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Are Carbon Emissions Associated with Stock Returns?*

Jitendra Aswani[1], Aneesh Raghunandan[2], Shiva Rajgopal[3]

[1]Harvard University, USA, [2]London School of Economics, UK, and [3]Columbia Business School, USA

Abstract

An influential emerging literature documents strong correlations between carbon emissions and stock returns. We re-examine those data and conclude that these associations are driven by two factors. First, stock returns are correlated only with unscaled emissions *estimated* by the data vendor, but not with unscaled emissions *actually disclosed* by firms. Vendor-estimated emissions systematically differ from firm-disclosed emissions and are highly correlated with financial fundamentals, suggesting that prior findings primarily capture the association between such fundamentals and returns. Second, unscaled emissions, the variable typically used in academic literature, is correlated with stock returns but emissions intensity (emissions scaled by firm size), an equally important measure used in practice, is not. While unscaled emissions represent an important metric for society, we argue that, for individual firms, emissions intensity is an appropriate measurement choice to assess carbon performance. The associations between emissions and returns disappear after accounting for either of the issues above.

Keywords: Carbon emissions, Stock returns, Trucost, Estimated emissions, Emissions disclosure

JEL classification: G12, G23, G30, D62, M14

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1. Introduction

This article evaluates whether carbon emissions are associated with stock returns and operating performance for a sample of US firms from 2005 to 2019. There is considerable interest in the disclosure and eventual reduction of US firms' carbon emissions among various parties such as the Securities and Exchange Commission, asset managers, proxy advisors, and the media. Investors are also interested in understanding whether emissions reduction by portfolio firms can contribute to greater expected stock returns and better operating performance. In response to such demand among policymakers and practitioners, an emerging set of influential papers (e.g., Matsumura, Prakash, and Vera-Muñoz, 2014; Bolton and Kacperczyk, 2021a, 2022) finds strong associations between emissions and fundamental measures of firms' financial performance such as stock returns, operating profitability, and Tobin's *Q*. However, these papers rely on (i) the assumption that vendor-estimated carbon emissions are accurate in the sense that they do not systematically differ from firm-disclosed carbon emissions and (ii) specific research design choices, most notably a reliance on unscaled emissions, to draw conclusions rather than a measure of emissions relative to firm size (i.e., emissions intensity). Our goal in this article is to examine (i) and (ii) in detail and, in turn, to revisit the findings from the papers cited above.

The carbon emissions literature cumulatively proposes two economic arguments that link emissions to stock returns. The first is risk driven. Given increasing societal pressure to "go green," if the government is likely to take action to combat climate change in "bad" (high-emissions) states of the world, then there is a risk of an increase in the cost of capital for high-emissions firms (Pastor, Stambaugh, and Taylor, 2021). This risk captures factors such as potential carbon taxes or mandated remedial pollution clean-up costs. The risk-based argument, underlying several studies (Bolton and Kacperczyk, 2021a; Pedersen, Fitzgibbons, and Pomorski, 2021), suggests a positive association between emissions and stock returns.

A second argument for why emissions could potentially relate to stock returns centers on investors' tastes. Several studies (e.g., Pastor, Stambaugh, and Taylor, 2021; Pedersen, Fitzgibbons, and Pomorski, 2021) argue that some investors may choose to shun companies in "brown" industries, on the grounds that firms in such industries cause substantial harm to society. If a large enough set of investors choose to avoid high-carbon stocks, then, as in the case of sin stocks (Hong and Kacperczyk, 2009), it should follow that "brown" stocks earn excess returns because a subset of investors shun them.

We take a closer look at this collective evidence on emissions and valuation in the current article. Our first main finding is that the relation between stock returns and emissions in the US, documented in prior research (e.g., Bolton and Kacperczyk, 2021a), is driven by vendor-estimated emissions, as opposed to firm-disclosed actual emissions. That is, while we observe a robust relation between vendor-estimated emissions and stock returns, we find minimal evidence of a relation between emissions and stock returns for firms that disclose actual emissions values.[1] Relatedly, we provide empirical evidence of systematic

1 Bolton and Kacperczyk (2021a, 2021b) do report a significant correlation between disclosed emissions and stock returns in the USA. However, we show that this result only holds with a specific choice of industry classification system (using Trucost industry definitions). When using other, more commonly seen industry definitions based on classifications such as SIC, Fama–French, or GICS, the results are statistically insignificant.

differences between vendor-disclosed and firm-estimated emissions figures. This finding is particularly important for researchers and practitioners because more than 70% of emissions figures in standard US emissions databases are vendor-estimated as opposed to voluntarily disclosed by firms. Moreover, data coverage has significantly expanded in recent years (e.g., since 2016 in the Trucost database we use). However, nearly all this coverage expansion reflects an increase in vendor-estimated, rather than firm-disclosed, emissions. As a result, studies focused on recent years—when carbon risk has become more politically relevant—will be particularly susceptible to this issue.

The finding above may arise in part because estimated emissions seem to be a nearly deterministic function of size, sales growth, industry, and time rather than capturing within-industry differences in carbon efficiency (e.g., the use of green technology). Our results suggest that prior findings of a link between stock returns and emissions are in fact simply documenting a link between returns and fundamentals (and/or may reflect multicollinearity that results from including both unscaled emissions and size in a single regression).[2]

A potential counterargument to our findings thus far is that firms that disclose emissions systematically differ from those that do not, in ways that would explain the stylized facts above. Indeed, a working paper by Bolton and Kacperczyk (2021b) argues that a carbon premium, where it exists, ought to be lower for firms that disclose emissions because emissions disclosure reduces uncertainty for investors. Even if this fully explains the results discussed in the preceding paragraphs, another issue arises in prior work: an emphasis on the relation between *unscaled* carbon emissions (i.e., total carbon emitted) and returns. Because of the economic nature of emissions with respect to a firm's production and output, it is not clear whether such correlations can be used to draw conclusions about the relation between a firm's stock returns and its carbon performance.

Emissions arise from a firm's core operations and, absent significant short-term innovations in a firm's production process, unscaled emissions are largely determined by the quantity of goods produced and sold. To this end, within-firm variation in unscaled carbon emissions is almost entirely driven by variation in units of goods produced and sold. Hence, we argue that on a standalone basis, a relation between unscaled emissions and stock returns can only be interpreted as evidence of a relation between a firm's productivity and its stock market performance. Conversely, emissions *intensity*—the ratio of emissions to net sales, a metric also commonly used in practice to assess progress toward decarbonization without sacrificing output—better captures a firm's emissions performance by avoiding mechanical correlations with firm size.[3] As an analogy, using unscaled emissions rather

2 While not the focus of our study, we note that multicollinearity may explain why Bolton and Kacperczyk (2021a) only find a relation between emissions and returns when controlling for size, but do not find any univariate link between emissions and returns.

3 We acknowledge one argument in favor of focusing on unscaled emissions rather than emissions intensity to measure firms' carbon performance: that from a regulatory perspective, aggregate emissions levels matter. However, this argument applies primarily to economy-wide emissions; it is unclear that such economy-wide targets would directly translate into firm-level emissions targets. Moreover, even if a cap-and-trade system (or other related mechanism) were implemented, such systems typically account for firm size when determining firms' initial emissions allocations; this is functionally equivalent to the regulator imposing restrictions on emissions intensity rather than unscaled emissions.

than emissions intensity to measure carbon performance is analogous to using net income rather than ratios such as return on assets (ROAs) to measure financial performance.

The distinction between total emissions and emissions intensity is crucial in light of our second main result: there is no relation between emissions intensity (either disclosed or vendor-estimated) and stock returns. We emphasize that we are not the first to document this result, which appears in Bolton and Kacperczyk (2021a, 2022). Rather, our goal is to argue for this result to receive greater prominence, as the studies above view emissions intensity as a mere robustness test and draw economic conclusions based on unscaled emissions.[4] Indeed, the introduction of Bolton and Kacperczyk (2022) explicitly lays out an argument for why carbon risk should be thought of in terms of total emissions rather than emissions intensity. However, such an argument conflates society's objective function with that of individual firms: ultimately, the impact of a societal emissions-reduction goal should affect individual firms proportional to their size. For example, if emissions are taxed per unit of emissions, larger firms will pay a higher carbon tax; but the impact of a higher tax bill is spread across higher revenues and income for these firms. Moreover, if society's and firms' goals are to retain similar output levels without burning a proportionate level of carbon, reducing emissions intensity assumes significant importance (Nordhaus, 2019). Thus, we argue that emissions intensity—which accounts for size—is an appropriate measurement choice to understand individual firms' carbon efficiency.[5] Emissions intensity also better captures the taste-based argument for why emissions may relate to returns: relying on unscaled emissions implies that investors with a distaste for carbon-inefficient firms will shun large firms in "dirty" industries but invest in smaller firms in those same industries because of their lower levels of total emissions. A taste-driven carbon-conscious investor should be more likely to shun *all* firms in a "dirty" industry, akin to how some investors shun all firms in "sin" industries (Hong and Kacperczyk, 2009).

While our findings thus far are not consistent with a carbon premium, it may be possible that emissions may indirectly affect returns via firm fundamentals. For example, if more emissions-intensive firms earn higher profits (perhaps due to not reinvesting these profits into greener production processes), a positive relation between profitability and stock returns could imply an indirect positive link between emissions and returns. In additional analyses, we thus consider the relation between emissions and several measures of operating performance. Our results are similar to the returns setting: while unscaled emissions are correlated with performance, accounting for vendor estimation as well as scaling emissions

4 In particular, we believe that the "prominence" aspect is important as—although Bolton and Kacperczyk (2021a, 2022) do correctly characterize their results concerning emissions intensity—these papers have been cited by multiple studies in top journals (e.g., Ilhan, Sautner, and Vilkov, 2021; Pastor, Stambaugh, and Taylor, 2021) as instead documenting a link between emissions intensity and returns. One goal of this study is to highlight the importance of distinguishing between the two measures.

5 As a thought experiment, consider a firm that has high absolute carbon emissions. If absolute emissions were the proper way to judge this firm's carbon footprint, then it follows that the firm could become "greener" simply by dividing itself into two separate legal entities and changing nothing else about its business model. Each of these two new entities would have half as much absolute emissions as the original (undivided) firm; focusing on absolute emissions to measure firm-level carbon performance would result in each firm being characterized as greener than the original firm and, yet, overall emissions in the economy would remain unchanged.

by firm size weakens or eliminates any positive associations between profitability and emissions.

