Paap F	5.380		0.840	

Table IA.XI. CO_2 Intensity and Price Gap

This table presents the Poisson regression results of CO_2 intensity on price gaps. Panel A reports results for public firms and Panel B for matched private firms. *EMC Price Gap* is the average price gap over the past year in the country/area. Columns (1) to (3), (4) to (6), (7) to (9), and (10) to (12) define *EMC Price Gap* as the value-weighted average price-to-book, price-to-sales, price-to-earnings, and price-to-cashflows of emission firms net of the value-weighted average of non-emission firms in the country/area, respectively. *S1int*, *S2int*, and *S3int* are total scope 1, scope 2 and scope 3 CO_2 emissions over total revenues. *Emission* is an indicator of high-emission industries based on IPCC's categorization. Control variables in Panel A consist of firm-level price ratios, *Log Total Assets*, *Book Leverage*, *Cash/Total Assets*, and *ROE*. Institutional ownership, ESG disclosure mandates, and their interaction terms with *Emission* are also included. Control variables in Panel B are firm revenue, ESG disclosure mandate and its interaction term with *Emission*. The sample includes the 26 markets listed in Table IA.I from 2007 to 2021. Standard errors are clustered by firm, and reported in parentheses. $^{*}p < .1$;$^{**}p < .05$;$^{***}p < .01$.

Panel A: Public Firms

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	PB			PS			PE			PCF		
	S1int	S2int	S3int	S1int	S2int	S3int	S1int	S2int	S3int	S1int	S2int	S3int
Emission×EMC Price Gap	-0.001	0.000	-0.004	0.001	0.020***	0.002	0.002	0.000	0.000	0.002	0.002*	-0.000
	(0.023)	(0.012)	(0.005)	(0.013)	(0.005)	(0.002)	(0.002)	(0.001)	(0.000)	(0.004)	(0.001)	(0.000)
Controls	Full	Full	Full	Full	Full	Full	Full	Full	Full	Full	Full	Full
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country×Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	87451	87548	87581	88566	88666	88697	74039	74114	74142	75835	75918	75949
Pseudo R^2	0.955	0.845	0.928	0.956	0.844	0.928	0.958	0.847	0.933	0.958	0.851	0.932

Panel B: Private Firms

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	PB			PS			PE			PCF		
	S1int	S2int	S3int	S1int	S2int	S3int	S1int	S2int	S3int	S1int	S2int	S3int
Emission×EMC Price Gap	0.014	0.014	0.002	0.005	-0.001	-0.002	-0.006	0.001	-0.000	-0.012	-0.013*	0.000
	(0.016)	(0.018)	(0.006)	(0.017)	(0.008)	(0.003)	(0.004)	(0.002)	(0.000)	(0.009)	(0.007)	(0.001)
Controls	Revenue	Revenue	Revenue	Revenue	Revenue	Revenue	Revenue	Revenue	Revenue	Revenue	Revenue	Revenue
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country×Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	62442	62442	62442	62442	62442	62442	62442	62442	62442	62442	62442	62442
Pseudo R^2	0.979	0.863	0.920	0.979	0.863	0.920	0.979	0.863	0.920	0.979	0.863	0.920

Table IA.XII. CO_2 Intensity and Price Gap: Hartzmark and Shue (2023) Replication

This table presents regression results of CO_2 intensity on price gaps for US and global public firms. Panel A reports results for US public firms and Panel B for global public firms. Column (1) replicates Hartzmark and Shue (2023) and uses the change in *S12int* as the dependent variable. Column (2) changes the dependent variable to *S12int*. Both columns (1) and (2) use simple linear model. Column (3) is similar to column (2) except that column (3) uses Poisson regression. Column (4) add firm fixed effects to the model in column (3). *EMC Price Gap* is the average price-to-book of emission firms net of the value-weighted average of non-emission firms in the country/area over the past year. *S12int* is the total scope 1 and 2 CO_2 emissions over total revenues. *Emission* is an indicator of high-emission industries based on IPCC's categorization. Control variables consist of firm-level price ratios, *Log Total Assets*, *Book Leverage*, *Cash/Total Assets*, and *ROE*. Institutional ownership, ESG disclosure mandates, and their interaction terms with *Emission* are also included. The sample is from 2007 to 2021. The sample in Panel B includes the 26 markets listed in Table IA.I. Standard errors are clustered by firm, and reported in parentheses. $^{*}p < .1$;$^{**}p < .05$;$^{***}p < .01$.

