# 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, but most research finds carbon emissions intensity, a measure targeted by ESG investors, is not priced. We show that: (i) most existing empirical tests suffer from measurement error and omitted variable bias, and (ii) if emissions intensity is priced, stock returns depend on expected emissions intensity and the product of the innovation in emissions intensity and the price-dividend ratio. Based on these new predictions, our empirical results confirm emissions intensity is priced, but the magnitude is largely driven by a few industries characterized by the presence of "super emitters."

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# 1 Introduction

Whether carbon emissions are priced in asset markets is important for understanding the extent to which markets incentivize the transition to a less carbonized economy. Carbon emitting firms may face a higher cost of capital if carbon transition risks are positively priced in asset markets or if investors who dislike carbon emissions invest less in carbon emitters, raising their cost of capital.

There is no consensus on whether carbon emissions are priced in stock markets. Bolton and Kacperczyk (2021) and Bolton and Kacperczyk (2023) regress firms' monthly stock returns on their (log) carbon emissions and other controls using a panel data analysis. They find that firms' carbon emissions are significant in explaining stock returns, which they interpret as evidence of transition risk being priced. Aswani et al. (2024) use a similar regression approach but argue that the evidence in Bolton and Kacperczyk (2021) is actually driven by emissions increasing with economic activity—and its risk being priced.[1] Aswani et al. (2024) further argue that "emissions *intensity*", defined as CO2 emissions divided by revenues, is a better measure of the extent to which firms' pollute as it scales emissions by a measure of firms' economic activity.

Emissions intensity is a metric also closely followed by investors who dislike carbon emissions: Bolton and Kacperczyk (2021) find that investment advisers' holdings are negatively correlated to firms' emissions intensity, with the magnitude being consistent with substantial pricing effects. Despite this correlation, the approaches that regress monthly returns on (log) emissions intensity (Bolton and Kacperczyk, 2021, 2023; Aswani et al., 2024) do not find that (log) emissions intensity is significant in explaining stock returns. Another approach for testing whether emissions intensity is priced consists of creating portfolios of stocks based on firms' emissions intensities and then testing whether high emissions intensity portfolios earn higher returns than low emissions intensity portfolios, after adjusting for risk. The findings from this portfolio approach are also mixed: Pedersen et al. (2021) find that emissions

[1] Aswani et al. (2024) also note that the results are sensitive to the use of vendor constructed data on emissions.

intensity is positively priced, though the evidence is weak, while Zhang (forthcoming) finds that emissions intensity is not priced.

In this paper, and contrary to much of the related literature, we provide strong new evidence that firms' emissions intensity is a positively priced characteristic in U.S. stock returns. This finding is based on a novel empirical approach. Specifically, we posit that firms' emissions intensity is well approximated as a random walk and is a priced characteristic.[2] Then, we use asset pricing theory (the log linear return decomposition in Campbell and Shiller (1988) and Campbell (1991)) to derive an equation relating the firms' annual returns to their emissions intensity in a setting where for simplicity emissions intensity is the only priced characteristic. This equation shows (i) how emissions intensity affects firms' expected returns and (ii) that the return residual is driven by the product of the firms' emissions intensity surprises with their price-dividend ratios:

$$r_{i,t} - r_{f,t} = \gamma e_{i,t-1} \overbrace{- \gamma \underbrace{\left(\frac{P_{i,t-1}}{D_{i,t-1}}\right)}_{\text{Price-dividend ratio}} \underbrace{\left(e_{i,t} - e_{i,t-1}\right)}_{\substack{\text{Emissions intensity} \\ \text{surprises}}}}^{\text{Residual}}, \tag{1}$$

where $r_{i,t} - r_{f,t}$ is the required return of firm $i$ at time $t$ and $e_{i,t-1}$ is emissions intensity of firm $i$ at time $t-1$.

Our pricing equation suggests that if emissions intensity is priced then some regression equations that have been used in the literature are mis-specified. Moreover, our pricing equation allows us to make predictions about how the mis-specification affects the empirical results. We use these predictions to test if emissions intensity is priced. Specifically, Equation (1) implies that a regression of excess stock returns on *realized* firms' emissions intensity over the same year would be characterized by (i) measurement error bias because the regressor should be *expected* emissions intensity and (ii) omitted variables bias because the regressor is correlated with the emissions intensity surprise, which appears in the regression residual.

[2]See appendix B.

We characterize these biases in detail and predict how they vary across different regression specifications and across various data sub-samples. We also show that the regression of stock excess returns on *lagged* emissions intensity eliminates both sources of bias.

Our theoretical insight yields three predictions that we then test in the data. First, the magnitude of the omitted variables bias depends on the average price-dividend ratio in the sample of observations used in the regression. Second, the omitted variable bias vanishes if the residual driven by the emissions intensity surprise is included in the regression of excess returns on emissions intensity—even if the regression has the wrong contemporaneous timing and is thus affected by measurement error. Third, there are specific sign restrictions associated with the estimation of our theoretically derived regression.

Our empirical analysis combines data on emissions from S&P Global Trucost with stock and firm information from CRSP and Compustat. We document that the distribution of emissions intensities is very skewed with a small subset of firms, within a few industries, having very large emissions intensities. Despite the strong skew in the data, our analysis shows that the level of emissions intensity is priced. However, the magnitude of the estimated effect that emissions intensity has on required stock returns is sensitive to the inclusion of some industries where some "super emitter" firms operate. We find that excluding some of these super emitters (such as firms operating in the electric power generation, transmission, and distribution sector) typically increases our estimate for the required stock return (or equity costs of capital) due to emissions intensity. Taken as a whole, our findings suggest that the equity cost of capital is approximately linear in expected emissions intensity for most firms, but likely departs from linearity for super emitter firms.

We also confirm in the data the three empirical predictions discussed above. First, the omitted variable bias is more severe if the regressions are run on subsets of firms with high price-dividend ratios and less severe for subsets of firms with low price-dividend ratios. Second, the comparison of coefficients across specifications predicted to have different biases are, for the most part, consistent with the predictions from theory. Third, the sign restrictions mentioned above are always satisfied. In sum, the statistically significant regression results and the consistency of our findings with the novel theoretical predictions present strong evidence that the level of emissions intensity is a priced characteristic.

Our theoretical framework also highlights some of the identification concerns in the existing empirical literature. First, it is hard to interpret the widely used specification where excess returns are regressed on contemporaneous emissions intensity, as the regressor is not decomposed into its expected and unexpected components. To overcome this issue, several papers use lagged log emissions intensity as a regressor, finding weak or no evidence that emissions intensity is priced. The discrepancy with our findings is likely driven by the use of logs or the use of monthly, instead of yearly, frequency. Given that the Trucost emissions data is only available at an annual frequency, the use of (inevitably repeated) contemporaneous emissions intensity re-introduces the inability to distinguish between the expected and the unexpected components of emissions intensity. Our paper addresses these identification challenge in two ways. First, we use the patterns of predicted biases to verify whether emissions intensity is priced. Second, by modeling both expected and unexpected emissions intensity, we confirm they enter our regressions in the ways predicted by theory if the level of emissions intensity is priced.

A second concern is most of the empirical literature runs monthly return regressions using annual measures of emissions intensity. This treatment likely introduces measurement error into the regression specification if investors learn about emissions intensities during the year. We overcome this problem by estimating our regressions at an annual frequency. Our theoretical analysis shows estimating at a lower frequency can help to overcome the measurement error biases that are induced by estimating at too high a frequency.

Third, for tests for pricing based on the performance of high and low emissions portfolios, the portfolio comparison approach has important limitations that make it difficult to detect pricing. In particular, because the returns of the portfolios that are being compared are weighted average of the returns of firms in different industries, the portfolio approach cannot control for industry as a determinant of required returns. This is potentially problematic because our baseline regressions using firms' returns show that the pricing of carbon emissions is, at least in part, *within* industries. In addition, portfolio based approaches cannot be used to test the rich predictions that we derive from well-specified and mis-specified predictions using *individual* firms returns.

Our finding that emissions intensity is priced may stem from the portfolio choice of investors who dislike investing in firms with high emissions intensity or from a remuneration required in compensation for exposure to 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. We believe this possibility is unlikely to be a concern in our setting since Aswani et al. (2024) and Atilgan et al. (2023) show that emissions intensity is uncorrelated with firms' cash flows and earnings surprises, respectively.

Our paper makes two contributions to the literature on asset pricing and sustainable finance. First, we present a new approach to test whether a characteristic is priced in asset markets. Our approach is based on the assumed stochastic properties of the characteristic and on the log-linear return decomposition of Campbell and Shiller (1988) and Campbell (1991). The approach generates several testable predictions. Our analysis focuses on carbon emissions but our theoretical framework can be applied more generally.

Second, we present new evidence to determine if emissions intensity is priced. Unlike almost all studies on climate finance, our tests use information from both the expected and unexpected parts of returns. We also exploit predictions on measurement error and omitted variables bias to determine if emissions intensity is priced. Finally, we use annual return regressions, which we argue reduce the incidence of measurement error compared with higher frequency regressions. In sum, we believe our approach improves the signal-to-noise ratio in determining if emissions intensity is priced. While ours is not the first paper attempting to reduce this signal-to-noise ratio (see for instance Berg et al. (2022), Eskildsen et al. (2024), and Pástor et al. (2022), we propose a novel way to do it: using required returns, relying on the unexpected part of realized returns, and exploiting new predictions on measurement error and omitted variables bias.

Our results help to reconcile the finding that emissions intensity significantly affects institutional investors demands (Pedersen et al., 2021) by amounts that are large enough to potentially be priced (Bolton and Kacperczyk, 2021), but appear to not be priced. Our tests show that emissions intensity is priced after all. These results support theories suggesting that investors' dislike for high carbon emitting firms plays an important role in the ability of emissions intensity to significantly explain stock returns (Pastor et al., 2021; Pedersen et al., 2021; Baker et al., 2022; Zerbib, 2022; Oehmke and Opp, 2023), but more analysis is needed to convincingly make this causal claim.

The remainder of the paper is organized as follows. Section 2 presents our data and summary statistics about carbon emissions. Section 3 presents the theoretical framework informing our analysis of the effect of carbon emissions on stocks' required returns. Section 4 presents our empirical results on the pricing of carbon emissions in the U.S. stock market. Section 5 concludes.

# 2 Data and empirical facts about emissions

We now present our data and discuss some key summary statistics. Section 2.1 illustrates our main data sources and how we combine them to obtain our final data set. Section 2.2 presents and discusses a set of summary statistics, mostly about carbon emissions across firms and industries.

## 2.1 Data

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

**Emissions.** Firm-level carbon emissions are obtained from S&P Trucost.[3] 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.[4] Emissions are reported in both 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). We will refer to this normalized measure as carbon emissions intensity.

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

[4]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.*"

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 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. Therefore, 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 (e.g., the emissions from the in-use phase of a company's products or services, such as the driving of a truck produced by an automobile manufacturer). We focus our analysis on scope-1 and scope-2 emissions.

**Constructing our data.** We use three data sets. First, we obtain emissions intensity at the firm-year level from S&P Trucost. The sample of firms covered in Trucost expands substantially from 2016 onward. We link emission data from Trucost with the Business Entity Cross Reference Service (BECRS) and the S&P company foundations files. The second source of data is CRSP/Compustat, which is merged with Trucost using the CIQ link table. Finally, the third data set is company-level fundamental data from Compustat. We calculate firm-level excess returns by merging CRSP stock return data with the risk-free rate obtained from Kenneth French's data library.

In sum, our final data set consists of an unbalanced panel of 21,857 observations featuring 2,834 firms across 23 industries (NAICS 2-digit codes) at an annual frequency from 2002 to 2022. The unit of observation is firm-year. The top-5 industries in terms of number of observations are (i) Manufacturing A (4,891 observations; 582 firms; NAICS code 33), (ii) Finance and Insurance (3,818 observations; 523 firms; NAICS code 52), (iii) Manufacturing B (2,885 observations; 485 firms; NAICS code 32), (iv) Information (1,949 observations; 302 firms; NAICS code 51), and (v) Mining, Quarrying, and Oil and Gas Extraction (1,126 observations; 124 firms; NAICS code 21).[5] As mentioned before, the Trucost coverage increases substantially starting from 2016. The number of observations jumps from an average of 667 per year in 2010-2015 to an average of 2,239 in 2016-2021 (and drops to 228 in 2022 as we are waiting for the data to be updated since our last download). See Table E.1 and Table E.2 for the annual breakdown of observations and the breakdown of observations across industries, respectively.

## 2.2 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 having very large emissions.[6] In our empirical analysis, we focus on emissions intensities, namely emissions normalized by firm revenues. The skewness of emissions intensities holds across years, as the cross-sectional distribution of emissions intensities does not change dramatically in the time-series dimension (see the left panel of Figure D.1). 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 2,711, 923, 671, and 518, respectively. The contrast with the least polluting industries is staggering as Finance and Insurance (NAICS code 52) and

[5] 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).

[6] Scope-1 and scope-2 emissions are never missing simultaneously. Only 11 firm-year observations have zero scope-1 emissions—2 firms in Construction industry (NAICS 23), 5 in Information industry (NAICS 51), and 4 in Real Estate and Rental and Leasing industry (NAICS 53). Only 13 firm-year observations have zero scope-2 emissions, all in the Utilities industry (NAICS code 22).

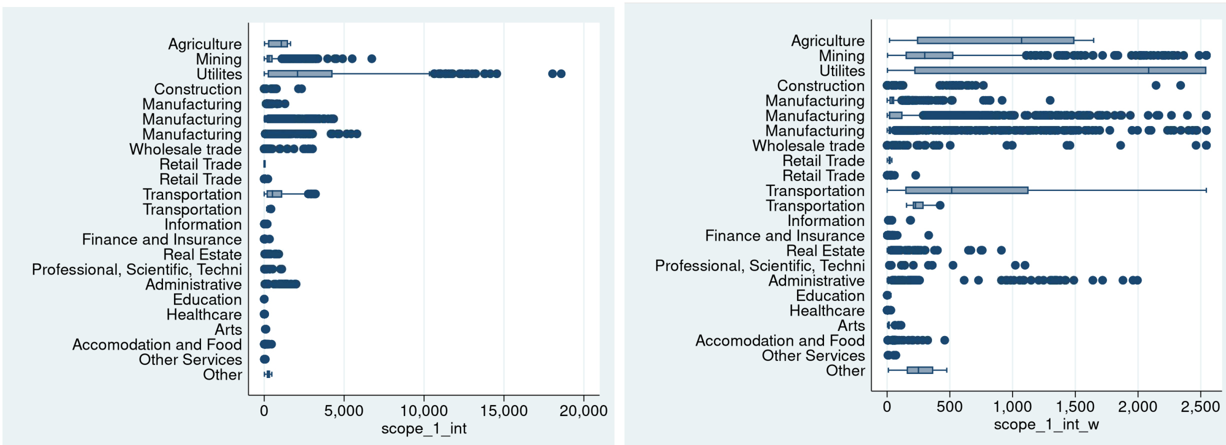


**Figure 1: Large cross-sectional variation in scope-1 emissions intensities within industries.** This figure shows the within-industry cross-sectional variation in scope-1 emissions intensities. Each dot is a firm-year observation in the period 2002-2022. Firm-year observations are grouped by firm 2-digit NAICS code on the y-axis. The box in each box plot includes observations in the second and third quartile of the within-industry cross-sectional distribution. Lines (whiskers) are drawn to span all data points within 1.5 interquartile (IQR) range of the nearer quartile. That is, one whisker extends to include all data points within 1.5 IQR of the upper quartile and stops at the largest such value, while the other whisker extends to include all data within 1.5 IQR of the lower quartile and stops at the smallest such value. The left figure includes the full sample. The right figure includes the full sample after a 95% winsorization (2.5% in each tail).