For external validity, we consider European firms. Emissions disclosure is much more common in Europe and, arguably, investors in European firms care more about non-financial performance (Gibson *et al.*, 2022). We find no relation between unscaled emissions and returns when we include industry fixed effects, although we observe a relation between scope 1 emissions and returns without industry fixed effects. This result suggests that to the extent that emissions influence investor demand for stocks in Europe, this occurs via distaste for specific industries. Similarly, when we do not include industry fixed effects, we find a relation between emissions intensity and returns; however, these disappear with industry fixed effects. Moreover, even the former results (without industry fixed effects) weaken or disappear for firm-disclosed emissions observations. Thus, while we observe differences between the US and European settings, the main issues we highlight in the article—the importance of accounting for vendor estimation and scaling emissions by firm size—continue to be relevant.

Our findings suggest that investors, policymakers, and academics may want to be cautious in interpreting correlations between carbon emissions and stock market performance. To be clear, we take no position on the desirability of disclosing and/or cutting emissions. Rather, our article is a comment on the methodological architecture and data underlying associations documented by prior research between emissions and returns. In this regard, our article relates to a contemporaneous working paper by Zhang (2023), who outlines other econometric reasons—for example, lookahead bias and the actual timing of data availability relative to that which is presupposed by prior work—that prior research suggesting a carbon premium should be treated cautiously.

The remainder of the article is laid out as follows. Section 2 reviews why emissions may be priced and the related literature. Section 3 describes the data. Section 4 highlights issues that arise when using vendor-estimated rather than firm-disclosed emissions figures. Sections 5 and 6 report analyses related to whether emissions are associated with stock returns and profitability. Section 7 considers the European setting. Section 8 concludes.

2. Why Should Emissions Be Associated with Stock Returns or Firm Fundamentals?

2.1 Prior Literature

A large emerging literature investigates whether climate risk is reflected in operating performance and valuation (e.g., Chava, 2014; Andersson, Bolton, and Samama, 2016; Hong, Li, and Xu, 2019). As with most such studies, our focus in this article is specifically on carbon risk measured using carbon emissions. We view this measure as of first-order importance given its prevalence in academic literature, the media, and among ESG rating agencies whose data are heavily relied upon by investors to assess firms' environmental performance.[6]

6 For instance, Sustainalytics provides as a supplementary product to its main ESG ratings a "Carbon Solutions Suite" and frequently references decarbonization commitments in its blog posts (see, e.g., https://www.sustainalytics.com/esg-blog/the-race-to-net-zero-decarbonization-commitments-in-the-oil-gas-industry/). Several other ratings providers offer similar products.

Prior literature linking emissions to financial performance primarily views carbon emissions as a source of risk, for which investors seek compensation. Such compensation would manifest as a risk premium, observable as a positive relation between emissions and stock returns. Carbon-related risk can arise from shocks resulting from governmental emissions-reduction actions (e.g., carbon taxes or remedial environmental costs that the emitter might be forced to incur) in bad states of the world. More recent studies also link a taste-based argument to the risk premium argument, albeit primarily in the context of investors. For example, Pastor, Stambaugh, and Taylor (2021) argue that certain investors enjoy holding green assets, in the sense that they are willing to sacrifice returns to hold their desired portfolios. In a follow-up paper, Pastor, Stambaugh, and Taylor (2022) argue that green stocks have outperformed in recent years due to previously unanticipated increases in society's environmental concerns.

In line with the theoretical arguments above, Matsumura, Prakash, and Vera-Muñoz (2014) find a relation between higher emissions and lower firm values. Other studies directly tie emissions performance to returns: for example, In, Park, and Monk (2019) find a positive stock returns alpha by buying (shorting) low (high)-emissions stocks. Finally, in two notable recent papers, Bolton and Kacperczyk (2021a, 2022) find a positive association between unscaled emissions and stock returns, arguing that this supports the risk premium argument. Notably, in their primary tests, these studies measure carbon performance differently; our goal in this article is to highlight the effect of such measurement choices.

2.2 Does a Relation between Emissions and Returns Actually Reflect a Carbon Risk Premium?

As discussed above, several studies document evidence of a relation between a firm's total emissions (in metric tons) and both lower firm values and higher stock returns, interpreted as evidence of a risk premium. It is useful to consider alternative reasons that a firm's total emissions may relate to its stock market performance, in terms of a firm's underlying economics. Specifically, carbon emissions arise as a byproduct of a firm's production process and, in the absence of sudden technical change, are likely to be highly correlated with the quantity of firms' output over time. In other words, emissions are a variable rather than fixed quantity for a firm, and not subject to the economies of scale that may arise in other parts of a firm's production process (e.g., overhead). To that end, if firms' production processes do not substantially change within a given time period, then it is difficult for a firm to substantially reduce its emissions per unit of goods produced.

In turn, emissions are highly correlated with size. Hence, year-over-year increases in total emissions may primarily indicate firm growth. This may explain Garvey, Iyer, and Nash's (2018) finding of a negative relation between the *change* in unscaled emissions and profitability, as growth firms can exhibit lower short-term profits while they incur up-front investment costs. It is unlikely that this result is driven by emissions; rather, it reflects the link between a key determinant of emissions (firm output) and capital market performance.

2.3 Measurement Issues

To test the competing theories laid out in the preceding two subsections, it is necessary to distinguish emissions from other measures of size. As we highlight in Section 2.2, however, it is very difficult to use a firm's *total* emissions output to do this, because of the mechanistic way in which emissions relate to production in the short term. To that end, a relation between emissions and operating or stock market performance may simply reflect the relation between size or growth and performance. As a result, we argue that, rather than using total emissions, emissions intensity (the ratio of emissions to measures of size, e.g., sales) represents an appropriate way to measure a firm's carbon footprint and risk. Emissions intensity also better captures a societal desire to (i) cut emissions while still being able to (ii) retain overall productivity in the economy (Nordhaus, 2019). One goal of this article is, thus, to highlight the different conclusions that a researcher can draw when using total emissions as opposed to emissions intensity as a measure of carbon footprint.

A potential alternative approach to relying on emissions intensity would be to control for firm size in a regression of stock returns on emissions. However, given how emissions relate to a firm's production process in the short term, this approach will result in significant multicollinearity, inducing a risk of spurious inferences.

3. Data and Descriptive Properties of Carbon Emissions

3.1 Financial Data

Our primary carbon emissions database is Trucost, which provides data for both US and global firms. Our initial sample, before merging to other databases, consists of 4,028 distinct US firms. We merge Trucost data with stock returns data from CRSP and fundamental financial data from COMPUSTAT by matching on CUSIP number. The intersection of CRSP, COMPUSTAT, and Trucost yields 3,282 unique firms; after deleting observations with missing control variables, we obtain 2,669 unique firms corresponding to balanced sample of 178,354 firm-month observations.[7] We outline our sample selection process in Table I, as well as descriptive statistics for all variables in our final sample in Table II.

3.2 Emissions Data

We obtain emissions data from Trucost. Trucost uses various publicly disclosed sources, such as company financial reports (annual reports, financial statements, 10-K/20-F reports, regulatory filings), environmental data sources [corporate social responsibility, sustainability, or environmental reports, the Carbon Disclosure Project (CDP), Environmental Protection Agency filings], and data published on company websites or other public sources. If a firm does not disclose emissions data voluntarily, Trucost states that it uses an environmentally extended input–output (EEIO) model to estimate environmental impacts for a company's own operations and across its global supply chain. The 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.

Emissions data are usually reported under the greenhouse gas (GHG) protocol and are measured in tons of CO_2 equivalent (tCO_2e) per year. The GHG protocol specifies three scopes of emissions. Scope 1 reflects direct emissions sources that are owned or controlled by a company. For example, scope 1 includes 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

7 Out of 4,023 firms covered by Trucost's US database, we retain firms that meet the following criteria: (i) ISIN and CUSIP identifiers are not missing; (ii) the firm's status is not "out of business"; (iii) we are able to match the firm to standard financial databases such as Compustat, Datastream, or Worldscope depending on the sample; and (iv) emissions and returns data are not missing.

Table I. Sample selection

This table outlines the process we use to select the firms underlying our sample from Trucost's North America carbon emissions database.

Filters	Number of distinct firms	
Start: Firms in Trucost North America database		4,028
Less: Firms labeled by Trucost as being based outside the continental USA	(458)	3,570
Less: Firms not matched with COMPUSTAT and CRSP	(288)	3,282
Less: Firms missing data for control variables	(613)	2,669

Table II. Summary statistics

This table provides summary statistics for variables used in our main regressions (i.e., Table IX). Following Bolton and Kacperczyk (2021a), we winsorize different variables at different values; where we do so, we provide the winsorization cutoff based on the percentage of observations in each tail of the distribution. Refer to Appendix A for variable definitions.

Variable	Winsorization [cutoff (%)]	Mean	Standard deviation	Median
Dependent variables				
Return	–	1.078	11.079	1.044
ROA	1	0.071	0.141	0.079
ROS	1	−0.104	2.161	0.128
EBIT margin	1	−0.104	2.161	0.128
EBITDA margin	1	−0.055	2.274	0.180
Emissions variables				
Log scope 1	–	10.338	3.017	10.379
Log scope 2	–	10.346	2.463	10.542
Log scope 3	–	12.250	2.321	12.480
Intensity scope 1	2.5	1.657	5.308	0.145
Intensity scope 2	2.5	0.282	0.334	0.165
Intensity scope 3	2.5	1.546	1.468	0.972
Controls				
Firm size	–	8.149	1.654	8.155
Leverage	2.5	0.204	0.185	0.174
Book to market	2.5	0.443	0.330	0.376
ROE	2.5	9.624	33.602	12.079
EPSGR	0.5	0.051	0.789	0.086
SalesGR	0.5	0.087	0.244	0.070
Log PPE	–	5.991	2.236	6.093
Invesment_Asset	2.5	0.041	0.042	0.028
HHI	–	0.136	0.068	0.123
Volatility	0.5	0.167	0.343	0.064
Momentum	0.5	0.126	0.374	0.098
Beta	–	1.034	0.657	0.939

from a company's direct operations. Scope 3 encompasses all other emissions associated with a company's operations that are not directly owned or controlled by the company.

