Understanding the Pricing of Carbon Emissions: New Evidence from the Stock Market[*]

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Abstract

Are carbon emissions priced in equity markets? The literature is split with different approaches yielding conflicting results. We develop a stylized model showing that, if emissions are priced, stock returns depend on expected emissions and the product of the innovation in emissions and the price-dividend ratio. Building on this insight, we derive and test new predictions. We find that emissions are priced in equity markets, but the magnitude of such pricing is highly sensitive to the inclusion of a few "super emitters" (mostly operating in electric power generation). Our theoretical insight also helps reconcile seemingly divergent results in the literature.

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1 Introduction

Whether carbon emissions are priced in asset markets is crucial for understanding if, and how, financial markets incentivize the transition to a less carbonized economy. Carbon-emitting firms may face a higher cost of capital if carbon transition risks are priced into asset markets, or if investors who oppose emissions reduce their investment in polluting firms. Surprisingly, there is still no consensus on whether polluting firms are forced to pay a premium to raise capital in the stock market—with different empirical approaches yielding divergent results.

In this paper, we develop a stylized model and derive new predictions that we then test using data from the U.S. stock market. We document that firms' emissions intensity, defined as CO_2 emissions divided by revenues, is a positively priced characteristic. Our analysis also shows that several regressions used in the literature are mis-specified in a way that hinders the ability to find evidence of pricing for emissions intensity, thus reconciling divergent existing results. Finally, we show that the magnitude of the pricing depends on whether "super emitters"—mostly firms operating in electric power generation—are included in the estimation.

Our empirical analysis is based on a theoretical insight that we illustrate in an intuitive model. We build on the stylized fact that firms' emissions intensities are very persistent and well approximated by a random walk. Assuming, for simplicity, that emissions intensity is the only priced characteristic, we then use the log linear stock return decomposition in Campbell and Shiller (1988) and Campbell (1991) to show that expected stock returns are driven by (i) emissions intensity and (ii) the product of firms' long-run average price-dividend ratios with their emissions intensity surprises—which capture the sensitivity of firms' realized stock return to a permanent change in their future required stock return:

$$\overbrace{\underbrace{r_{i,t} - r_{f,t}}_{\text{Excess stock return}} = \gamma e_{i,t-1}}^{\text{Standard regression}} \overbrace{- \gamma \times \underbrace{(\overline{PD_i})}_{\text{Price-dividend ratio}} \times \underbrace{\left(e_{i,t} - e_{i,t-1}\right)}_{\substack{\text{Emissions intensity} \\ \text{surprises}}}}^{\text{Standard regression residual}},$$

where $e_{i,t}$ is emissions intensity of firm i at time t.

We use this pricing equation to derive five new testable predictions. First, a regression of excess stock return on *lagged* emissions intensity yields unbiased and consistent estimates. Second, a similar regression of excess stock return on *contemporaneous* emissions intensity suffers from measurement error (the regressor should be *expected* emissions intensity) and omitted variable (the regressor is correlated with the emissions intensity surprise in the regression residual) biases. Third, the omitted variable bias in the contemporaneous regression is more pronounced among firms with high price-dividend ratios as their stock prices (and returns) are more sensitive to changes in future required stock returns. Fourth, the omitted variable bias in the contemporaneous regression vanishes if the residual driven by the product of the long-term price-dividend ratio and emissions intensity surprise is included in the regression. Fifth, if the residual term and the lagged (instead of contemporaneous) emissions intensity are both included in the regression, the omitted variable bias and the measurement error vanish, and specific sign restrictions in the regression should be satisfied.

We test these five predictions by combining data on emissions from S&P Trucost with stock and firm information from CRSP and Compustat. Our empirical results are structured in five parts. First, we show that emissions intensity is priced in equity markets by estimating our preferred lagged specification: we regress, at an annual frequency, stock returns on lagged emissions intensity, together with a set of lagged firm-level controls.[1] Our sample initially excludes firms operating in "Electric Power Generation, Transmission and Distribution" to avoid fitting these few super emitters with all other firms in the same regression model. The evidence in support of emissions intensity being priced is robust to the inclusion of industry fixed effects, to the choice of control variables, and to the use of only observations based on firm-reported (instead of data vendor-estimated) emissions intensities. However, this regression is highly sensitive to the inclusion of super emitters. Specifically, we show that

[1]Our finding that emissions intensity is priced may stem from the portfolio choice of investors who oppose investing in polluting firms or from investors requiring compensation for transition risk. There is, of course, the third possibility that emissions intensity is correlated with firms' cash flows, which might, in turn, be associated with a cash flow risk premium. This possibility is unlikely to be a concern in our setting since the literature has shown (i) that emissions intensity is uncorrelated with firms' cash flows (Aswani et al., 2024) and earnings surprises (Atilgan et al., 2023), (ii) that green firms outperform brown firms when climate change concerns increase unexpectedly (Pastor et al., 2021), and (iii) that high unexpected changes in climate change concerns increase the discount factor of brown firms with no effect on cash flows (Ardia et al., 2023).

the magnitude and significance of the estimated coefficients on emissions intensity increase substantially as we progressively drop super emitters from the sample.

Second, our data supports the second prediction by showing that the estimation of a specification of stock return on *contemporaneous* emissions intensity yields small and statistically insignificant coefficients—consistent with the small and statistically insignificant estimates in Bolton and Kacperczyk (2021) and the often negative estimates in Aswani et al. (2024). According to our model, these coefficients are consistent with an attenuation bias that pushes the coefficient on emissions intensity towards zero due to measurement error, and to an omitted variable bias that pushes the coefficient on emissions intensity in a negative direction.

We then show that our third prediction is also verified in the data. Specifically, the downward bias of the emissions intensity coefficient in the contemporanous regression is particularly severe in the subsample of firms with large price-dividend ratios as these stocks are particularly sensitive to a permanent change in the required rate of return.

Third, we show evidence in support of the last two predictions. Specifically, we include the theoretically-derived omitted variables in the contemporaneous and lagged regressions, thus fixing the omitted variable bias in the former and both the omitted variable bias and measurement error in the latter. Our estimates support the theoretical prediction as the estimated coefficient on emissions intensity increases as we progressively fix the biases. The estimation results also confirm the sign restrictions predicted by our model.

Fourth, we show that our results are driven by the post-Climate Accord period and are less pronounced for large firms. The first result supports the interpretation that our estimates are driven by a pricing factor related to emissions intensity. The second result helps reconcile our findings with the no-pricing results in Zhang (2025): regressions are weighted by firm size in Zhang (2025), giving less importance to observations where we find the evidence for pricing to be the strongest.

Fifth, we show that the pricing of emissions intensity is *negative* for super emitters, in stark contrast with the rest of our sample. While a detailed analysis of super emitters is beyond the scope of this paper, our results are consistent with (i) emissions intensities being a noisy measure of "greenness" among super emitters (for which we provide supporting evidence) and (ii) a linear model being ill-suited to capture carbon pricing for these firms.

Our framework helps trace conflicting results in the literature back to specific modeling choices. Once the regressions are correctly specified, the evidence points at emissions intensity being a priced characteristic. Specifically, our results help reconcile the finding that emissions intensity affects institutional investors' demand (Pedersen et al., 2021) by amounts that are large enough to be priced (Bolton and Kacperczyk, 2021), but appear not to be priced (Bolton and Kacperczyk, 2021, 2023; Aswani et al., 2024). We also show that all studies based on regressing *monthly* excess stock return on *annual* emissions intensity (all studies that use annual emissions intensity data, to our knowledge) suffer from measurement error and omitted variable bias if investors learn about emissions intensity through the year but emissions intensities are reported only annually. We show that estimations that use annual return data can reduce these biases.

Related literature. Our paper is related to the literature on the asset pricing implications of climate risk and ESG investing—and particularly to the strand of this literature studying whether firms' emissions are priced in equity markets. Within this literature, our paper is closely related to papers that regress stock returns on measures of carbon emissions, controlling for other factors known to explain stock returns. These include Bolton and Kacperczyk (2021), Bolton and Kacperczyk (2023), Lioui and Misra (2023), Garvey et al. (2018), Zhang (2025), Pedersen et al. (2021), and Aswani et al. (2024).

As shown in Table 1, while all these papers run regressions of stock returns on a measure of emissions and several controls, they do so using different timing (contemporaneous versus lagged emissions measure), data sample, and emissions variable (emissions versus emissions intensity).[2] These discrepancies lead to different results, in terms of emissions variables positively or negatively affecting stock returns. For instance, Bolton and Kacperczyk (2021), Bolton and Kacperczyk (2023), and Lioui and Misra (2023) find that firms with higher

[2]While some of these papers consider several measures of emissions in their analysis, in this table "emissions variable" refers to the variable used for the main results of the corresponding paper.

Paper	Timing	Data	Emission variable	Relation
Bolton and Kacperczyk (2021)	Contemporaneous	2005–2017	Emissions level	Positive
Bolton and Kacperczyk (2023)	Lagged	2005–2018	Emissions level	Positive
Lioui and Misra (2023)	Lagged	2009–2024	Emissions intensity	Positive
Garvey et al. (2018)	Lagged	2011–2015	Emissions intensity	Negative
Zhang (2025)	Lagged	2009–2021	Emissions intensity	Negative
Pedersen et al. (2021)	Lagged	2009–2019	Emissions intensity	Negative
Aswani et al. (2024)	Contemporaneous	2005–2019	Emissions intensity	None

Table 1: Studies regressing stock returns on emission variables. This table compares papers regressing stock returns on emission variables across several dimensions: timing (contemporaneous versus lagged), data sample, emission variable (emissions versus emissions intensity), and effect of the emission variable on stock returns (positive or negative). Despite some general agreement on the most relevant controls, the set of control variables is also somewhat different across these studies.

emissions obtain higher stock returns, while Garvey et al. (2018), Zhang (2025), and Pedersen et al. (2021) find that firms with higher emissions achieve lower stock returns. Meanwhile, Aswani et al. (2024) finds no effect of emissions on stock returns.[3]

Our work is also related to papers that explore the impact of emissions on stock return using either different methodologies (such as forming portfolios of firms sorted by their emissions), alternative emission measurements (such as MSCI ESG ratings, sensitivity to climate news, industrial pollution measures, etc.), or alternative estimates of firms performance (such as estimates of the firm's required cost of capital).[4] Within this more general literature, results are not conclusive either. For instance, Alessi et al. (2020), Hsu et al. (2023) and Eskildsen et al. (2024) find that more polluting firms offer higher stock return, while In et al. (2019), Cheema-Fox et al. (2021), Giese et al. (2021), Huij et al. (2021), Ardia et al. (2023), Bauer

[3]Using panel regressions, Bolton and Kacperczyk (2021) and Bolton and Kacperczyk (2023) find that high-emissions firms face a higher cost of capital than low-emissions firms, while emissions intensity does not appear to affect the cost of capital. Aswani et al. (2024) and Zhang (2025) argue that the evidence that emissions are priced might (i) be the result of economic activity being priced (firms emit more carbon when producing more) and (ii) be affected by the use of low quality emissions data—as carbon emissions are often estimated by data vendors rather than reported by firms. In turn, Lioui and Misra (2023) emphasizes the important differences in constructing firm's portfolios that are value weighted, as in Zhang (2025), versus those that are sustainability weighted, as in Pastor et al. (2021) and Pastor et al. (2022).

[4]The ultimate goal of this literature is to estimate the impact of a measure of emissions on required stock returns (or required cost of capital). While many papers, including all papers in Table 1, use realized stock returns as a proxy for required stock returns like we do, some papers impose additional assumptions to estimate required stock returns as the specific ex-ante expected component of realized stock returns.

et al. (2022), Pastor et al. (2022), Berg et al. (2022), and Karolyi et al. (2023) find the opposite. Meanwhile, Görgen et al. (2020), Alves et al. (2023), and Lindsey et al. (2024) find no effect of pollution on firms' stock returns.

Closely related to our work, Gormsen et al. (2024) analyzes firms' investor calls and finds that green firms *perceive* their cost of capital to be lower since 2016. In their model, there is a cross-firm channel of capital reallocation from brown to green firms and a within-firm channel inducing all firms to use more green capital relative to brown capital. In turn, Hsu et al. (2023) shows that a long-short portfolio constructed from firms with high versus low toxic emissions intensity generates a positive risk-adjusted stock return, interpreted as evidence of a new systematic risk related to environmental policy uncertainty. In a recent paper, Berk and Van Binsbergen (2025) concludes that, at current participation levels, the divestiture strategy is unlikely to have a large impact on the long-term cost of capital of targeted firms. Hence, using primary markets would be a more effective strategy to affect social change. Finally, Hartzmark and Shue (2024) shows that increasing financing costs for brown firms leads to large negative changes in firms' environmental impact.

Our paper is the first one to derive a theoretically grounded equation relating the expected and unexpected components of emissions intensity to stock returns. The resulting regression specification shows that, if emissions intensity is priced, the sensitivity of firms' stock returns to innovations in emissions intensities is approximately proportional to firms' price-dividend ratios. This insight underpins our empirical tests and helps explain conflicting results in the literature by tracing them to specific modeling choices.

Outline. The remainder of the paper is organized as follows. Section 2 presents the theoretical framework relating carbon emissions intensity to required stock return, derives five predictions, and discusses how to reconcile the divergent results in the literature. Section 3 introduces our data and discusses a few facts about the distribution of emissions intensity. Section 4 tests our predictions in the context of the U.S. stock market. Section 5 concludes.

2 Theoretical framework

Our theoretical framework is structured in three parts. Section 2.1 presents a stylized model showing how investors' preferences (i) about the mean and variance of their wealth and (ii) about investing in stocks issued by CO_2 emitters affect firms' required and realized stock return. Building on these results, Section 2.2 derives a new equation relating emissions to firm's stock returns in the case emissions are priced in the stock market. Section 2.3 uses this derived relationship to propose new empirical predictions, which we then test in Section 4. Section 2.4 discusses how our theoretical framework helps reconcile seemingly divergent results in the literature.

2.1 Stylized model

Our setting focuses on investors' preferences and the timing of information on emissions.[5]

Timeline. There are four dates: $0, t, 1, 2$. At date 0, investors trade assets and form portfolios of risky assets (stocks) and one-period risk-free assets. At date $t < 1$, investors receive information on the emissions of the firms that issued the risky assets. At date 1, investors re-optimize their portfolios by trading risky and risk-free assets. At date 2, the assets are liquidated and investors consume.

Assets. The economy has an infinitely elastic supply of risk-free assets with gross return r_f between $t = 1$ and $t = 2$. In addition, there are N risky assets. Their supply is denoted by the $N \times 1$ vector $\bar{X}$, where the units of $\bar{X}$ are shares of stock. The risky assets can only be liquidated at date 2. At that time, their value is given by the $N \times 1$ vector v, which has a distribution $v \sim \mathcal{N}(\bar{v}, \Omega)$.

Investors. There are M investors indexed by $m = 1, \ldots M$. Investors choose their portfolios to maximize their utility over date-2 consumption and date-2 emissions. Investor m's vector

[5] For fuller asset pricing models, see Pastor et al. (2021), Pedersen et al. (2021), and Baker et al. (2022).

of risky asset holdings is denoted by X_m. Investors have mean-variance preferences over their date-2 consumption and have a non-pecuniary dislike for holding shares of firms with high emissions.[6] Specifically, the utility of investor m is:

$$U_m[W_{m,2}, \mathbb{E}(e_{m,t})] = \mathbb{E}(W_{m,2}) - \frac{1}{2}A_m Var(W_{m,2}) - \nu_m \mathbb{E}(e_{m,t}), \tag{1}$$

where $W_{m,2}$ is the wealth of investor m at $t = 2$, A_m is investor m's risk aversion, $\mathbb{E}(e_{m,t})$ is the expected emissions of investor m's investments, and ν_m is investor m's dislike for emissions. We assume that positive values of $e_{m,t}$ are associated with more pollution. Hence, negative values of $e_{m,t}$ (e.g., from shorting polluting firms) are desirable.

While our discussion often refers to $e_{m,t}$ as the "emissions" of investor m's portfolio, our entire analysis is based on firm-level emissions normalized by firm revenues—a measure often referred to as "emissions *intensity*" in the literature. Similarly, our empirical analysis in Sections 3 and 4 is entirely based on emissions intensities. For a discussion of how institutional investors use emissions intensities to build ESG portfolios, see Bolton and Kacperczyk (2021).[7]

We assume the expected emissions from an investor's holdings of asset i are equal to the number of shares the investor holds times firms' expected emissions per share (e_i). Aggregating across firms, the expected emissions of investor m's holdings are:

$$\mathbb{E}(e_{m,t}) = X'_m e,$$

where e is the $N \times 1$ vector of firms' emissions per share.

[6] Baker et al. (2022) shows how, despite the hedging benefits of polluting stocks, environmentalists underweight polluting stocks in equilibrium when (i) they coordinate to internalize pollution or (ii) when they have nonpecuniary disutility from holding polluting stocks. We follow assumption (ii) to induce environmentalists to underweight polluting stocks.

[7] In addition, Aswani et al. (2024) and Zhang (2025) both suggest that emissions intensity, rather than emissions, is the best measure of firms' propensity to pollute. By scaling emissions with a measure of economic activity (revenues), emissions intensity can be interpreted as a measure of the cleanness of a firm's technology.

Solving the model. The model is solved by backward induction from the portfolio choice problem at $t = 1$. At $t = 1$, investors solve

$$\max_{X_{m,1}, B_{m,1}} U_m[W_{m,2}, \mathbb{E}(e_m, t)]$$

subject to the identity

$$W_{m,2} = X'_{m,1} v + B_{1,m} r_f, \tag{2}$$

and subject to the budget constraint

$$X'_{m,1} P_1 + B_{1,m} = W_{1,m}, \tag{3}$$

where $B_{1,m}$ is investor m's allocation in the risk-free asset at $t = 1$, r_f is the risk-free asset gross return, P_1 is the vector of prices of the risky assets at $t = 1$, and $W_{1,m}$ is investor m's wealth at $t = 1$.

First, we solve for $B_{1,m}$ in (3) and plug it into (2). Second, we plug this expression into (1) and further simplify, thus rewriting the optimization problem for investor m as

$$\max_{X_{m,1}} r_f W_{1,m} + X'_{m,1}(\bar{v} - r_f P_1) - \frac{1}{2} A_m X'_{m,1} \Omega X_{m,1} - \nu_m X'_{m,1} e.$$

The first order condition for investor m is

$$X_{m,1} = \frac{1}{A_m} \Omega^{-1} (\bar{v} - \nu_m e - r_f P_1).$$

Note that, relative to a standard mean-variance problem, expected emissions alters $\bar{v}$ to $\bar{v} - \nu_m e$.