Information (NAICS code 51) have mean scope-1 emissions intensities equal to 1.6 and 4.9, respectively. In the cross-section of industries, the distribution of mean industry-level scope-1 emissions intensities has a mean of 262, a median of 60, a standard deviation of 584, and a skewness of 3.5.

The large variation in emissions intensities is present also *within* industries, as documented in the left panel of Figure 1. The figure shows, for each industry on the y-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 two firm-year observations (same firm in 2007 and 2006) with emissions intensities above 18,000, 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 (947 observations), but is likely an important driver of any cross-sectional analysis of emissions intensity, even within industries. Utilities is inherently an heterogenous industry, which includes Water, Sewage and Other Systems (NAICS code 2213) with median scope-1 emissions intensity of 102, Natural Gas Distribution (NAICS code 2212) with median scope-1 emissions intensity of 237, and Electric Power Generation, Transmission and Distribution (NAICS code

2211) with a staggering median scope-1 emissions intensity of 3,218.

The right panel of Figure 1 shows the distribution of scope-1 emissions intensities following a 95 percent winsorization (2.5 percent per tail) over the entire set of firm-year observations. Note that the winsorization strongly affects the emissions intensities for firms operating in the Utilities industry. For example, there are 34 observations in this industry with emissions intensities greater than 10,000. After winsorization, these "super emitters" are truncated to the value 2,500, only 1/4 of their actual value. In Section 4, we discuss the role played by these extreme values in the analysis of carbon pricing in equity markets.

# 3 Theoretical framework

Our theoretical framework contains three parts. First, in Section 3.1, we present a stylized theoretical model which shows how investors' preferences (i) about the mean and variance of their wealth and (ii) about investing in $CO_2$ emitters affect firms' required and realized returns. Motivated by the relationships found within our model, in Section 3.2, we derive how emissions intensities are related to firm returns if emissions intensity is priced in the stock market. Third, in Section 3.3, we use this derived relationship to discuss (i) the biases in the existing literature and (ii) propose better ways to test whether emissions intensity is priced in the stock market.

## 3.1 Stylized model

Our stripped down setting focuses on investors' preferences and the timing of information on emissions.[7]

**Timeline.** We consider a stylized asset pricing model that has four dates: $0, t, 1, 2$. Date 0 is the beginning of the model. The other dates correspond to the number of years from date 0. At date 0, investors trade assets and form portfolios of risky and one period risk-free

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

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 dates 1 and 2. In addition, there are $N$ risky assets. Their supply is denoted by the $N \times 1$ vector $\bar{X}$. 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 distribution:

$$v \sim \mathcal{N}(\bar{v}, \Omega) \tag{2}$$

**Investors.** There are $M$ investors indexed $m = 1, \ldots M$. Investors choose their portfolios to maximize their utility over date 2 consumption and date 2 emissions intensity. Investor $m$'s vector of risky asset holdings is denoted $X_m$. Investors have mean-variance preferences over their date 2 consumption and have a non-pecuniary dislike of holding the shares of firms with high emissions intensity.[8] Specifically, the utility of investor $m$ is given by:

$$U_m[W_{m,2}, \mathbb{E}(e_{m,t})] = \mathbb{E}(W_{m,2}) - \frac{1}{2} A_m Var(W_{m,2}) - \nu_m \mathbb{E}(e_{m,t}) \tag{3}$$

where $W_{m,2}$ is the wealth of investor $m$ in period 2, $A_m$ is investor $m$'s risk aversion, $\mathbb{E}(e_{m,t})$ is the expected emissions intensity of investor $m$'s investments, and $\nu_m$ is investor $m$'s dislike for emissions intensity. We assume that positive values of $e_{m,t}$ are associated with more pollution. Hence, negative values of $e_{m,t}$, for example, from shorting firms with high emissions intensity, are good.

We assume that the expected emissions intensity from an investor's holdings of asset $i$ is equal to the number of shares the investor holds times the firm expected emissions intensity

[8] In our reduced form framework, we directly assume that investors dislike holding shares of polluting stocks. Baker et al. (2022) show how hedging needs and additional countervailing motives may lead to such preferences.

per share, $e_i$. Aggregating across firms, the expected emissions intensity of investor $m$'s holdings is given by:

$$\mathbb{E}(e_{m,t}) = X_m' e \tag{4}$$

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

**Solving the model.** The model is solved by backwards induction from the portfolio choice problem at date 1. At date 1, investors solve:

$$\max_{X_{m,1}, B_{m,1}} U_m[W_{m,2}, \mathbb{E}(e_m, t)] \tag{5}$$

subject to the identity:

$$W_{m,2} = X_{m,1}' v + B_{1,m} r_f, \tag{6}$$

and subject to the budget constraint:

$$X_{m,1}' P_1 + B_{1,m} = W_{1,m}, \tag{7}$$

where $B_{1,m}$ is investor $m$'s investment in the risk-free asset at date 1, $r_f$ is the risk-free asset gross return, $P_1$ is the vector of prices of the risky assets at the beginning of date 1, and $W_{1,m}$ is investor $m$'s wealth at the beginning of date 1. We solve for $B_{1,m}$ from Equation (7) and plug it into Equation (6). We then use these in the objective function in Equation (3) and further simplify, so the optimization problem for investor $m$ can be rewritten as:

$$\max_{X_{m,1}} r_f W_{1,m} + X_{m,1}'(\bar{v} - r_f P_1) - \frac{1}{2} A_m X_{m,1}' \Omega X_{m,1} - \nu_m X_{m,1}' e \tag{8}$$

The first order condition for investor $m$ is:

$$X_{m,1} = \frac{1}{A_m} \Omega^{-1} (\bar{v} - \nu_m e - r_f P_1) \tag{9}$$

Relative to a standard mean-variance optimization problem, the effect of firm's expected emissions intensity 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:

$$\sum_{m=1}^{M} \frac{1}{A_m} \Omega^{-1}(\bar{v} - \nu_m e - r_f P_1) = \bar{X} \tag{10}$$

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

$$P_1 = \frac{1}{r_f} \left( \bar{v} - \frac{\Omega \bar{X} + e \sum_{m=1}^{M} \frac{\nu_m}{A_m}}{\sum_{m=1}^{M} \frac{1}{A_m}} \right) \tag{11}$$

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

$$r_i = \bar{v}./P_1 = r_f \bar{v}./ \left( \bar{v} - \frac{\Omega \bar{X} + e \sum_{m=1}^{M} \frac{\nu_m}{A_m}}{\sum_{m=1}^{M} \frac{1}{A_m}} \right), \tag{12}$$

where the expression "./" represents the element-by-element division of the two vectors.

Furthermore, the assets' risk premium from period 1 to 2, $r_i - r_f$, is given by:

$$r_i - r_f = \bar{v}./P_1 - r_f = r_f \left[ \bar{v}./ \left( \bar{v} - \frac{\Omega \bar{X} + e \sum_{m=1}^{M} \frac{\nu_m}{A_m}}{\sum_{m=1}^{M} \frac{1}{A_m}} \right) - 1 \right]. \tag{13}$$

**Implications for the impact of news about emissions intensity on equity prices and required returns.** Our stylized model generates two main insights. Suppose that at time $t$, between periods 0 and 1, new information arrives suggesting that an asset's emissions intensity will increase next year. First, such news reduces the price of that asset in period 1, $P_1$, as shown in Equation (11). Thus the news lowers the realized return between periods 0 and 1 below what had been expected at date 0. Second, the lower price in period 1 implies the news increased the asset's required return, $r_i$, and risk premium, $r_i - r_f$, between periods 1 and 2, as shown in equations (12) and (13), respectively. More generally, the model shows that news that emissions intensity is higher than expected reduces realized returns in the period that the news arrives, and it increases required returns in future periods.

In the next section, we develop a set of empirical tests informed by the results in the stylized model presented above.[9]

## 3.2 Relating emissions intensity and excess returns

We now derive how emissions intensities are related to firm returns if emissions intensity is priced in the stock market. Our analysis begins from the decomposition of excess returns for stock $i$ at time $t$ into two components: (i) expected excess returns (i.e., required excess returns) conditional on time $t-1$ information and (ii) an innovation in excess returns based on information that arrives during period $t$.

$$r_{i,t} - r_{f,t} = \mathbb{E}_{t-1}(r_{i,t} - r_{f,t}) + [\mathbb{E}_t - \mathbb{E}_{t-1}](r_{i,t} - r_{f,t}) \tag{15}$$

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

$$[\mathbb{E}_t - \mathbb{E}_{t-1}](r_{i,t} - r_{f,t}) \approx [\mathbb{E}_t - \mathbb{E}_{t-1}] \left[ -\sum_{s=1}^{\infty} \rho_i^s (r_{i,t+s} - r_{f,t+s}) - \sum_{s=1}^{\infty} \rho_i^s r_{f,t+s} + \sum_{s=0}^{\infty} \rho_i^s g_{i,t+s} \right] \tag{16}$$

where $\rho_i$ 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 return for firm $i$. The decomposition is broken into three terms. The first term shows that positive

[9] Imposing market clearing and simplifying, we find that the change in investors' risky asset holdings at date 1 due to a change in expected emissions intensity is given by:

$$dX_m = \frac{1}{A_m} \left( \frac{\sum_{s=1}^{M} \frac{\nu_s}{A_s}}{\sum_{s=1}^{M} \frac{1}{A_s}} - \nu_m \right) \Omega^{-1} de, \tag{14}$$

so that, given positive (negative) news about expected emissions, each investor increases (decreases) her equity holdings if her dislike for emissions intensity, $\nu_m$, is lower (higher) than a risk tolerance weighted average of the dislike for emissions intensity of all investors in the economy.

innovations in future risk premia negatively affect returns at time $t$. The second term shows that positive innovations in future 1-year risk-free rates negatively affect contemporaneous returns. The last term shows that positive innovations in future dividend growth positively affect returns.

Our goal is to apply the insights from equations (15) and (16) in a simple setting where emissions intensity is priced. To this end, we make a few assumptions.

**Assumption 1.**

$$\mathbb{E}_{t-1}(r_{i,t} - r_{f,t}) = \gamma \mathbb{E}_{t-1}[e_{i,t}] \quad \textit{with} \quad \gamma > 0. \tag{17}$$

This assumption states that firm $i$'s required excess returns at time $t$ depend on time $t-1$ beliefs about firm $i$'s emissions intensity at time $t$, denoted $e_{i,t}$. The equation also implies that expected emissions intensity is a positively priced characteristic because $\gamma > 0$. Note that this assumption implies that emissions intensity is the *only* variable that determines required returns. This strong part of the assumption is only for exposition and we relax it in our empirical work (and could relax it in our theoretical work without altering the intuition).

**Assumption 2.**

$$e_{i,t} | I_{t-1} \sim N(e_{i,t-1}, \sigma_u^2) \qquad \forall t \tag{18}$$

This assumption implies that emissions intensity for each firm $i$ follows the equation:

$$e_{i,t} = e_{i,t-1} + u_{i,t}, \tag{19}$$

further implying that each firm's emissions intensity follows a random walk with the innovation $u_{i,t}$ distributed i.i.d. across firms as:

$$u_{i,t} \sim N(0, \sigma_u^2) \tag{20}$$

This assumption is a reasonable approximation of the data as the first order autocorrelation of emissions intensity is nearly 1.[10] Using annual data, Zhang (forthcoming) documents

[10]See Appendix B for an alternative derivation in which emissions intensity follow instead a AR(1) process.

annual autocorrelation coefficients for emissions intensities that are 0.99 for scope-1 emissions and 0.94 for scope-2 emissions. In addition, Bolton and Kacperczyk (2021) show, using autoregressions, that emissions and emissions intensity are both highly persistent.

Note that these assumptions on emissions intensity can be generalized to allow for expected technical progress, which would correspond to a random walk with downward drift. They can also be generalized to allow for innovations in emissions intensity ($u_{i,t}$) to be heteroskedastic across firms or industries. Neither of these refinements qualitatively alters the derivations below. For simplicity, we do not further explore them here.

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

This assumption on $r_f$ and $g_i$ is for simplicity in order to focus on emissions intensity in our theoretical analysis. This assumption and the law of iterated expectations imply

$$(\mathbb{E}_t - \mathbb{E}_{t-1})e_{i,t+s} = e_{i,t} - e_{i,t-1}, \tag{21}$$

for all $s \geq 0$. Applying this assumption together with Assumption 1 in Equation (15) while using Equation (16) yields:

$$r_{i,t} - r_f = \gamma e_{i,t-1} - \gamma \left[\sum_{s=1}^{\infty} \rho_i^s\right] (e_{i,t} - e_{i,t-1}) \tag{22}$$

Using the Gordon Growth model, the term $\sum_{s=1}^{\infty} \rho_i^s = \frac{\rho_i}{1-\rho_i}$ is approximately equal to $\frac{\bar{P_i}}{D_i}$, which is the long-run average price-dividend ratio for firm $i$.[11] An alternative, but less general, derivation of this equation (see Appendix A) replaces this ratio with $\frac{P_{i,t-1}}{D_{i,t-1}}$. We use this expression in our analysis below. Hence, our simplified relationship for how emissions

[11]More specifically:

$$\frac{\rho_i}{1-\rho_i} = \frac{e^{\bar{g_i}-\bar{r_i}}}{1-e^{\bar{g_i}-\bar{r_i}}} = \frac{e^{\bar{g_i}}}{e^{\bar{r_i}} - e^{\bar{g_i}}} \approx \frac{1+\bar{g_i}}{\bar{r_i}-\bar{g_i}} = \left(\frac{\bar{P_i}}{D_i}\right), \tag{23}$$

where $\left(\frac{\bar{P_i}}{D_i}\right)$ is the price-dividend ratio in the Gordon Growth model for a firm with constant dividend growth rate $\bar{g_i}$ and constant required return $\bar{r_i}$.

intensity affects returns is:

$$r_{i,t} - r_{f,t} = \gamma e_{i,t-1} - \gamma \left( \frac{P_{i,t-1}}{D_{i,t-1}} \right) (e_{i,t} - e_{i,t-1}) \tag{24}$$

Equation (24) is one of the key equations in our empirical analysis. It shows how emissions intensity should approximately affect returns (i) if required returns are priced linearly, (ii) if emissions intensity follows a random walk (a reasonable approximation), and (iii) if required returns during period $t$ are only a function of variables known before period $t$, as required by theory.

The first term on the right hand side of the equation is the required return conditional on time $t-1$ information. The second term captures how the innovation in emissions intensities during time $t$, $e_{i,t} - e_{i,t-1}$, affects contemporaneous returns. Being associated with future higher required returns, a positive innovation lowers contemporaneous returns. This insight is consistent with the Campbell (1991) equation and also with the second implication of our theoretical model illustrated at the end of Section 3.1. Furthermore, this equation shows that the response to the emissions innovation is proportional to firms' price-dividend ratios. The price-dividend ratio appears because the sensitivity of asset returns to permanent changes in required returns in the Gordon Growth model is proportional to the price-dividend ratio. Note that firms with high price-dividend ratios have either high dividend growth rates, or low required returns, or both. These characteristics make their asset prices and returns more sensitive to changes in future required returns.