Scope 3 emissions include several sources of indirect emissions in both the company's supply chain and from use by customers of the company's products. For example, if a shipping company purchases a truck from a truck manufacturer, then the emissions caused by the shipping company's usage of the truck contribute toward the shipping company's scope 1 emissions and the manufacturer's scope 3 emissions. Given the expansive definition of scope 3 emissions, scope 3 represents the majority of most companies' emissions footprints.

3.3 Trucost Expanded Coverage in 2016

Figure 1 depicts the yearly number of observations found in the Trucost database for US observations, both in total and by disclosed versus estimated status. Coverage in Trucost (before merging with other databases) ranges from 883 to 997 distinct firms for years between 2005 and 2015. Beginning in 2016, Trucost substantially expanded its coverage, nearly tripling from 997 observations in 2015 to 2,706 observations in 2016. However, most of this expanded coverage is a result of Trucost estimating emissions figures for these firms. Data for 2019 were incomplete as of when we obtained the data (October 2020). Because we conduct returns tests at the firm-month level following Bolton and Kacperczyk (2021a), the number of observations corresponds to approximately twelve times the number of firms per year.[8]

Table OA1 in the Supplementary Appendix details firm coverage by six-digit GICS industry. The table is sorted by the percentage of observations with estimated rather than disclosed emissions. The five most represented industries by the number of distinct firms are banks (248); biotechnology (171); software (129); machinery (108); and oil, gas, and consumable fuels (103). Apart from oil and gas, these industries are those that one would not expect to be large emitters of GHGs. Moreover, as Supplementary Appendix Table OA1 shows, the proportion of estimated emissions in these industries is much higher than the sample average (e.g., nearly *all* banks' emissions figures are estimated by the vendor rather than actual firm-provided figures).

3.4 Firm Size Is Highly Correlated with Unscaled Emissions and Returns

In Table III, we present data on correlations between the three types of carbon emissions (scope 1, 2, and 3), in terms of both raw emissions and emissions intensity, and three measures of firm size (the natural logarithms of market capitalization, total assets, and sales). For instance, the correlation between log scope 1 emissions and log sales is 0.699, between log scope 1 emissions and log market cap 0.525, and between log scope 1 emissions and log assets 0.463. Figure 2 provides visual evidence, via a scatter plot, of the correlation between emissions and size. The log of scope 3 emissions exhibits an even higher correlation with all three measures of firm size. This likely reflects measurement limitations; because scope 3 emissions are harder for the firm to directly measure, they are more likely to be estimated by the data vendor. Moreover, even in cases where a firm voluntarily discloses scope 3 emissions, the firm itself is likely to have relied on some degree of estimation to the extent

8 When a company has dual-class shares, we include return observations for both share classes, which is why the number of observations is sometimes greater than twelve times the number of distinct firms. In untabulated analyses, we verify that the deletion of dual-class shares does not alter any reported inferences.

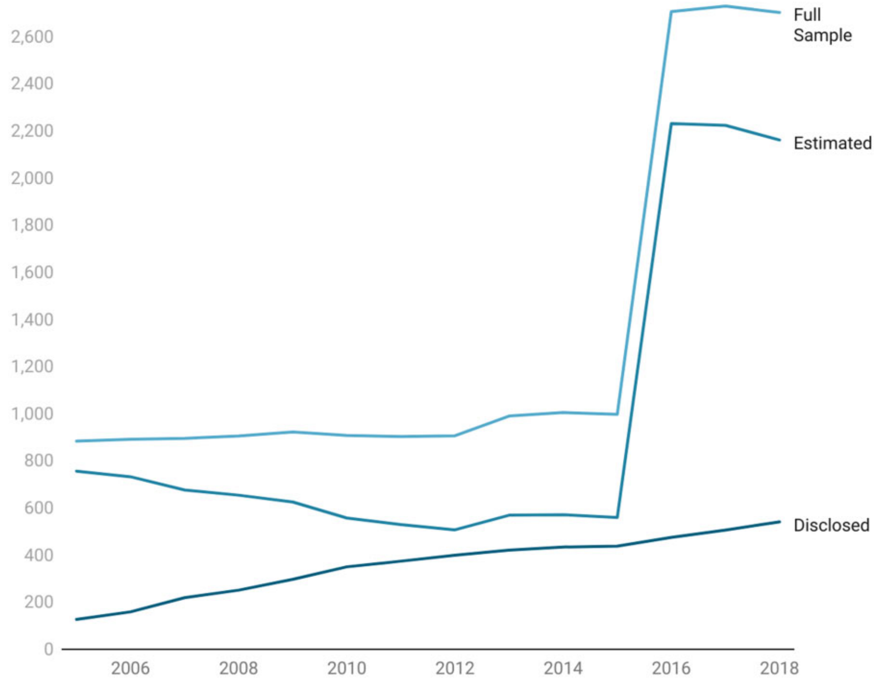

Figure 1. Observations by year. This figure presents a breakdown of the number of firms by year, both in total and broken down into disclosed versus vendor-estimated scope 1 emissions figures.

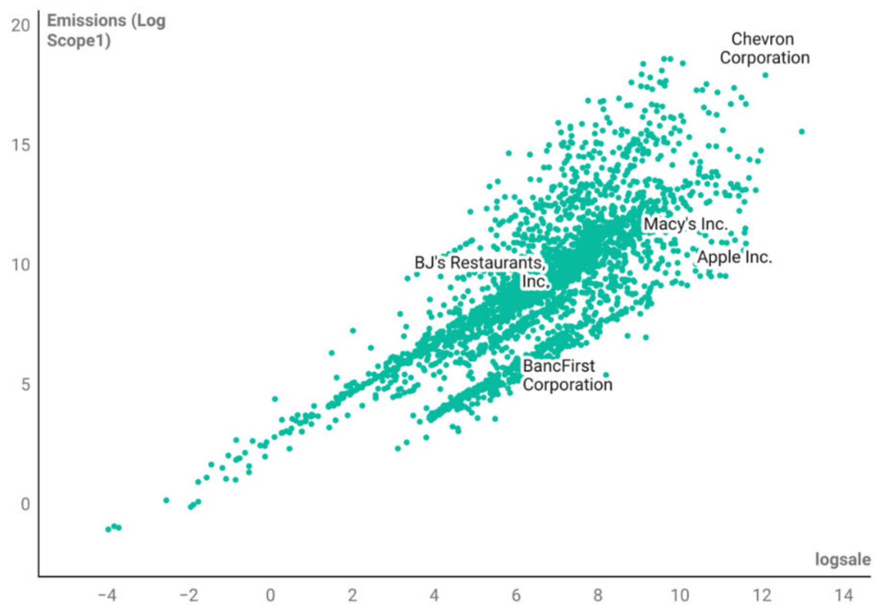

Figure 2. Emissions and revenues. This figure presents a scatterplot of log emissions and log sales for firms in our sample. Some representative firms, from different industries, are labeled.

Table III. Correlations

This table shows univariate correlations between our main emissions variables and measures of firm size. Refer to Appendix A for variable definitions.

	Log scope 1	Log scope 2	Log scope 3	Intensity scope 1	Intensity scope 2	Intensity scope 3	Log market cap	Log assets	Log sale
Log scope 1	1								
Log scope 2	0.776	1							
Log scope 3	0.842	0.891	1						
Intensity scope 1	0.532	0.072	0.211	1					
Intensity scope 2	0.418	0.519	0.284	0.194	1				
Intensity scope 3	0.522	0.346	0.535	0.354	0.383	1			
Log market cap	0.525	0.670	0.710	0.060	0.056	0.060	1		
Log assets	0.463	0.548	0.637	0.138	−0.005	0.005	0.825	1	
Log sale	0.699	0.847	0.905	0.090	0.118	0.171	0.820	0.811	1

that it is unable to perfectly measure upstream or downstream emissions associated with the production of inputs or use of its products. The correlations reported in Table III suggest that a key component of the models used to estimate scope 3 emissions is firm size. Table III also highlights another key point: the correlation between carbon intensity and firm size is much lower. For instance, the correlations between scope 1 emissions intensity and log market cap, log assets, and log sales are 0.060, 0.138, and 0.090, respectively. We observe similarly low figures for the correlations between scope 2 and 3 emissions intensity and firm size. Hence, measuring carbon emissions in terms of intensity, rather than its raw value, is much more effective in neutralizing any mechanical correlation with firm size and avoids potential multicollinearity that could otherwise arise if attempting to control for firm size in a regression with emissions as an independent variable.

4. Disclosed versus Vendor-Estimated Emissions

Trucost data contain a mix of emissions data directly disclosed by firms as well as Trucost-estimated emissions figures for non-disclosing firms. For each firm-year, Trucost provides the source of carbon information. The source variable falls into twenty-nine categories, which can be grouped into three major types: (i) estimated emissions for firms that do not disclose, (ii) directly disclosed total emissions, and (iii) total emissions figures derived through other firm-level emissions disclosures. We empirically identify (i), which we use as our estimated observations, as those which contain the keyword “Estimate.”[9] We treat (ii)

9 More formally, we define emissions to be estimated if Trucost describes the source as (i) an estimate based on partial data disclosure in either CDP, Environmental/CSR report, or personal communication; (ii) an estimate derived from production data; (iii) an estimate used in lieu of disclosure, either because data do not cover global operations or because the data are normalized without an aggregating factor; or (iv) estimated data, without further clarification. Category (iv) comprises the vast majority (98.2%) of “estimated” emissions in our sample.

and (iii) as disclosed; our rationale for treating (iii) as disclosed is another Trucost variable, the weighted carbon disclosure score, which reflects Trucost's attempt to score the quantity and quality of carbon disclosure information provided. This score is on a scale of 0–100; observations in category (i) have a mean score of less than 1 out of 100 while observations in categories (ii) and (iii) both have mean scores close to 95 out of 100. Nonetheless, in robustness tests, we verify that omitting category (iii) does not alter our statistical inferences. Supplementary Appendix Table OA1 provides the percentage of estimated observations by industry, where we observe substantial variation.