The market clearing condition requires the sum of investors' asset demands to equal the outstanding supply. Imposing market clearing yields

$$\sum_{m=1}^{M} \frac{1}{A_m} \Omega^{-1} (\bar{v} - \nu_m e - r_f P_1) = \bar{X},$$

where $\bar{X}$ is the vector of aggregate supply for each stock. Solving for the vector of prices of risky assets (P_1) yields

$$P_1 = \frac{1}{r_f}\left(\bar{v} - \frac{\Omega\bar{X} + e\sum_{m=1}^{M}\frac{\nu_m}{A_m}}{\sum_{m=1}^{M}\frac{1}{A_m}}\right). \tag{4}$$

We assume all elements of P_1 are positive. Under this assumption, the vector of gross expected returns on risky assets from $t = 1$ to $t = 2$, r_i, is

$$r_i = \bar{v}./P_1 = r_f\bar{v}./\left(\bar{v} - \frac{\Omega\bar{X} + e\sum_{m=1}^{M}\frac{\nu_m}{A_m}}{\sum_{m=1}^{M}\frac{1}{A_m}}\right), \tag{5}$$

where the expression "./" represents the element-by-element division of the two vectors. Furthermore, the assets' risk premium from $t = 1$ to $t = 2$, $r_i - r_f$, is given by

$$r_i - r_f = \bar{v}./P_1 - r_f = r_f\left[\bar{v}./\left(\bar{v} - \frac{\Omega\bar{X} + e\sum_{m=1}^{M}\frac{\nu_m}{A_m}}{\sum_{m=1}^{M}\frac{1}{A_m}}\right) - 1\right]. \tag{6}$$

Effect of news about emissions on equity prices and required returns. Our model generates two main insights. Suppose that, between $t = 0$ and $t = 1$, there is new information about higher emissions for asset i between $t = 1$ and $t = 2$. First, this news reduces the price of the asset at $t = 1$ (P_1) as shown in (4)—equivalently, this news lowers the *realized* stock return between $t = 0$ and $t = 1$ below what was expected at $t = 0$. Second, this news increases the asset's *required* stock return (r_i) and risk premium ($r_i - r_f$) between $t = 1$ and $t = 2$, as shown in (5) and (6), respectively. More generally, our model shows that news about an increase in expected emissions (i) reduces contemporaneous *realized* stock returns and (ii) increases *required* stock returns in future periods. The next section develops a few tests based on this intuition.[8]

[8]Imposing market clearing and simplifying, we find that the change in investors' holdings of risky assets at $t = 1$ due to a change in expected emissions is given by

$$dX_m = \frac{1}{A_m}\left(\frac{\sum_{s=1}^{M}\frac{\nu_s}{A_s}}{\sum_{s=1}^{M}\frac{1}{A_s}} - \nu_m\right)\Omega^{-1}de,$$

so that, given positive (negative) news about expected emissions, an investor increases (decrease) her allocation if her dislike for emissions (ν_m) is lower (higher) than a risk tolerance-weighted average of the dislike for emissions of all other investors in the economy.

2.2 Relating emissions and stock returns

We now derive how emissions are related to firm's stock returns when emissions are priced in the stock market. Our analysis begins with the decomposition of excess returns for risky asset i at time t into two components: (i) expected excess stock returns (i.e., required excess stock returns) conditional on time $t-1$ information and (ii) an innovation in excess stock returns based on information that arrives between $t-1$ and t

$$r_{i,t} - r_{f,t} = \mathbb{E}_{t-1}(r_{i,t} - r_{f,t}) + [\mathbb{E}_t - \mathbb{E}_{t-1}](r_{i,t} - r_{f,t}) \tag{7}$$

The first term on the right hand side shows that required stock returns between $t-1$ and t are based on time $t-1$ information. The second term is the innovation in stock returns. The Campbell (1991)'s log-linearization of the present value relationship shows that this second term is due to innovations in expected future required excess stock returns, expected future risk-free rates, and expected future dividend growth:

$$[\mathbb{E}_t - \mathbb{E}_{t-1}](r_{i,t} - r_{f,t}) \approx [\mathbb{E}_t - \mathbb{E}_{t-1}] \left[-\sum_{s=1}^{\infty} \rho_i^s (r_{i,t+s} - r_{f,t+s}) - \sum_{s=1}^{\infty} \rho_i^s r_{f,t+s} + \sum_{s=0}^{\infty} \rho_i^s g_{i,t+s} \right], \tag{8}$$

where ρ_i is a parameter of linearization (smaller than one) given by $e^{\bar{g}_i - \bar{r}_i}$ (where $\bar{g}_i$ is the average growth rate of firm $i's$ dividends, and $\bar{r}_i$ is the average expected future required stock return for firm i). The decomposition is broken into three terms. The first term shows that positive innovations in future risk premia negatively affect stock returns at time t. The second term shows that positive innovations in future one-year risk-free rates negatively affect contemporaneous stock returns. The third term shows that positive innovations in future dividend growth positively affect stock returns.

Our goal is to apply the insights in (7) and (8) in a simple setting where emissions is the only priced characteristic. To this end, we make a few assumptions.

Assumption 1.

$$\mathbb{E}_{t-1}(r_{i,t} - r_{f,t}) = \gamma \mathbb{E}_{t-1}[e_{i,t}] \quad \textit{with} \quad \gamma > 0.$$

This assumption states that firm i's required excess stock returns at time t depend on time $t-1$ beliefs about firm i's emissions at time t ($e_{i,t}$). This assumption also implies (i) that expected emissions are a positively priced characteristic ($\gamma > 0$) and (ii) that emissions is the only variable determining required stock returns—this strong part of the assumption is only for expositional purposes and we relax it in our empirical work (and could relax it in our theoretical work without altering the intuition).

Assumption 2.

$$e_{i,t}|I_{t-1} \sim N(e_{i,t-1}, \sigma_u^2) \qquad \forall t.$$

This assumption implies that emissions for each firm i follow a random walk

$$e_{i,t} = e_{i,t-1} + u_{i,t},$$

with the innovation $u_{i,t}$ distributed i.i.d. across firms, i.e., $u_{i,t} \sim N(0, \sigma_u^2)$.

We show in Appendix A that the random walk assumption is a reasonable approximation of the data when the first order autocorrelation of emissions intensity (our measure of emissions in the data) is close to 1. Using annual data, Zhang (2025) documents annual autocorrelation coefficients for emissions intensities of 0.99 for scope-1 emissions and 0.94 for scope-2 emissions. In addition, Bolton and Kacperczyk (2021) shows, using autoregressions, that emissions and emissions intensity are highly persistent.

As a final note, these two assumptions can be generalized to allow (i) for expected technical progress, which would correspond to a random walk with downward drift, and (ii) for innovations in emissions ($u_{i,t}$) to be heteroskedastic across firms or industries. Since these refinements do not qualitatively alter the derivations below, we do not explore them further.

Assumption 3. *r_f and and g_i are constant.*

This assumption is for simplicity in order to focus on emissions intensity in our theoretical analysis.

The last assumption and the law of iterated expectations imply:

$$(\mathbb{E}_t - \mathbb{E}_{t-1})e_{i,t+s} = e_{i,t} - e_{i,t-1}$$

for all $s \geq 0$. Applying this assumption together with Assumption 1, and using (8), yields

$$r_{i,t} - r_f = \gamma e_{i,t-1} - \gamma \left[\sum_{s=1}^{\infty} \rho_i^s \right] (e_{i,t} - e_{i,t-1}).$$

Using the Gordon Growth model, the term $\sum_{s=1}^{\infty} \rho_i^s = \frac{\rho_i}{1-\rho_i}$ is approximately equal to $\overline{PD_i}$, which is the long-run average price-dividend ratio for firm i.[9]

This algebra leads to the main theoretical result in this paper, which we highlighted in the introduction:

$$r_{i,t} - r_{f,t} = \gamma e_{i,t-1} - \gamma \ \overline{PD_i} \ (e_{i,t} - e_{i,t-1}). \tag{9}$$

Theoretically-derived equation. In our empirical analysis, we replace the unknown long-run average price-dividend ratio $\overline{PD_i}$ in equation (9) with an approximation based on the average of the price-dividend ratios at times $t-1$, $t-2$, and $t-3$.[10] To simplify, we label this approximation as $\left(\frac{P_{i,t-1}}{D_{i,t-1}}\right)$ in the expressions that follow, and treat the below expression that uses this approximation as the true theoretical equation that generates stock returns if emissions intensity is the only priced factor:

$$r_{i,t} - r_{f,t} = \gamma e_{i,t-1} - \gamma \left(\frac{P_{i,t-1}}{D_{i,t-1}}\right) (e_{i,t} - e_{i,t-1}). \tag{10}$$

This equation, a key part of our empirical analysis, shows how emissions approximately affect stock returns when (i) required returns are priced linearly, (ii) emissions follow a random walk (a reasonable approximation as previously discussed), and (iii) required excess stock returns during period t, $\mathbb{E}_{t-1}(r_{i,t} - r_{f,t})$, are only a function of variables known before

[9] More specifically:

$$\frac{\rho_i}{1-\rho_i} = \frac{e^{\bar{g}_i - \bar{r}_i}}{1 - e^{\bar{g}_i - \bar{r}_i}} = \frac{e^{\bar{g}_i}}{e^{\bar{r}_i} - e^{\bar{g}_i}} \approx \frac{1 + \bar{g}_i}{\bar{r}_i - \bar{g}_i} = \overline{PD_i},$$

where $\overline{PD_i}$ is the price-dividend ratio in the Gordon Growth model for a firm with constant dividend growth rate $\bar{g}_i$ and constant required stock return $\bar{r}_i$.

[10] The approximation for the price-dividend ratio is based on information known at time $t-1$ or earlier to avoid look-ahead bias in our empirical work.

period t.

The first term on the right hand side is the required return conditional on time $t-1$ information. The second term captures how the innovation in emissions during time t ($e_{i,t} - e_{i,t-1}$) affects contemporaneous stock returns—a positive innovation lowers contemporaneous stock returns. This insight is consistent with the Campbell (1991) equation and the second implication of our theoretical model illustrated at the end of Section 2.1. This equation also shows that the response to the innovation in emissions is proportional to firms' price-dividend ratios. This intuitive relationship originates from the sensitivity of stock returns to permanent changes in required stock returns being proportional to the price-dividend ratio in the Gordon Growth model. Note that firms with high price-dividend ratios have high dividend growth rates and/or low required stock returns—characteristics that make their stock prices more sensitive to changes in future required stock returns.

Equation (10) crucially relies on the assumption that the contemporaneous negative correlation between innovations in emissions and stock returns is driven only by news about discount rates. This assumption is consistent with the evidence found in Ardia et al. (2023), which empirically confirms the prediction in Pastor et al. (2021) that green firms outperform brown firms when climate change concerns increase unexpectedly. More importantly, Ardia et al. (2023) also finds that high unexpected changes in climate change concerns increase (decrease) the discount factor of brown (green) firms with no noticeable effect on cash flows. Also supporting this assumption, Atilgan et al. (2023) shows that emissions intensity is not a significant explanatory variable for earning surprises (a cash flow measure) but emissions (not normalized by firm revenues) and changes in emissions do explain earning surprises.

2.3 Five testable predictions

We now use the derived relationship between emissions intensity and excess stock returns to propose new ways to test whether emissions intensity is priced in equity markets.

Deriving new predictions. Recall that our theoretically derived equation (10) decomposes stock returns into an expected stock return component ($\gamma e_{i,t-1}$) and a residual component ($-\gamma(P_{i,t-1}/D_{i,t-1})(e_{i,t} - e_{i,t-1})$). Given that this residual component is uncorrelated with $e_{i,t-1}$

and has zero mean, an OLS regression of $r_{i,t} - r_{f,t}$ on $e_{i,t-1}$ yields unbiased and consistent estimates for γ. We refer to this specification as the "lagged" specification:

$$r_{i,t} - r_{f,t} = \alpha + \gamma e_{i,t-1} + \epsilon_{i,t}, \tag{11}$$

where the only regressor is emissions intensity in year $t-1$ (we will shortly motivate the choice of an *annual* frequency).

To derive additional predictions, we build on the following "contemporaneous" specification that is often used in the literature:

$$r_{i,t} - r_{f,t} = \alpha + \gamma e_{i,t} + \epsilon_{i,t}, \tag{12}$$

where the only regressor is emissions intensity in year t. For simplicity, we derive predictions when the regression is estimated by OLS in the cross-section. Assuming that the theoretically derived equation (10) is the true process through which stock returns are generated, the contemporaneous equation (12) is affected by both measurement error and omitted variable bias—the first shrinking the estimated coefficient γ towards 0 and the second shrinking it downward, potentially pushing it to negative values.

We now provide the intuition behind the measurement error and the omitted variable biases. The measurement error is classical. This is because the correct variable to use in equation (12) is $e_{i,t-1}$ instead of $e_{i,t}$, which is equal to the correct regressor plus noise:

$$e_{i,t} = e_{i,t-1} + u_{i,t}, \tag{13}$$

since emissions intensity is a random walk (Assumption 2). This classical measurement error shrinks the estimate of γ towards 0.

To provide intuition for the omitted variable bias, recall that the residual component in our theoretically derived equation (10) can be written as

$$\underbrace{\left[-\gamma \frac{P_{i,t-1}}{D_{i,t-1}}(e_{i,t} - e_{i,t-1})\right]}_{\text{Residual component in (10)}} = -\gamma \frac{P_{i,t-1}}{D_{i,t-1}} \times u_{i,t}. \tag{14}$$

Focusing only on a single firm i, the comparison of equations (13) and (14) shows that, conditional on time $t-1$ information, the regressor $e_{i,t}$ used in equation (12) covaries negatively with the residual in the correct theoretical equation:

$$\mathrm{Cov}_{t-1}\left(e_{i,t}, -\gamma\frac{P_{i,t-1}}{D_{i,t-1}} \times u_{i,t}\right) = -\gamma\frac{P_{i,t-1}}{D_{i,t-1}} \times \sigma_u^2. \tag{15}$$

The negative covariance between the regressor and the true residual biases the estimate of γ in equation (12) in a negative direction. The extent of the bias depends on the magnitude of firm i's price-dividend ratio. If the price-dividend ratio is large, the magnitude of the bias is also large. Hence, if emissions intensity is priced ($\gamma > 0$), an estimation of equation (12) using firms with high price-dividend ratios would be characterized by a large omitted variable bias. Conversely, the same estimation using firms with low price-dividend ratios would be characterized by a smaller omitted variable bias.

In Appendix B, we formalize these intuitions for measurement error and omitted variable bias for large samples when the contemporaneous equation (12) is estimated in a cross-sectional regression:

$$\text{plim } \hat{\gamma} = \gamma\left(\frac{\sigma_{e_{t-1}}^2}{\sigma_{e_{t-1}}^2 + \sigma_u^2}\right) - \gamma\left(\mathbb{E}\left(\frac{P_{i,t-1}}{D_{i,t-1}}\right)\frac{\sigma_u^2}{\sigma_{e_{t-1}}^2 + \sigma_u^2}\right), \tag{16}$$

where the first term is due to classical measurement error and the second term is due to omitted variable bias. In the expression for the omitted variable bias, $\mathbb{E}\left(\frac{P_{i,t-1}}{D_{i,t-1}}\right)$ is essentially the average price-dividend ratio among the sample of firms used in the regression, and shows that the omitted variable bias depends on this average.[11]

Having established the omitted variable bias, our analysis shows how we can fix it by adding $\left(\frac{P_{i,t-1}}{D_{i,t-1}}\right)(e_{i,t} - e_{i,t-1})$ as a regressor to the contemporaneous equation (12).

Five predictions. In sum, assuming that equation (10) is the true stock return generating process, our five predictions can be summarized as follows:

[11]The expressions σ_u^2 and $\sigma_{e_{t-1}}^2$ represent the cross-sectional variance of the innovation in emissions intensity during year t and the cross-sectional variance of emissions intensity at time $t-1$, respectively.

P1. The estimate of γ in the lagged equation (11) is unbiased and consistent.

P2. The estimate of γ in the contemporaneous equation (12) is biased towards 0 due to classical measurement error and downward biased due to omitted variable bias.

P3. The estimate of γ in the contemporaneous equation (12) increases in the subsample of observations with low (lagged) price-dividend ratios and decreases in the subsample of observations with high (lagged) price-dividend ratios.

P4. Adding $\left(\frac{P_{i,t-1}}{D_{i,t-1}}\right)(e_{i,t} - e_{i,t-1})$ as a regressor in the contemporaneous equation (12) eliminates the omitted variable bias, thus increasing the estimate of γ.

P5. The estimation of (10), written as

$$r_{i,t} - r_{f,t} = \alpha + \eta_1 e_{i,t-1} + \eta_2 \left(\frac{P_{i,t-1}}{D_{i,t-1}}\right) e_{i,t} + \eta_3 \left(\frac{P_{i,t-1}}{D_{i,t-1}}\right) e_{i,t-1},$$

yields the following parametric restrictions: (i) $\eta_1 > 0$, (ii) $\eta_2 < 0$, (iii) $\eta_3 > 0$, and (iv) $\eta_1 = -\eta_2 = \eta_3$. In addition, the coefficient on the lagged emissions intensity (η_1) is larger than the same coefficient on the contemporaneous regression in P4.

2.4 Interpreting results in the literature

Our theoretical framework, and the resulting testable predictions, help reconcile apparently conflicting results in the literature. Let's focus on two important specification choices adopted in existing empirical studies: (i) the use of the contemporaneous equation (12) and (ii) the use of *monthly* stock returns.

The contemporaneous regression is, as discussed, affected by measurement error and omitted variable bias that shrink the estimated coefficient on emissions toward zero, and potentially to negative values. This observation helps explain the small and statistically insignificant contemporaneous regression coefficients in Bolton and Kacperczyk (2021) and the often negative coefficient in Aswani et al. (2024).[12] Finally, the downward bias also helps reconcile the finding that the effect of divestment on carbon intensity does not seem to be priced even though its scale is large enough to move prices (Bolton and Kacperczyk, 2021).