Panel A: US Firms

	(1)	(2)	(3)	(4)
	Linear		Poisson	
	Chg. S12int	S12int	S12int	S12int
Emission×EMC Price Gap	-6.426***	69.769***	0.125**	0.118***
	(1.147)	(14.394)	(0.050)	(0.042)
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	
Firm FE				Yes
Obs.	18225	18225	18225	18225
Adj. R^2	0.043	0.598		
Pseudo R^2			0.780	0.950

Panel B: Global Firms

	(1)	(2)	(3)	(4)
	Linear		Poisson	
	Chg. S12int	S12int	S12int	S12int
EMC Price Gap	-1.602*	3.840	-0.019	-0.022
	(0.881)	(6.261)	(0.027)	(0.016)
Emission×EMC Price Gap	-3.297***	0.478	0.023	0.016
	(0.980)	(10.038)	(0.031)	(0.017)
Controls	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	
Country FE	Yes	Yes	Yes	
Firm FE				Yes
Obs.	75861	75861	75861	75861
Adj. R^2	0.009	0.397		
Pseudo R^2			0.701	0.947

Table IA.XIII. Trends of Institutional and Retail Ownership

This table presents the trends of institutional and retail ownership for emission vs. non-emission firms. *Post2015* equals one starting in 2015Q4 and equals zero before. *Retail and Inst. Ownership (%)*, *Retail Ownership (%)*, *IO(%)* are ownership by retail and institutional investors, retail investors, and institutional investors. *IO(%)* is divided into ownership by domestic institutions *Domestic IO(%)* and foreign institutions *Foreign IO(%)*. *Emission* is an indicator of high-emission industries based on IPCC's categorization. Control variables consist of *Log Total Assets*, *Book Leverage*, *Cash/Total Assets*, and *ROE*. The sample includes the 26 markets listed in Table IA.I from 2007Q1 to 2020Q4. Standard errors are clustered by firm and by year-quarter, and reported in parentheses. $^{*}p < .1$;$^{**}p < .05$;$^{***}p < .01$.

	(1)	(2)	(3)	(4)	(5)	(6)
	Retail and Inst. Ownership(%)		Retail Ownership(%)	IO(%)	Domestic IO(%)	Foreign IO(%)
Emission×Post2015	-1.172***	-0.855***	-0.678**	-0.177	-0.127	-0.051
	(0.281)	(0.303)	(0.314)	(0.137)	(0.121)	(0.055)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes					
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Country×Year-Quarter FE		Yes	Yes	Yes	Yes	Yes
Obs.	1229379	1229379	1229379	1229379	1229379	1229379
Adj. R^2	0.613	0.622	0.693	0.851	0.849	0.743

Table IA.XIV. Institutional and Retail Ownership and Natural Disasters

This table presents the results of regressing ownership on *Natural Disasters*. *Retail and Inst. Ownership (%)*, *Retail Ownership (%)*, *IO(%)* are ownership by retail and institutional investors, retail investors, and institutional investors. *IO(%)* is divided into ownership by domestic institutions *Domestic IO(%)* and foreign institutions *Foreign IO(%)*. *Emission* is an indicator of high-emission industries based on IPCC's categorization. *Natural Disasters* is the number of natural disasters that happen in a country-year-quarter. Control variables consist of *Log Total Assets*, *Book Leverage*, *Cash/Total Assets*, and *ROE*. The sample includes the 26 markets listed in Table IA.I from 2007Q1 to 2020Q4. Standard errors are clustered by firm and by year-quarter, and reported in parentheses. $^{*}p < .1;^{**} p < .05;^{***} p < .01$.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Retail and Inst. Ownership(%)			Retail Ownership(%)	IO(%)	Domestic IO(%)	Foreign IO(%)
Natural Disasters	-0.107						
	(0.161)						
Emission×Natural Disasters	-0.533***	-0.544***	-0.433***	-0.224	-0.209**	-0.200***	-0.009
	(0.120)	(0.116)	(0.146)	(0.161)	(0.080)	(0.071)	(0.022)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes						
Country×Year-Quarter FE		Yes	Yes	Yes	Yes	Yes	Yes
Emission×Year-Quarter FE			Yes				
Obs.	1229379	1229379	1229379	1229379	1229379	1229379	1229379
Adj. R^2	0.613	0.622	0.622	0.693	0.851	0.849	0.743