Estimating emissions for non-disclosing firms is standard among data vendors. Busch, Johnson, and Pioch (2022) study the emissions figures provided by various data vendors and document a high correlation (around 0.97) among disclosed emissions values reported by various commercial data providers such as CDP, Trucost, MSCI, Sustainalytics, and Refinitiv. These findings suggest that when actual emissions data exist, they are captured accurately by data providers. However, the correlation among estimated values reported by these vendors is only 0.66. This pattern raises concerns about the validity of proprietary estimation methods used by data providers. Moreover, proprietary estimation methods appear to rely heavily on firm fundamentals and industry-level factors; for example, in our sample, the univariate correlation between estimated scope 1 emissions and sales is 0.73 while the correlation between disclosed scope 1 emissions and sales is 0.25. If, for example, data vendors assume that all firms in a given industry use similar transportation or waste disposal practices, and accordingly estimate emissions generated through such activities, then two potential problems arise.

First, it would not be possible to use vendor-estimated emissions figures to assess within-industry differences in carbon performance because within-industry differences in estimated emissions figures would only reflect differences in financial fundamentals. Second, a correlation between estimated emissions and returns would primarily reflect correlations between various firm fundamentals and stock prices. For example, prior literature documents a positive relation between stock returns and sales growth rates. If estimated emissions are a mechanical function of growth, then a researcher who documents a positive correlation between estimated emissions and stock returns may improperly interpret this as evidence of a carbon risk premium when the result simply reflects a company's growth.

To highlight the importance of understanding whether differences between firm-disclosed and vendor-estimated emissions figures affect inferences, Figure 1 shows the pervasive nature of vendor-estimated emissions. The data underlying Figure 1 suggest that the proportion of estimated values is as high as 86% (84% in our final sample) in 2005, the first year that Trucost is available. Voluntary emissions disclosure steadily increases such that estimated values fall to a low of 54% (53% in our final sample) in 2015. However, the large increase in Trucost's coverage universe starting in 2015 is driven primarily by estimated values, which causes the proportion of estimated figures to again jump. The number of firms voluntarily disclosing emissions during this period increases slowly from 376 in 2015 to 424 in 2018, a year in which 77% of observations reported by Trucost are estimated.

The prevalence of estimated observations is important in part because estimated and disclosed observations appear to be drawn from different distributions. To visually illustrate this, Figure 3 provides kernel density curves for disclosed and estimated emissions; a Kolmogorov–Smirnov test confirms that these two distributions are different at the 1%

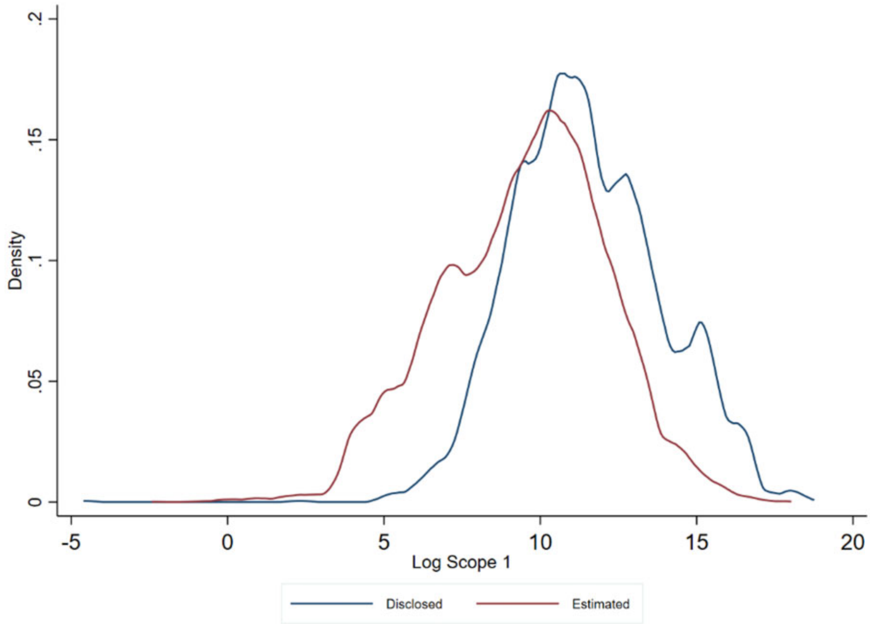

Figure 3. Distributions of disclosed and estimated emissions. This figure presents kernel density curves of the natural logarithms of disclosed and vendor-estimated scope 1 emissions for firms in our sample.

level. To shed further light on differences between estimated and disclosed emissions, we exploit the fact that firms gradually began disclosing emissions figures more frequently over the sample period. For these firms, we compare the first disclosing year against the last estimated year. In untabulated analyses, we find that disclosed scope 1 emissions are 4.2% lower than estimated scope 1 emissions ($p < 0.01$ for tests of differences from both zero and the full-sample average year-over-year change in emissions); conversely, disclosed scope 2 emissions are 2.3% higher than their prior-year estimated counterparts ($p < 0.01$ for a test of differences from both zero and the full-sample average year-over-year change in emissions). Disclosed scope 3 emissions are not significantly different from prior-year estimated scope 3 emissions.

To generalize the univariate analyses above, we next formally estimate a model of emissions as a function of firm characteristics and whether emissions figures are estimated:

$$\text{Emissions}_{it} = \alpha_0 + \alpha_1 \text{Estimated}_{it} + \alpha_2 \, Controls_{it} + \delta_{\text{industry}} + \gamma_t + \varepsilon_{it}. \tag{1}$$

In Equation (1), Emissions_{it} reflects the natural logarithm of either scope 1, 2, or 3 emissions, while Estimated_{it} is an indicator that equals 1 if the corresponding emissions figure was estimated. For example, if Emissions_{it} reflects scope 3 emissions, then Estimated_{it} equals 1 if firm i's scope 3 emissions figure for month-year t is vendor-estimated and zero if firm i's scope 3 emissions figure for month-year t is firm-disclosed. The quantities δ_{industry} and γ_t denote GICS industry and time fixed effects, respectively. We select control variables based on Bolton and Kacperczyk (2021a); these are leverage, book-to-market ratio, return on equity (ROE), EPS growth, sales growth, log PP&E, the ratio of investments to assets, within-firm sector HHI, volatility, momentum, and beta. Our inclusion of these controls means that Equation (1) can also be thought of as a determinants model of firm-level carbon emissions.

If Trucost estimates do not systematically differ from firm-disclosed emissions, α_1 should be insignificant. If α_1 is significant, there are two potential reasons: (i) Trucost's models do not properly capture within-industry heterogeneity in firms' production processes or (ii) firms strategically choose a time to begin disclosing emissions. Notably, a negative value of α_1—suggesting estimated emissions are lower than disclosed emissions—would not be consistent with (ii), as it is unlikely that firms would voluntarily begin disclosing *worse* emissions performance under no obligation to do so. In addition, (i) and (ii) are not mutually exclusive, and the high univariate correlation between estimated emissions and sales suggests that (i) cannot be ruled out even if α_1 is consistent with strategic disclosure.

Results from estimating Equation (1) are presented in Table IV. In Columns (1)–(3), we estimate a basic form of Equation (1), including only fixed effects and Estimated$_{it}$. Estimated scope 1 emissions appear systematically higher than firm-disclosed emissions, while estimated scope 2 and 3 emissions appear systematically lower than firm-disclosed emissions. The fact that our results for scope 1 and 2 go in opposite directions supports the notion that while strategic disclosure may occur, this alone cannot drive our findings. In Columns (4)–(6), we introduce control variables. Our results continue to hold. In addition, we observe a strong correlation between emissions (all of scope 1, 2, and 3) and firm size, sales growth, and PP&E, suggesting that size and growth are the primary drivers of emissions estimation models. This fact is somewhat unsurprising, as a vendor with an inability to observe a firm's actual outputs and potential investments into clean technology must rely on its industry-level knowledge of how output on average maps into carbon emissions.

5. Do Carbon Emissions Explain Stock Returns?

Several studies, most notably Bolton and Kacperczyk (2021a, 2021b, 2022), document a strong correlation between emissions and stock returns. In this section, we first attempt to replicate their findings and then extend them to argue that their conclusions are attributable to a combination of two factors. First, the association between emissions and returns is entirely attributable to vendor-estimated emissions numbers, which are a mechanistic function of financial fundamentals and systematically different from firm-disclosed emissions numbers (see Section 4). Second, unscaled emissions largely represent a proxy for firm size, and emissions scaled by size lose their predictive power for returns.

In our analyses, we also highlight an additional factor that researchers ought to be aware of when analyzing whether emissions are priced: the sensitivity of documented results to research design choices, most notably in the choice of control variables and fixed effects used. While we do not take a position in this article on which set of control variables and fixed effects is the "correct" one—as this may depend on what the researcher wishes to show—our goal is to highlight the sensitivity of conclusions to design choices. We emphasize one specific design choice, namely controlling for size and how it may induce multicollinearity in specifications using log (unscaled) emissions.

Table IV. Do estimated emissions systematically differ from disclosed emissions?

This table estimates an emissions prediction model for each of scope 1, 2, and 3 emissions. In Columns (1)–(3), the dependent variable is the natural logarithm of scope 1, 2, and 3 emissions, respectively. In Column (1), the independent variable of interest is Scope 1 estimated, an indicator for whether the firm's scope 1 emissions corresponding to month-year *t* are vendor-estimated; in Column (2), the independent variable of interest is Scope 2 estimated, an indicator for whether the firm's scope 2 emissions corresponding to month-year *t* are vendor-estimated; and in Column (3), the independent variable of interest is Scope 3 estimated, an indicator for whether the firm's scope 3 emissions corresponding to month-year *t* are vendor-estimated. Columns (1)–(3) include industry and month-year fixed effects but no other control variables. Columns (4)–(6) replicate the specifications in Columns (1)–(3) but with the inclusion of control variables. Standard errors are two-way clustered by firm and month-year. Refer to Appendix A for variable definitions. We report standard errors in parentheses beneath coefficient estimates. In all panels, *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.