There are two other testable implications associated with Equation (24). First, emissions intensity at time $t$ ($e_{i,t}$) does not enter the theoretically derived equation with a positive sign. Note that much of the empirical literature tests whether $e_{i,t}$ has a positive coefficient by regressing $r_{i,t} - r_{f,t}$ on $e_{i,t}$. Our results suggest that this approach commonly used in the existing literature is incorrect and may lead to misleading conclusions. Second, suppose we estimate the following equation by OLS:

$$r_{i,t} - r_{f,t} = \alpha + \eta_1 e_{i,t-1} + \eta_2 \left( \frac{P_{i,t-1}}{D_{i,t-1}} \right) e_{i,t} + \eta_3 \left( \frac{P_{i,t-1}}{D_{i,t-1}} \right) e_{i,t-1} \tag{25}$$

(or a variant with extra controls dated at time $t-1$). Equation (24) predicts $\eta_1 > 0$, $\eta_2 < 0$, and $\eta_3 > 0$. In addition, the theory predicts

$$\eta_1 = -\eta_2 = \eta_3. \tag{26}$$

## 3.3 Additional implications

We now use the derived relationship between emissions intensity and excess returns to discuss the biases in the existing literature and to propose better ways to test whether emissions intensity is priced in equity markets.

**Existing literature.** Several papers in the literature (Bolton and Kacperczyk, 2021; Aswani et al., 2024) ask whether emissions intensity (or emissions) is priced by estimating cross-section or panel regressions that take the form:[12]

$$r_{i,t} - r_{f,t} = \alpha + \gamma e_{i,s} + \beta controls_{i,s'} + \epsilon_{i,t} \tag{27}$$

On the left-hand side, the dependent variable is excess monthly returns over the risk-free rate, measured at a monthly frequency. On the right-hand side, is a measure of emissions (as discussed, in our work we use "emissions intensity"). This variable is measured annually. Given that returns are at a monthly frequency, in many specifications the emissions variable for each month in a year is set to be the same value as the emissions for the year [s = 12*ceiling(t/12)]; in some specifications the emissions variable is set to emissions for the prior year [s= 12*floor(t/12)]; and in some specifications the emissions variable is set to the previous publicly released value for emissions. The controls in the regression are measured at a monthly, quarterly, or annual frequencies. The dating of the controls is sometimes contemporaneous with the emissions ($s' = t$) or alternatively lagged one period.[13][14]

[12]Some specifications use time dummies and hence drop $r_{f,t}$ from the regression.

[13]A period corresponds to the frequency with which the control is measured.

[14]In Aswani et al. (2024), the controls are described as being contemporaneous with emissions intensity, but in our conversations, the authors stated that the controls they used in the paper are actually lagged to be consistent with Bolton and Kacperczyk (2021).

A potential problem with this regression specification, and its focus on monthly returns, is mis-specification of the timing of investors' information in Equation (27). For example, at the beginning of a year, investors cannot know the emissions intensity during that year, but even in the absence of publicly released information, they may have a much better indication of what the annual emissions intensity will be as time goes by and approaches the end of the year. This reasoning suggests the return regressions used in much of the literature may suffer from measurement error because the use of annual emissions data to represent investors' expectations at a monthly frequency implicitly assumes investors know too much or too little for months at the beginning or at the end of the year, respectively.

There is another concern in monthly return regressions. Although investors do not know $e_{i,t}$, they may be learning about it each month. Hence, the innovation in their beliefs about $e_{i,t}$ will affect the residual in the regression each month. In the regressions where investors are assumed to know too much, at the beginning of the year, the residual will be correlated with the emissions intensity regressor. Given that the regressor is correlated with the residual, we will refer to the resulting bias as omitted variables bias, and we will show below that adding an additional regressor can eliminate this bias. Because the learning occurs during the year, the magnitude of the omitted variables bias is also likely decreasing as the year progresses. In sum, due to these time varying biases, the monthly regressions are difficult to interpret.[15]

Given the timing and interpretation issues related to the use of monthly return data, we use annual returns in our empirical analysis. In Appendix C we show that if emissions intensity can be approximated by a random walk, which is consistent with the empirical evidence, estimating the regressions using annual data overcomes the measurement error issues that are present in the monthly return regressions. Our approach leads to arguably a cleaner interpretation of the data compared to the one based on monthly return data. A contribution of our work is to show that, if emissions intensities is priced, the magnitude of the omitted variables bias is a function of the lagged price-dividend ratios of the return

[15]An additional reason for moving to annual regressions is that investors information on climate is incorporated into returns as a lower than monthly frequency for small firms (Pástor et al., 2022).

observations used in the regression. Hence, by choosing observations conditioning on firms' lagged price-dividend ratios, we can (i) gauge the magnitude of the omitted variables bias, (ii) examine if the reduction in this bias is consistent with the theory, and (iii) provide evidence in favor of emissions intensity being priced.

To illustrate the biases in regressions using monthly data, but in a simpler setting, we focus on the following cross-sectional regression that uses annual return data and a single regressor, namely emissions intensity in year $t$:

$$r_{i,t} - r_{f,t} = \alpha + \gamma e_{i,t} + \epsilon_{i,t} \tag{28}$$

To interpret this regression, we assume that the theoretically derived Equation (24) is the true process through which returns are generated. Recall that Equation (24) decomposes returns into an expected return component $\gamma e_{i,t-1}$ and a residual component that is uncorrelated with $e_{i,t-1}$ and has zero mean. Because the residual is uncorrelated with the regressor and has zero mean, an OLS regression of $r_{i,t} - r_{f,t}$ on $e_{i,t-1}$ should produce unbiased and consistent estimates for $\gamma$.

Equation (28), if estimated with $e_{i,t}$ instead of $e_{i,t-1}$ as a regressor, produces a bias due to measurement error. Given that emissions intensity follows a random walk, the emissions intensity at time $t$ is equal to emissions intensity at time $t-1$ plus noise (see Equation (19)). Hence, the measurement error should create a bias by shrinking the estimate of $\gamma$ towards 0.

The residual in the theoretically derived Equation (24) is:

$$-\gamma \left( \frac{P_{i,t-1}}{D_{i,t-1}} \right) (e_{i,t} - e_{i,t-1}) \tag{29}$$

Note that the role of $e_{i,t}$ as a regressor can be decomposed into two components: its expectation as of time $t-1$ ($e_{i,t-1}$) and $u_{i,t}$ ($e_{i,t} - e_{i,t-1}$), which is the innovation in emissions intensity. If markets are informationally efficient, the first component should not be correlated with the residual. However, since the residual term in the true equation consists of parameters and variables assumed known at time $t-1$ multiplied by $-(e_{i,t} - e_{i,t-1})$, the residual conditional on time $t-1$ information is negatively correlated with the second component. Hence, the true regression residual is negatively correlated with the regressor $e_{i,t}$; this is the omitted variables bias we referred to earlier. By adding $\left(\frac{P_{i,t-1}}{D_{i,t-1}}\right)(e_{i,t} - e_{i,t-1})$ as a regressor in Equation (28), the regressor will not be correlated with the regression residual anymore, thus fixing the omitted variables bias.

If the omitted variables bias is not corrected, the estimation generates a negative bias in the estimated coefficient $\gamma$. This omitted variables bias can push the estimated $\gamma$ below zero when the true $\gamma$ is positive. The magnitude of the bias depends on the lagged price-dividend ratios (since the price-dividend ratio affects the covariance between the regressor and the residual)

If $\gamma$ is estimated via OLS in Equation (28) (and excess returns are generated by Equation (24)), we have:

$$\hat{\gamma} = \frac{\widehat{\text{CSCov}}(r_{i,t} - r_{f,t}, e_{i,t})}{\widehat{\text{CSVar}}(e_{i,t})} \tag{30}$$

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 (24), the probability limit for $\gamma$ is:

$$\text{plim } \hat{\gamma} = \frac{\text{plim } \widehat{\text{CSCov}}(\gamma e_{i,t-1} - \gamma \frac{P_{i,t-1}}{D_{i,t-1}} u_{i,t}, e_{i,t})}{\text{plim} \widehat{\text{CSVar}}(e_{i,t})} \tag{31}$$

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:[16]

$$\text{plim } \hat{\gamma} = \gamma \left( \frac{\sigma^2_{e_{t-1}}}{\sigma^2_{e_{t-1}} + \sigma^2_u} \right) - \gamma \left( \mathbb{E}(\frac{P_{i,t-1}}{D_{i,t-1}}) \frac{\sigma^2_u}{\sigma^2_{e_{t-1}} + \sigma^2_u} \right). \tag{32}$$

The first term is due to classical measurement error and occurs because $e_{i,t}$ is a noisy measure of expected emissions at time $t$ as of time $t-1$ information—and thus causes shrinkage of $\gamma$ towards zero. The second term is due to surprises in $e_{i,t}$ relative to time $t-1$

[16] More specifically, $\mathbb{E}(r_{i,t} - r_f | I_{t-1}) = \gamma e_{i,t-1}$, and $\mathbb{E}(e_{i,t}|I_{t-1}) = e_{i,t-1}$. Therefore, $\text{Cov}[\mathbb{E}(r_{i,t} - r_f|I_{t-1}), \mathbb{E}(e_{i,t}|I_{t-1})] = \gamma \sigma^2_{e_{t-1}}$. 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 $\text{Var}(e_{i,t}) = \sigma^2_{e_{i,t-1}} + \sigma^2_u$. These expressions produce the result in Equation (32).

information. The magnitude of such surprises associated with changes in expectations of future return is measured by $\sigma_u^2$. Positive emissions surprises increase future required returns and thus generate a negative capital gain (the second term is negative and can be of any magnitude). Hence, if $\gamma$ is positive, the estimated $\gamma$ in large samples could potentially turn negative. The total effect of this term depends on the average price-dividend ratio across the firms in the sample, and on the variability in $\sigma_u^2$. Note that the price-dividend ratio can potentially be large. It is currently above 50 for the Wilshire 5000.

It is unclear how large $\sigma_u^2$ is. But, the larger it is, the more it exacerbates the shrinkage towards 0 due to measurement error (the first term of the bias) and also exacerbates the pull towards a negative estimate due to omitted variables bias. Collectively, these biases may explain why in contemporaneous regressions of returns on emissions intensity, the coefficient on emissions intensity is usually small and statistically insignificant (Bolton and Kacperczyk, 2021) and often negative (Aswani et al., 2024).[17] These biases may also help reconcile the finding in Bolton and Kacperczyk (2021) (see page 541) that the effect of divestment based on carbon intensity through investment advisers seems to be on a scale large enough to move prices, but nevertheless does not seem to be priced empirically.

An important implication of Equation (32) is the following: if emissions intensity is priced ($\gamma > 0$), the magnitude of the second term depends on the average price-dividend ratio among the data observations used in the regression. This insight implies that the bias term will be smaller and the estimate of $\gamma$ will be larger if we run the regression only using observations with small lagged price-dividend ratios. Conversely, the estimate of $\gamma$ will be smaller (and possibly even negative) if we run the regression only using observations with higher than average values of the lagged price-dividend ratio.

It is important to note that our results on conditioning on price-dividend ratios rely 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 prices to required

[17]For example, Table 8 in Aswani et al. (2024) estimates several variants of contemporaneous regressions of returns on emissions intensity, and reports a negative sign on emissions intensity in two-thirds of the regressions and negative coefficients that are statistically significant in a third of the regressions.

returns. But these approximations may not be reasonable for some firms. Many firms do not pay dividends, but use share repurchases, or some firms may not currently make distributions to shareholders but may in the future. The appropriate way to handle these cases is by using alternative frameworks to compute the sensitivity of stock prices to permanent changes in required returns and then conditioning on this sensitivity instead of price-dividend ratios. In our empirical analysis that conditions on lagged price-dividend ratios, we only use data for those firms for which the lagged price-dividend ratio is well defined (i.e., finite).

**Fixing the biases and testing the theory.** Finally, let us note that these results on biases are due to $e_{i,t}$ being used as the regressor in Equation (28) instead of $e_{i,t-1}$. Using $e_{i,t-1}$ should reduce the shrinkage towards 0 because of classical measurement error bias. In addition, if markets are efficient, $e_{i,t-1}$ should then be uncorrelated with the regression residual, thus eliminating the omitted variables bias too.

The additional insights from the theory are summarized below:

1. If Equation (32) is the true equation generating returns and $e_{i,t-1}$ is used as a regressor in estimating Equation (28) using cross-sectional OLS regression, the estimate of $\gamma$ should then be unbiased and consistent.

2. If Equation (32) is the true equation generating returns and $e_{i,t}$ is used as a regressor in estimating Equation (A1), the estimate of $\gamma$ will then be biased towards 0 because of classical measurement error and the estimate of $\gamma$ will be biased downwards because of omitted variable bias. The omitted variable bias can drive $\gamma$ below 0.

3. The omitted variables can be controlled by choosing regression observations conditioning on firms' lagged price-dividend ratios. If emissions intensity is priced, the estimate of $\gamma$ in Equation (28) in the subsample of low lagged price-dividend ratios should increase. Conversely, the conditioning on observations with high lagged price-dividend ratios should decrease estimates of $\gamma$, and could push them even below 0.

4. The omitted variable bias in Equation (28) with the independent variable $e_{i,t}$ can be eliminated by adding $\left(\frac{P_{i,t-1}}{D_{i,t-1}}\right) \times (e_{i,t} - e_{i,t-1})$ as a regressor.

Guided by these theoretical insights, we now turn to the empirical evidence to test if emissions are priced.

# 4 Empirical evidence

In this section, we present our empirical evidence which suggests that carbon emissions intensity is priced in equity returns. First, in Section 4.1, we present the main empirical specification that we use to test whether carbon emissions intensity is priced in equity markets. Second, in Section 4.2, consistent with our theoretical framework, we document that the estimated coefficients are substantially different based on whether we use contemporaneous or lagged emissions intensities as independent variables—where the latter is our preferred choice. Third, in Section 4.3, we show that the magnitude of the pricing of emissions intensities is heavily dependent on how we treat firms that are "super emitters", i.e., on how we winsorize emissions intensities and on whether we exclude some key industries from the sample. Finally, in Section 4.4, we test our new predictions on whether emissions intensity is priced. These predictions stem from modeling how innovations in emissions intensity should affect returns if emissions intensity is priced.

## 4.1 Our preferred specification

Informed by our theoretical framework, our preferred specification is:

$$R_{it} = \alpha + \boldsymbol{\beta'} \boldsymbol{X}_{it-1} + \mu_t + \gamma_i + \epsilon_{it} \tag{33}$$

where $i$ is a firm and $t$ is a year. The sample period runs at an annual frequency from 2002 to 2022. We choose the annual frequency because the data on emissions from Trucost is at an annual frequency. As discussed, ours is a departure from the literature that tends to regress monthly returns on annual emissions. The independent variable is the annual stock return of firm $i$, from $t-1$ to $t$. The vector $\boldsymbol{X}_{it-1}$ includes a set of firm-level variables, lagged by one year. Crucially, this vector includes firm-level emissions intensity, defined in Section 2.1. In some specifications, we include scope-1 emissions intensity. In other specifications, we include the sum of scope-1 and scope-2 emissions intensity. Finally, in some specifications, we include industry fixed effects (based on the 2-digit NAICS code).