Several papers (e.g., Bolton and Kacperczyk, 2021; Aswani et al., 2024) analyze whether emissions intensity (or emissions) is priced by estimating a specification where the dependent variable is *monthly* excess stock returns even though emissions are measured at an *annual* frequency. Specifically, the emissions variable for each month in a year is set to be (i) the same value as the emissions for that year in some specifications, (ii) the same value as the emissions for the previous year in others, or (iii) the same value as the emissions publicly released most recently (Zhang, 2025).[13] The higher frequency of stock returns compared with emissions creates two potential concerns. First, investors might receive other information about emissions at a higher frequency than annual, thus inducing a measurement error when using annual emissions repeated at a monthly frequency. This measurement error shrinks the estimated monthly coefficient γ toward zero. Second, year t emissions are not known to investors during year t but are correlated with what investors likely learn about emissions during the year. In other words, year t emissions are correlated with the innovation in emissions, creating an omitted variable problem—yet another source of downward bias in γ. In Appendix C, we show that both concerns can be fixed if the regressions are estimated using annual frequency data, as we do in our empirical analysis.[14]

In sum, measurement error and omitted variable bias help explain the often negative (or insignificant) findings in the literature on whether emissions intensity is priced in the stock

[12]Specifically, Table 8 in Aswani et al. (2024) shows the estimation of several variants of the contemporaneous regression. Two thirds of the estimated coefficients on emissions intensity are negative, and one third are negative and statistically significant.

[13]The controls in these regressions are measured at a monthly, quarterly, or annual frequency, depending on the paper. The dating of the controls is sometimes contemporaneous with the emissions, or alternatively lagged by one period, where a period corresponds to the frequency with which the control is measured.

[14]Specifically, we show that, even if investors learn about emissions intensity during the year, estimating the regressions with annual data overcomes the measurement error and omitted variable bias present in the monthly stock return regressions if (i) emissions intensity is a random walk and (ii) investors learn about emissions intensities for each year t by the end of year t. An additional reason for using annual frequency regressions is that investors' information on climate is incorporated into stock returns at a lower than monthly frequency for small firms (Pastor et al., 2022).

market. In Section 3 and Section 4, we test the five predictions developed in this section using annual stock returns.

3 Data and empirical facts about emissions

We now present our data and discuss some key summary statistics. Section 3.1 illustrates our main data sources and how we combine them to obtain our final data. Section 3.2 presents a set of summary statistics, mostly about emissions intensities across firms and industries.

3.1 Data

Our data set is the result of combining carbon emissions intensities from S&P Global Trucost, and stock returns and firm information from CRSP and Compustat, respectively.

Carbon emissions. Firm-level carbon emissions are obtained from S&P Trucost.[15] Trucost provides information at an annual frequency on firms' greenhouse gas (GHG) emissions, which Trucost obtains from publicly disclosed sources (e.g., annual reports) or, in absence of disclosures, from Trucost's proprietary input-output model.[16] Emissions are reported in absolute values (tonnes of carbon dioxide equivalent emissions, or tCO2e) and normalized by the company's annual consolidated revenues in millions of U.S. dollars (tCO2e/USD 1 million revenue). As discussed, we refer to this normalized measure as emissions *intensity*.

Following the Greenhouse Gas Protocol (available at `https://ghgprotocol.org`), Trucost distinguishes between three types of emissions. The definition provided by S&P is as follows. Scope-1 emissions are from directly emitting sources that are owned or controlled by a company. For example, scope-1 emissions include the emissions produced by the internal

[15]See `www.spglobal.com/spdji/en/documents/additional-material/faq-TruCost.pdf` for details about the data coverage, data collection, and variable definitions.

[16]According to Trucost, "Trucost's environmentally extended input-output (EEIO) model combines industry-specific environmental impact data with quantitative macroeconomic data on the flow of goods and services between different sectors in the economy." As we discuss later, our analysis is robust to the exclusion of observations estimated by Trucost.

combustion engines of a trucking company's trucking fleet. Scope-2 emissions are from the consumption of purchased electricity, steam, or other sources of energy generated upstream from a company's direct operations. Scope-3 emissions encompass all other emissions associated with a company's operations that are not directly owned or controlled by the company. Hence, scope-3 emissions include several sources of indirect emissions in both the company's supply chain and downstream from the company's owned or controlled operations. We follow the literature and focus our analysis on scope-1 and scope-2 emissions intensities.

Constructing our data. We combine data from three sources. First, we obtain firm-year emissions intensity data from S&P Trucost. Trucost's coverage begins in 2002 for large-cap companies and expands significantly from 2016 onward to include small- and mid-cap firms. We merge this data with the S&P Company Foundation file to obtain more detailed company and industry-level information. We restrict the sample to firms headquartered in the U.S. Additionally, we link the Trucost data with the Business Entity Cross Reference Service (BECRS) to obtain a company ID variable for further merging.

Second, we obtain stock prices from the CRSP monthly stock file. Using the Capital IQ link table, we match the company ID variable from BECRS to the corresponding GVKEY in CRSP.[17] From the effective month-year end date, we aggregate stock return data over the preceding 12 months. We calculate firm-level excess returns by subtracting the yield of a one-year zero coupon U.S. Treasury bond that matures at the end of the firm's fiscal year from one-year stock returns.[18] For each firm, we keep only common stocks. If a firm has multiple classes of common stocks, we keep the class with the highest number of shares outstanding. To maintain consistency in assigning stock returns to specific years, the year

[17] Note that Trucost reports emissions data based on fiscal year-end dates, which vary across firms and do not always align with the calendar year. To address this inconsistency, we define an effective month-year end date for each firm. If the fiscal year ends within the first 14 days of a month, we assign the previous month as the effective month-year end. Conversely, if the fiscal year ends within the second half of the month, we assign the current month as the effective month-year end. In our final sample, 18,418 of the 24,971 firm-year observations have the period end date in the second half of December, aligning with the calendar year. This subsample represents approximately 74% of the sample.

[18] The zero-coupon yields are from the Federal Reserve Board's website and are computed using the methodology in Gurkaynak et al. (2007).

variable for each observation is adjusted based on the effective month-year end date. If the month falls in the first half of the calendar year, the stock returns are assigned to the preceding year. Otherwise, they are assigned to the same calendar year. In sum, our yearly returns are based on fiscal years.

Third, we obtain firm-level financials from Compustat. We merge this data by matching on GVKEY and aligning with the year variable assigned to each firm's stock return aggregation.

Final data. Our final data set consists of an unbalanced panel of 24,971 observations featuring 3,125 firms across 22 industries (NAICS 2-digit codes) at an annual frequency from 2002 to 2023. The unit of observation is firm-year. The top-5 industries in terms of number of observations are (i) "Manufacturing A" (5,960 observations; 752 firms; NAICS code 33), (ii) "Professional, Scientific, and Technical Services" (2,932 observations; 642 firms; NAICS code 54), (iii) "Manufacturing B" (2,749 observations; 405 firms; NAICS code 32), (iv) "Information" (2,534 observations; 424 firms; NAICS code 51), and (v) "Mining, Quarrying, and Oil and Gas Extraction" (1,552 observations; 181 firms; NAICS code 21).[19] As mentioned before, the Trucost coverage increases substantially starting from 2016. The number of observations jumps from an average of 739 per year in 2010–15 to an average of 2,085 in 2016–21. See Table E.1 and Table E.2 for the annual breakdown of observations and the breakdown of observations across industries, respectively. Table E.3 shows the summary statistics of the main variables used in our empirical work.

[19] Note that the NAICS codes 32 and 33 both correspond to "Manufacturing." The NAICS code 32 is composed of the following industries: "Wood Product Manufacturing" (NAICS 321), "Paper Manufacturing" (NAICS 322), "Printing and Related Support Activities" (NAICS 323), "Petroleum and Coal Products Manufacturing" (NAICS 324), "Chemical Manufacturing" (NAICS 325), "Plastics and Rubber Products Manufacturing" (NAICS 326), and "Nonmetallic Mineral Product Manufacturing" (NAICS 327). The NAICS code 33 is composed of the following industries: "Primary Metal Manufacturing" (NAICS 331), "Fabricated Metal Product Manufacturing" (NAICS 332), "Machinery Manufacturing" (NAICS 333), "Computer and Electronic Product Manufacturing" (NAICS 334), "Electrical Equipment, Appliance, and Component" (NAICS 335), "Transportation Equipment Manufacturing" (NAICS 336), "Furniture and Related Product Manufacturing" (NAICS 337), and "Miscellaneous Manufacturing" (NAICS 339).

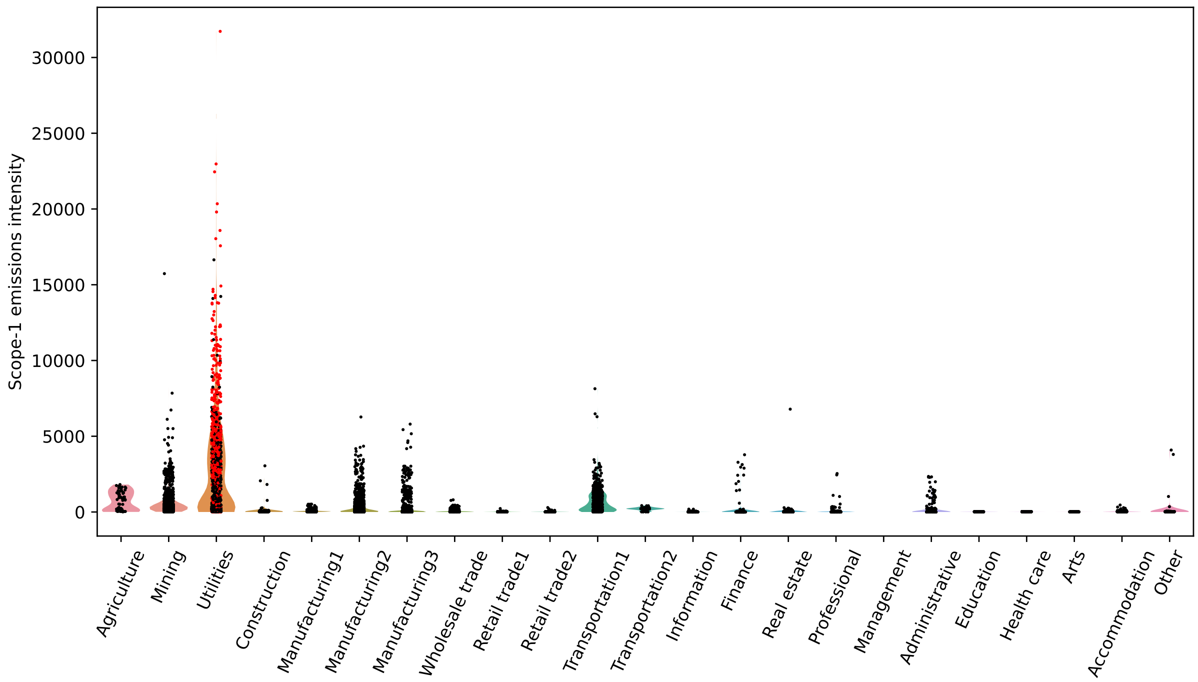

Figure 1: Large cross-sectional variation in scope-1 emissions intensities across and within industries. This figure shows the (within-industry and across-industry) cross-sectional variation in scope-1 emissions intensities from 2002 to 2023. Firm-year observations are grouped by their 2-digit NAICS code on the x-axis. The violin plots show the distribution of emissions intensities within each industry, where the width of the plot at a given value reflects the relative frequency of observations at that level. Each dot represents a firm-year observation, with red dots in "Utilities" highlighting firms in the "Electric Power Generation, Transmission and Distribution" subsector (NAICS code 2211).

3.2 Empirical facts about emissions

The distribution of emissions intensities across firms and across industries is very skewed with a few firms and a few industries responsible for a sizable share of emissions. Across industries, the most polluting ones are (i) "Utilities" (NAICS code 22), (ii) "Agriculture, Forestry, Fishing and Hunting" (NAICS code 11), (iii) "Transportation and Warehousing" (NAICS code 48), and (iv) "Mining, Quarrying, and Oil and Gas Extraction" (NAICS code 21). Specifically, the mean scope-1 emissions intensities, over the entire sample period for these four industries are 2,866, 725, 657, and 561, respectively. The contrast with the least polluting industries is staggering: "Information" (NAICS code 51) and "Finance and Insurance" (NAICS code 52) have mean scope-1 emissions intensities equal to 4.16 and 10.33, respectively. In the cross-section of industries, the distribution of mean industry-level scope-1 emissions intensities has a mean of 265, a median of 55, and a skewness of 3.6.

The large variation in emissions intensities is present also *within* industries, as documented in Figure 1. The figure shows, for each industry (2-digit NAICS code) on the x-axis, the distribution of firm-year observations in terms of their scope-1 emissions intensities. Utilities (NAICS code 22) has by far the largest cross-sectional variation in scope-1 emissions intensities. In addition to a few firm-year observations with emissions intensities above 20,000, this industry is characterized by both firms with high and low emissions intensities. Note that this industry is ranked only sixth in our data in terms of firm-year observations (1,220 observations), but is likely an important driver of any cross-sectional analysis of emissions intensity, even within industries. This observation is logical: "Utilities" is inherently an heterogenous industry, which includes "Water, Sewage and Other Systems" (NAICS code 2213) with median scope-1 emissions intensity of 100, "Natural Gas Distribution" (NAICS code 2212) with median scope-1 emissions intensity of 646, and "Electric Power Generation, Transmission and Distribution" (NAICS code 2211) with a staggering median scope-1 emissions intensity of 4,269. The red dots in the figure indicate the emissions intensities of firms operating in "Electric Power Generation, Transmission and Distribution."

4 Empirical evidence

We now show empirical evidence suggesting that carbon emissions intensity is priced in equity markets. Section 4.1 presents the estimation of our preferred specification. Section 4.2 shows that this estimation is highly sensitive to the inclusion of "super emitters"—observations characterized by very high values of emissions intensity, mostly by firms operating in "Electric Power Generation, Transmission, and Distribution." Section 4.3 presents additional results based on testing our theoretical predictions. Section 4.4 shows that our results are driven by the post-Climate Accord period and analyzes how the pricing varies across the firm size distribution. Finally, Section 4.5 shows that the pricing of carbon emissions is substantially different among super emitters.

4.1 Our preferred specification

Following our first prediction (P1), our preferred specification is based on the lagged equation (11) as follows:

$$R_{it} = \alpha + \boldsymbol{\beta}' \boldsymbol{X}_{it-1} + \mu_t + \epsilon_{it}, \tag{17}$$

where i is a firm and t is a year. The independent variable is the annual excess stock return of firm i over the one-year risk-free rate from the end of year $t-1$ to the end of year t. The vector $\boldsymbol{X}_{it-1}$ includes a set of firm-level variables, lagged by one year. The regression also includes time fixed effects (μ_t) for all specifications, and industry fixed effects (based on 2-digit NAICS codes) in some specifications. We cluster standard errors at the firm level.

The firm-level variables include firm-level emissions intensity, defined (i) as scope-1 emissions intensity or (ii) as the sum of scope-1 and scope-2 emissions intensities. The other firm-level variables are meant to capture the influence of other characteristics potentially correlated with both emissions intensity and stock returns. These firm-level controls included in the vector $\boldsymbol{X}_{it-1}$ are (i) the log of firm's market capitalization, (ii) firm's leverage (defined as total debt divided by total assets), (iii) firm's investments normalized by total assets, (iv) firm's stock return on equity (defined as net income divided by shareholders' equity), (v) the volatility of the firm's stock (defined as the standard deviation of monthly stock returns over a 12-month period), (vi) firm's beta (defined as the CAPM beta calculated over a 12-month period), and (vii) firm's book-to-market ratio.

While informed by economic theory, there is, of course, a degree of judgment in deciding which control variables to include in this regression. For this reason, we will check how our estimated coefficients of interest are robust to the inclusion of different control variables below. Finally, we estimate equation (17) in the sample of firms excluding firms operating in "Electric Power Generation, Transmission and Distribution." As shown in Figure 1, these firms tend to have extremely high emissions intensities that would be challenging to fit in the same linear regression model with firms with much lower emissions intensities. We discuss the role of these super emitters in Section 4.2 and Section 4.5.

The estimation results in Table 2 are structured as follows. The first three columns only

	R_{it}					
	(1)	(2)	(3)	(4)	(5)	(6)
Scope-1 emission$_{it-1}$		0.0996**			0.1548***	
		(0.0474)			(0.0521)	
Scope-1+Scope-2 emission$_{it-1}$			0.1080**			0.1620***
			(0.0460)			(0.0499)
MCAP$_{it-1}$	−0.1267	−0.1392	−0.1441	−0.1459	−0.1550	−0.1605
	(0.2308)	(0.2308)	(0.2309)	(0.2366)	(0.2365)	(0.2366)
LEV$_{it-1}$	−0.0020	−0.0025	−0.0026	−0.0023	−0.0024	−0.0025
	(0.0019)	(0.0019)	(0.0020)	(0.0022)	(0.0022)	(0.0022)
INVEST/A$_{it-1}$	−0.4488***	−0.4645***	−0.4677***	−0.4176***	−0.4167***	−0.4167***
	(0.0762)	(0.0771)	(0.0771)	(0.0916)	(0.0918)	(0.0918)
ROE$_{it-1}$	0.0415***	0.0415***	0.0415***	0.0395***	0.0394***	0.0394***
	(0.0078)	(0.0078)	(0.0078)	(0.0078)	(0.0078)	(0.0078)
VOL$_{it-1}$	−1.270	−1.251	−1.258	−0.9091	−0.9388	−0.9484
	(0.9024)	(0.9026)	(0.9024)	(0.9243)	(0.9238)	(0.9240)
BETA$_{it-1}$	0.8588***	0.8657***	0.8644***	0.7706**	0.7718**	0.7704**
	(0.3274)	(0.3274)	(0.3274)	(0.3298)	(0.3296)	(0.3296)
B/M$_{it-1}$	1.864**	1.638**	1.603*	1.826**	1.663*	1.633*
	(0.8236)	(0.8234)	(0.8245)	(0.8549)	(0.8499)	(0.8506)
Year FE	✓	✓	✓	✓	✓	✓
Industry FE				✓	✓	✓
Observations	22,225	22,225	22,225	22,225	22,225	22,225
R^2	0.2482	0.2484	0.2484	0.2500	0.2502	0.2503

Table 2: Effect of lagged emissions on stock returns. This table shows the estimation results of equation (17). The unit of observation is firm-year. The sample runs at an annual frequency from 2001 to 2023. The sample excludes observations of firms classified under "Electric Power Generation, Transmission and Distribution" (NAICS 2211). Scope-1 emission$_{it-1}$ and Scope-1+Scope-2 emission$_{it-1}$ are the lagged scope-1 emissions intensity and the sum of scope-1 and scope-2 emissions intensities, respectively. The reported coefficients on emissions intensities are multiplied by 100 for readability. The control variables are lagged by one year, winsorized at the 2nd and 98th percentiles, and defined as follows: MCAP$_{it-1}$ is log of market capitalization; LEV$_{it-1}$ is total debt divided by total assets; INVEST/A$_{it-1}$ is investment divided by total assets; ROE$_{it-1}$ is net income divided by shareholders' equity (multiplied by 100); VOL$_{it-1}$ is the standard deviation of monthly stock returns over a 12-month period; BETA$_{it-1}$ is the CAPM beta over a 12-month period; B/M$_{it-1}$ is the book-to-market ratio. Standard errors clustered at the firm level in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

include year fixed effects, while the last three columns include industry and year fixed effects. Columns (2) and (5) use scope-1 emissions intensity as a measure of firm-level emissions. Columns (3) and (6) use the sum of scope-1 and scope-2 emissions intensity as a measure of firm-level emissions. Finally, Columns (1) and (4) are estimated without firm-level emissions intensity.