Variables	(1) Log scope 1	(2) Log scope 2	(3) Log scope 3	(4) Intensity scope 1	(5) Intensity scope 2	(6) Intensity scope 3
Estimated indicator	0.416***			−0.675***		
	(0.073)			(0.186)		
		−0.270***			−0.097***	
		(0.051)			(0.015)	
			−0.137***			−0.000
			(0.032)			(0.038)
Firm size	0.260***	0.401***	0.432***	−0.357***	−0.033***	−0.064***
	(0.028)	(0.026)	(0.021)	(0.072)	(0.005)	(0.015)
Leverage	0.448***	0.473***	0.495***	0.492**	−0.036*	0.021
	(0.126)	(0.114)	(0.093)	(0.211)	(0.020)	(0.070)
Book to market	0.266***	0.395***	0.364***	−0.181	−0.019	−0.050
	(0.078)	(0.072)	(0.057)	(0.227)	(0.016)	(0.047)
ROE	0.002***	0.002***	0.003***	0.001	−0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)
EPSGR	0.009	−0.007	−0.008	0.044**	0.001	0.008
	(0.010)	(0.009)	(0.009)	(0.021)	(0.002)	(0.006)
SalesGR	0.178***	0.170***	0.184***	0.052	0.006	0.018
	(0.060)	(0.061)	(0.059)	(0.071)	(0.008)	(0.023)
Log PPE	0.607***	0.471***	0.454***	0.269***	0.030***	0.081***
	(0.027)	(0.024)	(0.020)	(0.066)	(0.004)	(0.012)
Investment_Asset	−3.943***	−3.074***	−4.608***	−0.342	0.320**	−1.008**
	(0.714)	(0.583)	(0.461)	(1.953)	(0.140)	(0.389)
HHI	−1.403***	−1.185***	−1.366***	1.640*	0.047	−0.108
	(0.315)	(0.274)	(0.239)	(0.888)	(0.057)	(0.179)
Volatility	−0.011	0.145**	0.038	−0.112	−0.002	−0.045
	(0.074)	(0.066)	(0.044)	(0.115)	(0.012)	(0.028)
Momentum	0.055**	0.043*	0.051**	0.025	0.006	0.037***
	(0.025)	(0.023)	(0.022)	(0.044)	(0.004)	(0.014)
Beta	−0.058*	−0.048*	−0.071***	0.037	0.017***	0.020
	(0.031)	(0.028)	(0.024)	(0.077)	(0.006)	(0.017)

(continued)

Table IV. Continued

Variables	(1) Log scope 1	(2) Log scope 2	(3) Log scope 3	(4) Intensity scope 1	(5) Intensity scope 2	(6) Intensity scope 3
Constant	4.441***	4.447***	6.234***	3.174***	0.419***	1.636***
	(0.192)	(0.168)	(0.134)	(0.471)	(0.037)	(0.119)
Observations	178,354	178,354	178,354	178,354	178,354	178,354
R^2	0.883	0.858	0.906	0.710	0.569	0.782
Industry	Yes	Yes	Yes	Yes	Yes	Yes
Month-year	Yes	Yes	Yes	Yes	Yes	Yes

5.1 Baseline Specification

Before discussing the implications of estimated emissions figures and scaling, we first replicate the baseline finding, from prior literature, that unscaled emissions appear to be positively correlated with stock returns. We estimate the following cross-sectional regression:

$$RET_{it} = \alpha_0 + \alpha_1\ Emissions_{it} + \alpha_2\ Controls_{it} + \gamma_t\ + \delta_{\text{industry}} + \varepsilon_{it}. \tag{2}$$

The dependent variable (RET) in Equation (2) is monthly stock returns for firm i in month-year t.[10] In this specification, the main independent variable Emissions takes the form of log unscaled emissions for each of scope 1, 2, and 3.[11] Controls include a host of firm-specific variables known to be associated with stock returns, following Bolton and Kacperczyk (2021a). We provide a full list of control variables in Appendix A; in Supplementary Appendix Table OA2, we also compare the summary statistics for our sample and theirs. The coefficients γ_t and δ_{industry} represent month-year and GICS industry fixed effects. Standard errors are two-way clustered at the firm and month-year level, following Bolton and Kacperczyk (2021a).

Table V presents the results from estimating Equation (2). Columns 1–3 correspond to the natural logarithm of scope 1, 2, and 3 emissions and report a minimal specification, not including control variables or industry fixed effects (but including month-year fixed effects). We find, in Columns (1)–(3), no relation between emissions and stock returns. Columns (4)–(6) introduce industry fixed effects to the model, but we continue to find no relation between emissions and returns. Columns (7)–(9) add just firm size as a control variable; doing so causes the signs on log scope 1, 2, and 3 emissions to flip to positive and become highly significant, consistent with a carbon premium. The disparity between these columns, and those that do not control for firm size, may be attributable to multicollinearity in Columns (7)–(9) given the high correlation between log emissions and firm size. It is

10 We work with contemporaneous monthly returns to be consistent with the design choice adopted by Bolton and Kacperczyk (2021a). Our inferences are robust to re-estimating Equation (2) using 1-month ahead returns.

11 Trucost provides emissions data on a calendar year basis. However, to remain consistent with prior literature (e.g., Bolton and Kacperczyk, 2021a, 2022), we match returns with emissions in the same calendar year and estimate our regressions at the firm-month-year level rather than the firm-year level. In untabulated work, we find that our results are robust to substituting lagged emissions values.

Table V. Stock returns and carbon emissions

This table provides results from regressions of monthly stock returns on emissions. In Columns (1)–(3), we estimate regressions without controls or industry fixed effects; in Columns (4)–(6), we add industry fixed effects; in Columns (7)–(9), we add firm size; and in Columns (10)–(12), we add all remaining control variables. Refer to Appendix A for variable definitions. Standard errors are two-way clustered by firm and month-year. Refer to Appendix A for variable definitions. We report standard errors in parentheses beneath coefficient estimates. In all panels, *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Variables	Ret	Ret	Ret	Ret	Ret	Ret	Ret	Ret	Ret	Ret	Ret	Ret
Log scope 1	−0.034			−0.048			0.089**			0.060*		
	(0.029)			(0.039)			(0.040)			(0.033)		
Log scope 2		−0.039			−0.047			0.139***			0.120***	
		(0.034)			(0.041)			(0.049)			(0.040)	
Log scope 3			−0.041			−0.044			0.245***			0.262***
			(0.041)			(0.051)			(0.069)			(0.061)
Firm size							−0.238***	−0.292***	−0.386***	−0.331***	−0.368***	−0.433***
							(0.087)	(0.097)	(0.106)	(0.104)	(0.108)	(0.112)
Observations	178,354	178,354	178,354	178,354	178,354	178,354	178,354	178,354	178,354	178,354	178,354	178,354
R^2	0.189	0.189	0.189	0.190	0.190	0.190	0.191	0.191	0.191	0.191	0.192	0.192
Other controls	No	No	No	No	No	No	No	No	No	Yes	Yes	Yes
Industry	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month-year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

also important to note that *both* industry fixed effects and controlling for size are required to generate a positive and significant coefficient on the emissions variables; estimating a similar specification to Columns (7)–(9), but not including industry fixed effects, leads the coefficients on log scope 1, 2, and 3 emissions to become statistically insignificant (untabulated). This finding underscores the need for the researcher to decide whether including industry fixed effects or not is a more appropriate design choice based on their research question. More generally, our results in Columns (1)–(9) of Table V highlight the sensitivity to model specification of the conclusions that a researcher can draw about the existence of a carbon premium.

In Columns (10)–(12), we employ the full set of control variables used in Bolton and Kacperczyk (2021a).[12] For brevity, we do not tabulate these coefficients. Our results are similar to Columns (7)–(9), although coefficients on the emissions variables are lower in magnitude. The following control variables retain statistical significance: (i) positive coefficients on ROE and sales growth and (ii) negative coefficients on leverage and investments. These results are consistent with prior literature linking stock returns to firm fundamentals, suggesting that returns are higher for growing and profitable firms and lower for firms with greater leverage and investments. In untabulated additional analyses, we confirm that these results are robust to using future stock returns in lieu of concurrent returns as our dependent variable.

5.2 Vendor-Estimated versus Firm-Disclosed Emissions

Although Columns (10)–(12) of Table V show a positive relation between emissions and returns, these results are derived from a pooled sample of firm-year observations with both disclosed and estimated emissions. As shown in Section 4, there are systematic differences between estimated and disclosed emissions, which are unlikely to be fully attributable to firms strategically disclosing emissions. Given potential issues with vendor estimation procedures (Busch, Johnson, and Pioch 2022), we view it as important to understand whether emissions are related to stock returns for firms with actual observable emissions data. We partition the sample based on whether emissions for a given firm-year are disclosed or estimated and then re-estimate the "full" version of Equation (2) that includes all control variables and fixed effects.

In Columns (1)–(3) of Table VI, we consider firm-disclosed emissions observations only and show that the coefficient on disclosed values of unscaled emissions is statistically insignificant for scope 1 and 2 emissions. These findings are economically meaningful relative to our "full" specification. For example, while Column (10) of Table V implies that a firm moving from the 25th to the 75th percentile of log emissions, ceteris paribus, would enjoy stock returns that are 22.8% higher, Column (1) of Table VI implies that the effect is marginally negative (albeit statistically indistinguishable from zero).

We note that our findings in Columns (1)–(3) of Table VI do not align with the weakly positive and significant relation between disclosed emissions and returns found in Bolton and Kacperczyk (2021a). Prior research suggests that studies of stock return comovements can be sensitive to the choice of industry fixed effect used (Kahle and Walkling, 1996; Bhojraj, Lee, and Oler, 2003); in Supplementary Appendix Table OA3, we therefore examine this difference by considering four different industry definitions (GICS; four-digit SIC;

12 We follow the winsorization cutoffs given in Bolton and Kacperczyk (2021a). Our inferences are robust to winsorizing at the 1% level instead.

Table VI. Returns and disclosed versus vendor-estimated emissions

This table replicates the specifications provided in Columns (10)–(12) of Table VI, regressing monthly stock returns on the natural logarithm of scope 1, 2, and 3 emissions. We partition the sample according to whether an observation has estimated scope 1 emissions or firm-disclosed emissions; we then run analyses separately for these two subsamples. In Columns (1)–(3), we estimate this relation on the set of observations with firm-disclosed emissions values; in Columns (4)–(6), we estimate this relation on the set of observations with vendor-estimated emissions values. Standard errors are two-way clustered by firm and month-year. Refer to Appendix A for variable definitions. We report standard errors in parentheses beneath coefficient estimates. In all panels, *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.