The other firm-level variables are control variables, namely variables meant to capture the influence of other omitted factors that are correlated with both emissions intensity and returns. Note that the use of emissions *intensity*, namely emissions normalized by revenues, addresses the natural concern that firms tend to have higher emissions when their revenues are also elevated. The 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 return on equity (defined as net income divided by shareholders' equity), (v) the volatility of the firm stock (defined as the standard deviation of monthly returns over a 12-month period), (vi) firm beta (defined as the CAPM beta calculated over a 12-month period), and (vii) firm book-to-market ratio. While informed by economic theory, there is, of course, a degree of judgement in deciding which control variables to include in this regression. For this reason, in Section 4.2, we conduct a robustness analysis of our estimated coefficients of interest to the inclusion of different sets of control variables.

## 4.2 Contemporaneous versus lagged emissions intensity

Before focusing on our preferred specification, Table 1 shows the estimation results from a specification similar to (33) with the only exception being that firm-level emissions intensities are *contemporaneous* and not lagged, which is a specification commonly used in the literature. The first three columns only 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 and 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.

Note that, following the theoretical discussion in Section 3.3, the regressions of returns on emissions intensities are affected (i) by measurement error, which leads the associated coefficient to shrink towards zero, and (ii) omitted variable bias, which is negative, pulling the estimated coefficient towards zero and even potentially to a negative value. The results

| | $R_{it}$ | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Scope-1 emission$_{it}$ | | 0.001 | | | 0.0016 | |
| | | (0.0008) | | | (0.001) | |
| Scope-1+Scope-2 emission$_{it}$ | | | 0.001 | | | 0.0016 |
| | | | (0.0008) | | | (0.0009) |
| MCAP$_{it-1}$ | −1.512*** | −1.514*** | −1.515*** | −1.522*** | −1.544*** | −1.550*** |
| | (0.2562) | (0.2567) | (0.2567) | (0.2601) | (0.2604) | (0.2605) |
| LEV$_{it-1}$ | −0.0029 | −0.0030 | −0.0030 | −0.0042 | −0.0047 | −0.0047 |
| | (0.0030) | (0.0031) | (0.0031) | (0.0036) | (0.0036) | (0.0036) |
| INVEST/A$_{it-1}$ | −0.3416*** | −0.3434*** | −0.3441*** | −0.1408 | −0.1469 | −0.1486 |
| | (0.1018) | (0.1027) | (0.1028) | (0.1200) | (0.1200) | (0.1200) |
| ROE$_{it-1}$ | 0.0353*** | 0.0354*** | 0.0354*** | 0.0317*** | 0.0317*** | 0.0316*** |
| | (0.0104) | (0.0104) | (0.0104) | (0.0105) | (0.0105) | (0.0105) |
| VOL$_{it-1}$ | 0.7868 | 0.7890 | 0.7892 | 1.084** | 1.079** | 1.079** |
| | (0.5344) | (0.5347) | (0.5346) | (0.5417) | (0.5417) | (0.5417) |
| BETA$_{it-1}$ | 0.6451** | 0.6464** | 0.6464** | 0.6986*** | 0.6957*** | 0.6931*** |
| | (0.2556) | (0.2558) | (0.2557) | (0.2584) | (0.2584) | (0.2584) |
| B/M$_{it-1}$ | −4.307*** | −4.336*** | −4.345*** | −3.910*** | −4.111*** | −4.149*** |
| | (0.9707) | (0.9949) | (0.9954) | (1.012) | (1.020) | (1.021) |
| Year FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Industry FE | | | | ✓ | ✓ | ✓ |
| Observations | 15,539 | 15,539 | 15,539 | 15,539 | 15,539 | 15,539 |
| R-squared | 0.0847 | 0.0847 | 0.0847 | 0.0885 | 0.0887 | 0.0887 |

**Table 1: Effect of contemporaneous emissions on returns.** This table shows the estimation results of specification (33). The unit of observation is firm-year. The sample runs at at annual frequency from 2002 to 2022. Scope-1 emission$_{it}$ is the contemporaneous scope-1 emissions intensity. Scope-1+scope-2 emission$_{it}$ is the sum of scope-1 and scope-2 emissions intensities. Emissions intensity is defined in Section 2.1 and are winsorized at the 95 percent level. The control variables are lagged by one year and are defined as follows: MCAP$_{it-1}$ is log of market capitalization; LEV$_{it-1}$ is total debt divided by total assets, winsorized at the 95 percent level (multiplied by 100); INVEST/A$_{it-1}$ is investment divided by total assets, winsorized at the 97.5 percent level (multiplied by 100); ROE$_{it-1}$ is net income divided by shareholders' equity (multiplied by 100); VOL$_{it-1}$ is the standard deviation of mothly 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, winsorized at the 97.5 percent level. *** p<0.01, ** p<0.05, * p<0.1.

in Table 1 show that the estimated coefficients on firm-level emissions intensity are small and not statistically significant, a result holding regardless of the level of the fixed effects and regardless of the definition used to measure firm-level emissions. This result is in line with the small and statistically insignificant estimated coefficient obtained by Bolton and Kacperczyk (2021).

Having presented the estimation results based on *contemporaneous* emissions intensity, we now move to our preferred specification based on *lagged* emissions intensity. The results are presented in Table 2, which follows the same structure of Table 1. The estimated coefficients crucially depend on the level of the fixed effects included in the regression. On the one

| | $R_{it}$ | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Scope-1 emission$_{it-1}$ | | 0.0011 | | | 0.0027*** | |
| | | (0.0007) | | | (0.0009) | |
| Scope-1+Scope-2 emission$_{it-1}$ | | | 0.0011 | | | 0.0027*** |
| | | | (0.0007) | | | (0.0008) |
| MCAP$_{it-1}$ | −1.170*** | −1.191*** | −1.195*** | −1.187*** | −1.225*** | −1.233*** |
| | (0.2318) | (0.2322) | (0.2323) | (0.2354) | (0.2356) | (0.2357) |
| LEV$_{it-1}$ | −0.0011 | −0.0022 | −0.0023 | −0.0021 | −0.0029 | −0.0030 |
| | (0.0027) | (0.0028) | (0.0028) | (0.0032) | (0.0033) | (0.0033) |
| INVEST/A$_{it-1}$ | −0.2578*** | −0.2759*** | −0.2785*** | −0.2523** | −0.2616** | −0.2637** |
| | (0.0946) | (0.0954) | (0.0955) | (0.1102) | (0.1103) | (0.1103) |
| ROE$_{it-1}$ | 0.0580*** | 0.0585*** | 0.0585*** | 0.0537*** | 0.0537*** | 0.0537*** |
| | (0.0093) | (0.0093) | (0.0093) | (0.0094) | (0.0094) | (0.0094) |
| VOL$_{it-1}$ | −0.9938** | −0.9712** | −0.9726** | −0.8602* | −0.8637* | −0.8633* |
| | (0.4582) | (0.4585) | (0.4584) | (0.4648) | (0.4647) | (0.4647) |
| BETA$_{it-1}$ | 0.7216*** | 0.7331*** | 0.7316*** | 0.7011*** | 0.6956*** | 0.6921*** |
| | (0.2248) | (0.2249) | (0.2249) | (0.2267) | (0.2266) | (0.2266) |
| B/M$_{it-1}$ | 0.5476 | 0.2561 | 0.2305 | 0.5695 | 0.2087 | 0.1654 |
| | (0.8757) | (0.8981) | (0.8984) | (0.9142) | (0.9218) | (0.9228) |
| Year FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Industry FE | | | | ✓ | ✓ | ✓ |
| Observations | 17,168 | 17,168 | 17,168 | 17,168 | 17,168 | 17,168 |
| R-squared | 0.1281 | 0.1282 | 0.1282 | 0.1301 | 0.1306 | 0.1306 |

**Table 2: Effect of lagged emissions on returns.** This table shows the estimation results of specification (33). The unit of observation is firm-year. The sample runs at an annual frequency from 2002 to 2022. Scope-1 emission$_{it-1}$ is the scope-1 emissions intensity lagged by one year. Scope-1+scope-2 emission$_{it}$ is the sum of scope-1 and scope-2 emissions intensities lagged by one-year. Emissions intensities are defined in Section 2.1 and are winsorized at the 95 percent level. The control variables are lagged by one year and are defined as follows: MCAP$_{it-1}$ is log of market capitalization; LEV$_{it-1}$ is total debt divided by total assets, winsorized at the 95 percent level (multiplied by 100); INVEST/A$_{it-1}$ is investment divided by total assets, winsorized at the 97.5 percent level (multiplied by 100); ROE$_{it-1}$ is net income divided by shareholders' equity (multiplied by 100); VOL$_{it-1}$ is the standard deviation of mothly 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, winsorized at the 97.5 percent level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

hand, columns (2) and (3), which include only year fixed effects, show a small and statistical insignificant effect of lagged emissions intensity on returns. On the other hand, columns (5) and (6), which include industry and year fixed effects, show a much larger (more than double) and highly statistically significant effect of lagged emissions intensity on returns.

Before delving into the interpretation of the results, let us note that Table 3 shows that the estimated coefficients with industry and fixed effects are remarkably stable as we progressively saturate the specification with control variables, adding them one by one. Panel A shows such stability for scope-1 emissions intensity and Panel B shows such stability for the sum of scope-1 and scope-2 emissions intensities. In sum, this table shows that the estimated

| | $R_{it}$ | | | | | | |
|---|---|---|---|---|---|---|---|
| Panel A | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| Scope-1 emission$_{it-1}$ | 0.0026*** | 0.0027*** | 0.0028*** | 0.0027*** | 0.0027*** | 0.0027*** | 0.0028*** |
| | (0.0008) | (0.0009) | (0.0009) | (0.0009) | (0.0009) | (0.0009) | (0.0009) |
| LEV$_{it-1}$ | | −0.0056* | −0.0049 | −0.0047 | −0.0047 | −0.0051 | −0.0029 |
| | | (0.0032) | (0.0032) | (0.0032) | (0.0032) | (0.0032) | (0.0032) |
| INVEST/A$_{it-1}$ | | | −0.2345** | −0.2630** | −0.2618** | −0.2629** | −0.2627** |
| | | | (0.1100) | (0.1102) | (0.1103) | (0.1102) | (0.1101) |
| ROE$_{it-1}$ | | | | 0.0423*** | 0.0432*** | 0.0441*** | 0.0538*** |
| | | | | (0.0090) | (0.0092) | (0.0092) | (0.0093) |
| VOL$_{it-1}$ | | | | | 0.1820 | −0.0007 | −0.8590* |
| | | | | | (0.4337) | (0.4375) | (0.4642) |
| BETA$_{it-1}$ | | | | | | 0.7028*** | 0.6974*** |
| | | | | | | (0.2267) | (0.2265) |
| MCAP$_{it-1}$ | | | | | | | −1.240*** |
| | | | | | | | (0.2256) |
| Year FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Industry FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Observations | 21,142 | 17,214 | 17,214 | 17,168 | 17,168 | 17,168 | 17,168 |
| R-squared | 0.13711 | 0.1272 | 0.1275 | 0.1285 | 0.1285 | 0.1290 | 0.1306 |

| | $R_{it}$ | | | | | | |
|---|---|---|---|---|---|---|---|
| Panel B | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| Scope-1+Scope-2 emission$_{it-1}$ | 0.0026*** | 0.0026*** | 0.0027*** | 0.0026*** | 0.0026*** | 0.0026*** | 0.0027*** |
| | (0.0008) | (0.0008) | (0.0008) | (0.0008) | (0.0008) | (0.0008) | (0.0008) |
| LEV$_{it-1}$ | | −0.0057* | −0.0050 | −0.0048 | −0.0048 | −0.0051 | −0.0030 |
| | | (0.0032) | (0.0032) | (0.0032) | (0.0032) | (0.0032) | (0.0033) |
| INVEST/A$_{it-1}$ | | | −0.2364** | −0.2648** | −0.2636** | −0.2647** | −0.2637 |
| | | | (0.1100) | (0.1102) | (0.1103) | (0.1102) | (0.1103) |
| ROE$_{it-1}$ | | | | 0.0422*** | 0.0430*** | 0.0440*** | 0.0537*** |
| | | | | (0.0090) | (0.0092) | (0.0092) | 0.0094 |
| VOL$_{it-1}$ | | | | | 0.1837 | 0.0019 | −0.8633* |
| | | | | | (0.4337) | (0.4375) | (0.4647) |
| BETA$_{it-1}$ | | | | | | 0.6992*** | 0.6921*** |
| | | | | | | (0.2267) | (0.2266) |
| MCAP$_{it-1}$ | | | | | | | −1.233*** |
| | | | | | | | (0.2357) |
| Year FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Industry FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Observations | 21,142 | 17,214 | 17,214 | 17,168 | 17,168 | 17,168 | 17,168 |
| R-squared | 0.1372 | 0.1273 | 0.1275 | 0.1286 | 0.1286 | 0.1291 | 0.1306 |

**Table 3: Effect of lagged emissions on returns, robustness with respect of control variables.** This table shows the estimation results of specification (33). The unit of observation is firm-year. The sample runs at an annual frequency from 2002 to 2022. Scope-1 emission$_{it-1}$ is the scope-1 emissions intensity lagged by one year. Scope-1+scope-2 emission$_{it}$ is the sum of scope-1 and scope-2 emissions intensities lagged by one year. Emissions intensities are defined in Section 2.1 and are winsorized at the 95 percent level. The control variables are lagged by one year and are defined as follows: MCAP$_{it-1}$ is log of market capitalization; LEV$_{it-1}$ is total debt divided by total assets, winsorized at the 95 percent level (multiplied by 100); INVEST/A$_{it-1}$ is investment divided by total assets, winsorized at the 97.5 percent level (multiplied by 100); ROE$_{it-1}$ is net income divided by shareholders' equity (multiplied by 100); VOL$_{it-1}$ is the standard deviation of mothly 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, winsorized at the 97.5 percent level. *** p<0.01, ** p<0.05, * p<0.1.

coefficients of interest with industry and fixed effects are robust across different sets of control variables. Finally, Section E shows that our results are stronger in the period from 2016 to 2022, namely after the Paris Agreement.

The divergence between the estimation results with and without industry fixed effects might be driven by the cross-sectional variation of emissions intensity. By focusing on within-industry variation, the specification with industry fixed effects may be helping the OLS estimator isolate the correlation between emissions intensity and returns. This interpretation is in line with the distribution of emissions intensity across and within industries presented in Section 2.2. Specifically, Figure 1 shows that a large portion of the cross-sectional variation in emissions intensity is actually *within* five industries: utilities, transportation, manufacturing, mining, and wholesale trade.

## 4.3 Key industries and "super emitters"

The estimation results presented so far suggest that carbon emissions intensity is likely priced in equity markets. However, the highly skewed distribution of emissions intensity raises the possibility that a few industries and firms might be driving such pricing. We now show that the magnitude and the extent of the pricing are indeed sensitive to the inclusion of some extreme values of emissions intensity in the regression sample, namely observations corresponding to firms that we label "super emitters."

First, Figure 1 showed that, within the Utilities sector, some firms are indeed characterized by very large emissions intensities. Interestingly, almost all of these firms belong to the "electric power generation, transmission and distribution" sector, i.e., NAICS 2211. Table 4 shows the estimation of our preferred specification, excluding this sector from the sample. The comparison of the estimated coefficients with those in Table 2 shows that, in the subsample that excludes these super emitters, (i) carbon emissions intensity seems to be priced even without industry fixed effects and (ii) the coefficients of emissions intensity with industry and year fixed effects are around 50% larger.