The estimation results provide strong and robust evidence that emissions intensity is priced. This result (i) is robust to including, or not including, industry fixed effects, and (ii) survives in the subsample that excludes emissions estimated by Trucost using their proprietary input-output model (Table E.4). In sum, our results contrast with the empirical literature suggesting that evidence for pricing is fragile to whether emissions are reported by firms or estimated by data vendors and to whether industry fixed effects are included in the estimation (Aswani et al., 2024; Zhang, 2025). Table E.5 and Table E.6 show that the estimated coefficients are also remarkably stable as we progressively saturate the specification with control variables, adding them one by one.[20]

To provide an economic interpretation of our estimated coefficients, we compute, for each firm-year observation of emissions intensity, the required stock return associated with that level of emissions intensity. Figure F.1 shows the cumulative distribution function of these estimated required stock returns. The required stock returns for scope-1 emissions intensity are no more than 50 basis points per year for around 90% of the firm-year observations—and no more than 10 basis points per year for around 80% of firm-year observations. To compare these results with the literature, note that existing work often estimates a "greenium" as the cost of capital difference between "brown" and "green" firms (i.e., firms that have high and low emissions, respectively). For example, Gormsen et al. (2024)'s summary of the literature measures the greenium as the required return for firms with greenness one standard deviation below the median minus the required return for firms with greenness one standard deviation above the median. Based on this definition, our estimate is at about the 75^{th} percentile among the range of studies summarized.

4.2 Dealing with super emitters

We now show that the regression results discussed above are highly sensitive to the inclusion of observations of firms with very high emissions, which tend to operate in "Electric Power Generation, Transmission and Distribution." As prima facie evidence, Table E.7 shows a

[20]Specifically, Table E.5 shows the estimation results with industry-year fixed effects and Table E.6 shows the estimation results with year fixed effects. In each table, Panel A shows the coefficient stability for scope-1 emissions intensity and Panel B shows the coefficient stability for the sum of scope-1 and scope-2 emissions intensities. The number of observations in these tables diminishes as we add more control variables due to some missing values for the control variables. In unreported results, we confirm that the estimated coefficients on scope-1 emissions intensity and scope-1+scope-2 emissions intensity are virtually unchanged if we re-estimate these regressions in the subsample of observations where all control variables are non-missing.

PANEL A	R_{it} (1)	(2)	(3)	(4)
Scope-1 emission$_{it-1}$	−0.0066	0.0394	0.1168	0.4061
	(0.0269)	(0.0428)	(0.1023)	(0.2482)
Winsorization	None	2%	5%	10%
Controls	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Industry FE				
Observations	22,693	22,693	22,693	22,693
R^2	0.2507	0.2508	0.2508	0.2508

PANEL B	R_{it} (1)	(2)	(3)	(4)
Scope-1 emission$_{it-1}$	0.0220	0.1389***	0.3620***	1.327***
	(0.0356)	(0.0539)	(0.1225)	(0.3138)
Winsorization	None	2%	5%	10%
Controls	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓
Observations	22,693	22,693	22,693	22,693
R^2	0.2525	0.2526	0.2527	0.2530

Table 3: Effect of lagged emissions on stock returns, sensitivity with respect to winsorization of emissions intensity. This table shows the estimation results of specification (17). The unit of observation is firm-year. The sample runs annually from 2001 to 2023. Panel A includes only year fixed effects, while Panel B includes both year and industry fixed effects. Scope-1 emission$_{it-1}$ is the lagged scope-1 emissions intensity. The reported coefficients on emissions intensities are multiplied by 100 for readability. Emissions intensites are unwinsorized in Column (1), winsorized at the 2nd and 98th percentiles in Column (2), the 5th and 95th percentiles in Column (3), and the 10th and 90th percentiles in Column (4). The set of control variables included in our baseline specification are also included in these two panels but omitted for brevity. The control variables are lagged by one year, winsorized at the 2nd and 98th percentiles, and defined as follows: MCAP$_{it-1}$ is log of market capitalization; LEV$_{it-1}$ is total debt divided by total assets; INVEST/A$_{it-1}$ is investment divided by total assets; ROE$_{it-1}$ is net income divided by shareholders' equity (multiplied by 100); VOL$_{it-1}$ is the standard deviation of monthly stock returns over a 12-month period; BETA$_{it-1}$ is the CAPM beta over a 12-month period; B/M$_{it-1}$ is the book-to-market ratio. Standard errors clustered at the firm level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

version of Table 2 estimated over the full sample of firms, thus including these super emitters. The coefficients of interest are statistically insignificant and very close to zero.

Table 3 analyses this sensitivity in a more systematic way by showing the estimated coefficients on scope-1 emissions intensities in the full sample of firms (including super emitters) as the level of winsorization of this variable changes. Panel A focuses on the regressions with year fixed effects and Panel B focuses on the regressions with both year and industry fixed effects. The control variables are included in the estimation but omitted from the table for brevity. In each panel, Column (1) shows the results with no winsorization. Columns (2) to (4) consider winsorization levels at the 2 percent, 5 percent, and 10 percent level, respectively. The estimated coefficients and their statistical significance increase as the winsorization becomes more restrictive. Table E.8 shows consistent results for the sum of scope-1 and scope-2 emissions intensities.

Taken together, the results presented so far suggest that emissions intensity is likely priced in equity markets but the magnitude of such pricing is highly dependent on how super emitters are modeled. Section 4.5 shows that the pricing of carbon emissions is substantially different among super emitters compared with the rest of the firms in our sample. The analysis in Section 4.3 and Section 4.4 focuses, again, on the sample of firms excluding super emitters.

4.3 Testing more model predictions

We now test the last four predictions from our theoretical framework.

P2: Attenuated coefficient in a contemporaneous regression. Our second prediction is based on the contemporaneous equation (12), i.e., the regression of period-t stock returns on period-t emissions intensity. Our theoretical discussion points out that this specification is affected by measurement error and omitted variable bias. The former attenuates the estimated coefficient on emissions toward zero. The latter is negative, pulling the estimated coefficient on emissions toward zero, and even potentially to a negative value.

Table 4 shows the estimation of this contemporaneous specification that is often used in the literature.The estimated coefficients on emissions intensity are small and not statistically significant, a result holding regardless of the level of fixed effects and regardless of the definition used to measure firm-level emissions (scope-1 vs. sum of scope-1 and scope-2). This result is in line with the small and statistically insignificant estimates in Bolton and Kacperczyk (2021) and the often negative estimates in Aswani et al. (2024).

	R_{it}					
	(1)	(2)	(3)	(4)	(5)	(6)
Scope-1 emission$_{it}$		0.0320			0.0627	
		(0.0542)			(0.0617)	
Scope-1+Scope-2 emission$_{it}$			0.0338			0.0637
			(0.0498)			(0.0555)
MCAP$_{it-1}$	−0.2750	−0.2791	−0.2808	−0.2991	−0.3033	−0.3057
	(0.2393)	(0.2396)	(0.2398)	(0.2454)	(0.2455)	(0.2456)
LEV$_{it-1}$	−0.0017	−0.0019	−0.0019	−0.0022	−0.0022	−0.0022
	(0.0020)	(0.0021)	(0.0021)	(0.0023)	(0.0024)	(0.0024)
INVEST/A$_{it-1}$	−0.4094***	−0.4146***	−0.4156***	−0.3784***	−0.3791***	−0.3793***
	(0.0784)	(0.0794)	(0.0795)	(0.0936)	(0.0938)	(0.0938)
ROE$_{it-1}$	0.0463***	0.0464***	0.0464***	0.0445***	0.0445***	0.0445***
	(0.0087)	(0.0087)	(0.0087)	(0.0087)	(0.0087)	(0.0087)
VOL$_{it-1}$	−0.2397	−0.2352	−0.2386	0.0250	0.0081	0.0026
	(0.9644)	(0.9646)	(0.9644)	(0.9882)	(0.9886)	(0.9890)
BETA$_{it-1}$	0.8180**	0.8206**	0.8206**	0.7635**	0.7651**	0.7652**
	(0.3410)	(0.3411)	(0.3411)	(0.3443)	(0.3443)	(0.3443)
B/M$_{it-1}$	1.769**	1.701*	1.692*	1.689*	1.628*	1.618*
	(0.8627)	(0.8715)	(0.8719)	(0.8951)	(0.8950)	(0.8956)
Year FE	✓	✓	✓	✓	✓	✓
Industry FE				✓	✓	✓
Observations	21,034	21,034	21,034	21,034	21,034	21,034
R^2	0.2454	0.2454	0.2454	0.2468	0.2468	0.2468

Table 4: Effect of contemporaneous emissions on stock returns. This table shows the estimation results of equation (17) but with contemporaneous, not lagged, emissions intensity. The unit of observation is firm-year. The sample runs at at annual frequency from 2001 to 2023. The sample excludes observations of firms classified under "Electric Power Generation, Transmission and Distribution" (NAICS 2211). Scope-1 emission$_{it}$ and Scope-1+Scope-2 emission$_{it}$ are the scope-1 emissions intensity and the sum of scope-1 and scope-2 emissions intensities, respectively. The reported coefficients on emissions intensities are multiplied by 100 for readability. The control variables are lagged by one year, winsorized at the 2nd and 98th percentiles, and defined as follows: MCAP$_{it-1}$ is log of market capitalization; LEV$_{it-1}$ is total debt divided by total assets; INVEST/A$_{it-1}$ is investment divided by total assets; ROE$_{it-1}$ is net income divided by shareholders' equity (multiplied by 100); VOL$_{it-1}$ is the standard deviation of monthly stock returns over a 12-month period; BETA$_{it-1}$ is the CAPM beta over a 12-month period; B/M$_{it-1}$ is the book-to-market ratio. Standard errors clustered at the firm level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

P3: The omitted variable bias varies across firms' price-dividend ratios. Our third test is based on the prediction that, if emissions intensity is priced, the omitted variable bias discussed above is more severe in the subsample of firms with larger price-dividend ratios, as these stocks are more sensitive to a permanent change in the required rate of return compared to stocks with low price-dividend ratios. As discussed, this prediction relies on the Gordon Growth model—or generalizations in the spirit of Campbell (1991) and Campbell and Shiller (1988)—to produce reasonable approximations of the sensitivity of stock prices to required returns.

	R_{it}			
PANEL A: Below median PD	(1)	(2)	(3)	(4)
Scope-1 emission$_{it}$	0.1482***		0.1143*	
	(0.0569)		(0.0681)	
Scope-1+Scope-2 emission$_{it}$		0.1489***		0.1182*
		(0.0551)		(0.0653)
Controls	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Industry FE			✓	✓
Observations	5,444	5,444	5,444	5,444
R^2	0.4118	0.4119	0.4154	0.4155

	R_{it}			
PANEL B: Above median PD	(1)	(2)	(3)	(4)
Scope-1 emission$_{it}$	−0.1662		−0.1605	
	(0.1104)		(0.1087)	
Scope-1+Scope-2 emission$_{it}$		−0.1723*		−0.1715*
		(0.1000)		(0.0983)
Controls	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Industry FE			✓	✓
Observations	5,444	5,444	5,444	5,444
R^2	0.3940	0.3940	0.3972	0.3973

PANEL C: Coefficient Test ($H_A : \beta_{\text{below median PD}} < \beta_{\text{above median PD}}$)				
Z-statistic industry clustering	1.7804**	1.8612**	1.4718*	1.6061*
p-value industry clustering	(0.0375)	(0.0314)	(0.0705)	(0.0541)
Z-statistic firm clustering	2.6597***	2.9691***	2.2668**	2.6122***
p-value firm clustering	(0.0039)	(0.0015)	(0.0117)	(0.0045)
Z-statistic time-industry clustering	1.6582**	1.7198**	1.5015*	1.6365**
p-value time-industry clustering	(0.0486)	(0.0427)	(0.0666)	(0.0509)
Z-statistic time-firm clustering	2.1685**	2.3165***	2.3228***	2.5514***
p-value time-firm clustering	(0.0151)	(0.0103)	(0.0101)	(0.0054)

Table 5: Effect of contemporaneous emissions intensity on stock returns, subsamples of below median and above median price-dividend ratio. This table shows the estimation results of specification (17) but with contemporaneous, not lagged, emissions intensity. The unit of observation is firm-year. The sample runs annually from 2001 to 2023. The sample excludes observations of firms classified under "Electric Power Generation, Transmission and Distribution" (NAICS 2211). For each year, firms data are split into subsamples based on whether their price-dividend ratios for that year are above or below the median for that year. Panel A only uses data for the below median price-dividend ratio subsample. Panel B only uses data for the above median price-dividend ratio subsample. The price-dividend ratio of firm i at time t is calculated as the average of the price-dividend ratios at time $t-1$, $t-2$, and $t-3$, respectively. Scope-1 emission$_{it}$ and Scope-1+Scope-2 emission$_{it}$ are the scope-1 emissions intensity and the sum of scope-1 and scope-2 emissions intensities, respectively. The reported coefficients on emissions intensities are multiplied by 100 for readability. The set of control variables included in our baseline specification are also included in these two panels but omitted for brevity. The control variables are lagged by one year, winsorized at the 2nd and 98th percentiles, and defined as follows: MCAP$_{it-1}$ is log of market capitalization; LEV$_{it-1}$ is total debt divided by total assets; INVEST/A$_{it-1}$ is investment divided by total assets; ROE$_{it-1}$ is net income divided by shareholders' equity (multiplied by 100); VOL$_{it-1}$ is the standard deviation of monthly stock returns over a 12-month period; BETA$_{it-1}$ is the CAPM beta over a 12-month period; B/M$_{it-1}$ is the book-to-market ratio. Panel C tests that the difference of the coefficients in Panels A and B is greater than 0 (with four different assumptions about standard errors as discussed in Appendix D). Standard errors clustered at the firm level are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

To test this prediction, we compute price-dividend ratios for each of our firm-year observations using data on dividends paid on common shares. Specifically, to limit the importance of outliers, for each firm i at each date t, we compute the price-dividend ratio as the average of the price-dividend ratios at times $t-1$, $t-2$, and $t-3$.[21] We can compute such ratios for around half of our observations as a large number of firm-year observations are characterized by zero dividends (and a much smaller number of observations have missing dividends). We refer to the subsample with firm-year observations that allow the calculation of price-dividend ratios as the "price-dividend sample." We divide this sample into (i) a subsample of observations with below median price-dividend ratios and (ii) a subsample of observations with above median price-dividend ratios, where medians are calculated in the cross-section of firms every year. Panels A and B in Table 5 show the estimation results in these two subsamples.[22]

Recall that the theory predicts that, if emissions intensity is priced, the contemporaneous regression suffers from omitted variable bias, and that such bias is less severe for the below median price-dividend ratio subsample and more severe for the above median price-dividend ratio subsample. The estimation results in Table 5 confirm this prediction. Every coefficient in Panel A is greater than the corresponding coefficient in Panel B. Furthermore, the theory predicts that a severe omitted variable bias can cause the estimated coefficients on emissions intensity to turn negative, as we observe in Panel B. Panel C shows that the difference

[21]There is an alternative justification for this approach. In our most general derivation of equation (10), the Campbell and Shiller (1988) log-linearization requires the use of the *long-run* average price-dividend ratio for each firm in our regressions. However, the use all our data to estimate this quantity would generate look-ahead bias (since some regressors for stock returns at time t would be based on information dated after time t). To avoid such bias, we estimate the price-dividend ratio for predicting stock returns at time t as a weighted average of price-dividend ratios dated before date t.

[22]By using the price-dividend ratios only to assign firms to subsamples, our Z-tests in Panel C are unlikely to be influenced by the price-dividend ratios being necessarily a noisy estimate of the long-run average price-dividend ratio that theory suggests we should use to sort firms into subsamples. To provide the intuition behind this claim, note that the difference in the regression coefficients from data subsample-A and data subsample-B is driven by the difference in the long-run average price-dividend ratios in each of the subsamples. If there is no noise in the estimated price-dividend ratios, the data are properly sorted into the two subsamples. Hypothetical noise can be problematic if it causes the composition of the subsamples to change in ways that substantially alter the true long-run average price-dividend ratio in each subsample. This possibility is unlikely because the firms that have the most influence on the average price-dividend ratios in each subsample are those with price-dividend ratios far from the median. Hence, these firms are the least likely to be reassigned to the other group due to noise.

between the coefficients in Panel A and Panel B is statistically greater than zero. To do so, we compute Z-statistics for the difference between the two sets of coefficients, estimating the covariance between the coefficients in Panels A and B allowing correlations across the parameter estimates in each subsample by industry, firm, time and industry, and firm and time.[23]

Taken together, these comparisons are consistent with our theory, supporting the interpretation that emissions intensity is priced.

P4: Addressing the omitted variable bias. We now test the fourth prediction of our model: if emissions intensity is priced, the omitted variable bias (but not the measurement error) in the contemporaneous regression is addressed by adding, as a regressor, the lagged price-dividend ratio interacted with the innovation in emissions intensity. The estimated coefficient on emissions intensity is expected to increase with this "fix."