	Firm-disclosed emissions			Vendor-estimated emissions		
	(1)	(2)	(3)	(4)	(5)	(6)
Variables	Ret	Ret	Ret	Ret	Ret	Ret
Log scope 1	−0.022			0.135***		
	(0.047)			(0.051)		
Log scope 2		0.028			0.204***	
		(0.032)			(0.063)	
Log scope 3			0.223***			0.300***
			(0.082)			(0.073)
Observations	50,816	50,816	50,816	127,538	127,538	127,538
R^2	0.265	0.265	0.265	0.183	0.183	0.183
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes	Yes
Month-year	Yes	Yes	Yes	Yes	Yes	Yes

Fama–French 48; and Trucost sector) to construct fixed effects as well as a more conservative method of measuring emissions disclosure based on direct disclosures (reflecting 53% of observations we flag as disclosed in our main tests).[13] The first three industry measures are common in prior asset pricing studies. The fourth, while uncommon, follows Bolton and Kacperczyk (2021a). Of the eight specifications we run, we only document a positive and significant relation in a single specification: using the more conservative disclosure measure and with Trucost industry fixed effects. While there is room for debate as to how best to measure disclosure, the fact that the result does not hold for other industry definitions leads us to conclude that there is minimal evidence, at best, that disclosed emissions are correlated with stock returns for US firms.

In Columns (4)–(6) of Table VI, we consider only vendor-estimated emissions observations and find that the coefficient on estimated unscaled emissions is positive and significant at the 1% level for each of scope 1, 2, and 3 emissions. While scope 3 emissions are significant for both sets of emissions, we note that even disclosed scope 3 emissions figures likely involve substantial estimation by the firm itself due to potential difficulty in obtaining upstream and downstream emissions figures; firm-estimated scope 3 emissions may thus not

13 We identify directly disclosed emissions as those where the Trucost source variable is either "Exact Value from CDP" or "Exact Value from Environmental/CSR Reports."

be immune to some of the issues that arise in vendors' estimation procedures. Collectively, our results in Table VI suggest that the positive relation between returns and emissions found in prior work stems from estimated emissions values generated by Trucost.

To further alleviate the concern that self-selection into disclosure may drive our results in Table VI, we employ a Heckman correction. For these analyses, we do not use Trucost-estimated emissions figures, instead treating firms that do not voluntarily disclose emissions as simply having missing emissions. In the first step of the model, we estimate a probit model of self-selection into disclosing emissions (for each of scope 1, 2, and 3 separately), from which we obtain the inverse Mills ratio. The probit model includes a subset of our control variables that are likely related to the decision to disclose emissions. In the second step of the model, we then include the inverse Mills ratio in a regression of emissions on stock returns. Table VII presents the results from the Heckman model. Columns 1, 3, and 5 present the first-stage probit models of the decision to disclose scope 1, 2, and 3 emissions, respectively; Columns 2, 4, and 6 present the corresponding second-stage regressions of stock returns on carbon emissions. Our results suggest that OLS estimates of stock returns on (disclosed) emissions are unbiased; the Heckman model sigma is statistically insignificant.

5.3 Unscaled versus Scaled Emissions

We argue that the evidence in Tables IV, VI, and VII suggests that the link between emissions and returns primarily reflects vendors' estimation procedures. Nonetheless, we acknowledge the possibility that firms that disclose emissions differ from firms that do not, in a way that explains our findings; Bolton and Kacperczyk (2021b) consider the issue in detail and provide economic arguments for why a carbon premium should be lower for disclosing relative to non-disclosing firms. Even if this were the case, however, we note that until now, to facilitate comparability with prior work, our analyses have used *total* (unscaled) emissions to measure firms' carbon performance and risk. In this section, we argue that unscaled emissions are not the best way to measure firm-level carbon risk for at least two reasons.

First, it is not clear how much incremental information can be gained from studying total emissions other than as a measure of firm output. Because emissions arise from a firm's core operations, in the short term, unscaled emissions are likely to be highly correlated with the quantity of goods produced or sold. Thus, a primary driver of within-firm variation in total emissions is total productivity, and hence a regression of returns on total emissions may simply pick up the link between stock returns and productivity even in the presence of successful emissions-reduction efforts.[14] Second, while total emissions reflect an appropriate way to measure the carbon footprint of and pollution in society, the impact of a society-wide emissions-reduction target should be felt by individual firms proportional to their size (e.g., carbon taxes are likely proportional to revenue, while the introduction of

14 As an example, consider a firm that concurrently achieves 10% sales growth and a 2% reduction in carbon emissions per unit of production, as a result of green investments, relative to the prior year. The firm's emissions in the current year will be 7.8% higher (1.10×0.98) than the prior year, despite the 2% efficiency gain. A positive relation between total emissions and stock returns for this firm is more likely to reflect the sales growth rather than a carbon premium, given the company's demonstrable investments to reduce future carbon risk.

Table VII. Heckman selection model for disclosed emissions

This table reports results from estimating a Heckman selection model of emissions disclosure for each of scope 1, 2, and 3 emissions. In the first stage (selection), we estimate a probit model where the dependent variable is an indicator variable for whether the firm disclosed the relevant emissions figure (scope 1, 2, or 3). In the second stage of the model, we regress stock returns on log emissions, including the inverse Mills ratio from the first-stage model along with industry and month-year fixed effects. Columns (1) and (2) report results for Scope 1 emissions; Columns (3) and (4) report results for Scope 2 emissions; and Columns (5) and (6) report results for Scope 3 emissions. Standard errors are two-way clustered by firm and month-year. Refer to Appendix A for variable definitions. We report standard errors in parentheses beneath coefficient estimates. In all panels, *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.

	Scope 1		Scope 2		Scope 3	
Variables	(1) Selection	(2) Main model	(3) Selection	(4) Main model	(5) Selection	(6) Main model
Log scope 1		0.015				
		(0.037)				
Log scope 2				−0.025		
				(0.038)		
Log scope 3						0.118
						(0.073)
Size (market cap)		−0.270**		−0.278**		−0.312**
		(0.134)		(0.133)		(0.139)
Leverage	−0.729***	0.543	−0.729***	0.523	−0.729***	0.521
	(0.036)	(0.424)	(0.036)	(0.426)	(0.036)	(0.425)
Book to market	−0.393***	0.586*	−0.392***	0.579*	−0.393***	0.550
	(0.021)	(0.336)	(0.021)	(0.336)	(0.021)	(0.337)
ROE	0.002***	0.005***	0.002***	0.005***	0.002***	0.005***
	(0.000)	(0.002)	(0.000)	(0.002)	(0.000)	(0.002)
EPSGR	−0.022***	0.087	−0.022***	0.088	−0.022***	0.087
	(0.007)	(0.072)	(0.007)	(0.072)	(0.007)	(0.072)
SalesGR		−0.412		−0.411		−0.403
		(0.368)		(0.368)		(0.368)
Log PPE	0.239***	0.068	0.239***	0.111	0.239***	0.048
	(0.006)	(0.112)	(0.006)	(0.106)	(0.006)	(0.100)
Investment_Asset		−6.089***		−6.225***		−5.776***
		(2.169)		(2.170)		(2.160)
Log revenue	0.668***		0.668***		0.668***	
	(0.008)		(0.008)		(0.008)	
Constant	−9.840***	1.118	−9.840***	1.388	−9.840***	0.007
	(0.083)	(1.497)	(0.083)	(1.473)	(0.083)	(1.525)
Rho	−0.016		−0.018		−0.008	
	(0.012)		(0.012)		(0.011)	
Sigma	6.778		6.778		6.777	
	(0.068)		(0.068)		(0.068)	
Lambda	−0.113		−0.121		−0.057	
	(0.081)		(0.081)		(0.076)	

(continued)

Table VII. Continued

	Scope 1		Scope 2		Scope 3	
Variables	(1) Selection	(2) Main model	(3) Selection	(4) Main model	(5) Selection	(6) Main model
Observations	159,951	159,951	159,951	159,951	159,951	159,951
Pseudo R^2	0.521		0.521		0.521	
Other controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes
Clustering	Yes	Yes	Yes	Yes	Yes	Yes

a cap-and-trade arrangement would likely award initial allocations to firms on the basis of size).

Both arguments above highlight the need to normalize total emissions by size or productivity to appropriately measure firm-specific carbon performance or risk. To this end, we argue that emissions intensity—empirically measured as the ratio of emissions to sales—is a more appropriate measure of carbon performance. While ours is not the first study to consider this measure, prior work (e.g., Bolton and Kacperczyk, 2021a, 2022) considers emissions intensity largely for the sake of robustness. We argue, conversely, that emissions intensity ought to be a primary way of assessing firm-specific carbon performance.

In Table VIII, we re-run our main analyses shown in Tables V and VI using emissions intensity rather than total emissions as our proxy for carbon performance. In Columns (1)–(3), we use all firm-month-year observations for scope 1, 2, and 3 emissions, respectively, irrespective of whether the emissions figure is vendor-estimated or firm-disclosed; in Columns (4)–(6), we use only firm-disclosed observations; and in Columns (7)–(9), we use only vendor-estimated observations. We find no evidence consistent with a carbon premium (i.e., a positive coefficient on emissions intensity) in any specification; in fact, we find a negative relation between returns and both vendor-estimated scope 1 intensity and firm-disclosed scope 2 intensity.

Our two main proxies thus far for emissions performance (total emissions and emissions intensity) are derived from a single period. We acknowledge, however, that many researchers and practitioners may instead find it more relevant to consider changes over time in emissions. In Table OA4 of the Supplementary Appendix, we therefore also provide results using two additional proxies for emissions that have been used in prior research: (i) the year-over-year growth in unscaled emissions and (ii) the year-over-year change in emissions intensity. These two independent variables, along with the two used thus far, are meant to cover the most-commonly used carbon variables in prior academic work and in practice. We find, in Supplementary Appendix Table OA3, limited evidence of a relation between these measures and stock returns.

