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# Carbon Returns across the Globe

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**ABSTRACT**

The pricing of carbon transition risk is central to the debate on climate-aware investments. Emissions are tightly linked to sales and are available to investors only with significant lags. The positive carbon return, or brown-minus-green return differential, documented in previous studies arises from forward-looking firm performance information contained in emissions rather than a risk premium in ex ante expected returns. After accounting for the data release lag, carbon returns turn negative in the United States and insignificant globally. Developed markets experience lower carbon returns due to intense climate concern shocks, while countries with stringent climate policies exhibit higher carbon returns.

The pricing of carbon transition risk is a central question as investors consider climate-aware investments. Theoretically, brown firms are more exposed to policy risk during the transition to net zero and should earn higher expected returns in equilibrium (Hsu, Li, and Tsou, 2023). Green firms, however, can outperform when policy shocks kick in, consumer attention turns, and investor tastes shift in transition to net-zero (Pastor, Stambaugh, and Taylor, 2021). Empirically, Bolton and Kacperczyk (2021) and Bolton and Kacperczyk (2023) (BK, 2021, 2023) find brown stocks exhibit outperformance (or,

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a carbon premium) both within the United States and globally, suggesting that carbon transition risk is already priced in equity markets. However, In, Park, and Monky (2017), Garvey, Iyer, and Nash (2018), Duan, Li, and Wen (2023), Pastor, Stambaugh, and Taylor (2022), and Pedersen, Fitzgibbons, and Pomorski (2021) find that green investments outperform in global equity, U.S. equity, and U.S. corporate bonds, consistent with an ongoing transition to the "carbon-aware" equilibrium. In addition, Görgen et al. (2020), Aswani, Raghunandan, and Rajgopal (2024), and Lindsey, Pruitt, and Schiller (2021) find mixed evidence. In light of the debates and challenges, while over 200 asset managers have committed to the Net Zero Asset Management initiative, the two largest asset managers, Blackrock and Vanguard, have decided not to divest brown firms.[1]

In this paper, I revisit the carbon return, which is the return spread between brown and green firms, and find that the previously documented carbon premium arises from forward-looking sales information contained in emissions instead of a risk premium in ex ante expected returns. After accounting for the data release lag, the realized carbon return is significantly negative in the United States in recent years and varies across countries as a function of cash flow shocks, shifts in investor preferences, and local climate policies. Overall, the evidence suggests that carbon transition risk is at least partially reflected in global equity prices, but carbon returns in recent years are consistent with an ongoing transition to a "carbon-aware" equilibrium.

A key empirical challenge in assessing carbon returns is real-time measurement of emissions known to investors due to the gradual release of carbon data. I provide a first assessment of the lag of emission data release and find that the lag is longer than that of typical accounting variables. The median lags are 10 and 12 months after the emission fiscal year-end for the U.S. and international samples, respectively. Because carbon emissions are often estimated as a weighted sum of economic activity scaled by emission factors (Eggleston et al., 2006), carbon emissions are tightly linked to firm sales in the data. Specifically, firm sales contemporaneously account for 50% of the variation in U.S. scope 1 emissions and 71% of the variation in scope 2 emissions. Consequently, emissions contain substantial information about firm performance and should be lagged sufficiently to avoid forward-looking bias (or look-ahead bias).

The main measure of carbon transition risk is carbon intensity or emissions scaled by sales. Compared to total emissions, carbon intensity better captures firm-level carbon transition risk for two reasons. First, because emissions grow with firm operations, it is more informative to compare intensity across firms. Second, while regulatory policies like cap-and-trade or carbon taxes focus on total emissions, they affect the profitability of larger companies less than that of smaller firms for a given level of carbon emissions.

[1] See the statements by Blackrock at https://www.blackrock.com/corporate/about-us/our-2021-sustainability-update/2030-net-zero-statement and by Vanguard at https://corporate.vanguard.com/content/corporatesite/us/en/corp/climate-change.html.

Using the point-in-time carbon emission data available to investors, I show that brown firms as classified by carbon intensity earn significantly lower returns than green firms in the United States. Value-weighted carbon return spreads per month are −0.39% and −0.27% for scope 1 and 2 carbon intensities. The negative carbon return is robust to factor adjustments and various robustness checks, including using firm-disclosed emissions only. Cross-industry variation in emission intensity explains much of the variation in carbon excess returns across firms. Globally, more carbon-intensive firms again tend to underperform, though the return spread is insignificant. In contrast, portfolios based on year-over-year emissions growth or total emissions yield negative or insignificant positive carbon returns in the United States or globally.