Note that, throughout the analysis, we have so far winsorized the emissions intensity at the 95 percent level (i.e., 2.5 percent on each tail of the distribution). Table 5 shows the sensitivity of the estimated coefficients on scope-1 emissions intensities to changing the level

| | $R_{it}$ | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Scope-1 emission$_{it-1}$ | | 0.0024** | | | 0.0043*** | |
| | | (0.0011) | | | (0.0012) | |
| Scope-1+Scope-2 emission$_{it-1}$ | | | 0.0023** | | | 0.0040*** |
| | | | (0.001) | | | (0.0011) |
| MCAP$_{it-1}$ | −1.197*** | −1.209*** | −1.214*** | −1.220*** | −1.236*** | −1.246*** |
| | (0.2385) | (0.2386) | (0.2386) | (0.2428) | (0.2428) | (0.2428) |
| LEV$_{it-1}$ | -0.0014 | −0.0022 | −0.0023 | −0.0029 | −0.0041 | −0.0041 |
| | (0.0029) | (0.0030) | (0.0030) | (0.0034) | (0.0034) | (0.0034) |
| INVEST/A$_{it-1}$ | −0.2535*** | −0.2939*** | −0.2966*** | −0.2533** | −0.2755** | −0.2777** |
| | (0.0970) | (0.0987) | (0.0988) | (0.1133) | (0.1134) | (0.1134) |
| ROE$_{it-1}$ | 0.0597*** | 0.0599*** | 0.0599*** | 0.0556*** | 0.0551*** | 0.0550*** |
| | (0.0094) | (0.0094) | (0.0094) | (0.0095) | (0.0095) | (0.0095) |
| VOL$_{it-1}$ | −1.085** | −1.096** | −1.101** | −0.9436** | −0.9347** | −0.9346** |
| | (0.4674) | (0.4674) | (0.4674) | (0.4734) | (0.4732) | (0.4732) |
| BETA$_{it-1}$ | 0.6485*** | 0.6383*** | 0.6344*** | 0.6350*** | 0.6223*** | 0.6175*** |
| | (0.2300) | (0.2300) | (0.2300) | (0.2312) | (0.2311) | (0.2311) |
| B/M$_{it-1}$ | 0.6088 | 0.2567 | 0.2380 | 0.5702 | 0.1274 | 0.0827 |
| | (0.9159) | (0.9300) | (0.9301) | (0.9451) | (0.9528) | (0.9538) |
| Year FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Industry FE | | | | ✓ | ✓ | ✓ |
| Observations | 16,501 | 16,501 | 16,501 | 16,501 | 16,501 | 16,501 |
| R-squared | 0.1286 | 0.1288 | 0.1289 | 0.1306 | 0.1313 | 0.1313 |

**Table 4: Effect of lagged emissions on returns, excluding electric power generation, transmission and distribution.** This table shows the estimation results of specification (33). The unit of observation is firm-year. The sample runs at annual frequency from 2002 to 2022. The sample does not include observations in industry NAICS code 2211. Scope-1 emission$_{it-1}$ is the scope-1 emissions intensity lagged by one-year. Scope-1+scope-2 emission$_{it}$ is the sum of scope-1 and scope-2 emissions intensities lagged by one year. Emissions intensities are defined in Section 2.1 and are winsorized at the 95 percent level. The control variables are lagged by one year and are defined as follows: MCAP$_{it-1}$ is log of market capitalization; LEV$_{it-1}$ is total debt divided by total assets, winsorized at the 95 percent level (multiplied by 100); INVEST/A$_{it-1}$ is investment divided by total assets, winsorized at the 97.5 percent level (multiplied by 100); ROE$_{it-1}$ is net income divided by shareholders' equity (multiplied by 100); VOL$_{it-1}$ is the standard deviation of mothly 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, winsorized at the 97.5 percent level. *** p<0.01, ** p<0.05, * p<0.1.

of winsorization. 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 a winsorization at the 99.5 percent level. Columns (2) to (4) consider winsorization levels at the 99 percent, 98 percent, and 90 percent level, respectively. The estimated coefficients decrease in the winsorization level, but are only significant with industry and year fixed effects. Appendix D shows consistent results for the sum of scope-1 and scope-2 emissions intensities. Appendix E shows how the distributions of firm-year observations are affected by different levels of winsorizations. Panel B in Figure 1 shows the

| | $R_{it}$ | | | |
|---|---|---|---|---|
| PANEL A | (1) | (2) | (3) | (4) |
| Scope-1 emission$_{it-1}$ | 0.0003 | 0.0006 | 0.0007 | 0.0022 |
| | (0.0004) | (0.0005) | (0.0005) | (0.0015) |
| Winsorization | 99.5 | 99 | 98 | 90 |
| Controls | ✓ | ✓ | ✓ | ✓ |
| Year FE | ✓ | ✓ | ✓ | ✓ |
| Observations | 17,168 | 17,168 | 17,168 | 17,168 |
| R-squared | 0.1281 | 0.1282 | 0.1282 | 0.1282 |

| | $R_{it}$ | | | |
|---|---|---|---|---|
| PANEL B | (1) | (2) | (3) | (4) |
| Scope-1 emission$_{it-1}$ | 0.0008* | 0.0014** | 0.0018*** | 0.0067*** |
| | (0.0005) | (0.0006) | (0.0005) | (0.0019) |
| Winsorization | 99.5 | 99 | 98 | 90 |
| Controls | ✓ | ✓ | ✓ | ✓ |
| Year FE | ✓ | ✓ | ✓ | ✓ |
| Industry FE | ✓ | ✓ | ✓ | ✓ |
| Observations | 17,168 | 17,168 | 17,168 | 17,168 |
| R-squared | 0.1302 | 0.1304 | 0.1305 | 0.1308 |

**Table 5: Effect of lagged emissions on returns, sensitivity with respect to winsorization of emissions intensity.** This table shows the estimation results of specification (33). The unit of observation is firm-year. The sample runs annually from 2002 to 2022. Panel A only includes year fixed effects. Panel B includes both year and industry fixed effects. Scope-1 emission$_{it-1}$ is the scope-1 emissions intensity lagged by one year. Emissions intensities are defined in Section 2.1 and are winsorized at the 99.5 percent level in Column (1), 99 percent level in Column (2), 98 percent level in Column (3), and 90 percent level in Column (4). The set of control variables included in our baseline specification are included in these two panels but omitted for brevity. The control variables are lagged by one year and are defined as follows: MCAP$_{it-1}$ is log of market capitalization; LEV$_{it-1}$ is total debt divided by total assets, winsorized at the 95 percent level (multiplied by 100); INVEST/A$_{it-1}$ is investment divided by total assets, winsorized at the 97.5 percent level (multiplied by 100); ROE$_{it-1}$ is net income divided by shareholders' equity (multiplied by 100); VOL$_{it-1}$ is the standard deviation of mothly 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, winsorized at the 97.5 percent level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

distribution of firm-year observations across industries once emissions intensity is winsorized at a 95 percent level.

In sum, the results in Table 4 and Table 5 suggest that the analysis of the pricing of emissions intensity in equity markets is substantially affected by the presence of super emitters in the sample. These firms are largely concentrated in the utilities sector, and, within this sector, in electric power generation, transmission, and distribution.

## 4.4 Testing the new predictions

We now test our new predictions on whether emissions intensity is priced. Our first prediction, discussed in Section 3, is that in regressions of contemporaneous returns on contemporary emissions intensity, the omitted variables bias will be more severe in subsamples of data with larger average price-dividend ratios. We compute such 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 $t-3$.[18] 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).

The test is based on the "contemporanous" regression estimated in Table 1. Since we are now constrained to a smaller subsample (to include price-dividend ratios), we confirm in Appendix E that the estimated coefficients for this smaller subsample of observations in which price-dividend ratios are available are similar to those in Table 1.

Table 6 shows estimation results that are consistent with our first prediction. The table shows the estimated coefficients of the "contemporaneous regression" specification run in the subsample of firms with a below-median price-dividend ratio (top panel) and above-median price-dividend ratio (bottom panel), where medians are calculated in the cross-section of firms every year. Note that the usual control variables are included in the regression specifications but omitted from the table for brevity. In the low price-dividend ratio subsample, emissions intensity appears to be priced in the specification without industry fixed effects. The point estimates (both with and without industry fixed effects) are also substantially higher compared with the same estimates in Table 1 and Table E.5. Finally,

[18]There is an alternative justification for this approach. In our most general derivation of Equation (24), the Campbell and Shiller (1988) log-linearization requires the use the long-run average price-dividend ratio for each firm in our regressions. But, using all our data to estimate this quantity and to use it in our return regressions will generate look-ahead bias (since some regressors for returns at time $t$ would be based on information dated after time $t$). To avoid such look-ahead bias, we estimate the price-dividend ratio for predicting returns at time $t$ as a weighted average of price-dividend ratios dated before date $t$.

| | $R_{it}$ | | | |
|---|---|---|---|---|
| Panel A: Below Median PD | (1) | (2) | (3) | (4) |
| Scope-1 emission$_{it}$ | 0.0027*** | | 0.0008 | |
| | (0.0007) | | (0.0008) | |
| Scope-1+Scope-2 emission$_{it}$ | | 0.0025*** | | 0.0008 |
| | | (0.0007) | | (0.0008) |
| Controls | ✓ | ✓ | ✓ | ✓ |
| Year FE | ✓ | ✓ | ✓ | ✓ |
| Industry FE | | | ✓ | ✓ |
| Observations | 4,073 | 4,073 | 4,073 | 4,073 |
| R-squared | 0.1777 | 0.1776 | 0.1886 | 0.1886 |

| | $R_{it}$ | | | |
|---|---|---|---|---|
| Panel B: Above Median PD | (1) | (2) | (3) | (4) |
| Scope-1 emission$_{it}$ | −0.0008 | | −0.0003 | |
| | (0.0013) | | (0.0014) | |
| Scope-1+Scope-2 emission$_{it}$ | | −0.0009 | | −0.0004 |
| | | (0.0012) | | (0.0013) |
| Controls | ✓ | ✓ | ✓ | ✓ |
| Year FE | ✓ | ✓ | ✓ | ✓ |
| Industry FE | | | ✓ | ✓ |
| Observations | 4,530 | 4,530 | 4,530 | 4,530 |
| R-squared | 0.1779 | 0.1779 | 0.1821 | 0.1821 |

**Table 6: Effect of contemporaneous emissions intensity on returns, subsamples of below median and above median price-dividend ratio.** This table shows the estimation results of specification (33). The unit of observation is firm-year. The sample runs annually from 2002 to 2022. Panel A only includes firms with a below median price-dividend ratio. Panel B only includes firms with an above median price-dividend ratio. 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$_{it-1}$ is the scope-1 emissions intensity lagged by one year. Emissions intensities are winsorized at the 95 percent level. The set of control variables included in our baseline specification are included in these two panels but omitted for brevity. The control variables are lagged by one year and are defined as follows: MCAP$_{it-1}$ is log of market capitalization; LEV$_{it-1}$ is total debt divided by total assets, winsorized at the 95 percent level (multiplied by 100); INVEST/A$_{it-1}$ is investment divided by total assets, winsorized at the 97.5 percent level (multiplied by 100); ROE$_{it-1}$ is net income divided by shareholders' equity (multiplied by 100); VOL$_{it-1}$ is the standard deviation of mothly 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, winsorized at the 97.5 percent level. *** p<0.01, ** p<0.05, * p<0.1.

Table E.6 shows that the coefficients on emissions intensity in the below median price to dividend ratio sample strengthen further and are statistically significant with and without industry fixed effects for scope-1 and for scope-1 and scope-2 emissions intensity after we drop firms in the Utilities sector from the sample.

These results are in line with our first prediction. The omitted variable bias in Panel A is predicted to be milder than in Panel B, as the price of the stocks in Panel A is less sensitive to a permanent change in the required rate of return compared to the price of stocks in Panel B. Consistent with these predictions, the estimated coefficients are large and significant (without industry fixed effects) in Panel A and insignificant and negative in Panel B, where the stronger omitted variable bias "pulls" the regression coefficients on emissions intensity down potentially to values below zero.

At this point it is important to recall that for our most-general derivation of Equation (24), the price-dividend ratio that should ideally be used in our analysis is the long-run average price-dividend ratio. Instead, for our empirical analysis we necessarily use a noisy estimate of this ratio. The evidence in Table 6 is robust to this noise because the price-dividend ratio is only used to assign firms to the subsamples used for Panel A and Panel B, and the inference from comparing the estimates in these panels is unlikely to be influenced by the noise in price-dividend ratio estimates.[19] The robustness of the results in Table 6 provides novel evidence that emissions intensity is priced.

Although the statistical significance of some regression coefficients is weaker than in Table 6, our next two analyses show that the price-dividend ratios affect the regressions in ways predicted by theory.

Table 7 tests the second prediction: if emissions intensity is priced, the omitted variables bias (but not the measurement error) in a regression of returns on contemporaneous emissions intensity is addressed by adding the lagged price-dividend ratio interacted with the innovation in emissions intensity as regressors. Consistent with the theory, we observe that (i) some of the contemporaneous coefficients are larger and statistically significant compared with the

[19]To provide intuition for this robustness, the difference in the regression coefficients on emissions intensity 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, then the data are properly sorted into the below and above the median subsamples. If there is some noise, this will only 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 is unlikely to happen because the firms that have the most influence on the average price-dividend ratios in each sub-sample are those whose price-dividend ratios are far from the median. These firms are the least likely to be reassigned to the other group due to noise. Conversely, the firms that are most likely to be reassigned because of noise are those whose price-dividend ratios are close to the median. But the price-dividend ratios that are close to the median are close to each other, so mis-assignment for these observation will not significantly change the average price-dividend ratios in either group.

| | $R_{it}$ | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Scope-1 emission$_{it}$ | 0.0012* | 0.0000 | | |
| | (0.0007) | (0.0009) | | |
| Scope-1 emission$_{it}$ × PD Ratio$_{it-1}$ | −0.0041* | −0.0033 | | |
| | (0.0021) | (0.0021) | | |
| Scope-1 emission$_{it-1}$ × PD Ratio$_{it-1}$ | 0.0024 | 0.0022 | | |
| | (0.0020) | (0.0020) | | |
| Scope-1+Scope-2 emission$_{it}$ | | | 0.0012* | 0.0002 |
| | | | (0.0007) | (0.0008) |
| Scope-1+Scope-2 emission$_{it}$ × PD Ratio$_{it-1}$ | | | −0.0042** | −0.0035* |
| | | | (0.0020) | (0.0020) |
| Scope-1+Scope-2 emission$_{it-1}$ × PD Ratio$_{it-1}$ | | | 0.002 | 0.0023 |
| | | | (0.0019) | (0.0019) |
| Year FE | ✓ | ✓ | ✓ | ✓ |
| Industry FE | | ✓ | | ✓ |
| Observations | 8,551 | 8,551 | 8,551 | 8,551 |
| R-squared | 0.1650 | 0.1688 | 0.1651 | 0.1689 |

**Table 7: Estimation of Equation (24) to address the omitted variable bias.** This table shows the estimation results of specification (24), where the uninteracted emissions intensity is contemporaneous. The unit of observation is firm-year. The sample runs annually from 2002 to 2022. The price-dividend ratio of firm $i$ at time $t$ (PD Ratio) 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$_{it-1}$ is the scope-1 emissions intensity lagged by one-year. Emissions intensities are winsorized at the 95 percent level. The set of control variables included in our baseline specification are included in these two panels but omitted for brevity. The control variables are lagged by one year and are defined as follows: MCAP$_{it-1}$ is log of market capitalization; LEV$_{it-1}$ is total debt divided by total assets, winsorized at the 95 percent level (multiplied by 100); INVEST/A$_{it-1}$ is investment divided by total assets, winsorized at the 97.5 percent level (multiplied by 100); ROE$_{it-1}$ is net income divided by shareholders' equity (multiplied by 100); VOL$_{it-1}$ is the standard deviation of monthly 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, winsorized at the 97.5 percent level. *** p<0.01, ** p<0.05, * p<0.1.

estimates in Table 1 and (ii) the price-dividend interaction terms have the signs predicted by theory and many of the interaction terms are statistically significant.