6. Do Carbon Emissions Explain Operating Performance?

A possible explanation for our results thus far is that emissions may have an *indirect* effect on stock returns via a link to profitability. If emissions-reduction efforts temporarily lead to

Table VIII. Stock returns and carbon emissions intensity

This table provides results from estimating regressions of stock returns on carbon emissions intensity. In all columns, we estimate the relation between monthly stock returns and scope 1, 2, and 3 carbon emissions intensity, where intensity is measured as the ratio of emissions to sales. Columns (1)–(3) consider the relation between emissions and returns for all observations; Columns (4)–(6) consider only firm-disclosed emissions figures; and Columns (7)–(9) consider only vendor-estimated emissions figures. All specifications include the full set of control variables as well as industry and month-year fixed effects. Standard errors are two-way clustered by firm and month-year. Refer to Appendix A for variable definitions. We report standard errors in parentheses beneath coefficient estimates. In all panels, *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.

	All observations			Firm-disclosed emissions			Vendor-estimated emissions		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Variables	Ret	Ret	Ret	Ret	Ret	Ret	Ret	Ret	Ret
Carbon intensity scope 1	−0.013**			−0.008			−0.018*		
	(0.005)			(0.007)			(0.011)		
Carbon intensity scope 2		−0.152			−0.307**			−0.175	
		(0.118)			(0.119)			(0.234)	
Carbon intensity scope 3			0.033			0.015			0.068
			(0.035)			(0.043)			(0.051)
Firm size	−0.322***	−0.322***	−0.315***	−0.366***	−0.396***	−0.361**	−0.394***	−0.394***	−0.386***
	(0.102)	(0.102)	(0.102)	(0.148)	(0.151)	(0.148)	(0.111)	(0.110)	(0.111)
Observations	178,354	178,354	178,354	50,816	50,816	50,816	127,538	127,538	127,538
R^2	0.191	0.191	0.191	0.265	0.265	0.265	0.183	0.183	0.183
Other controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month-year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

higher costs and reduced production during the transition period, then, inasmuch as carbon risk primarily affects a firm's future rather than current performance, a firm may forgo such investment—or invest "piece-wise" rather than all at once. Doing so would result in both higher emissions and higher productivity (and, hence, profitability) in the short run relative to peers that bear more of their carbon transition costs up front. If this excess productivity is unanticipated—for example, because investors expected the firm to engage in more emissions-reduction efforts—that could result in higher stock returns.

To assess this possibility, we test the relation between emissions and four popular measures of profitability or operating performance: (i) ROA_{it}, which is ROAs and is measured as the ratio of operating income after depreciation to total assets for firm *i* in year *t*; (ii) ROS_{it}, which is return on sales, measured as the ratio of operating income after depreciation to sales for firm *i* in year *t*; (iii) EBIT $Margin_{it}$, which is the ratio of earnings before interest and taxes (EBIT) to sales for firm *i* in year *t*; and (iv) EBITDA $Margin_{it}$, which is the ratio of earnings before interest, taxes, depreciation, and amortization (EBITDA) to sales for firm *i* in year *t*. We estimate the following regression:

$$\text{Performance}_{it} = \alpha_0 + \alpha_1\, Emissions_{it} + \alpha_2\, Controls_{it} + \gamma_t\ + \delta_{\text{industry}} + \varepsilon_{it}. \tag{3}$$

The dependent variable, Performance_{it}, is one of the four measures described above for firm *i* and month-year *t*. The variable Emissions takes the form of log unscaled emissions or carbon intensity. We use the same controls as in Equation (2). To address time-invariant and industry-invariant unobservable characteristics, we employ month-year fixed effects (γ_t) and GICS industry fixed effects (δ_{industry}). Standard errors are clustered by firm and month-year.

Table IX reports the results from this specification. For brevity, we tabulate results using only scope 1 emissions. In addition, we tabulate only results using log emissions and emissions intensity; additional results using our other two measures of carbon emissions (emissions growth as well as change in emissions intensity) are available in Supplementary Appendix Table OA5. While Columns (1)–(4) of Panel A show that all four performance measures are positively associated with unscaled scope 1 emissions, in Columns (5)–(8), we show that emissions intensity is not associated with profitability. Moreover, even the results in Columns (1)–(4) of Panel A are sensitive to whether emissions are disclosed or estimated. In Panel B of Table IX, we re-estimate Equation (3) separately for disclosed and estimated emissions observations, using unscaled emissions. We find that while vendor-estimated emissions are highly correlated with performance [Columns (5)–(8)], there is no such relation for firm-disclosed emissions [Columns (1)–(4)]. In sum, we do not find compelling evidence that emissions indirectly affect stock returns through a link with firm fundamentals.

7. Europe

Our results thus far focus on US firms, in line with much of the prior literature we cite. However, one limitation of a US focus is that the financial and regulatory environment in the USA may significantly differ from those of other countries, which in turn may lead to a relation between carbon emissions and financial or stock market performance in those settings. Should such a relation exist, we argue that it is likely to be in areas of the world with the strongest pressures to "go green," because these are the areas in which investors are likely to be most conscious of carbon risk. We therefore directly test for a potential relation between stock market performance and carbon emissions in one such setting: European

Table IX. Operating performance and carbon emissions

This table provides results from regressions of four measures of operating performance and profitability—EBIT margin (the ratio of EBIT to assets), EBITDA margin (the ratio of EBITDA to assets), ROAs, and ROS (return on sales)—on both log carbon emissions and emissions intensity. For brevity, we only tabulate results using scope 1 emissions. Panel A considers the relation between operating performance and our two main carbon emissions measures: the natural logarithm of total carbon emissions and carbon emissions intensity. Panel B replicates Columns (1)–(4) of Panel A but partitions the sample according to whether an observation has estimated emissions or firm-disclosed emissions; we then run analyses separately for these two subsamples. All specifications include the full set of control variables along with industry and month-year fixed effects. Standard errors are two-way clustered by firm and month-year. Refer to Appendix A for variable definitions. We report standard errors in parentheses beneath coefficient estimates. In all panels, *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively. Panel A: This panel provides results from regressions of operating performance on both the natural logarithm of scope 1 carbon emissions as well as scope 1 emissions intensity. In Column (1), the dependent variable is ROA; in Column (2), the dependent variable is ROS; in Column (3), the dependent variable is EBIT margin; and in Column (4), the dependent variable is EBITDA Margin. Columns (5)–(8) replicate the specification of Columns (1)–(4) but with carbon intensity measure. Panel B: This panel provides results from regressions of operating performance on the natural logarithm of Scope 1 carbon emissions but partitions the sample according to whether an observation has estimated emissions or firm-disclosed emissions. Columns (1)–(4) report results for firm-disclosed emissions observations. In Column (1), the dependent variable is ROA margin; in Column (2), the dependent variable is ROS; in Column (3), the dependent variable is EBIT margin; and in Column (4), the dependent variable is EBITDA margin. Columns (5)–(8) replicate the specifications in Columns (1)–(4) but for vendor-estimated observations.

Panel A: Unscaled emissions versus scaled emissions

Variables	(1) ROA	(2) ROS	(3) EBIT margin	(4) EBITDA margin	(5) ROA	(6) ROS	(7) EBIT margin	(8) EBITDA margin
Log scope 1	0.016***	0.581***	0.581***	0.608***				
	(0.002)	(0.079)	(0.079)	(0.085)				
Intensity scope 1					0.000	−0.002	−0.002	−0.002
					(0.000)	(0.003)	(0.003)	(0.004)
Observations	178,354	178,354	178,342	178,226	178,354	178,354	178,342	178,226
R^2	0.499	0.355	0.355	0.345	0.485	0.277	0.277	0.268
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month-year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

(continued)

Table IX. Continued

Panel B: Disclosed versus estimated

	Firm-disclosed emissions				Vendor-estimated emissions			
Variables	(1) ROA	(2) ROS	(3) EBIT margin	(4) EBITDA margin	(5) ROA	(6) ROS	(7) EBIT margin	(8) EBITDA margin
Log scope 1	0.001	0.005	0.005	0.001	0.027***	0.983***	0.983***	1.031***
	(0.002)	(0.006)	(0.006)	(0.006)	(0.003)	(0.117)	(0.117)	(0.126)
Observations	50,816	50,816	50,816	50,816	127,538	127,538	127,526	127,410
R^2	0.554	0.268	0.268	0.307	0.543	0.435	0.435	0.424
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month-year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

firms. Existing literature (e.g., Gibson *et al.*, 2022) argues that European investors appear more credible in their commitments to responsible investing than American investors, which in turn may lead to a genuine relation between carbon emissions and stock returns in Europe even if no such relation exists in the USA. In doing so, our tests in this section can also be thought of as a (partial) validation exercise of Bolton and Kacperczyk (2022).

7.1 European Data

As with our US data, we obtain carbon emissions data from the European setting from Trucost. In Supplementary Appendix Table OA6, we provide a detailed breakdown (analogous to Tables I–III) of our European sample by year, industry, and country, as well as according to the proportion of observations that are estimated versus disclosed. Of note is the fact that emissions are much more commonly disclosed in Europe vis-à-vis the USA: 55% of firm-years disclose emissions figures in Europe relative to the 25% figure in our sample. We observe significant heterogeneity across countries; for instance, 62% of UK firm-years disclose emissions figures while only 44% of Swiss firm-years make such disclosures. As with the USA, the proportion of firms that disclose emissions steadily rises over time until 2016, when Trucost's data expansion injects a number of firms with estimated figures into the sample.

To construct tests for European firms, we obtain financial fundamental and stock returns data from Datastream, Worldscope, and Compustat Global. After imposing similar screens to the US setting, and before removing observations for which we are not able to construct control variables, we obtain 236,526 firm-month observations spanning thirty-six countries between 2005 and 2019. Countries most commonly occurring in our sample are the UK (31.2% of observations), France (10.6%), Germany (8.8%), and Switzerland (7.7%).

7.2 Results

We present results pertaining to European firms in Table X. For brevity, we do not tabulate a complete set of results corresponding to what we have presented thus far for US firms.

Table X. Are emissions priced in Europe?