Table 6 shows the estimation results. Consistent with the theory, the inclusion of the omitted variables raises the coefficients on emissions intensity compared with Table 4, although they do not reach statistical significance. We also observe that the price-dividend interaction terms have the predicted signs (more on this in our test of P5).

P5: Addressing the omitted variable bias and measurement error. Our final test mimics the previous estimation with one difference: we replace the contemporaneous un-interacted emissions intensity with the lagged emissions intensity. Our model suggests that, if emissions intensity is priced, this estimation solves both the omitted variable bias and the measurement error. In other words, we estimate equation (10).

Table 7 shows the estimation results. Consistent with the theory, the coefficient on the (now lagged) emissions intensity variable increases even more compared with the previous table and is now more statistically significant. Additionally, the coefficients on the interaction

[23]We allow correlations across the parameter estimates in each subsample and use clustering logic to capture the correlation. When we use clustering to capture the parameter correlations, for consistency, we also use it to capture parameter variances. See Appendix D for details.

	R_{it}			
	(1)	(2)	(3)	(4)
Scope-1 emission$_{it}$	0.0877	0.0634		
	(0.0628)	(0.0751)		
Scope-1 emission$_{it}$ × PD Ratio$_{it-1}$	−0.2371	−0.2234		
	(0.1886)	(0.1869)		
Scope-1 emission$_{it-1}$ × PD Ratio$_{it-1}$	0.2573	0.2537		
	(0.2030)	(0.2014)		
Scope-1+Scope-2 emission$_{it}$			0.0807	0.0557
			(0.0594)	(0.0706)
Scope-1+Scope-2 emission$_{it}$ × PD Ratio$_{it-1}$			−0.2082	−0.1962
			(0.1423)	(0.1409)
Scope-1+Scope-2 emission$_{it-1}$ × PD Ratio$_{it-1}$			0.2317	0.2296
			(0.1641)	(0.1634)
Controls	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Industry FE		✓		✓
Observations	10,637	10,637	10,637	10,637
R^2	0.3984	0.4006	0.3984	0.4006

Table 6: Estimation of equation (10) to address the omitted variable bias. This table shows the estimation results of equation (10), where the uninteracted emissions intensity is contemporaneous. The unit of observation is firm-year. The sample runs annually from 2001 to 2023. The sample excludes observations of firms classified under "Electric Power Generation, Transmission and Distribution" (NAICS 2211). The price-dividend ratio (PD Ratio) of firm i at time t is calculated as the average of the price-dividend ratios at time $t-1$, $t-2$, and $t-3$, respectively. We divide PD Ratio by 100 for readability. Scope-1 emission$_{it}$ and Scope-1+Scope-2 emission$_{it}$ are the scope-1 emissions intensity and the sum of scope-1 and scope-2 emissions intensities, respectively. The reported coefficients on emissions intensities are multiplied by 100 for readability. The set of control variables included in our baseline specification are included but omitted for brevity. The control variables are lagged by one year, winsorized at the 2nd and 98th percentiles, and defined as follows: MCAP$_{it-1}$ is log of market capitalization; LEV$_{it-1}$ is total debt divided by total assets; INVEST/A$_{it-1}$ is investment divided by total assets; ROE$_{it-1}$ is net income divided by shareholders' equity (multiplied by 100); VOL$_{it-1}$ is the standard deviation of monthly stock returns over a 12-month period; BETA$_{it-1}$ is the CAPM beta over a 12-month period; B/M$_{it-1}$ is the book-to-market ratio. Standard errors clustered at the firm level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

terms between price-dividend ratio and the contemporaneous and lagged emissions intensities continue to have the correct signs. Finally, the magnitude of the coefficients on the emissions intensity variables and the interaction terms are not statistically different, consistent with the fifth and last prediction of the model.

Taken together, the results in this section strongly support our theoretical predictions, suggesting that emissions intensity is a priced characteristics in the U.S. stock market.

	R_{it}			
	(1)	(2)	(3)	(4)
Scope-1 emission$_{it-1}$	0.0978**	0.0758		
	(0.0474)	(0.0538)		
Scope-1 emission$_{it}$ × PD Ratio$_{it-1}$	−0.1980	−0.1950		
	(0.1897)	(0.1898)		
Scope-1 emission$_{it-1}$ × PD Ratio$_{it-1}$	0.2150	0.2216		
	(0.2028)	(0.2033)		
Scope-1+Scope-2 emission$_{it-1}$			0.0946**	0.0726
			(0.0446)	(0.0503)
Scope-1+Scope-2 emission$_{it}$ × PD Ratio$_{it-1}$			−0.1759	−0.1737
			(0.1446)	(0.1443)
Scope-1+Scope-2 emission$_{it-1}$ × PD Ratio$_{it-1}$			0.1944	0.2016
			(0.1648)	(0.1656)
Controls	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Industry FE		✓		✓
Observations	10,637	10,637	10,637	10,637
R^2	0.3985	0.4006	0.3985	0.4006

Table 7: Estimation of equation (10) to address the omitted variable bias and measurement error. This table shows the estimation results of specification (10), where the uninteracted emissions intensity is lagged. The unit of observation is firm-year. The sample runs annually from 2001 to 2023. The sample excludes observations of firms classified under "Electric Power Generation, Transmission and Distribution" (NAICS 2211). The price-dividend ratio (PD Ratio) of firm i at time t is calculated as the average of the price-dividend ratios at time $t-1$, $t-2$, and $t-3$, respectively. Scope-1 emission$_{it-1}$ and Scope-1+Scope-2 emission$_{it-1}$ are the lagged scope-1 emissions intensity and the sum of scope-1 and scope-2 emissions intensities, respectively. The reported coefficients on emissions intensities are multiplied by 100 for readability. The set of control variables included in our baseline specification are included but omitted for brevity. The control variables are lagged by one year, winsorized at the 2nd and 98th percentiles, and defined as follows: MCAP$_{it-1}$ is log of market capitalization; LEV$_{it-1}$ is total debt divided by total assets; INVEST/A$_{it-1}$ is investment divided by total assets; ROE$_{it-1}$ is net income divided by shareholders' equity (multiplied by 100); VOL$_{it-1}$ is the standard deviation of monthly stock returns over a 12-month period; BETA$_{it-1}$ is the CAPM beta over a 12-month period; B/M$_{it-1}$ is the book-to-market ratio. Standard errors clustered at the firm level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

4.4 Additional results

We now present two additional results. First, we show that our results are driven by the post-Climate Accord period (supporting the interpretation that our results are driven by pricing related to CO_2). Second, we show how our results vary across the firm size distribution, reconciling our findings with Zhang (2025).

The first analysis examines whether emissions intensity is priced due to a potential correlation with some other non-CO_2 related priced factor (or characteristic) that is omitted from our regression. In that case, its pricing should be unrelated to an event that focused investors' attention on carbon emissions such as the 2015 Paris Climate Accord. To this end,

PANEL A: Period 2001–15	R_{it} (1)	(2)	(3)	(4)
Scope-1 emission$_{it-1}$	0.0212		0.0085	
	(0.0517)		(0.0586)	
Scope-1+Scope-2 emission$_{it-1}$		0.0250		0.0164
		(0.0511)		(0.0572)
Controls	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Industry FE			✓	✓
Observations	8,444	8,444	8,444	8,444
R^2	0.5143	0.5143	0.5174	0.5174

PANEL B: Period 2016–23	R_{it} (1)	(2)	(3)	(4)
Scope-1 emission$_{it-1}$	0.2215***		0.3148***	
	(0.0855)		(0.0968)	
Scope-1+Scope-2 emission$_{it-1}$		0.2204***		0.3050***
		(0.0774)		(0.0854)
Controls	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Industry FE			✓	✓
Observations	13,743	13,743	13,743	13,743
R^2	0.1001	0.1002	0.1031	0.1032

Table 8: Effect of lagged emissions intensity on stock returns, pre- vs. post-Paris Accord. This table shows the estimation results of specification (17). The unit of observation is firm-year. The sample runs at at annual frequency from 2001 to 2023. The sample excludes observations of firms classified under "Electric Power Generation, Transmission and Distribution" (NAICS 2211). Panel A includes observations in the sample period from 2001 to 2015, while Panel B includes observation in the sample period from 2016 to 2023. Scope-1 emission$_{it-1}$ and Scope-1+Scope-2 emission$_{it-1}$ are the lagged scope-1 emissions intensity and the sum of scope-1 and scope-2 emissions intensities, respectively. The reported coefficients on emissions intensities are multiplied by 100 for readability. The set of control variables included in our baseline specification are included in the specification but omitted for brevity. The control variables are lagged by one year, winsorized at the 2nd and 98th percentiles, and defined as follows: MCAP$_{it-1}$ is log of market capitalization; LEV$_{it-1}$ is total debt divided by total assets; INVEST/A$_{it-1}$ is investment divided by total assets; ROE$_{it-1}$ is net income divided by shareholders' equity (multiplied by 100); VOL$_{it-1}$ is the standard deviation of monthly stock returns over a 12-month period; BETA$_{it-1}$ is the CAPM beta over a 12-month period; B/M$_{it-1}$ is the book-to-market ratio. Standard errors clustered at the firm level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

we estimate equation (10) using data from the pre- and post-Paris Climate Accord period.

Table 8 shows that the pricing for emissions intensity using our full sample is driven by the post-Paris Accord data. During this most recent period, the effect of emissions intensity is larger than during the pre-Paris Accord period, and statistically significant for all of our specifications. In sum, these results suggest that emissions intensity is priced because it is related to climate and CO_2, and not because it is correlated with some omitted factor.

	R_{it}			
	(1)	(2)	(3)	(4)
Scope-1 emission$_{it-1}$ × Asset Q1$_{it-1}$	0.1843		0.2651*	
	(0.1368)		(0.1468)	
Scope-1 emission$_{it-1}$ × Asset Q2$_{it-1}$	0.1835		0.2270*	
	(0.1337)		(0.1365)	
Scope-1 emission$_{it-1}$ × Asset Q3$_{it-1}$	0.0653		0.1183	
	(0.0867)		(0.0864)	
Scope-1 emission$_{it-1}$ × Asset Q4$_{it-1}$	0.1466		0.2006*	
	(0.1131)		(0.1144)	
Scope-1 emission$_{it-1}$ × Asset Q5$_{it-1}$	−0.0060		0.0375	
	(0.0596)		(0.0607)	
Scope-1+Scope-2 emission$_{it-1}$ × Asset Q1$_{it-1}$		0.1958		0.2798*
		(0.1359)		(0.1461)
Scope-1+Scope-2 emission$_{it-1}$ × Asset Q2$_{it-1}$		0.2073		0.2556*
		(0.1322)		(0.1355)
Scope-1+Scope-2 emission$_{it-1}$ × Asset Q3$_{it-1}$		0.0710		0.1187
		(0.0824)		(0.0821)
Scope-1+Scope-2 emission$_{it-1}$ × Asset Q4$_{it-1}$		0.1490		0.2032*
		(0.1040)		(0.1048)
Scope-1+Scope-2 emission$_{it-1}$ × Asset Q5$_{it-1}$		0.0031		0.0454
		(0.0566)		(0.0587)
Controls	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Industry FE			✓	✓
Observations	22,225	22,225	22,225	22,225
R^2	0.2485	0.2485	0.2503	0.2504

Table 9: Effect of lagged emissions intensity on stock returns, firm asset size quintile interactions. This table shows the estimation results of specification (17), augmented with interactions with size quintiles. Firm size quintiles are calculated yearly in the cross-section of firms using asset size (variable "act" in Compustat). Asset Q1$_{it-1}$ is the lowest quintile and Asset Q5$_{it-1}$ is the highest quintile. The sample runs at at annual frequency from 2001 to 2023. The sample excludes observations of firms classified under "Electric Power Generation, Transmission and Distribution" (NAICS 2211). Scope-1 emission$_{it-1}$ and Scope-1+Scope-2 emission$_{it-1}$ are the lagged scope-1 emissions intensity and the sum of scope-1 and scope-2 emissions intensities, respectively. The reported coefficients on emissions intensities are multiplied by 100 for readability. The set of control variables included in our baseline specification are included but omitted for brevity. The control variables are lagged by one year, winsorized at the 2nd and 98th percentiles, and defined as follows: MCAP$_{it-1}$ is log of market capitalization; LEV$_{it-1}$ is total debt divided by total assets; INVEST/A$_{it-1}$ is investment divided by total assets; ROE$_{it-1}$ is net income divided by shareholders' equity (multiplied by 100); VOL$_{it-1}$ is the standard deviation of monthly stock returns over a 12-month period; BETA$_{it-1}$ is the CAPM beta over a 12-month period; B/M$_{it-1}$ is the book-to-market ratio. Standard errors clustered at the firm level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

The second analysis examines how the pricing varies across the firm size distribution, reconciling our findings with Zhang (2025), which estimates a specification similar to equation (17) (e.g., Table 6 in Zhang (2025)) but finds that emissions intensity is not priced, or is priced negatively. Two important differences in our specifications likely drive our contrasting results. First, we use lagged emissions intensity instead of lagged *log* emissions intensity as a regressor. Logs impose a particular functional form on the relationship between emissions intensity and required stock returns for both low- and very-high-emissions-intensity firms. Given that the theoretical motivation for using log as a functional form is unclear, we use a more flexible approach. Second, regressions are weighted by firm size in Zhang (2025), effectively down-weighting the effects of small firms. We do not weight by firm size (i) as we are interested in understanding how emissions intensity affects the cost of capital for firms of *all* sizes, (ii) as doing so may reduce the precision of the regression estimates (e.g., weighting increases standard errors in the case of homoskedasticity), and (iii) as pricing effects are more likely to be found in thinly traded and less widely held stocks.

To investigate the role of firm size on pricing, we regress stock returns on emissions intensity interacted with firm size quintile dummies, dropping again firms operating in "Electric Power Generation, Transmission and Distribution" from the sample. This specification allows us to examine whether firms of different sizes face different costs of capital due to their emissions intensity. The point estimates in Table 9 suggest that emissions intensity is particularly priced in the smallest two quintiles and such pricing is much weaker, or non-existent, in the top quintile. These results suggest that the regressions in Zhang (2025) might be weighted toward firms with weaker pricing of emissions.

Overall, the two additional results presented in this section suggest that emissions intensity is not spuriously priced due to a correlation with an omitted factor and that such pricing is more pronounced for smaller firms—which, to our knowledge, is a new stylized fact.

4.5 Emissions pricing among super emitters

Up till now, our empirical analysis has focused on firms excluding super emitters, namely firms operating in "Electric Power Generation, Transmission and Distribution" (NAICS code 2211). Our decision to exclude these firms is based on Figure 1, which documents that the emissions intensities of super emitters are extreme outliers and thus unlikely to be accurately modeled using a linear specification.

While a detailed analysis of super emitters is beyond the scope of this paper (we also

	R_{it}					
	(1)	(2)	(3)	(4)	(5)	(6)
Scope-1 emission$_{it-1}$		-0.0712^{*}			-0.0712^{*}	
		(0.0406)			(0.0406)	
Scope-1+Scope-2 emission$_{it-1}$			-0.0725^{*}			-0.0725^{*}
			(0.0404)			(0.0404)
MCAP$_{it-1}$	1.850^{*}	2.024^{*}	2.031^{*}	1.850^{*}	2.024^{*}	2.031^{*}
	(0.9821)	(1.034)	(1.034)	(0.9821)	(1.034)	(1.034)
LEV$_{it-1}$	0.0052	0.0049	0.0048	0.0052	0.0049	0.0048
	(0.0079)	(0.0075)	(0.0074)	(0.0079)	(0.0075)	(0.0074)
INVEST/A$_{it-1}$	0.3556	0.3439	0.3478	0.3556	0.3439	0.3478
	(0.4008)	(0.4182)	(0.4189)	(0.4008)	(0.4182)	(0.4189)
ROE$_{it-1}$	−0.0534	−0.0791	−0.0795	−0.0534	−0.0791	−0.0795
	(0.1562)	(0.1446)	(0.1446)	(0.1562)	(0.1446)	(0.1446)
VOL$_{it-1}$	7.663	6.769	6.749	7.663	6.769	6.749
	(5.806)	(5.520)	(5.512)	(5.806)	(5.520)	(5.512)
BETA$_{it-1}$	1.104	1.264	1.262	1.104	1.264	1.262
	(2.066)	(2.079)	(2.078)	(2.066)	(2.079)	(2.078)
B/M$_{it-1}$	−0.6054	1.006	1.049	−0.6054	1.006	1.049
	(4.859)	(4.095)	(4.089)	(4.859)	(4.095)	(4.089)
Year FE	✓	✓	✓	✓	✓	✓
Industry FE				✓	✓	✓
Observations	468	468	468	468	468	468
R^2	0.6648	0.6703	0.6705	0.6648	0.6703	0.6705

Table 10: Effect of lagged emissions on stock returns subsample of "Electric Power Generation, Transmission and Distribution" firms. This table shows the estimation results of equation (17). The unit of observation is firm-year. The sample runs at an annual frequency from 2001 to 2023. The sample includes only observations of firms classified under "Electric Power Generation, Transmission and Distribution" (NAICS 2211). Scope-1 emission$_{it-1}$ and Scope-1+Scope-2 emission$_{it-1}$ are the lagged scope-1 emissions intensity and the sum of scope-1 and scope-2 emissions intensities, respectively. The reported coefficients on emissions intensities are multiplied by 100 for readability. The control variables are lagged by one year, winsorized at the 2nd and 98th percentiles, and defined as follows: MCAP$_{it-1}$ is log of market capitalization; LEV$_{it-1}$ is total debt divided by total assets; INVEST/A$_{it-1}$ is investment divided by total assets; ROE$_{it-1}$ is net income divided by shareholders' equity (multiplied by 100); VOL$_{it-1}$ is the standard deviation of monthly stock returns over a 12-month period; BETA$_{it-1}$ is the CAPM beta over a 12-month period; B/M$_{it-1}$ is the book-to-market ratio. Standard errors clustered at the firm level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

lack statistical power), we now show that the pricing of carbon emissions is substantially different within this group of firms and discuss potential explanations for such empirical pattern. Table 10 shows the estimation results of our preferred specification (specification (17)) in the subsample of super emitters. The estimated coefficients on emissions intensities are *negative*, in stark contrast with the estimation presented in Table 2.