Table 8 tests the third prediction: replacing the contemporaneous uninteracted emissions intensity in Table 7 with the lagged emissions intensity solves both the omitted variables bias and the bias due to measurement error. In other words, this table shows the estimation of Equation (24). Consistent with the theory, the coefficient on the (now lagged) emissions intensity variable increases further compared with the previous table, and the coefficients on the interaction terms between price-dividend ratio and the contemporaneous and lagged emissions intensities continue to have the correct signs.

In summary, our analysis confirms that the pricing equation we derived for how emissions

| | $R_{it}$ | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Scope-1 emission$_{it-1}$ | 0.0017** | 0.0008 | | |
| | (0.0007) | (0.0009) | | |
| Scope-1 emission$_{it}$ $\times$ PD Ratio$_{it-1}$ | $-0.0035$* | $-0.0033$ | | |
| | (0.0021) | (0.0021) | | |
| Scope-1 emission$_{it-1}$ $\times$ PD Ratio$_{it-1}$ | 0.0016 | 0.0020 | | |
| | (0.0020) | (0.0020) | | |
| Scope-1+Scope-2 emission$_{it-1}$ | | | 0.0017** | 0.0008 |
| | | | (0.0007) | (0.0008) |
| Scope-1+Scope-2 emission$_{it}$ $\times$ PD Ratio$_{it-1}$ | | | $-0.0036$* | $-0.0035$* |
| | | | (0.0020) | (0.0020) |
| Scope-1+Scope-2 emission$_{it-1}$ $\times$ PD Ratio$_{it-1}$ | | | 0.0017 | 0.0021 |
| | | | (0.0019) | (0.0019) |
| Year FE | ✓ | ✓ | ✓ | ✓ |
| Industry FE | | ✓ | | ✓ |
| Observations | 8,551 | 8,551 | 8,551 | 8,551 |
| R-squared | 0.1652 | 0.1689 | 0.1654 | 0.1690 |

**Table 8: Estimation of Equation (24) to address the omitted variable bias and measurement error.** This table shows the estimation results of specification (24). The unit of observation is firm-year. The sample runs annually from 2002 to 2022. The price-dividend ratio of firm $i$ at time $t$ (PD Ratio) is calculated as the average of the price-dividend ratios at time $t-1$, $t-2$, and $t-3$, respectively. Scope-1 emission$_{it-1}$ is the scope-1 emissions intensity lagged by one-year. Emissions intensities are winsorized at the 95 percent level. We divide the PD Ratio by 100 for readability. The set of control variables included in our baseline specification are included in these two panels but omitted for brevity. The control variables are lagged by one year and are defined as follows: MCAP$_{it-1}$ is log of market capitalization; LEV$_{it-1}$ is total debt divided by total assets, winsorized at the 95 percent level (multiplied by 100); INVEST/A$_{it-1}$ is investment divided by total assets, winsorized at the 97.5 percent level (multiplied by 100); ROE$_{it-1}$ is net income divided by shareholders' equity (multiplied by 100); VOL$_{it-1}$ is the standard deviation of monthly 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, winsorized at the 97.5 percent level. *** p<0.01, ** p<0.05, * p<0.1.

intensity should affect expected returns and the innovation in returns (if emissions intensity is a priced characteristic) are approximately satisfied in the data. Additional predictions stemming from the pricing equation on the biases in various versions of the regression of returns on contemporaneous emissions intensity are also satisfied.

## 4.5 Robustness analysis

We perform two additional robustness tests for our results. The first examines whether emissions intensity is priced because it is correlated with some other non-$CO_2$ related priced factor (or characteristic) that is omitted from our regression specification. If emissions intensity is priced because it proxies for a non $CO_2$ related factor, we would then expect its pricing to be unrelated to the Paris Climate Accord of 2015 which focused investors attention on carbon emissions. To test whether the Paris Accord changed pricing, we estimated Equation (24) using data from the pre- and post-Paris Climate Accord. Our results show that the pricing we have found for emissions intensity using our full sample comes from the post-Paris Accord data. The effects of emissions intensity on pricing is quantitatively larger after the Paris Accord and statistically significant for all of our specifications, both with and without industry fixed effects, and for Scope-1, or Scope-1 plus Scope-2 emissions. By contrast, the coefficients on emissions intensity are positive but not statistically significant using only the pre-Paris Accord data, as shown in Table 9. These results suggest that emissions intensity is likely priced because it is related to climate and $CO_2$ and not because it is correlated with some omitted factor.

Our second robustness test examines the effect of firm size on the results. As part of the analysis in Zhang (forthcoming), an equation similar to Equation (33) is estimated (see Table 6 in Zhang (forthcoming)). In contrast to our results, Zhang (forthcoming) finds emissions intensity is not priced or is priced negatively. Our different results are probably driven by two important differences between our specifications. First, we use lagged emissions intensity instead of lagged log emissions intensity as a regressor.[20] Second, regressions are weighted by firm size in Zhang (forthcoming), effectively down-weighting the effects of small firms on regression estimates. We do not apply weights by firm size for three reasons. First, doing so may reduce the precision of the regression estimates.[21] Second, if emissions intensity is priced because investors dislike investing in emitters, this effect is more likely to be found in stocks that are more thinly traded and less widely held. If these stock attributes are negatively correlated with size, then weighting by size makes it harder to detect these effects if they are present. Third, we are interested in computing how emissions intensity affects the costs of capital for firms of all sizes.

To investigate the role that firm size may have in our results, we regress returns on

[20] We know Table 6 in Zhang (forthcoming) uses log emissions intensity from communications with the author.

[21] If the regressions are homoskedastic, weighting increases standard errors.

| | $R_{it}$ | | | |
|---|---|---|---|---|
| PANEL A: Period 2002-15 | (1) | (2) | (3) | (4) |
| Scope-1 emission$_{it-1}$ | 0.0007 | | 0.0004 | |
| | (0.0008) | | (0.0010) | |
| Scope-1+Scope-2 emission$_{it-1}$ | | 0.0006 | | 0.0004 |
| | | (0.0008) | | (0.0010) |
| Year FE | ✓ | ✓ | ✓ | ✓ |
| Industry FE | | | ✓ | ✓ |
| Observations | 6,766 | 6,766 | 6,766 | 6,766 |
| R-squared | 0.1826 | 0.1826 | 0.1875 | 0.1875 |

| | $R_{it}$ | | | |
|---|---|---|---|---|
| PANEL B: Period 2016-22 | (1) | (2) | (3) | (4) |
| Scope-1 emission$_{it-1}$ | 0.0024* | | 0.0045*** | |
| | (0.0012) | | (0.014) | |
| Scope-1+Scope-2 emission$_{it-1}$ | | 0.0024** | | 0.0044*** |
| | | (0.0012) | | (0.0013) |
| Year FE | ✓ | ✓ | ✓ | ✓ |
| Industry FE | | | ✓ | ✓ |
| Observations | 10,402 | 10,402 | 10,402 | 10,402 |
| R-squared | 0.1125 | 0.1126 | 0.1156 | 0.1156 |

**Table 9: Effect of lagged emissions intensity on returns, pre- vs. post-Paris Accord.** This table shows the estimation results of specification (33) in the sample period from 2002 to 2015 (Panel A) and the sample period from 2016 to 2022 (Panel B). The unit of observation is firm-year. The sample runs at at annual frequency from 2002 to 2022. Scope-1 emission$_{it-1}$ is the lagged scope-1 emissions intensity. Scope-1+scope-2 emission$_{it-1}$ is the sum of lagged scope-1 and scope-2 emissions intensities. Emissions intensity is defined in Section 2.1 and are winsorized at the 95 percent level. The control variables are included in the regression but omitted in this table for brevity. They are lagged by one year and are defined as follows: MCAP$_{it-1}$ is log of market capitalization; LEV$_{it-1}$ is total debt divided by total assets, winsorized at the 95 percent level (multiplied by 100); INVEST/A$_{it-1}$ is investment divided by total assets, winsorized at the 97.5 percent level (multiplied by 100); ROE$_{it-1}$ is net income divided by shareholders' equity (multiplied by 100); VOL$_{it-1}$ is the standard deviation of mothly 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, winsorized at the 97.5 percent level. *** p<0.01, ** p<0.05, * p<0.1.

emissions intensity interacted with firm size quintile dummies to examine whether firms of different sizes face different costs of capital for their emissions intensities. The results presented in Table 10 show that when we interact firm size quintiles with Scope 1 and 2 emissions intensity and we control for both time and industry, emissions intensity is priced for the two smallest and largest size quintiles. In addition, the marginal cost of emissions intensity is smaller for large firms than for small ones. The statistical significance of these results strengthen once we cluster standard errors by firm. These regression results are helpul for reconciling our findings with Zhang (forthcoming). In particular our results show that the

| | $R_{it}$ | | | |
|---|---|---|---|---|
| Scope-1 emission$_{it-1}$ × Asset Q1$_{it}$ | 0.0023 | | 0.0041** | |
| | (0.0018) | | (0.0019) | |
| Scope-1 emission$_{it-1}$ × Asset Q2$_{it}$ | 0.0026* | | 0.0040* | |
| | (0.0015) | | (0.0016) | |
| Scope-1 emission$_{it-1}$ × Asset Q3$_{it}$ | 0.0006 | | 0.0021 | |
| | (0.0015) | | (0.0016) | |
| Scope-1 emission$_{it-1}$ × Asset Q4$_{it}$ | 0.0001 | | 0.0016 | |
| | (0.0012) | | (0.0014) | |
| Scope-1 emission$_{it-1}$ × Asset Q5$_{it}$ | 0.0008 | | 0.0025 | |
| | (0.0014) | | (0.0015) | |
| Scope-1+Scope-2 emission$_{it-1}$ ×Asset Q1$_{it}$ | | 0.0025 | | 0.0043** |
| | | (0.0017) | | (0.0018) |
| Scope-1+Scope-2 emission$_{it-1}$ × Asset Q2$_{it}$ | | 0.0024* | | 0.0037** |
| | | (0.0014) | | (0.0015) |
| Scope-1+Scope-2 emission$_{it-1}$ × Asset Q3$_{it}$ | | 0.0007 | | 0.0022 |
| | | (0.0014) | | (0.0015) |
| Scope-1+Scope-2 emission$_{it-1}$ × Asset Q4$_{it}$ | | 0.0002 | | 0.0017 |
| | | (0.0012) | | (0.0013) |
| Scope-1+Scope-2 emission$_{it-1}$ × Asset Q5$_{it}$ | | 0.0009 | | 0.0024* |
| | | (0.0013) | | (0.0014) |
| Year FE | ✓ | ✓ | ✓ | ✓ |
| Industry FE | | | ✓ | ✓ |
| Observations | 17,168 | 17,168 | 17,168 | 17,168 |
| R-squared | 0.1283 | 0.1283 | 0.1307 | 0.1307 |

**Table 10: Effect of lagged emissions intensity on returns, firm asset size quintile interactions.** This table shows the estimation results of specification (33), augmented with interactions with size quintiles. Firm size quintiles are calculated yearly in the cross-section of firms using asset size (act in Compustat). Asset Q1$_{it}$ is the lowest quintile and Asset Q5$_{it}$ is the highest quintile. The sample runs at at annual frequency from 2002 to 2022. Scope-1 emission$_{it-1}$ is the lagged scope-1 emissions intensity. Scope-1+scope-2 emission$_{it-1}$ is the sum of lagged scope-1 and scope-2 emissions intensities. Emissions intensity is defined in Section 2.1 and are winsorized at the 95 percent level. The control variables are included in the regression but omitted in this table for brevity. They are lagged by one year and are defined as follows: MCAP$_{it-1}$ is log of market capitalization; LEV$_{it-1}$ is total debt divided by total assets, winsorized at the 95 percent level (multiplied by 100); INVEST/A$_{it-1}$ is investment divided by total assets, winsorized at the 97.5 percent level (multiplied by 100); ROE$_{it-1}$ is net income divided by shareholders' equity (multiplied by 100); VOL$_{it-1}$ is the standard deviation of mothly 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, winsorized at the 97.5 percent level. *** p<0.01, ** p<0.05, * p<0.1.

regressions in Zhang (forthcoming) are weighted toward firms where the evidence for pricing is weaker. Such weighting scheme makes it hard to detect pricing if it is present.

Overall, our robustness results show that emissions intensity is not spuriously priced because it is correlated with an omitted factor. Our results also show the magnitude of emissions intensity pricing is related to firm size. This is a new stylized fact which may help identifying the channels by which emissions intensity appears to be priced.

# 5 Conclusion

Financial markets can play an important role in helping the productive sector reduce its carbon emissions. The idea is simple. 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 (across various asset classes) 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 pricing theory, to analyze how emissions intensity should affect required returns if emissions intensity is a priced characteristic. Using this framework, we show that studies in the current empirical literature that regress stock returns on contemporaneous emissions intensity likely suffer from measurement error and an omitted variables bias—and that both forces bias the coefficient on emissions intensity downward and potentially below 0.

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, or across specifications that add regressors defined as "omitted" by our theory. Virtually all predictions of our theory are confirmed in the data. In sum, our findings provide convincing evidence that emissions intensity is priced in equity markets.

The magnitude of the pricing is heavily dependent on how we treat "super emitter" firms, consistent with the extremely skewed distribution of firm-level emissions intensity across and within industries. This observation suggests that the market treats super emitter firms differently—or that the assumption that required returns are linear in emissions intensity is not a good approximation for super emitters.

Future research should, in our view, focus on finding the driver of the pricing of emissions. One logical direction is to examine whether the pricing originates from ESG preferences shifting investors' portfolios away from firms with high carbon emissions intensity towards greener firms. We believe this is a promising direction because the asset holdings of some institutional investors are strongly declining in firms' emissions intensity (Bolton and Kacperczyk, 2021). Another direction is the analysis of whether the pricing for emissions intensity simply reflects compensation for holding transition risk. This hypothesis can be tested using measures of transition risk, calling for the development of such measures at the firm-level.[22] This type of work is, in our view, a promising avenue for future research.

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# Appendix

## A Alternative derivation of Equation (24)

To motivate our empirical analysis, we consider the two types of regression specifications that are used in the literature on climate and asset pricing. The first are contemporaneous regressions in which all variables are in the same time period. These take the form:

$$r_{i,t} - r_{f,t} = \alpha + X_{i,t}\theta + ei_{i,t}\gamma + u_{i,t}, \tag{A1}$$

where $X_{i,t}$ is a set of control variables and $ei_{i,t}$ denotes emissions intensity for firm $i$ at time $t$. Note in this regression the emissions intensity during time $t$ is not known during period $t-1$ when investors are forming expectations about $P_{i,t-1}$, one of the inputs in the definition of $r_{i,t}$. To interpret the regression theoretically, it is useful to express $e_{i,t}$ as the sum of two components, its expectation as of time $t-1$ and an innovation component:

$$e_{i,t} = \mathbb{E}(e_{i,t}|I_{t-1}) + [e_{i,t} - \mathbb{E}(e_{i,t}|I_{t-1})] \tag{A2}$$

The question we examine in this section is whether firms having higher emissions intensity—and thus higher required returns—necessarily implies that the estimated $\gamma$ in the regression (A1) is greater than 0. The answer is not necessarily.