This table provides results on the relation between carbon emissions and stock returns for European firms. Panel A considers the relation between stock returns and the natural logarithm of total carbon emissions for each of scope 1, 2, and 3, while Panel B instead considers emissions intensity in lieu of total emissions. In Panels C and D, we replicate Panels A and B but partition the sample according to whether an observation has estimated emissions or firm-disclosed emissions; we then run analyses separately for these two subsamples. All specifications include the full set of control variables along with country fixed effects and month-year fixed effects; industry fixed effects appear in some but not all columns, as indicated. Standard errors are two-way clustered by firm and month-year. Refer to Appendix A for variable definitions. We report standard errors in parentheses beneath coefficient estimates. In all panels, *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively. Panel A: This panel provides results from regressions of monthly stock returns on log total emissions for European firms. Columns (1)–(3) do not include industry fixed effects while Columns (4)–(6) include industry fixed effects. Panel B: This panel provides results from regressions of monthly stock returns on emissions intensity for European firms. Columns (1)–(3) do not include industry fixed effects while Columns (4)–(6) include industry fixed effects. Panel C: This panel provides results from regressions of monthly stock returns on the natural logarithm of total carbon emissions and emissions intensity based on whether an observation has estimated emissions or firm-disclosed emissions. Columns (1)–(6) report the results of firm-disclosed emissions observations while Columns (7)–(12) report results for vendor-estimated observations. None of the specifications below include industry fixed effects.

Panel A: Stock returns and log emissions

Variables	(1) Return	(2) Return	(3) Return	(4) Return	(5) Return	(6) Return
Log scope 1	0.050***			−0.007		
	(0.017)			(0.018)		
Log scope 2		−0.006			−0.055*	
		(0.026)			(0.028)	
Log scope 3			−0.010			−0.180***
			(0.030)			(0.041)
Observations	156,087	156,087	156,087	156,087	156,087	156,087
R^2	0.192	0.192	0.192	0.194	0.194	0.194
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Country	Yes	Yes	Yes	Yes	Yes	Yes
Industry	No	No	No	Yes	Yes	Yes
Month-year	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Stock returns and emissions intensity

Variables	(1)	(2)	(3)	(4)	(5)	(6)
Carbon intensity scope 1	0.037***			0.012		
	(0.012)			(0.008)		
Carbon intensity scope 2		0.191**			0.046	
		(0.090)			(0.054)	
Carbon intensity scope 3			0.059**			−0.015
			(0.022)			(0.027)
Observations	156,087	156,087	156,087	156,087	156,087	156,087
R^2	0.192	0.192	0.192	0.194	0.194	0.194
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Country	Yes	Yes	Yes	Yes	Yes	Yes
Industry	No	No	No	Yes	Yes	Yes
Month-year	Yes	Yes	Yes	Yes	Yes	Yes

Table X. Continued

Panel C: Returns and disclosed versus estimated emissions in Europe—no industry fixed effects

	Firm-disclosed emissions						Vendor-estimated emissions					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Variables	Return	Return	Return	Return	Return	Return	Return	Return	Return	Return	Return	Return
Log scope 1	0.056***						0.043					
	(0.018)						(0.028)					
Log scope 2		0.012						−0.039				
		(0.026)						(0.039)				
Log scope 3			0.009						−0.005			
			(0.034)						(0.046)			
Intensity scope 1				0.030**						0.058**		
				(0.012)						(0.023)		
Intensity scope 2					0.167						0.365***	
					(0.099)						(0.122)	
Intensity scope 3						0.053**						0.079***
						(0.025)						(0.029)
Observations	87,496	87,496	87,496	87,496	87,496	87,496	68,591	68,591	68,591	68,591	68,591	68,591
R-squared	0.196	0.196	0.196	0.196	0.196	0.196	0.194	0.194	0.194	0.194	0.194	0.194
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry	No	No	No	No	No	No	No	No	No	No	No	No
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

We instead focus, in this section, on (i) the importance of industry fixed effects for the conclusions that can be drawn; (ii) differences in using disclosed and estimated emissions figures; and (iii) the distinction between unscaled carbon emissions and emissions intensity.

In Panel A of Table X, we re-estimate Equation (2) using the natural logarithm of unscaled emissions, with one minor modification: because we are now using a cross-country sample, we incorporate country fixed effects. We begin in Columns (1)–(3) with a specification that does not include industry fixed effects (but which does include all other control variables and fixed effects); in Columns (4)–(6), we add industry fixed effects. Panel B has the same six columns but uses emissions intensity instead of unscaled emissions. Both panels highlight the importance of industry fixed effects in the European setting relative to the US setting: while we observe evidence consistent with a carbon premium in Columns (1)–(3) of Panels A and B, in Columns (4)–(6) the relation disappears. These results suggest that in Europe, a link between emissions and returns may manifest as distaste for certain industries rather than for specific firms within an industry. Our results for emissions intensity suggest that, to some extent, investors in European firms may care more about emissions than for US firms.

In Panel C, we turn to the distinction between estimated and disclosed emissions. For brevity, we only tabulate results without industry fixed effects; if we use industry fixed effects, we observe no evidence consistent with a carbon premium for either disclosed or estimated observations. Without industry fixed effects, we do observe a positive relation between vendor-estimated emissions and returns in some specifications; however, even where this is significant, the relation is weaker for disclosed emissions relative to estimated emissions (consistent with Bolton and Kacperczyk, 2022). Collectively, our results in this section highlight that the issues we discuss in this article—the need to account for vendors' estimation procedures as well as to focus on emissions intensity—remain relevant in non-US settings as well.

8. Conclusion

Research on climate finance has exploded in recent years driven by demand from both policy and practice. Researchers have documented mixed results with respect to the value relevance of emissions. For instance, Bolton and Kacperczyk (2021a, 2022) document a positive relation between unscaled carbon emissions and stock returns while Matsumura, Prakash, and Vera-Muñoz (2014) find a negative relation between firm value and emissions.

Consistent with Bolton and Kacperczyk (2021a), we find a positive relation between the natural logarithm of unscaled emissions and stock returns. However, these results weaken or disappear once we (i) account for differences between vendor-estimated and firm-disclosed emissions figures or (ii) scale emissions by firm size (revenue); we view the latter as a more economically appropriate measure of firm-specific carbon performance. Estimated emissions are far more strongly correlated with firm fundamentals than firm-disclosed emissions, suggesting that a statistical relation between "carbon emissions" and stock returns in prior work reflects correlations between firm fundamentals and stock returns (and/or may be driven by multicollinearity between unscaled emissions and measures of size).

In sum, this article shows that the relation between carbon emissions and stock returns or firm value documented in past papers is driven by two main factors: (i) carbon emissions data vendors' estimation procedures and (ii) a research design choice made in several prior studies to emphasize unscaled emissions, which are mechanically correlated with productivity and size. Researchers, practitioners, and policymakers might want to be careful about interpreting statistical associations between carbon emissions and returns.

Supplementary Material

Supplementary data are available at *Review of Finance* online.

Data Availability

All of the data underlying the article's empirical analyses are publicly available from the sources listed in the article. Most of these sources require a paid subscription, but our understanding is that any researcher who wishes to purchase any of the data may freely do so.

Appendix A: Variable Definitions

Variable	Definition	Data source
Returns	Monthly stock return (expressed in percentage).	CRSP
ROS	Return on sales, measured as the ratio of operating income after depreciation to total year-end sales.	Compustat
ROA	ROAs, measured as the ratio of operating income after depreciation to year-end total assets.	Compustat
EBIT Margin	Ratio of EBIT to total sales at year end.	Compustat
EBITDA Margin	Ratio of EBITDA to total sales at year end.	Compustat
HHI	Herfindahl concentration index of sector-level firm sales, relative to the full firm (i.e., a within-firm measure).	Compustat
ROE	ROE, measured as the ratio of net income divided by the value of its equity.	Compustat
Firm size	Natural logarithm of firm's total market capitalization.	CRSP
Invest/A	Ratio of capital expenditures to year-end total assets.	Compustat
Log PPE	Natural logarithm of property, plant, and equipment.	Compustat
Leverage	Ratio of long-term debt to assets.	Compustat
SalesGR	Change in annual firm revenues normalized by prior-year revenue.	Compustat
EPSGR	Change in annual earnings per share normalized by prior-year earnings per share.	Compustat
Log market cap	Natural logarithm of total market capitalization of a firm in a given year.	CRSP
Total assets	Total assets for a firm in a given year.	Compustat
Log sale	Natural logarithm of total sales of a firm in a given year.	Compustat
Volatility	Monthly stock return volatility calculated over the 1-year period.	CRSP
Momentum	Total stock return over the past 12 months ignoring the previous month.	CRSP
Beta	CAPM beta calculated over the 1-year period.	CRSP

(continued)

Continued

Variable	Definition	Data source
Book-to-market ratio	The ratio of book value of equity to market value of equity.	Compustat
Log scope 1	Natural logarithm of scope 1 emissions (measured in tCO_2e). Scope 1 emissions cover direct emissions from establishments that are owned or controlled by the company and include all emissions from fossil fuels used in production.	Trucost
Log scope 2	Natural logarithm of scope 2 emissions (measured in tCO_2e). Scope 2 emissions come from the generation of purchased heat, steam, and electricity consumed by the company.	Trucost
Log scope 3	Natural logarithm of scope 3 emissions (measured in tCO_2e). Scope 3 emissions are caused by the operations and products of the company but occur from sources not owned or controlled by the company.	Trucost
Carbon intensity scope 1	Ratio of scope 1 emissions (tCO_2e) to revenues (millions of dollars).	Trucost
Carbon intensity scope 2	Ratio of scope 2 emissions (tCO_2e) to revenues (millions of dollars).	Trucost
Carbon intensity scope 3	Ratio of scope 3 emissions (tCO_2e) to revenues (millions of dollars).	Trucost
Scope 1 growth	Change in scope 1 emissions divided by prior-year scope 1 emissions.	Trucost
Scope 2 growth	Change in scope 2 emissions divided by prior-year scope 3 emissions.	Trucost
Scope 3 growth	Change in scope 3 emissions divided by prior-year scope 3 emissions.	Trucost
Change in carbon intensity scope 1	Year-over-year change in scope 1 emissions intensity.	Trucost
Change in carbon intensity scope 2	Year-over-year change in scope 2 emissions intensity.	Trucost
Change in carbon intensity scope 3	Year-over-year change in scope 3 emissions intensity.	Trucost
Estimated values	Indicator variable for whether emissions values are estimated by Trucost. We label an observation to be estimated if Trucost's "source of carbon disclosure" variable contains the word "Estimate."	Trucost

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