These estimations may be the result of emissions intensity being a noisy—and possibly misleading—proxy for greenness among super emitters. To illustrate the issue, recall that we measure scope-1 emissions in units of carbon emissions per dollar of revenues (i.e., per dollar

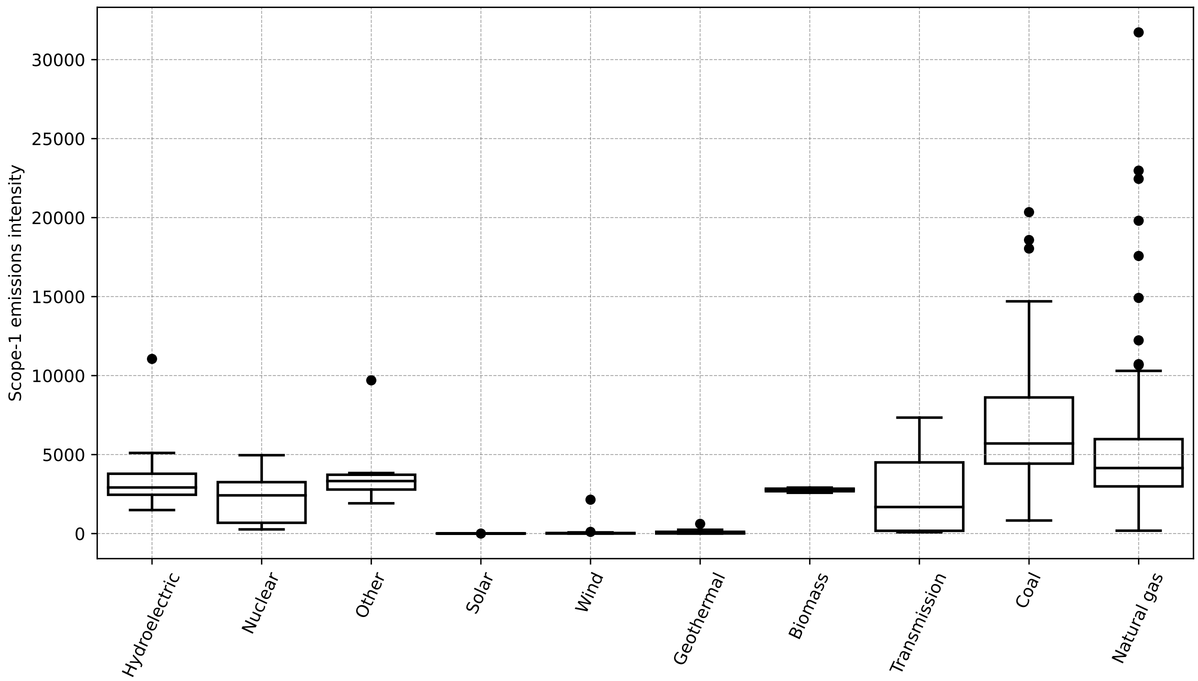

Figure 2: Variation in scope-1 emissions intensities within the "Electric Power Generation, Transmission and Distribution" sector. This figure shows the within-industry cross-sectional variation in scope-1 emissions intensities from 2002 to 2023 for firms in the "Electric Power Generation, Transmission and Distribution" sector. Firm-year observations are grouped by sub-industry (6-digit NAICS code) on the x-axis. The box plots show the distribution of scope-1 emissions intensities within each sub-industry.

value of output). As such, emissions intensity might not be a good measure of greenness for industries that produce homogeneous goods using technologies with significantly different costs and, consequently, potentially different prices. As shown in Figure 2, electricity producers fall in this category as they use very different technologies to produce a homogeneous good.

As an example, consider two electricity producers. Utility A emits 1 pound of CO_2 per kilowatt hour (kwh) of electricity production; Utility B emits 1/2 pound of CO_2 per kwh of electricity production. They both set their prices to be just enough to cover their costs. Utility A charges \$0.10 per kwh (its emissions intensity is $\frac{\text{emissions/kwh}}{\text{revenue/kwh}} = 1/.1 = 10$). Utility B charges \$0.01 per kwh (its emissions intensity is $0.5/.01 = 50$). Note that A has a lower emissions intensity than B even though B is *greener* than A. In sum, by using the price of the electricity sold to measure output, emissions intensity understates the greenness of low-cost electricity producers.

Figure 2 suggests that emissions intensity may severely mismeasure greenness among super emitters. The average emissions intensity for electrical generation from coal is 10%

higher than that from natural gas. By contrast, the U.S. Energy Information Administration estimated that, in 2023, electricity production from coal generated more than double the CO_2 emissions per kwh than electricity production from natural gas—a *tenfold* difference compared with the assessment based on emissions intensity.[24] Finally, note that the highest emissions intensities in our entire sample are for electrical generation using natural gas, raising the concern that such emissions intensities might be misleading.

There is yet another reason why emissions intensity may fail to reflect the greenness of super emitters accurately: emissions intensity ignores differences across firms' divisions. For example, Gormsen et al. (2024) documents how the largest energy and utility firms have different perceived costs of capital for their brown and green divisions (e.g., a division using fossil fuels vs. a division using renewables), suggesting that a single firm-wide emissions intensity does not accurately capture its greenness.

In sum, the relationship between greenness and emissions intensity may be particularly noisy among super emitters, which helps explain why the pricing of carbon emissions is substantially different within this group of firms.

5 Conclusion

Financial markets can play an important role in helping the productive sector reduce its carbon emissions. The idea is intuitive. Polluting firms that pay high financing costs due to their emissions have an incentive to become greener. While this theoretical argument is sound, its empirical relevance is still debated. Specifically, the evidence on whether carbon emissions lead to higher financing costs is mixed.

In this paper, we ask whether carbon emissions intensity, a measure of carbon emissions watched closely by ESG investors, is priced in equity markets. To this end, we develop a theoretical framework, based on the stochastic properties of emissions intensity and asset

[24]Electricity production from coal generated 2.3 pounds of CO_2 per kwh, while natural gas generated 0.96 pounds of CO_2 per kwh.

pricing theory, to analyze how emissions intensity should affect stock returns when emissions intensity is a priced characteristic. Using this framework, we show that studies that regress stock returns on contemporaneous emissions intensity likely suffer from measurement error and an omitted variable bias—and that both these forces bias the coefficient on emissions intensity downward and potentially below zero.

Our theoretical framework makes new predictions about (i) the form of the correct regression specification and (ii) how the biases in the existing literature vary across specifications run in different subsamples, across specifications run using different variable timing, and across specifications that add regressors defined as "omitted" by our theory. Virtually all the predictions from our theory are confirmed in the data, providing convincing evidence that emissions intensity is priced in equity markets. The magnitude of the pricing is heavily dependent on how super emitters are treated, consistent with the extremely skewed distribution of firm-level emissions intensity. This result is also consistent with the market potentially treating super emitters differently, the linear specification being ill-suited to model these firms, or emissions intensities being a noisy measure of greenness for super emitters.

Future empirical research should focus, in our view, on (i) modeling emissions pricing for super emitters and (ii) examining the role of investors' ESG preferences for pricing, in light of the finding in Bolton and Kacperczyk (2021) that the asset holdings of some institutional investors are declining in firms' emissions intensity. On the theoretical side, more work is needed to understand how financial markets can best support the transition to a less polluting economy. The pricing of emissions might not be sufficient, as recent work suggests that such pricing might provide weak or even wrong incentives for high-emitting firms (Chittaro et al., 2025; Hartzmark and Shue, 2024; Berk and Van Binsbergen, 2025). These directions constitute, in our view, a promising avenue for future research.

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Appendix

A The process for emissions intensity as a random walk

For parsimony, in our analysis, we derive equation (10) approximating emissions intensity as a random walk. To justify this simplification, in this section we maintain all assumptions in Section 2.2 except Assumption 2 that is replaced with the assumption that annual emissions intensity for each firm i is a very slowly mean reverting AR(1) process. We then use a Taylor series to show that the random walk specification produces a reasonable approximation of the residual in equation (10). The AR(1) process for emissions intensity is given by:

$$(e_{i,t+1} - \mu_i) = \theta_i(e_{i,t} - \mu_i) + u_{i,t} \tag{A1}$$

where μ_i is the long-run mean of emissions intensity for firm i and θ_i is close to, but less, than 1. If emissions intensity is the only priced characteristic, ρ_i is well defined in the Campbell and Shiller (1988) log-linearization (because it is mean-reverting) and given by $\rho_i = e^{g_i-(r_f+\gamma\mu_i)}$.

Furthermore, using the properties of the autoregressive process, it is straightforward to show that:

$$[\mathbb{E}_{t+1} - \mathbb{E}_t]e_{i,t+k} = \theta^{k-1}[(e_{i,t+1} - \mu_i) - \theta_i(e_{i,t} - \mu_i)] \tag{A2}$$

Plugging this expression in the Campbell (1991) log-linearization and simplifying, we obtain:

$$(\mathbb{E}_{t+1} - \mathbb{E}_t)[r_{i,t+1} - r_f] \approx -\gamma\left(\frac{\rho_i}{1-\rho_i\theta_i}\right)[(e_{i,t+1} - \mu_i) - \theta_i(e_{i,t} - \mu_i)] \tag{A3}$$

The right hand side can be approximated as a Taylor series around $\theta_i = 1$. The leading term on the right is the same as in equation (10), and the size of the residual term in the approximation vanishes when $\theta_i = 1$ (and is small when θ_i is in a neighborhood close to 1). This shows our use of the random walk approximation for emissions intensity. Also note that the equation we derive is a reasonable approximation for the true stock return innovation term in equation (10) if emissions intensity is a highly persistent AR(1) process with $\theta_i < 1$.

B Measurement error and omitted variable bias

To illustrate the measurement error and omitted variable biases together, if γ is estimated via OLS in equation (12) (and excess stock returns are generated by equation (10)), we have:

$$\hat{\gamma} = \frac{\widehat{\text{CSCov}}(r_{i,t} - r_{f,t}, e_{i,t})}{\widehat{\text{CSVar}}(e_{i,t})} \tag{B1}$$

where CSCov and CSVar are estimates of the covariance and the variance in the cross-section, and "$\widehat{z}$" denotes the sample estimate of z. Substituting for $r_{i,t} - r_{f,t}$ from equation (10), the probability limit for γ is:

$$\text{plim } \hat{\gamma} = \frac{\text{plim } \widehat{\text{CSCov}}(\gamma e_{i,t-1} - \gamma \frac{P_{i,t-1}}{D_{i,t-1}} u_{i,t}, e_{i,t})}{\text{plim}\widehat{\text{CSVar}}(e_{i,t})}$$

Finally, using $\text{Cov}(x, y) = \text{Cov}(\mathbb{E}(x|I), \mathbb{E}(y|I)) + \mathbb{E}(\text{Cov}(x, y|I))$, we obtain:

$$\text{plim } \hat{\gamma} = \gamma \left(\frac{\sigma^2_{e_{t-1}}}{\sigma^2_{e_{t-1}} + \sigma^2_u} \right) - \gamma \left(\mathbb{E}(\frac{P_{i,t-1}}{D_{i,t-1}}) \frac{\sigma^2_u}{\sigma^2_{e_{t-1}} + \sigma^2_u} \right). \tag{B2}$$

More specifically, to obtain this result, we use $\mathbb{E}(r_{i,t} - r_f | I_{t-1}) = \gamma e_{i,t-1}$ and $\mathbb{E}(e_{i,t}|I_{t-1}) = e_{i,t-1}$. Hence, $\text{Cov}[\mathbb{E}(r_{i,t} - r_f|I_{t-1}), \mathbb{E}(e_{i,t}|I_{t-1})] = \gamma \sigma^2_{e_{t-1}}$. Furthermore, $\text{Cov}(r_{i,t} - r_f, e_{i,t}|I_{t-1}) = \text{Cov}(-\gamma \frac{P_{i,t-1}}{D_{i,t-1}} u_{i,t},\ e_{i,t}|I_{t-1}) = -\gamma \frac{P_{i,t-1}}{D_{i,t-1}} \sigma^2_u$. Hence, $\mathbb{E}(\text{Cov}(r_{i,t} - r_f, e_{i,t}|I_{t-1}) = -\gamma \mathbb{E}(\frac{P_{i,t-1}}{D_{i,t-1}}) \sigma^2_u$. Finally, $\text{Var}(e_{i,t}) = \sigma^2_{e_{i,t-1}} + \sigma^2_u$.

As discussed in the main body, the first term in equation (B2) is due to classical measurement error and thus causes shrinkage of γ towards zero. The second term is the result of omitted variable bias. This bias is negative and causes the stock return innovation to be unexpectedly low when emissions intensity is unexpectedy high (i.e., the omitted variable is negatively correlated with the regressor). If γ is positive, the omitted variable bias could cause the estimated γ to become negative.

C Estimation frequency and measurement error

In this section, we analyze how measurement error may be related to estimation frequency. To do so, we slightly modify the framework to let t denote time measured in years and to let m denote time measured in months, with $m = 0$ denoting the end of year $t - 1$ and $m = 1, 2, ...12$ denoting the ends of months 1 through 12 of year t. For simplicity, we focus on a cross-sectional regression using one year of stock return data, measured at an annual or a monthly frequency. In addition, to simplify aggregation, we measure stock returns in logs, i.e., in this appendix $r_{i,t}$ is the log gross annual stock return during year t and $r_{i,m}$ is the log gross monthly stock return in month m of year t. Given that we switched to log stock returns, we have:

$$r_{i,t} = \sum_{m=1}^{12} r_m. \tag{C1}$$

To further simplify, we assume the log gross risk-free rate is zero both annually and monthly, so we do not have to keep track of the risk-free rate in the derivation.

In the text, we modeled stock returns at an annual frequency. This modeling approach implicitly assumes that information arrives only at the end of each year. To analyze estimation frequency, we now model stock returns monthly and then aggregate up to an annual frequency. To do so, we assume stock returns are monthly, and continue to maintain that beliefs about emissions intensity drive stock returns. Specifically, we assume stock returns in each month m follow the process:

$$r_{i,m} = \gamma_m \mathbb{E}(e_{i,t}|I_{m-1}) - \gamma_m \ \frac{P_{i,m}}{D_{i,m}} \left[\mathbb{E}(e_{i,t}|I_m) - \mathbb{E}(e_{i,t}|I_{m-1})\right]. \tag{C2}$$

This equation is simply the expression we would have derived for stock returns at a monthly frequency if annual emissions intensity is priced. The equation is the monthly equivalent of equation (10).

In equation (C2), $\gamma_m = \frac{\gamma}{12}$ and $\frac{P_{i,m}}{D_{i,m}} = \frac{\rho_{i,m}}{1-\rho_{i,m}} = \frac{e^{\frac{\bar{g}_i}{12}}}{e^{\frac{\bar{r}_i}{12}} - e^{\frac{\bar{g}_i}{12}}}$ are monthly equivalents of γ and the price-dividend ratio in the Gordon Growth model, respectively. In turn, $\frac{\bar{r}_i}{12}$ and $\frac{g_i}{12}$ are the long-run average monthly stock returns and dividend growth rates for firm i.

Equation (C2) shows that, at the beginning of each month m during year t, required stock returns $r_{i,m}$ depend on expected emissions intensity during year t conditional on investors information sets at the end of month $m-1$, $\gamma_m \mathbb{E}(e_{i,t}|I_{m-1})$. In addition, the unexpected part of stock returns during month m depends on the change in expectations about emissions intensity between months $m-1$ and m, $-\gamma_m \ \frac{P_{i,m}}{D_{i,m}} \left[\mathbb{E}(e_{i,t}|I_m) - \mathbb{E}(e_{i,t}|I_{m-1})\right]$.

Consider an empirical analysis of the monthly data that takes the form:

$$r_{i,m} = \gamma_m e_{i,s} + u_{i,s}, \tag{C3}$$

where $e_{i,s}$ is emissions intensity measured at either $s = t$ or $s = t-1$. These regressions suffer from measurement error in monthly data because required stock returns during the month depend on $\mathbb{E}(e_{i,t}|_{m-1})$, which may be different from $e_{i,t}$ and $e_{i,t-1}$ if investors gather information during the year to predict emissions intensities.

To investigate whether regressions with annual data perform better, we first aggregate the data to derive the process for annual stock returns implied by monthly stock returns. We obtain:

$$\begin{aligned}
r_{i,t} &= \sum_{m=1}^{12} r_{i,m} = \gamma_m \sum_{m=1}^{12} \mathbb{E}(e_{i,t}|I_{m-1}) - \sum_{m=1}^{12} \gamma_m \frac{P_{i,m}}{D_{i,m}} \left[\mathbb{E}(e_{i,t}|I_m) - \mathbb{E}(e_{i,t}|I_{m-1})\right] \\
&= \gamma_m \sum_{m=1}^{12} \mathbb{E}(e_{i,t}|I_{m-1}) - \gamma_m \ \frac{P_{i,m}}{D_{i,m}} \sum_{m=1}^{12} \left[\mathbb{E}(e_{i,t}|I_m) - \mathbb{E}(e_{i,t}|I_{m-1})\right] \\
&= \gamma_m \sum_{m=1}^{12} \mathbb{E}(e_{i,t}|I_{m-1}) - \gamma_m \ \frac{P_{i,m}}{D_{i,m}} \left[\mathbb{E}(e_{i,t}|I_{12}) - \mathbb{E}(e_{i,t}|I_0)\right],
\end{aligned} \tag{C4}$$

where we pull γ_m and $pd_{i,m}$ outside the summation because they are constants that do not change with month m.

We assume that the emissions intensity for each year t is learned by the end of year t. This assumption, together with the assumption that emissions intensity follows a random walk, implies:

$$r_{i,t} = \gamma_m \sum_{m=1}^{12} \mathbb{E}(e_{i,t}|I_{m-1}) - \gamma_m \frac{P_{i,m}}{D_{i,m}} (e_{i,t} - e_{i,t-1}) \approx \gamma_m \sum_{m=1}^{12} \mathbb{E}(e_{i,t}|I_{m-1}) - \gamma \frac{P_i}{D_i} (e_{i,t} - e_{i,t-1}), \tag{C5}$$

where the approximation follows from noting that $\frac{P_{i,m}}{D_{i,m}}$ is the monthly price-dividend ratio. Using the approximation that the monthly dividend is the annual dividend D divided by 12, we have $\frac{P_{i,m}}{D_{i,m}} \approx \frac{P_i}{D_i/12} = 12\frac{P_i}{D_i}$, where $\frac{P_i}{D_i}$ is the long-run price-annual dividend ratio for firm i. A little algebra then shows $\gamma_m \frac{P_{i,m}}{D_{i,m}} = \gamma \frac{P_i}{D_i}$.