To better interpret the regression Equation (A1), we analyze it in the context of a stylized theoretical model linking asset prices to required returns.

In the model, the only variable related to required returns is emissions intensity. The true data generating process for excess returns is assumed to be:

$$r_{i,t} - r_{f,t} = \mathbb{E}(ei_{i,t}|I_{t-1})\gamma + \epsilon_{i,t}, \tag{A3}$$

where $\gamma > 0$ and $\mathbb{E}(ei_{i,t}|I_{t-1})$ is the expected emissions intensity at time $t$ given the publicly available information at time $t-1$. In the equation, the required returns during each period can only depend on the information known at the beginning of the period.

The term $\epsilon_{i,t}$ is the residual of the regression equation. It is determined from the rest of the economic model below, and then utilized to interpret the regression Equation (A1).

Let $P_{i,t}$ be the price of stock $i$ at the end of year $t$ and $D_{i,t}$ be the dividend paid by stock $i$ at the end of year $t$. Furthermore, $r_{i,t}$ is given by:

$$r_{i,t} = \frac{P_{i,t} + D_{i,t}}{P_{i,t-1}} \tag{A4}$$

We make the following additional assumptions in the example.

**Assumption 4.** *Asset prices at each time $t$ satisfy the dividend discount model:*

$$P_{i,t} = \frac{\mathbb{E}(D_{i,t+1}|I_t) + \mathbb{E}(P_{i,t+1}|I_t)}{1 + r_f + \gamma\mathbb{E}(ei_{i,t+1}|I_t)} \tag{A5}$$

Because dividends and the risk-free rate do not play an essential role in the analysis, it is assumed:

**Assumption 5.** *Dividends for each stock $i$ are non-stochastic and grow at a constant growth rate $g_i$.*

**Assumption 6.** *The risk-free rate in all periods is constant and given by $r_f$.*

**Assumption 7.** *For each firm $i$, and each time period $t$, and for each possible realization of emissions intensity $r_f + \gamma ei_{i,t+1} > g_i$.*

The above assumption ensures that required returns in each period are greater than dividend growth rates. This condition is necessary to ensure stock prices in the model are finite.

We also make the following assumptions on earnings intensities. These assumptions help in interpreting the regression Equation (A1).

**Assumption 8.** *Emissions intensities in periods 1, 2 and $t > 2$ are distributed as follows:*

$$ei_{i,1} \sim i.i.d.(\mu_i, \sigma_1^2) \tag{A6}$$

$$ei_{i,2} = ei_{i,1} + u_{i,2} \quad where\ u_{i,2} \sim (0, \sigma_u^2) \tag{A7}$$

$$ei_{i,t} = ei_{i,2}\ for\ all\ t > 2. \tag{A8}$$

Equation (A7) ensures there is a broad cross-section of emissions intensities in period 1. Equation (A8) implies the required return in period 2 for each firm $i$ is $r_f + \gamma ei_{i,1}$ since $ei_{i,1}$ is $i$'s expected emissions intensity in period 2. The $\sigma_u^2$ term ensures that $e_{i,2}$ is not perfectly correlated with required returns during period 2. This is realistic since investors do not have perfect foresight, and $ei_{i,2}$ is not known at the beginning of period 2. In addition, note that $\sigma_u^2$ is not restricted to be the same as $\sigma_1^2$ and could be much smaller. Such difference would be consistent with emissions intensities in period 1 being determined by firms' choices of industry by firms choices of technology within their industry in period 2. Finally, Equation (A8) guarantees that firms' required returns after period 2 are constant. This vastly simplifies the model. In addition, it is consistent with required returns being persistent, which is, again, realistic.

Under the assumptions of the model, at the end of period 2, the asset pricing setting satisfies the Gordon Growth Model. Hence:

$$P_{i,2} = \frac{D_{i,2}(1 + g_i)}{r_f + \gamma ei_{i,2} - g_i} \tag{A9}$$

In period 1, investors do not know $ei_{i,2}$ but asset prices will satisfy the dividend discount model. Given our assumptions that dividends are non-stochastic and grow at a constant rate, this implies:

$$P_{i,1} = \frac{D_{i,2} + \mathbb{E}(P_{i,2}|I_1)}{1 + r_f + \gamma ei_{i,1}} \tag{A10}$$

It is convenient to substitute for $\mathbb{E}(P_{i,2}|I_1)$ in the algebra. To do so, we define $ei^*_{i,2}$ as the value of $ei_{i,2}$ that, if it occurred with certainty, would set $P_{i,2}$ at time 2 to its expectation conditional on date 1 information.

$$\mathbb{E}(P_{i,2}|I_1) = E\left(\frac{D_{i,2}(1+g_i)}{r_f+\gamma ei_{i,2}-g_i}|I_1\right) \tag{A11}$$

$$= \frac{D_{i,2}(1+g_i)}{r_f+\gamma ei^*_{i,2}-g_i} \tag{A12}$$

Substituting for $\mathbb{E}(P_{i,2}|I_1)$ with the expression on the right hand side of Equation A12 we get:

$$r_{i,2}-r_f = \gamma ei_{i,1} + \left[\frac{1+r_f+\gamma ei_{i,1}}{1+r_f+\gamma ei^*_{i,2}}\right]\left[(1+g_i)\left(\frac{r_f+\gamma ei^*_{i,2}-g_i}{r_f+\gamma ei_{i,2}-g_i}-1\right)\right] \tag{A13}$$

The equation shows that the excess return decomposes into its time 1 expectation $\gamma e_{i,1}$ and into a residual component that has mean zero conditional on time 1 information.[23] To make further progress with the expression for excess returns, we need to approximate $e^*_{i,2}$. We do so to first order in a neighborhood when $\sigma^2_u$ is close to zero; this yields $e^*_{i,2} \approx e_{i,1}$. A second order approximation produces qualitatively similar results in our analysis but does not add further insight.[24]

With the first order approximation, the expression for excess returns becomes:

$$r_{i,2}-r_f = \gamma ei_{i,1} + \left[(1+g_i)\left(\frac{r_f+\gamma ei_{i,1}-g_i}{r_f+\gamma ei_{i,2}-g_i}-1\right)\right] \tag{A14}$$

To simplify further, we express the term in braces using a first order Taylor series around $ei_{i,2} = ei_{i,1}$. Doing so yields:

$$r_{i,2}-r_f = \gamma ei_{i,1} - \frac{1+g_i}{r_f+\gamma ei_{i,1}-g_i} \times \gamma(ei_{i,2}-ei_{i,1}) \tag{A15}$$

Using $ei_{i,2}-ei_{i,1} = u_{i,2}$, and noting from the Gordon Growth Model that $\frac{1+g_i}{r_f+\gamma ei_{i,1}-g_i} = \frac{P_{i,1}}{D_{i,1}}$, which is the price-dividend ratio for stock $i$ at time 1, we get:

$$r_{i,2}-r_f = \gamma\ e_{i,1} - \gamma\left(\frac{P_{i,1}}{D_{i,1}}\right)\ u_{i,2} \tag{A16}$$

The second term in the above equation is a first order approximation of how returns during period 2 respond to a permanent change in required returns at the end of period 2 in

[23]To see this, note that the second term is the product of a term in parenthesis and a term in braces. The term in parenthesis is known at time 1. The term in braces is the product of the constant $(1+g_i)$ times a second random term that has expectation 0.

[24]Doing a second order approximation produces $e^*_{i,2} \approx e_{i,1} - .5\gamma\frac{\sigma^2_u}{r_f+\gamma e_{i,1}-g_i}$

the Gordon Growth model. The term $-\frac{P_{i,1}}{D_{i,1}}$ is the first order sensitivity of returns during time 2 to the change in required returns. It multiplies $\gamma u_{i,2}$, which is the innovation in required returns.[25] The equation shows that, in the model, firms with higher price-dividend ratios have higher sensitivity of their date 2 returns to changes in required returns. This is intuitive since firms with higher price-dividend ratios either have high dividend growth, low discount factors or both—and, in dividend discount models, price and return sensitivities are larger when firms have higher dividends or lower discount factors.

# B Approximating the process for emissions intensity as a random walk

For parsimony in our analysis we derive Equation (24) while approximating emissions intensity as a random walk. To justify this simplification, in this section we maintain all assumptions in section 3.2 except we replace assumption 2 by the assumption that annual emissions intensity for each firm $i$ is a very slowly mean reverting AR(1) process, and then using a Taylor series show the random walk specification produces a reasonable approximation to the residual in Equation 24. The AR(1) process for emissions intensity is given by:

$$(e_{i,t+1} - \mu_i) = \theta_i(e_{i,t} - \mu_i) + u_{i,t} \tag{B1}$$

where $\mu_i$ is the long-run mean of emissions intensity for firm $i$, and $\theta_i$ is close to but less than 1. If emissions intensity is on the only priced characteristic, because it is mean-reverting, $\rho_i$ in the Campbell and Shiller (1988) log-linearization is well defined 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

$$[\mathbb{E}_{t+1} - \mathbb{E}_t]e_{i,t+k} = \theta^{k-1}[(e_{i,t+1} - \mu_i) - \theta_i(e_{i,t} - \mu_i)] \tag{B2}$$

Plugging this expression in the Campbell (1991) log-linearization and simplifying then shows

$$(\mathbb{E}_{t+1} - \mathbb{E}_t)[r_{i,t+1} - r_f] \approx -\gamma\left(\frac{\rho_i}{1-\rho_i\theta_i}\right)[(e_{i,t+1} - \mu_i) - \theta_i(e_{i,t} - \mu_i)] \tag{B3}$$

The right hand side can be approximated as a Taylor series around $\theta_i = 1$. When doing so the leading term on the right is the same as in Equation (24), and the size of the residual term in the approximation vanishes when $\theta_i = 1$ and is small when $\theta_i$ is in a neighborhood close to 1. This shows our use of the random walk approximation for emissions intensity and the equation we derive is a reasonable approximation for the true return innovation term in Equation (24) if emissions intensity is a highly persistent AR(1) process with $\theta_i < 1$.

[25] The expression for the sensitivity is $\frac{1}{P_{i,1}}\frac{\partial P_{i,2}}{\partial ei_{i,2}}$ evaluated at $ei_{i,2} = ei_{i,1}$.

# C Frequency of regression estimation and measurement error

In this section, we analyze how measurement error may be related to estimation frequency. To do so, we modify the framework slightly 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 return data, measured at an annual or a monthly frequency. In addition, to simplify aggregation, we measure returns in logs, i.e., in this appendix $r_{i,t}$ is the log gross annual return during year $t$ and $r_{i,m}$ is the log gross monthly return in month $m$ of year $t$. Given that we switched to log 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 returns at an annual frequency. This modeling approach implicitly assumed that information arrived only at the ends of each year. To analyze estimation frequency, we now model returns monthly and then aggregate up to an annual frequency. To do so, we assume returns are monthly, and continue to maintain that beliefs about emissions intensity drive returns. Specifically, we assume 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 returns at a monthly frequency if annual emissions intensity is priced. The equation is the monthly equivalent of Equation (24).

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 $\gamma$ and the price to 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 returns and dividend growth rates for firm $i$.

Equation (C2) shows that, at the beginning of each month $m$ during year $t$, required 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 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 estimates regressions that take 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 will suffer from measurement error in monthly data because required 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 if regressions from annual data might perform better, we first aggregate to derive the process for annual returns implied by monthly returns. This yields:

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

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

We assume 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

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

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 to 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:

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

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

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

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 those Equation

(24), but it has been derived by aggregating up from monthly returns. The third term in the right hand side captures the learning about emissions that occurs each month of the year and alters required returns in the following month. Because emissions intensity is a random walk, both the second and third terms in the right hand side are uncorrelated with $e_{i,t-1}$. Therefore, the cross-sectional regression

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

using annual return data, will produce unbiased and consistent estimates for $\gamma$ provided 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 in 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)ref, 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 return data is very similar to Equation (24) based on annual 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 (24) are so slight, the analytical and empirical results on omitted variables biases and measurement error biases that were derived in annual return setting also work in this richer setting aggregated up from monthly data.

To summarize, in this appendix, 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, then monthly return regressions will 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 $t$, then a regressions of annual returns on one-year lagged emissions intensity produces unbiased and consistent estimates for $\gamma$; iii) the equation relating annual returns to lagged emissions intensity when aggregated up from our return model at a monthly frequency very closely resembles the equation for returns from our model at a annual frequency. Therefore, the results that we derived in our annual return model for regressions using annual data are essentially unchanged for our model derived from monthly returns with learning that are aggregated up to an annual level.

# D Additional figures

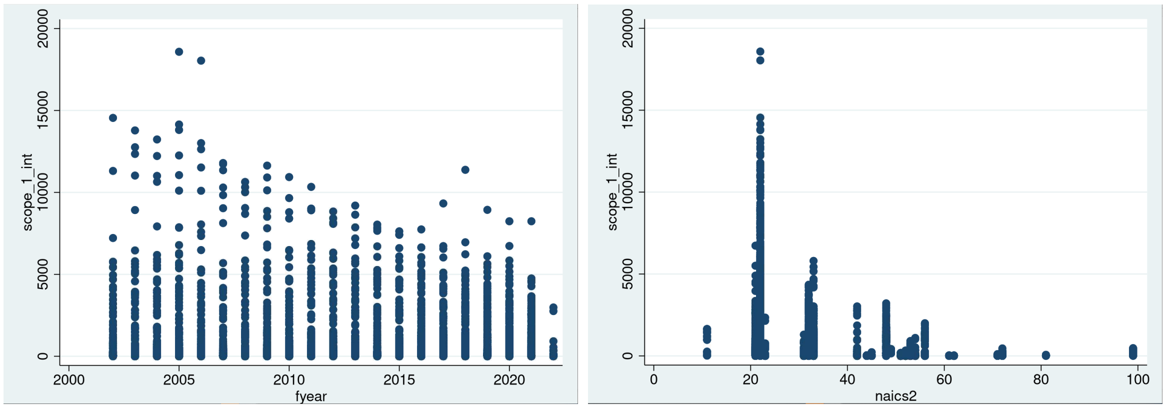


**Figure D.1: Variation in scope-1 emissions intensity.** This figure shows the large cross-sectional variation in scope-1 emissions intensities. Each dot is a firm-year observation in the period 2002-2022. Firm-year observations are grouped by year on the x-axis in the left panel. Firm-year observations are grouped by firm 2-digit NAICS code on the x-axis in the right panel.