To highlight the role of forward-looking sales information, I replicate the analysis in BK (2021, 2023), who relate emissions to returns before the actual release of emissions and accounting information for the emitting period. Like BK, I find that stock returns are positively associated with contemporaneous and one-month-lagged emissions growth and total emissions in the United States and globally. However, once firm performance during the same emission period is taken into account, total emissions and emissions growth are no longer positively associated with stock returns. The corrected carbon coefficients tend to be negative, consistent with my baseline analysis. In sum, the carbon premium documented in previous studies only sources from strong performance of brown firms during the emitting period and does not reflect a risk premium associated with carbon transition risk.

In additional analysis, I examine country-level evidence further to shed light on the factors that drive carbon returns. Carbon returns exhibit large variation across countries and are lower in developed markets than in emerging markets. International carbon returns can reflect disparities in expected risk premia as well as unanticipated in-sample shocks, including cash flow shocks and climate concern shifts. I find that developed countries have experienced stronger growth in climate concerns, as measured by country-level sustainable flows and climate concern surveys, leading to lower carbon returns in these countries. In addition, cash flow shocks explain up to 7% of carbon return variation. After controlling for in-sample shocks, carbon returns tend to be higher in countries with tighter climate policies, reflecting compensation for heightened policy risk as in equilibrium. Overall, the evidence suggests that investors have started to price in carbon transition risk, but the risk premium associated with brown stocks is muted in recent years.

This paper contributes to the literature on the pricing of carbon risks by examining a critical methodological choice and reconciling conflicting findings in previous studies. In addition, this paper contributes to international and country-level evidence on climate finance. BK (2023) interpret cross-country carbon return variation as expected return variation. In contrast, results in this paper show that lower carbon returns in developed markets instead reflect stronger climate concern shifts. Dyck et al. (2019) and Gibson Brandon et al. (2022) study responsible institutional investing around the world but do not address pricing implications. Görgen et al. (2020) and Aswani, Raghunandan, and Rajgopal (2024) also study international or regional carbon returns but do not examine cross-country differences, which is a focus of this paper.

This paper also adds to the literature that analyzes the role of institutional investors and ESG investing. Pastor, Stambaugh, and Taylor (2022) characterize U.S. stock returns during the carbon transition, Berk and van Binsbergen (2021), van der Beck (2021), Ardia et al. (2023), and Alekseev et al. (2022) study price impacts of institutional investors in the United States and Hong, Wang, and Yang (2021) study welfare implications. This paper extends this work by turning to international markets and examines cross-country implications. Krueger, Sautner, and Starks (2020) document that the average respondent believes that climate risk is not fully priced in a survey-based study. This paper provides complementary evidence based on asset prices. Finally, Choi, Gao, and Jiang (2020) study short-term price implications when retail investors revise their beliefs about climate change. This paper examines longer term cross-country price impacts.

The remainder of the paper proceeds as follows. Section I discusses data and characterizes the information set of investors. Section II studies U.S. and global evidence. Section III benchmarks the analysis against previous studies. Section IV analyzes what drives cross-country variation in carbon returns. Finally, Section V concludes.

## I. Data and Methodology

### A. Data

Data on firm-level climate performance come from S&P Trucost, which provides annual information on firm-level carbon emissions in tons of carbon dioxide equivalent (tCO2e). Firm-level stock market and accounting information source from CRSP and Compustat for the United States and from Compustat Global for the international sample. I restrict the sample to common stocks and focus only on the primary security listed on the primary exchange. Trucost data are matched to the stock-level information by CUSIP, ISIN, and SEDOL. Finally, I augment the data by natural gas price, Brent oil price, and commodity index from FRED at the St. Louis Fed and by country-level information extracted from World Bank, World Risk Poll, and Climate Change Performance Index.

I study scope 1 and 2 emissions. Scope 1 greenhouse gas (GHG) emissions cover direct emissions from sources owned or controlled by the firm, such as company vehicles or emissions from manufacturing facilities. Scope 2 GHG emissions cover indirect emissions from the generation of purchased electricity, steam, heating, and cooling consumed by the reporting company.

### B. Sample and Summary Statistics

While most databases do not provide the date when emission data are made available, Trucost updates various environmental variables simultaneously and provides the date when the final data are made available. In this paper, I use the most recent carbon emission and accounting data based on their respective data release dates. The final sample is the intersection between monthly stock return data and annual carbon emissions data, ensuring that carbon data are available before the stock return is known. The matched sample covers returns from June 2009 to December 2021.

The main measure of carbon transition risk is carbon intensity—emissions scaled by sales—for a few reasons. First, because carbon emissions scale with firms' operations, it is more reasonable and informative to compare the intensity across firms. Second, investors focus almost exclusively on carbon intensity when discussing net-zero investment (see BK (2021), Hartzmark and Shue (2023), and a statement by Blackrock.[2]) As such, one can expect carbon intensity to be associated with stock returns if investors care about carbon transition risk. Third, regulating policies, such as cap-and-trade or carbon taxes, focus on total emissions but have less impact on the profitability of larger firms, conditional on the same amount of carbon emissions. To benchmark against the literature, I also construct measures of emissions growth, or year-over-year (log) growth of emissions, and (log) total emissions. If the latest carbon data for the fiscal year are not released yet, I fill in missing variables, emissions, growth, or carbon intensity, with the latest available number.