Taking expectations of both sides of the equation conditional on information at time $t-1$ (which is equivalent to conditioning on month 0) yields:

$$\begin{aligned}
\mathbb{E}(r_{i,t}|I_{t-1}) &= \gamma_m \sum_{m=1}^{12} \mathbb{E}[\mathbb{E}(e_{i,t}|I_{m-1})|I_{t-1}] - \gamma \frac{P_i}{D_i} \mathbb{E}[(e_{i,t} - e_{i,t-1})|I_{t-1}] \\
&= \gamma_m \times 12 \times e_{i,t-1} \\
&= \gamma e_{i,t-1}
\end{aligned} \tag{C6}$$

Hence, aggregating up from monthly stock returns and combining equations (C6) and (C5), annual stock returns can be decomposed into an expected stock return component followed by two innovation terms as follows, all in square braces:

$$r_{i,t} = [\gamma e_{i,t-1}] - \left[\gamma \frac{P_i}{D_i}(e_{i,t} - e_{i,t-1})\right] + \left[\gamma_m \sum_{m=1}^{12} (\mathbb{E}(e_{i,t}|I_{m-1}) - e_{i,t-1})\right]. \tag{C7}$$

Recalling that the risk-free rate is set to zero for simplicity, the left hand side of the above equation and the first two terms on the right hand side are reminiscent of equation (10). The third term on the right hand side captures the learning about emissions that occurs each month of the year and alters required stock returns in the following month. Because emissions intensity is a random walk, both the second and third terms on the right hand side are uncorrelated with $e_{i,t-1}$. Hence, the cross-sectional regression

$$r_{i,t} = \gamma e_{i,t-1} + u_{i,t} \tag{C8}$$

using annual stock return data produces unbiased and consistent estimates for γ provided that emissions intensity for each year t is known by the end of the year. This may be a reasonable approximation provided that investors learn about emissions intensity through the year (but before it is publicly released).

Finally, the third term on the right hand side of equation (C7) can be simplified as:

$$\gamma_m \sum_{m=1}^{12} (\mathbb{E}(e_{i,t}|I_{m-1} - e_{i,t-1}) = \gamma \frac{1}{12} \sum_{m=1}^{12} (\mathbb{E}(e_{i,t}|I_{m-1} - e_{i,t-1}) \approx \gamma(e_{i,t} - e_{i,t-1}) + \gamma \zeta_{i,t} \tag{C9}$$

where the approximation follows by recognizing that $\frac{1}{12}\sum_{m=1}^{12} \mathbb{E}(e_{i,t}|I_{m-1})$ is an average of forecasts of $e_{i,t}$, which can be represented as the quantity being forecasted, $e_{i,t}$, plus an average forecast error $\zeta_{i,t}$ that has a mean of 0 if forecasts are unbiased.

Using equation (C9), equation (C7) can be rewritten as:

$$r_{i,t} \approx \gamma e_{i,t-1} - \gamma \left(\frac{P_i}{D_i} - 1\right)(e_{i,t} - e_{i,t-1}) + \gamma \zeta_{i,t} \tag{C10}$$

This equation, based on time-aggregation from monthly to annual stock return data is very similar to equation (10) based on annual stock returns, with the exception that the price-dividend ratio interaction term is modified slightly, and there is an expectational error-term $\zeta_{i,t}$. Because the differences from equation (10) are so slight, the analytical and empirical results on omitted variable biases and measurement error biases that were derived in the annual stock return setting also work in this richer setting aggregated up from monthly data.

To summarize, we have shown three results: (i) If annual emissions intensity is priced and follows a random walk, and if investors learn about it during the year, monthly stock return regressions suffer from measurement error if the variable used to measure beliefs about emissions intensity is the actual or lagged emissions intensity for the year; (ii) If emissions intensity follows a random walk and if emissions intensity for each year t is known by investors by the end of year t, a regressions of annual stock returns on one-year lagged emissions intensity produces unbiased and consistent estimates for γ; (iii) The equation relating annual stock returns to lagged emissions intensity when aggregated up from our stock return model at a monthly frequency very closely resembles the equation for stock returns from our model at an annual frequency. Hence, the results we derived in our annual stock return model for regressions using annual data are essentially unchanged for our model derived from monthly stock returns with learning that are aggregated up to an annual level.

D High vs. low P/D: Are coefficients different?

This section derives how to test for differences in coefficients when we sort the data each year into firms that are above and below the median price-dividend ratio.

$Y_{a,t}$ and $Y_{b,t}$ are the vector of dependent variables for firms that have above and below median average price-dividend ratios based on the three years before period t, respectively. $X_{a,t}$, $X_{b,t}$, $\epsilon_{a,t}$ and $\epsilon_{b,t}$ are the corresponding independent variable vectors and residual vectors. Y_a, Y_b X_a, X_b, ϵ_a, and ϵ_b are the corresponding stacked vectors across time. Each vector has a total of N observations.

The regression models are:

$$Y_a = X_a\beta_a + \epsilon_a \tag{D1}$$

$$Y_b = X_b\beta_b + \epsilon_b \tag{D2}$$

In these regression models one of the components of β_a is $\beta_{a,ei}$, which is the the coefficient associated with the emissions intensity variable. Similar notation applies to β_b. The null hypothesis is that there is no omitted variable bias, and therefore that $\beta_{a,ei} = \beta_{b,ei}$. The alternative hypothesis is that the omitted variable bias is larger for firms with higher price-dividend ratio and therefore $\beta_{b,ei} > \beta_{a,ei}$

The test for the null is:

$$Z = \frac{\hat{\beta}_{b,ei} - \hat{\beta}_{a,ei}}{\sqrt{\hat{Var}(\hat{\beta}_{b,ei} - \hat{\beta}_{a,ei})}} \tag{D3}$$

Z should be asymptotically normally distributed under the null hypothesis; and the null is rejected in favor of the alternative for high enough values of Z. Hence, we reject the null at the p percent confidence level if $1 - \Phi(z) < p$.

The coefficient estimates for β_a are given by:

$$\begin{aligned}\hat{\beta}_a &= (X_a'X_a)^{-1}X_a'Y_a \\ &= \beta_a + (X_a'X_a)^{-1}X_a'\epsilon_a\end{aligned}$$

The coefficient estimates for $\hat{\beta}_b$ are analogous.

We estimate the Z statistic using three different assumptions about the denominator. In the first case, we assume $Cov(\hat{\beta}_{b,ei}, \hat{\beta}_{a,ei}) = 0$. In this case, we just compute the standard OLS variances for the coefficients. For the second and third cases, we account for the covariances between the parameter estimates in the different regressions using an approach analogous to clustering. We consider clustering by time or clustering by time and industry. For consistency, we also compute the variances in each regression using clustering when we compute covariances using clustering. Details on the clustering approaches are below.

Time clustering. We assume that the elements of the matrix $X_a'\epsilon_a$ are correlated within time periods, but not across time periods. The variance of $\hat{\beta}_a$ is:

$$Var(\hat{\beta}_a)|X_a = (X_a'X_a)^{-1}[E(X_a'\epsilon_a\epsilon_a'X_a)](X_a'X_a)^{-1},$$

which is estimated as:

$$\hat{Var}\hat{\beta}_a = (X_a'X_a)^{-1}\left[\sum_{t=1}^{T} X_{a,t}'\epsilon_{a,t}\epsilon_{a,t}'X_{a,t}\right](X_a'X_a)^{-1} \tag{D4}$$

where the observations in the regression and the residuals have been stacked by time period. The expression for the variance of β_b is analogous.

The expression for their covariance is, by definition:

$$Cov(\hat{\beta}_a, \hat{\beta}_b)|(X_a, X_b) = (X_a'X_a)^{-1}[E(X_a'\epsilon_a\epsilon_b'X_b)](X_b'X_b)^{-1}$$

Using the analogy to time clustering, this is estimated as:

$$\hat{\text{Cov}}(\hat{\beta}_a, \hat{\beta}_b) = (X_a'X_a)^{-1}\left[\sum_{t=1}^{T} X_{a,t}'\epsilon_{a,t}\epsilon_{b,t}'X_{b,t}\right](X_b'X_b)^{-1} \tag{D5}$$

Using these expressions:

$$\hat{Var}(\hat{\beta}_{b,ei} - \hat{\beta}_{a,ei}) = \hat{Var}(\hat{\beta}_{b,ei}) + \hat{Var}(\hat{\beta}_{a,ei}) - 2\hat{Cov}(\hat{\beta}_{b,ei}, \hat{\beta}_{a,ei}). \tag{D6}$$

Double clustering. We now calculate the variance of the coefficients and their covariance assuming the residuals in the regression are correlated across time and also across a second dimension, such as either industry or firm.

For brevity, we let industry be the second dimension. Analogous expressions apply when clustering by time and firm. To derive the correct expressions, let $\epsilon_{a,ind}$ be the vector of residuals from equation (D1) partitioned by industry, i.e., the first sub-vector of observations are residuals for industry 1 for periods $1, \dots T$, the second sub-vector is for industry 2, and so on. Similary, let $\epsilon_{a,ind,t}$ and $X_{a,ind,t}$ represent the sub-vector of the residuals and the X matrix for industry "ind" and time period t.

The variance estimate with double clustering (derived independently by Miglioretti and Heagerty (2007), Thompson (2011), and Cameron et al. (2011)) is given by:[25]

$$\begin{aligned}
\hat{\text{Var}}(\hat{\beta}_a)|X_a &= (X_a'X_a)^{-1}\left[\sum_{t=1}^{T} X_{a,t}'\epsilon_{a,t}\epsilon_{a,t}'X_{a,t}\right](X_a'X_a)^{-1} \\
&+ (X_a'X_a)^{-1}\left[\sum_{Ind=1}^{N_{Ind}} X_{a,Ind}'\epsilon_{a,Ind}\epsilon_{a,Ind}'X_{a,Ind}\right](X_a'X_a)^{-1} \\
&- (X_a'X_a)^{-1}\left[\sum_{t=1}^{T}\sum_{Ind=1}^{N_{Ind}} X_{a,t,Ind}'\epsilon_{a,t,Ind}\epsilon_{a,t,Ind}'X_{a,t,Ind}\right](X_a'X_a)^{-1}
\end{aligned} \tag{D7}$$

The first line of the expression captures the effect of just clustering by time; the second captures the effect of just clustering by industry. The first and second lines lead to some double-counting because both lines capture the effect of industry observations that occur in the same time periods. The third line adjusts by subtracting off the double-counted term. The expression for $\hat{\text{Var}}(\hat{\beta}_b)$ is analogous.

To estimate $Cov(\hat{\beta}_a, \hat{\beta}_b)$, we follow an analogous approach to that in equation (D5):

$$\begin{aligned}
&\hat{Cov}(\hat{\beta}_a,\hat{\beta}_b)|(X_a, X_b) \\
&\quad=(X_a'X_a)^{-1}\left[\frac{1}{N}\sum_{t=1}^{T} X_{a,t}'\epsilon_{a,t}\epsilon_{b,t}'X_{b,t}\right](X_b'X_b)^{-1} \\
&\quad+ (X_a'X_a)^{-1}\left[\sum_{Ind=1}^{N_Ind} X_{a,Ind}'\epsilon_{a,Ind}\epsilon_{b,Ind}'X_{b,Ind}\right](X_b'X_b)^{-1} \\
&\quad- (X_a'X_a)^{-1}\left[\sum_{t=1}^{T}\sum_{Ind=1}^{N_{Ind}} X_{a,t,Ind}'\epsilon_{a,t,Ind}\epsilon_{b,t,Ind}'X_{b,t,Ind}\right](X_b'X_b)^{-1}
\end{aligned} \tag{D8}$$

The approach for testing the null hypothesis proceeds in the same way as in the single-clustering case.

[25]See also MacKinnon et al. (2023)'s review article on clustering.

E Additional tables

Year	No. of Firms
2001	38
2002	320
2003	442
2004	513
2005	665
2006	654
2007	648
2008	661
2009	679
2010	675
2011	677
2012	680
2013	744
2014	724
2015	886
2016	1951
2017	2029
2018	2066
2019	2047
2020	2150
2021	2242
2022	2212
2023	1268

Table E.1: Number of observations by year. This table shows the number of firm-year observations in Trucost by year.

NAICS2	Industry	Observations	No. Firms
11	Agriculture, forestry, fishing and hunting	70	14
21	Mining, quarrying, and oil and gas extraction	1552	181
22	Utilities	1220	110
23	Construction	227	46
31	Manufacturing	962	115
32	Manufacturing	2749	405
33	Manufacturing	5960	752
42	Wholesale trade	862	132
44	Retail trade	1018	114
45	Retail trade	575	85
48	Transportation and warehousing	807	115
49	Transportation and warehousing	51	7
51	Information	2534	424
52	Finance and insurance	552	86
53	Real estate and rental and leasing	825	216
54	Professional, scientific, and technical services	2932	642
56	Management of companies and enterprises	515	79
61	Educational services	154	21
62	Health care and social assistance	512	79
71	Arts, entertainment, and recreation	154	31
72	Accomodation and food services	591	75
81	Other services	149	33

Table E.2: Number of observations by industry. This table shows the number of firm-year observations and the number of unique firms in Trucost by industry (2-digit NAICS code). Firms that change industries across years are included in the count for each industry they belong to during the sample period. Among the final sample of unique firms, 2,550 remain in the same industry for the whole sample period, 518 are observed in two industries, 53 in 3 industries, 3 in 4 industries, and 1 firm is counted in 5 industries.

PANEL A: Full Sample	N	Mean	SD	P75	P50	P25
R_{it}	22693	−8.48	50.02	18.34	−9.53	−40.44
Scope-1 emission$_{it-1}$	22693	265.92	1070.74	52.17	17.94	8.48
Scope-1+Scope-2 emission$_{it-1}$	22693	306.01	1088.43	103.84	43.32	23.97
MCAP$_{it-1}$	22693	14.76	1.72	15.92	14.78	13.59
LEV$_{it-1}$	22693	123.58	170.83	148.84	61.39	17.85
INVEST/A$_{it-1}$	22693	4.40	4.38	5.68	3.03	1.49
ROE$_{it-1}$	22693	2.47	54.91	19.19	10.01	−2.32
VOL$_{it-1}$	22693	0.98	0.60	1.21	0.81	0.56
BETA$_{it-1}$	22693	1.21	1.21	1.79	1.11	0.55
B/M$_{it-1}$	22693	0.52	0.45	0.70	0.41	0.22

PANEL B: Excluding NAICS 2211	N	Mean	SD	P75	P50	P25
R_{it}	22225	−8.45	50.29	18.60	−9.63	−40.76
Scope-1 emission$_{it-1}$	22225	167.51	604.69	46.20	17.47	8.35
Scope-1+Scope-2 emission$_{it-1}$	22225	207.57	637.29	97.25	42.34	23.63
MCAP$_{it-1}$	22225	14.74	1.73	15.90	14.77	13.56
LEV$_{it-1}$	22225	118.66	167.28	139.98	59.30	17.00
INVEST/A$_{it-1}$	22225	4.36	4.40	5.56	2.97	1.46
ROE$_{it-1}$	22225	2.40	55.41	19.42	10.10	−2.66
VOL$_{it-1}$	22225	0.99	0.60	1.22	0.82	0.57
BETA$_{it-1}$	22225	1.23	1.21	1.80	1.13	0.56
B/M$_{it-1}$	22225	0.51	0.45	0.69	0.40	0.21

Table E.3: Summary statistics. This table shows the summary statistics for the main variables used in our empirical analysis. Panel A focuses on the full sample of firms. Panel B focuses on the full sample excluding firms operating in “Electric Power Generation, Transmission, and Distribution” (NAICS 2211).