Table IA.XV. CO_2 Emission, Price Gap and Carbon Divestment

This table presents the Poisson regression results of total CO_2 emission on price gap and carbon divestment. Columns (1)–(3) are for public firms and columns (4)–(6) are for matched private firms. *EMC Price Gap* is the value-weighted average price-to-book gap between emission and non-emission firms over the past year in the country/area. *EMC Ownership Gap* is calculated as the value weighted average institution and retail ownership on emission firms net of the average ownership on non-emission firms in the country/area. *S1tot*, *S2tot*, and *S3tot* are the scope 1, scope 2, and scope 3 CO_2 emissions (in million tons). *Emission* is an indicator of high-emission industries based on IPCC's categorization. Control variables for public firms consist of firm-level price-to-book ratio, *Log Total Assets*, *Book Leverage*, *Cash/Total Assets*, and *ROE*. Institutional ownership, ESG disclosure mandates, and their interaction terms with *Emission* are also included. Control variables for private firms are firm revenue, ESG disclosure mandate and its interaction term with *Emission*. The sample includes the 26 markets listed in Table IA.I from 2007 to 2021. Standard errors are clustered by firm, and reported in parentheses. $^{*}p < .1$;$^{**}p < .05$;$^{***}p < .01$.

	(1)	(2)	(3)	(4)	(5)	(6)
	Public Firms			Private Firms		
	S1tot	S2tot	S3tot	S1tot	S2tot	S3tot
Emission×EMC Price Gap	0.157***	0.028	0.057***	-0.076	-0.183**	-0.034
	(0.037)	(0.018)	(0.013)	(0.048)	(0.080)	(0.057)
Emission×EMC Ownership Gap	1.389	-0.251	-0.876***	0.208	-0.009	-0.639
	(0.847)	(0.391)	(0.235)	(1.464)	(0.710)	(0.542)
Controls	Full	Full	Full	Revenue	Revenue	Revenue
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Country×Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	87457	87548	87581	62442	62442	62442
Pseudo R^2	0.823	0.448	0.616	0.624	0.435	0.669

Table IA.XVI. Green Patents, Price Gap and Carbon Divestment

This table reports the Poisson regression results of green patents on price gap and carbon divestment. Columns (1)–(4) are for public firms and columns (5)–(8) are for matched private firms. *EMC Price Gap* is the value-weighted average price-to-book gap between emission and non-emission firms over the past four quarters (in columns (1)–(2) and (5)–(6)) or twelve quarters (in columns (3)–(4) and (7)–(8)). *EMC Ownership Gap* is calculated as the value weighted average institution and retail ownership on emission firms net of the average ownership on non-emission firms in the country/area. The dependent variables are *Green*, the number of green patents that the firm files in the year-quarter. Control variables for public firms consist of *Log Total Patents*, firm-level *PB*, *Log Total Assets*, *Book Leverage*, *Cash/Total Assets*, and *ROE*. Institutional ownership, ESG disclosure mandates, and their interaction terms with *Emission* are also included. Control variables for private firms are *Log Total Patents*, *Log Total Assets*, ESG disclosure mandate and its interaction term with *Emission*. The sample includes the 26 markets listed in Table IA.I from 2011Q1 to 2018Q4. Standard errors are clustered by firm, and reported in parentheses. $^{*}p < .1;^{**}p < .05;^{***}p < .01$.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Public Firms				Private Firms			
	One Year		Three Years		One Year		Three Years	
EMC Price Gap	0.056		0.100		-0.173**		-0.201**	
	(0.098)		(0.140)		(0.070)		(0.093)	
Emission×EMC Price Gap	-0.204*	-0.186***	-0.216	-0.288**	0.064	-0.004	-0.008	-0.023
	(0.106)	(0.071)	(0.148)	(0.112)	(0.082)	(0.078)	(0.110)	(0.127)
EMC Ownership Gap	-0.141		3.548		0.485		-0.316	
	(2.708)		(5.006)		(1.812)		(3.482)	
Emission×EMC Ownership Gap	-1.046	-1.696	-8.128	-5.015	-0.379	-1.642	-0.182	0.060
	(2.785)	(2.095)	(5.050)	(4.666)	(1.949)	(2.371)	(3.568)	(4.507)
Controls	Full	Full	Full	Full	AT	AT	AT	AT
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes		Yes		Yes		Yes	
Country×Year-Quarter FE		Yes		Yes		Yes		Yes
Obs.	52267	50874	52267	50874	90208	88063	90208	88063
Pseudo R^2	0.814	0.819	0.814	0.819	0.817	0.823	0.817	0.823