Table I presents the distribution of countries and regions of firms as well as summary statistics of average firm-level (log) carbon intensity, that is, log emissions per million U.S. dollars of sales.[3] Developed markets make up 67% of the sample, with the United States and Japan presenting most observations in the sample (22% and 14%). Among emerging markets, China represents the largest fraction of the sample (6.1%), followed by Korea and Taiwan (5.9% and 5.1%).

Table II presents summary statistics for firm-level carbon measures in the United States and in the global sample with all countries, respectively. For the United States, both (log) scope 1 and 2 carbon intensity have a mean of 2.71 log tCO2e per million U.S. dollars while scope 1 intensity has a higher standard deviation (2.19) than scope 2 (1.4). Carbon intensities are persistent, with annual autocorrelations of 0.99 and 0.93 for scope 1 and 2 measures, respectively. For the international sample, I screen international stock returns following Hou, Karolyi, and Kho (2011) to minimize the impact of outliers. All nominal variables are denominated in U.S. dollars. Global summary statistics are comparable to those of the United States, with slightly higher mean intensity (3.04 and 2.92). Controls include market beta estimated over a 60-month rolling window, size calculated as log year-end market capitalization, (log) book-to-market, momentum, idiosyncratic volatility from Fama-French three-factor model, return on assets (ROA), asset growth, leverage, log PPE,

[2] Available at https://www.blackrock.com/corporate/about-us/our-2021-sustainability-update/2030-net-zero-statement.

[3] Average carbon intensity is calculated using all available data points in the sample and covers different sample periods for different countries.

**Table I**

**Summary Statistics by Country**

This table presents the sample frequency and average scope 1 and 2 firm-level carbon intensities by country.

| Country | Observations | Year | Scope 1 Intensity | Scope 2 Intensity |
|---|---|---|---|---|
| Panel A: Developed Markets | | | | |
| AUS | 32,551 | 2009 | 3.20 | 3.33 |
| AUT | 3,469 | 2009 | 3.44 | 2.88 |
| BEL | 5,175 | 2009 | 2.97 | 2.90 |
| CAN | 24,681 | 2009 | 3.50 | 3.13 |
| CHE | 15,707 | 2009 | 2.28 | 2.38 |
| DEU | 18,958 | 2009 | 2.84 | 2.86 |
| DNK | 4,087 | 2009 | 2.82 | 2.39 |
| ESP | 6,895 | 2009 | 2.72 | 2.46 |
| FIN | 5,288 | 2009 | 2.87 | 2.89 |
| FRA | 22,249 | 2009 | 2.54 | 2.52 |
| GBR | 53,161 | 2009 | 2.44 | 2.67 |
| HKG | 44,117 | 2009 | 3.34 | 3.24 |
| IRL | 1,589 | 2009 | 3.81 | 3.16 |
| ISR | 7,269 | 2009 | 2.60 | 2.78 |
| ITA | 8,667 | 2009 | 2.87 | 2.62 |
| JPN | 133,323 | 2009 | 3.00 | 3.06 |
| NLD | 5,048 | 2009 | 2.50 | 2.43 |
| NOR | 6,632 | 2009 | 3.28 | 2.25 |
| PRT | 1,847 | 2009 | 3.22 | 2.89 |
| SGP | 9,806 | 2009 | 3.13 | 3.24 |
| SWE | 9,412 | 2009 | 2.02 | 2.47 |
| USA | 211,495 | 2009 | 2.71 | 2.71 |
| Panel B: Emerging Markets | | | | |
| ARE | 1,928 | 2009 | 2.37 | 2.72 |
| ARG | 1,110 | 2009 | 3.62 | 2.85 |
| BGD | 441 | 2015 | 3.48 | 3.06 |
| BGR | 270 | 2015 | 3.33 | 3.16 |
| BHR | 295 | 2015 | 0.18 | 1.42 |
| BMU | 29 | 2019 | −0.16 | 0.10 |
| BRA | 8,012 | 2009 | 3.14 | 2.30 |
| BWA | 18 | 2020 | −0.55 | −0.30 |
| CHL | 4,090 | 2009 | 3.46 | 2.20 |
| CHN | 57,325 | 2009 | 3.68 | 3.22 |
| CIV | 172 | 2015 | 2.35 | 2.74 |
| COL | 1,047 | 2009 | 3.94 | 1.89 |
| CYP | 33 | 2019 | 0.04 | 1.06 |
| CZE | 868 | 2009 | 2.75 | 2.39 |
| EGY | 3,562 | 2009 | 3.53 | 3.04 |
| EST | 132 | 2015 | 4.12 | 3.40 |
| GHA | 136 | 2015 | 3.47 | 3.37 |
| GRC | 2,645 | 2009 | 3.41 | 2.94 |