	R_{it}					
	(1)	(2)	(3)	(4)	(5)	(6)
Scope-1 emission$_{it-1}$		0.0785			0.1231**	
		(0.0487)			(0.0570)	
Scope-1+Scope-2 emission$_{it-1}$			0.0814*			0.1180**
			(0.0490)			(0.0559)
MCAP$_{it-1}$	0.7920**	0.8531**	0.8587**	0.8143**	0.8999**	0.9020**
	(0.3603)	(0.3637)	(0.3634)	(0.3775)	(0.3801)	(0.3797)
LEV$_{it-1}$	0.0001	−0.0010	−0.0010	−0.0005	−0.0007	−0.0008
	(0.0031)	(0.0033)	(0.0033)	(0.0038)	(0.0038)	(0.0038)
INVEST/A$_{it-1}$	−0.4815***	−0.5014***	−0.5044***	−0.4401***	−0.4438***	−0.4448***
	(0.1227)	(0.1232)	(0.1231)	(0.1364)	(0.1359)	(0.1358)
ROE$_{it-1}$	0.0158	0.0159	0.0158	0.0168	0.0168	0.0167
	(0.0115)	(0.0115)	(0.0115)	(0.0114)	(0.0114)	(0.0114)
VOL$_{it-1}$	7.605***	7.757***	7.738***	7.882***	7.866***	7.842***
	(1.970)	(1.977)	(1.973)	(2.095)	(2.090)	(2.092)
BETA$_{it-1}$	−0.4063	−0.3851	−0.3878	−0.6545	−0.6479	−0.6513
	(0.6786)	(0.6769)	(0.6771)	(0.6775)	(0.6753)	(0.6753)
B/M$_{it-1}$	4.370***	4.036***	4.007***	4.784***	4.637***	4.619***
	(1.393)	(1.404)	(1.407)	(1.486)	(1.479)	(1.481)
Year FE	✓	✓	✓	✓	✓	✓
Industry FE				✓	✓	✓
Observations	6,623	6,623	6,623	6,623	6,623	6,623
R^2	0.3533	0.3535	0.3536	0.3579	0.3584	0.3584

Table E.4: Effect of lagged emissions on stock returns, subsample of firms with disclosed emissions. This table shows the estimation results of equation (17). The unit of observation is firm-year. The sample runs at an annual frequency from 2001 to 2023. The sample excludes observations of firms classified under "Electric Power Generation, Transmission and Distribution" (NAICS 2211) or observations with Trucost-estimated emissions. Following Aswani et al. (2024), we define "estimated" emissions as those for which the Trucost carbon information source includes the keyword "estimate." Scope-1 emission$_{it-1}$ and Scope-1+Scope-2 emission$_{it-1}$ are the lagged scope-1 emissions intensity and the sum of scope-1 and scope-2 emissions intensities, respectively. The reported coefficients on emissions intensities are multiplied by 100 for readability. The control variables are lagged by one year, winsorized at the 2nd and 98th percentiles, and defined as follows: MCAP$_{it-1}$ is log of market capitalization; LEV$_{it-1}$ is total debt divided by total assets; INVEST/A$_{it-1}$ is investment divided by total assets; ROE$_{it-1}$ is net income divided by shareholders' equity (multiplied by 100); VOL$_{it-1}$ is the standard deviation of monthly stock returns over a 12-month period; BETA$_{it-1}$ is the CAPM beta over a 12-month period; B/M$_{it-1}$ is the book-to-market ratio. Standard errors clustered at the firm level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

PANEL A	(1)	(2)	(3)	R_{it} (4)	(5)	(6)	(7)
Scope-1 emission$_{it-1}$	0.1660***	0.1672***	0.1658***	0.1661***	0.1664***	0.1663***	0.1659***
	(0.0525)	(0.0528)	(0.0528)	(0.0526)	(0.0525)	(0.0524)	(0.0525)
LEV$_{it-1}$		−0.0030	−0.0020	−0.0022	−0.0022	−0.0024	−0.0022
		(0.0022)	(0.0022)	(0.0022)	(0.0022)	(0.0022)	(0.0022)
INVEST/A$_{it-1}$			−0.4128***	−0.4263***	−0.4306***	−0.4302***	−0.4349***
			(0.0922)	(0.0915)	(0.0917)	(0.0915)	(0.0918)
ROE$_{it-1}$				0.0399***	0.0408***	0.0403***	0.0411***
				(0.0075)	(0.0078)	(0.0078)	(0.0078)
VOL$_{it-1}$					0.1984	−0.3959	−0.8096
					(0.7772)	(0.8406)	(0.9210)
BETA$_{it-1}$						0.7061**	0.7539**
						(0.3294)	(0.3300)
MCAP$_{it-1}$							−0.2779
							(0.2220)
Year FE	✓	✓	✓	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓	✓	✓	✓
Observations	22,498	22,459	22,453	22,453	22,448	22,448	22,445
R^2	0.24792	0.24794	0.24877	0.25062	0.25075	0.25098	0.25099

PANEL B	(1)	(2)	(3)	R_{it} (4)	(5)	(6)	(7)
Scope-1+Scope-2 emission$_{it-1}$	0.1734***	0.1750***	0.1738***	0.1730***	0.1734***	0.1728***	0.1729***
	(0.0506)	(0.0509)	(0.0506)	(0.0501)	(0.0500)	(0.0500)	(0.0501)
LEV$_{it-1}$		−0.0031	−0.0021	−0.0022	−0.0022	−0.0024	−0.0022
		(0.0022)	(0.0022)	(0.0022)	(0.0022)	(0.0022)	(0.0022)
INVEST/A$_{it-1}$			−0.4127***	−0.4262***	−0.4305***	−0.4301***	−0.4349***
			(0.0922)	(0.0914)	(0.0916)	(0.0915)	(0.0918)
ROE$_{it-1}$				0.0399***	0.0408***	0.0403***	0.0411***
				(0.0075)	(0.0078)	(0.0078)	(0.0078)
VOL$_{it-1}$					0.1920	−0.4001	−0.8186
					(0.7773)	(0.8406)	(0.9212)
BETA$_{it-1}$						0.7036**	0.7519**
						(0.3293)	(0.3300)
MCAP$_{it-1}$							−0.2811
							(0.2221)
Year FE	✓	✓	✓	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓	✓	✓	✓
Observations	22,498	22,459	22,453	22,453	22,448	22,448	22,445
R^2	0.2480	0.2480	0.2488	0.2507	0.2508	0.2510	0.2510

Table E.5: Effect of lagged emissions intensity on stock returns, sensitivity with respect to control variables, year and industry fixed effects. This table shows the estimation results of specification (17). The unit of observation is firm-year. The sample runs at an annual frequency from 2001 to 2023. The sample excludes observations of firms classified under "Electric Power Generation, Transmission and Distribution" (NAICS 2211). Scope-1 emission$_{it-1}$ and Scope-1+Scope-2 emission$_{it-1}$ are the lagged scope-1 emissions intensity and the sum of scope-1 and scope-2 emissions intensities, respectively. The reported coefficients on emissions intensities are multiplied by 100 for readability. The control variables are lagged by one year, winsorized at the 2nd and 98th percentiles, and defined as follows: MCAP$_{it-1}$ is log of market capitalization; LEV$_{it-1}$ is total debt divided by total assets; INVEST/A$_{it-1}$ is investment divided by total assets; ROE$_{it-1}$ is net income divided by shareholders' equity (multiplied by 100); VOL$_{it-1}$ is the standard deviation of monthly stock returns over a 12-month period; BETA$_{it-1}$ is the CAPM beta over a 12-month period; B/M$_{it-1}$ is the book-to-market ratio. Standard errors clustered at the firm level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

PANEL A	(1)	(2)	(3)	R_{it} (4)	(5)	(6)	(7)
Scope-1 emission$_{it-1}$	0.0554	0.0802*	0.1178**	0.1169**	0.1176**	0.1188**	0.1181**
	(0.0450)	(0.0468)	(0.0480)	(0.0478)	(0.0479)	(0.0476)	(0.0478)
LEV$_{it-1}$		−0.0048**	−0.0021	−0.0022	−0.0022	−0.0023	−0.0021
		(0.0019)	(0.0019)	(0.0019)	(0.0019)	(0.0019)	(0.0019)
INVEST/A$_{it-1}$			−0.4338***	−0.4496***	−0.4551***	−0.4589***	−0.4629***
			(0.0765)	(0.0759)	(0.0764)	(0.0763)	(0.0767)
ROE$_{it-1}$				0.0429***	0.0432***	0.0426***	0.0434***
				(0.0074)	(0.0078)	(0.0078)	(0.0078)
VOL$_{it-1}$					−0.0448	−0.7386	−1.121
					(0.7560)	(0.8225)	(0.9001)
BETA$_{it-1}$						0.8059**	0.8481***
						(0.3271)	(0.3278)
MCAP$_{it-1}$							−0.2542
							(0.2179)
Year FE	✓	✓	✓	✓	✓	✓	✓
Industry FE							
Observations	22,498	22,459	22,453	22,453	22,448	22,448	22,445
R^2	0.2451	0.2453	0.2465	0.2487	0.2488	0.2491	0.2491

PANEL B	(1)	(2)	(3)	R_{it} (4)	(5)	(6)	(7)
Scope-1+Scope-2 emission$_{it-1}$	0.0641	0.0885*	0.1265***	0.1247***	0.1254***	0.1259***	0.1257***
	(0.0439)	(0.0455)	(0.0466)	(0.0461)	(0.0462)	(0.0459)	(0.0460)
LEV$_{it-1}$		−0.0049***	−0.0022	−0.0023	−0.0023	−0.0024	−0.0022
		(0.0019)	(0.0019)	(0.0019)	(0.0019)	(0.0019)	(0.0019)
INVEST/A$_{it-1}$			−0.4377***	−0.4534***	−0.4588***	−0.4625***	−0.4666***
			(0.0766)	(0.0759)	(0.0764)	(0.0764)	(0.0768)
ROE$_{it-1}$				0.0428***	0.0432***	0.0425***	0.0433***
				(0.0074)	(0.0078)	(0.0078)	(0.0078)
VOL$_{it-1}$					−0.0502	−0.7420	−1.128
					(0.7557)	(0.8223)	(0.8998)
BETA$_{it-1}$						0.8033**	0.8459***
						(0.3270)	(0.3277)
MCAP$_{it-1}$							−0.2567
							(0.2179)
Year FE	✓	✓	✓	✓	✓	✓	✓
Industry FE							
Observations	22,498	22,459	22,453	22,453	22,448	22,448	22,445
R^2	0.2452	0.2453	0.2466	0.2488	0.2489	0.2492	0.2492

Table E.6: Effect of lagged emissions intensity on stock returns, sensitivity with respect to control variables, year fixed effects. This table shows the estimation results of specification (17). The unit of observation is firm-year. The sample runs at an annual frequency from 2001 to 2023. The sample excludes observations of firms classified under "Electric Power Generation, Transmission and Distribution" (NAICS 2211). Scope-1 emission$_{it-1}$ and Scope-1+Scope-2 emission$_{it-1}$ are the lagged scope-1 emissions intensity and the sum of scope-1 and scope-2 emissions intensities, respectively. The reported coefficients on emissions intensities are multiplied by 100 for readability. The control variables are lagged by one year, winsorized at the 2nd and 98th percentiles, and defined as follows: MCAP$_{it-1}$ is log of market capitalization; LEV$_{it-1}$ is total debt divided by total assets; INVEST/A$_{it-1}$ is investment divided by total assets; ROE$_{it-1}$ is net income divided by shareholders' equity (multiplied by 100); VOL$_{it-1}$ is the standard deviation of monthly stock returns over a 12-month period; BETA$_{it-1}$ is the CAPM beta over a 12-month period; B/M$_{it-1}$ is the book-to-market ratio. Standard errors clustered at the firm level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

	R_{it}					
	(1)	(2)	(3)	(4)	(5)	(6)
Scope-1 emission$_{it-1}$		−0.0066			0.0220	
		(0.0269)			(0.0356)	
Scope-1+Scope-2 emission$_{it-1}$			−0.0005			0.0301
			(0.0273)			(0.0358)
MCAP$_{it-1}$	−0.1061	−0.1044	−0.1059	−0.1212	−0.1245	−0.1266
	(0.2275)	(0.2279)	(0.2281)	(0.2331)	(0.2334)	(0.2335)
LEV$_{it-1}$	−0.0022	−0.0021	−0.0022	−0.0020	−0.0020	−0.0020
	(0.0018)	(0.0019)	(0.0019)	(0.0022)	(0.0022)	(0.0022)
INVEST/A$_{it-1}$	−0.4459***	−0.4451***	−0.4459***	−0.4115***	−0.4104***	−0.4100***
	(0.0756)	(0.0759)	(0.0760)	(0.0905)	(0.0905)	(0.0905)
ROE$_{it-1}$	0.0413***	0.0412***	0.0413***	0.0391***	0.0391***	0.0391***
	(0.0078)	(0.0078)	(0.0078)	(0.0078)	(0.0078)	(0.0078)
VOL$_{it-1}$	−1.111	−1.116	−1.111	−0.7902	−0.8001	−0.8051
	(0.8953)	(0.8962)	(0.8960)	(0.9173)	(0.9177)	(0.9178)
BETA$_{it-1}$	0.8949***	0.8928***	0.8948***	0.7936**	0.7945**	0.7946**
	(0.3249)	(0.3250)	(0.3250)	(0.3276)	(0.3275)	(0.3275)
B/M$_{it-1}$	1.735**	1.763**	1.737**	1.784**	1.748**	1.730**
	(0.8064)	(0.8131)	(0.8139)	(0.8444)	(0.8414)	(0.8418)
Year FE	✓	✓	✓	✓	✓	✓
Industry FE				✓	✓	✓
Observations	22,693	22,693	22,693	22,693	22,693	22,693
R^2	0.2507	0.2507	0.2507	0.2525	0.2525	0.2525

Table E.7: Effect of lagged emissions on stock returns, full sample. This table shows the estimation results of equation (17). The unit of observation is firm-year. The sample runs at an annual frequency from 2001 to 2023. Scope-1 emission$_{it-1}$ and Scope-1+Scope-2 emission$_{it-1}$ are the lagged scope-1 emissions intensity and the sum of scope-1 and scope-2 emissions intensities, respectively. The reported coefficients on emissions intensities are multiplied by 100 for readability. The control variables are lagged by one year, winsorized at the 2nd and 98th percentiles, and defined as follows: MCAP$_{it-1}$ is log of market capitalization; LEV$_{it-1}$ is total debt divided by total assets; INVEST/A$_{it-1}$ is investment divided by total assets; ROE$_{it-1}$ is net income divided by shareholders' equity (multiplied by 100); VOL$_{it-1}$ is the standard deviation of monthly stock returns over a 12-month period; BETA$_{it-1}$ is the CAPM beta over a 12-month period; B/M$_{it-1}$ is the book-to-market ratio. Standard errors clustered at the firm level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

	R_{it}			
PANEL A	(1)	(2)	(3)	(4)
Scope-1+Scope-2 emission$_{it-1}$	-0.0005	0.0466	0.1182	0.2932
	(0.0273)	(0.0416)	(0.0949)	(0.2133)
Winsorization	None	2%	5%	10%
Controls	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Industry FE				
Observations	22,693	22,693	22,693	22,693
R^2	0.2507	0.2508	0.2508	0.2508

	R_{it}			
PANEL B	(1)	(2)	(3)	(4)
Scope-1+Scope-2 emission$_{it-1}$	0.0301	0.1437***	0.3427***	0.9511***
	(0.0358)	(0.0513)	(0.1116)	(0.2608)
Winsorization	None	2%	5%	10%
Controls	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓
Observations	22,693	22,693	22,693	22,693
R^2	0.2525	0.2527	0.2527	0.2529

Table E.8: Effect of lagged emissions on stock returns, sensitivity with respect to winsorization of emissions intensity, scope-1+scope-2 emissions intensity. This table shows the estimation results of specification (17). The unit of observation is firm-year. The sample runs annually from 2001 to 2023. Panel A includes only year fixed effects, while Panel B includes both year and industry fixed effects. Scope-1+Scope-2 emission$_{it-1}$ is the lagged sum of scope-1 and scope-2 emissions intensities. The reported coefficients on emissions intensities are multiplied by 100 for readability. Emissions intensites are unwinsorized in Column (1), winsorized at the 2nd and 98th percentiles in Column (2), the 5th and 95th percentiles in Column (3), and the 10th and 90th percentiles in Column (4). The set of control variables included in our baseline specification are also included in these two panels but omitted for brevity. The control variables are lagged by one year, winsorized at the 2nd and 98th percentiles, and defined as follows: MCAP$_{it-1}$ is log of market capitalization; LEV$_{it-1}$ is total debt divided by total assets; INVEST/A$_{it-1}$ is investment divided by total assets; ROE$_{it-1}$ is net income divided by shareholders' equity (multiplied by 100); VOL$_{it-1}$ is the standard deviation of monthly stock returns over a 12-month period; BETA$_{it-1}$ is the CAPM beta over a 12-month period; B/M$_{it-1}$ is the book-to-market ratio. Standard errors clustered at the firm level in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

F Additional figures

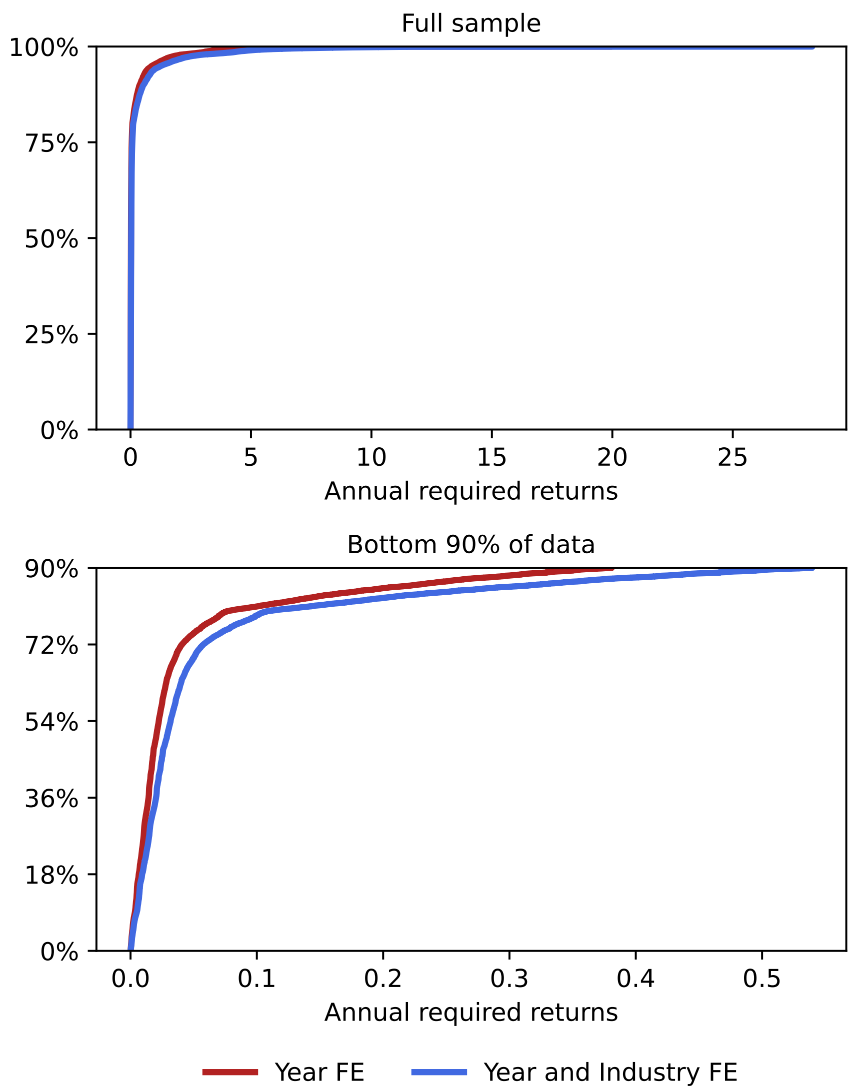

Figure F.1: Cumulative distribution function (CDF) of estimated required stock returns for scope-1 emissions intensity. This figure shows the CDFs of estimated annual required stock returns for firms in the period 2002–23 using our preferred specification from Table 2. Required stock returns are calculated by multiplying each firm-year's scope-1 emissions intensity by the corresponding coefficient from Table 2, 0.10 for the specification with year fixed effects (red curve) and 0.15 for the specification with year and industry fixed effects (blue curve). This analysis excludes observations of firms classified under "Electric Power Generation, Transmission and Distribution" (NAICS 2211). The top panel displays results for the full sample, while the bottom panel displays results for firms whose scope-1 emissions are within the bottom 90% of the distribution.