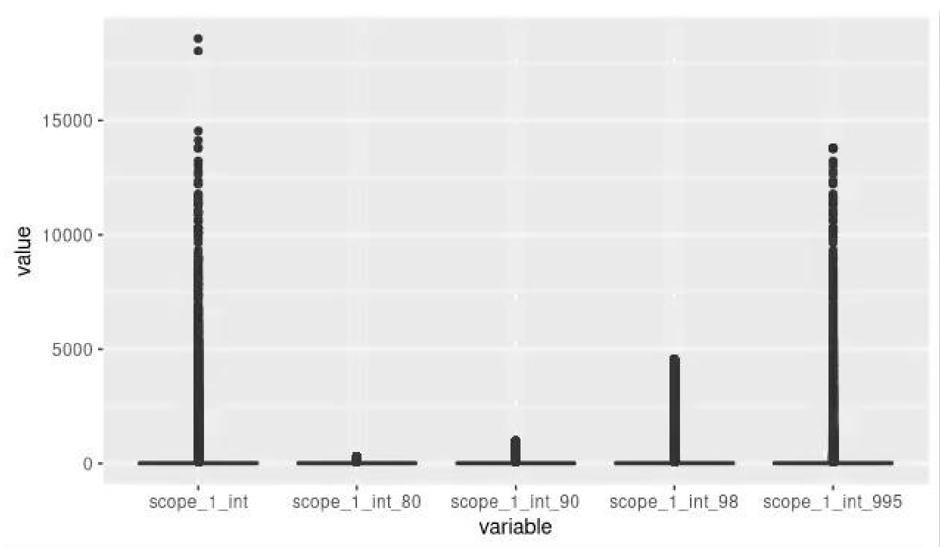


**Figure D.2: Effect of winsorization on scope-1 emissions intensity.** This figure shows the the cross-sectional variation in scope-1 emissions intensity with different levels of winsorization. Each dot is a firm-year observation in the period 2002-2022. From left to right, the chart shows the distribution with no winsorization, with an 80 percent winsorization, with a 90 percent winsorization, with a 98 percent winsorization, and with a 99.5 percent winsorization.

# E Additional tables

| Year | No. of firms |
|---|---|
| 2002 | 289 |
| 2003 | 420 |
| 2004 | 483 |
| 2005 | 594 |
| 2006 | 608 |
| 2007 | 568 |
| 2008 | 601 |
| 2009 | 628 |
| 2010 | 625 |
| 2011 | 599 |
| 2012 | 632 |
| 2013 | 696 |
| 2014 | 703 |
| 2015 | 749 |
| 2016 | 1911 |
| 2017 | 2040 |
| 2018 | 2085 |
| 2019 | 2270 |
| 2020 | 2463 |
| 2021 | 2665 |
| 2022 | 228 |

**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 | 22 | 5 |
| 21 | Mining | 1126 | 124 |
| 22 | Utilities | 947 | 76 |
| 23 | Construction | 392 | 46 |
| 31 | Manufacturing | 848 | 90 |
| 32 | Manufacturing | 2885 | 485 |
| 33 | Manufacturing | 4891 | 582 |
| 42 | Wholesale Trade | 666 | 81 |
| 44 | Retail Trade | 464 | 53 |
| 45 | Retail Trade | 654 | 69 |
| 48 | Transportation | 548 | 65 |
| 49 | Transportation | 40 | 2 |
| 51 | Information | 1949 | 302 |
| 52 | Finance and Insurance | 3818 | 523 |
| 53 | Real Estate | 399 | 50 |
| 54 | Professional, Scientific and Technical | 628 | 80 |
| 56 | Administrative and Waste Management | 438 | 50 |
| 61 | Education | 122 | 15 |
| 62 | Healthcare | 363 | 50 |
| 71 | Arts | 96 | 21 |
| 72 | Accomodation and Food | 450 | 52 |
| 81 | Other Services | 74 | 6 |
| 99 | Other | 37 | 6 |

**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).

| | $R_{it}$ | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Scope-1 emission$_{it-1}$ | | 0.0024$^{*}$ | | | 0.0045$^{***}$ | |
| | | (0.0012) | | | (0.0014) | |
| Scope-1+Scope-2 emission$_{it-1}$ | | | 0.0024$^{**}$ | | | 0.0044$^{***}$ |
| | | | (0.0012) | | | (0.0013) |
| MCAP$_{it-1}$ | -1.220$^{***}$ | -1.261$^{***}$ | -1.265$^{***}$ | -1.265$^{***}$ | -1.325$^{***}$ | -1.336$^{***}$ |
| | (0.3060) | (0.3067) | (0.3068) | (0.3108) | (0.3112) | (0.3114) |
| LEV$_{it-1}$ | -0.0030 | -0.0049 | -0.0050 | -0.0038 | -0.0054 | -0.0055 |
| | (0.0037) | (0.0039) | (0.0039) | (0.0044) | (0.0045) | (0.0045) |
| INVEST/A$_{it-1}$ | -0.1769 | -0.2230 | -0.2266 | -0.1815 | -0.2060 | -0.2090 |
| | (0.1435) | (0.1454) | (0.1456) | (0.1606) | (0.1607) | (0.1607) |
| ROE$_{it-1}$ | 0.0849$^{***}$ | 0.0855$^{***}$ | 0.0856$^{***}$ | 0.0776$^{***}$ | 0.0777$^{***}$ | 0.0776$^{***}$ |
| | (0.0118) | (0.0118) | (0.0118) | (0.0120) | (0.0120) | (0.0120) |
| VOL$_{it-1}$ | $-0.9938$** | -1.711$^{***}$ | -1.694$^{***}$ | -1.696$^{***}$ | -1.556$^{***}$ | -1.554$^{***}$ |
| -1.552$^{***}$ | | | | | | |
| | (0.5373) | (0.5373) | (0.5373) | (0.5458) | (0.5455) | (0.5455) |
| BETA$_{it-1}$ | 0.3996 | 0.4092 | 0.4064 | 0.3940 | 0.3913 | 0.3875 |
| | (0.2703) | (0.2703) | (0.2703) | (0.2721) | (0.2720) | (0.2720) |
| B/M$_{it-1}$ | 0.1689 | -0.2884 | -0.3247 | -0.0495 | -0.5753 | -0.6448 |
| | (1.203) | (1.226) | (1.227) | (1.258) | (1.269) | (1.271) |
| Year FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Industry FE | | | | ✓ | ✓ | ✓ |
| Observations | 10,402 | 10,402 | 10,402 | 10,402 | 10,402 | 10,402 |
| R-squared | 0.11222 | 0.11254 | 0.11257 | 0.11472 | 0.11557 | 0.11564 |

**Table E.3: Effect of lagged emissions intensity on returns, subsample from 2016 to 2022.** This table shows the estimation results of specification (33). The unit of observation is firm-year. The sample runs at an annual frequency from 2016 to 2022. Scope-1 emission$_{it-1}$ is the scope-1 emissions intensity lagged by one year. Scope-1+scope-2 emission$_{it}$ is the sum of scope-1 and scope-2 emissions intensities lagged by one-year. Emissions intensities are defined in Section 2.1 and are winsorized at the 95 percent level. The control variables are lagged by one year and are defined as follows: MCAP$_{it-1}$ is log of market capitalization; LEV$_{it-1}$ is total debt divided by total assets, winsorized at the 95 percent level (multiplied by 100); INVEST/A$_{it-1}$ is investment divided by total assets, winsorized at the 97.5 percent level (multiplied by 100); ROE$_{it-1}$ is net income divided by shareholders' equity (multiplied by 100); VOL$_{it-1}$ is the standard deviation of mothly 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, winsorized at the 97.5 percent level. *** p<0.01, ** p<0.05, * p<0.1.

| | $R_{it}$ | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Scope-1+Scope-2 emission$_{it-1}$ | 0.0009* | 0.0015*** | 0.0018*** | 0.0060*** |
| | (0.0005) | (0.0006) | (0.0006) | (0.0016) |
| Winsorization | 99.5 | 99 | 98 | 90 |
| Controls | ✓ | ✓ | ✓ | ✓ |
| Year FE | ✓ | ✓ | ✓ | ✓ |
| Observations | 17,168 | 17,168 | 17,168 | 17,168 |
| R-squared | 0.1303 | 0.1305 | 0.1305 | 0.1308 |

| | $R_{it}$ | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Scope-1+Scope-2 emission$_{it-1}$ | 0.0003 | 0.0006 | 0.0008 | 0.0021 |
| | (0.0004) | (0.0005) | (0.0005) | (0.0014) |
| Winsorization | 99.5 | 99 | 98 | 90 |
| Controls | ✓ | ✓ | ✓ | ✓ |
| Industry FE | ✓ | ✓ | ✓ | ✓ |
| Year FE | ✓ | ✓ | ✓ | ✓ |
| Observations | 17,168 | 17,168 | 17,168 | 17,168 |
| R-squared | 0.1282 | 0.1282 | 0.1282 | 0.1282 |

**Table E.4: Effect of lagged emissions intensity on returns, sensitivity with respect to winsorization of emissions intensity, scope-1+scope-2 emissions intensity.** This table shows the estimation results of specification (33). The unit of observation is firm-year. The sample runs at annual frequency from 2002 to 2022. Panel A only includes year fixed effects. Panel B includes both year and industry fixed effects. Scope-1+scope-2 emission$_{it}$ is the sum of scope-1 and scope-2 emissions intensities lagged by one year. Emissions intensities are defined in Section 2.1 and are winsorized at the 99.5 percent level in Column (1), 99 percent level in Column (2), 98 percent level in Column (3), and 90 percent level in Column (4). The set of control variables included in our baseline specification are included in these two panels but omitted for brevity. The control variables are lagged by one year and are defined as follows: MCAP$_{it-1}$ is log of market capitalization; LEV$_{it-1}$ is total debt divided by total assets, winsorized at the 95 percent level (multiplied by 100); INVEST/A$_{it-1}$ is investment divided by total assets, winsorized at the 97.5 percent level (multiplied by 100); ROE$_{it-1}$ is net income divided by shareholders' equity (multiplied by 100); VOL$_{it-1}$ is the standard deviation of monthly 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, winsorized at the 97.5 percent level. *** p<0.01, ** p<0.05, * p<0.1.

| | $R_{it}$ | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Scope-1 emission$_{it}$ | | 0.0009 | | | 0.0003 | |
| | | (0.0006) | | | (0.0007) | |
| Scope-1+Scope-2 emission$_{it}$ | | | 0.0008 | | | 0.0002 |
| | | | (0.0006) | | | (0.0007) |
| MCAP$_{it-1}$ | 0.0491 | 0.0342 | 0.0341 | 0.1408 | 0.1341 | 0.1357 |
| | (0.2434) | (0.2436) | (0.2437) | (0.2499) | (0.2504) | (0.2504) |
| LEV$_{it-1}$ | −0.0030 | −0.0043 | −0.0042 | −0.0090*** | −0.0091*** | −0.0090*** |
| | (0.0027) | (0.0028) | (0.0028) | (0.0034) | (0.0034) | (0.0034) |
| INVEST/A$_{it-1}$ | −0.3657*** | −0.3892*** | −0.3874*** | −0.3008*** | −0.3030*** | −0.3026*** |
| | (0.0961) | (0.0974) | (0.0975) | (0.1164) | (0.1165) | (0.1166) |
| ROE$_{it-1}$ | 0.0320** | 0.0319** | 0.0319** | 0.0300** | 0.0300** | 0.0300** |
| | (0.0129) | (0.0129) | (0.0129) | (0.0129) | (0.0129) | (0.0129) |
| VOL$_{it-1}$ | 9.603*** | 9.675*** | 9.654*** | 10.60*** | 10.58*** | 10.59*** |
| | (1.085) | (1.086) | (1.086) | (1.125) | (1.126) | (1.126) |
| BETA$_{it-1}$ | 0.4578 | 0.4829 | 0.4764 | 0.4962 | 0.4979 | 0.4967 |
| | (0.3606) | (0.3610) | (0.3609) | (0.3659) | (0.3660) | (0.3660) |
| B/M$_{it-1}$ | −0.1740 | −0.5433 | −0.4949 | −0.2790 | −0.3336 | −0.3198 |
| | (0.9959) | (1.026) | (1.025) | (1.054) | (1.061) | (1.062) |
| Year FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Industry FE | | | | ✓ | ✓ | ✓ |
| Observations | 8,603 | 8,603 | 8,603 | 8,603 | 8,603 | 8,603 |
| R-squared | 0.1699 | 0.1701 | 0.1701 | 0.1740 | 0.1740 | 0.1740 |

**Table E.5: Effect of contemporaneous emissions intensity on returns, subsample of firm-year observations with available price-dividend ratios.** This table shows the estimation results of specification (33) but with contemporaneous not lagged emissions intensity. The unit of observation is firm-year. The sample runs at an annual frequency from 2002 to 2022. The sample includes only firms with data available on price-dividend ratios. Scope-1 emission$_{it}$ is the scope-1 emissions intensity. Scope-1+scope-2 emission$_{it}$ is the sum of scope-1 and scope-2 emissions intensities. Emissions intensities are defined in Section 2.1 and are winsorized at the 95 percent level. The control variables are lagged by one year and are defined as follows: MCAP$_{it-1}$ is log of market capitalization; LEV$_{it-1}$ is total debt divided by total assets, winsorized at the 95 percent level (multiplied by 100); INVEST/A$_{it-1}$ is investment divided by total assets, winsorized at the 97.5 percent level (multiplied by 100); ROE$_{it-1}$ is net income divided by shareholders' equity (multiplied by 100); VOL$_{it-1}$ is the standard deviation of mothly 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, winsorized at the 97.5 percent level. *** p<0.01, ** p<0.05, * p<0.1.

| | $R_{it}$ | | | |
|---|---|---|---|---|
| Panel A: Below Median PD | (1) | (2) | (3) | (4) |
| Scope-1 emission$_{it}$ | 0.0032** | | 0.0030* | |
| | (0.0015) | | (0.0017) | |
| Scope-1+Scope-2 emission$_{it}$ | | 0.0028** | | 0.0027** |
| | | (0.0013) | | (0.0015) |
| Controls | ✓ | ✓ | ✓ | ✓ |
| Year FE | ✓ | ✓ | ✓ | ✓ |
| Industry FE | | | ✓ | ✓ |
| Observations | 3,332 | 3,332 | 3,332 | 3,332 |
| R-squared | 0.1804 | 0.1803 | 0.1878 | 0.1878 |

| | $R_{it}$ | | | |
|---|---|---|---|---|
| Panel B: Above Median PD | (1) | (2) | (3) | (4) |
| Scope-1 emission$_{it}$ | −0.0012 | | −0.0005 | |
| | (0.0014) | | (0.0015) | |
| Scope-1+Scope-2 emission$_{it}$ | | −0.0012 | | −0.0007 |
| | | (0.0013) | | (0.0014) |
| Controls | ✓ | ✓ | ✓ | ✓ |
| Year FE | ✓ | ✓ | ✓ | ✓ |
| Industry FE | | | ✓ | ✓ |
| Observations | 4,462 | 4,462 | 4,462 | 4,462 |
| R-squared | 0.1787 | 0.1788 | 0.1829 | 0.1830 |

**Table E.6: Effect of contemporaneous emissions intensity on returns, subsamples of below median and above median price-dividend, excluding Utilities.** This table shows the estimation results of specification (33). The unit of observation is firm-year. The sample runs annually from 2002 to 2022. The sample excludes firms operating in the Utilities industry. Panel A only includes firms with a below median price-dividend ratio. Panel B only includes firms with an above median price-dividend ratio. 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$_{it-1}$ is the scope-1 emissions intensity lagged by one year. Scope-2 emission$_{it-1}$ is the scope-1 emissions intensity lagged by one year. Emissions intensities are winsorized at the 5 percent level. The set of control variables included in our baseline specification are included in these two panels but omitted for brevity. The control variables are lagged by one year and are defined as follows: MCAP$_{it-1}$ is log of market capitalization; LEV$_{it-1}$ is total debt divided by total assets, winsorized at the 95 percent level (multiplied by 100); INVEST/A$_{it-1}$ is investment divided by total assets, winsorized at the 97.5 percent level (multiplied by 100); ROE$_{it-1}$ is net income divided by shareholders' equity (multiplied by 100); VOL$_{it-1}$ is the standard deviation of monthly 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, winsorized at the 97.5 percent level. *** p<0.01, ** p<0.05, * p<0.1.