(*Continued*)

**Table I**—*Continued*

| Panel B: Emerging Markets | | | | |
|---|---|---|---|---|
| Country | Observations | Year | Scope 1 | Scope 2 |
| HRV | 239 | 2009 | 2.66 | 3.39 |
| HUN | 473 | 2009 | 2.35 | 2.43 |
| IDN | 8,456 | 2009 | 3.53 | 2.98 |
| IND | 30,646 | 2009 | 3.54 | 2.82 |
| JAM | 45 | 2018 | −0.14 | 1.24 |
| JOR | 398 | 2015 | 1.83 | 2.36 |
| KAZ | 161 | 2014 | 1.09 | 0.85 |
| KEN | 833 | 2012 | 2.44 | 1.41 |
| KOR | 56,209 | 2009 | 3.28 | 3.12 |
| KWT | 1,188 | 2009 | 1.63 | 2.31 |
| LBN | 225 | 2015 | 0.72 | 2.22 |
| LKA | 591 | 2009 | 2.53 | 2.88 |
| LTU | 160 | 2015 | 2.07 | 3.21 |
| LUX | 169 | 2013 | −0.87 | 1.42 |
| MAR | 1,427 | 2009 | 4.30 | 3.74 |
| MEX | 5,261 | 2009 | 3.20 | 3.27 |
| MUS | 98 | 2015 | −0.06 | 1.11 |
| MYS | 14,116 | 2009 | 3.59 | 2.96 |
| NAM | 84 | 2015 | 2.64 | 3.79 |
| NGA | 1,663 | 2011 | 2.68 | 2.36 |
| NZL | 2,885 | 2009 | 3.04 | 2.38 |
| OMN | 786 | 2010 | 2.11 | 1.85 |
| PAK | 4,299 | 2009 | 4.36 | 2.84 |
| PER | 1,658 | 2009 | 4.16 | 3.73 |
| PHL | 4,744 | 2009 | 3.86 | 3.11 |
| POL | 5,665 | 2009 | 3.08 | 2.79 |
| QAT | 1,947 | 2014 | 2.90 | 2.48 |
| ROU | 342 | 2014 | 3.13 | 1.38 |
| RUS | 3,964 | 2009 | 4.94 | 2.92 |
| SAU | 2,532 | 2018 | 3.63 | 3.30 |
| SRB | 15 | 2015 | −0.07 | −0.25 |
| SVN | 408 | 2009 | 2.40 | 2.93 |
| THA | 8,613 | 2009 | 3.31 | 2.90 |
| TUN | 164 | 2015 | −0.27 | −0.19 |
| TUR | 7,337 | 2009 | 3.78 | 3.12 |
| TWN | 48,137 | 2009 | 3.31 | 3.29 |
| UKR | 89 | 2015 | 4.56 | 3.49 |
| VNM | 1,123 | 2012 | 3.22 | 2.64 |
| ZAF | 12,980 | 2009 | 2.96 | 3.88 |
| ZWE | 175 | 2016 | 4.13 | 3.91 |

sales growth, EPS growth, and exposures to natural gas, oil, and commodity returns estimated over a 60-month rolling window. The carbon variables and controls are winsorized at the 1% and 99% levels when used as explanatory variables in regressions.

**Table II**
**Summary Statistics**

This table reports summary statistics of variables in the analysis. Carbon intensity is calculated as the log ratio of total emissions to the year-end sales (tCO2e per million U.S. dollars); ΔEmissions is the log emissions growth. The autocorrelations (AR) are calculated at the annual frequency. Exposure to natural gas, oil, and commodity is the loading of stock returns on corresponding commodity returns over a 60-month rolling window. Size is log year-end market equity; beta is estimated over a 60-month rolling window; the (log) book-to-market ratio is the log ratio of book value of equity to market value of equity; ROA is net income scaled by total assets; asset growth is the percentage change of total assets; momentum is past 12-month return skipping the most recent month; leverage is book leverage defined as the book value of debt divided by the book value of assets; ivol is idiosyncratic volatility from the Fama-French 3-factor model; and ΔSales and ΔEPS are log four-quarter sales and EPS growth.

| | U.S. | | | Global | | |
|---|---|---|---|---|---|---|
| | AR | Mean | *SD* | AR | Mean | *SD* |
| Scope 1 Intensity | 0.99 | 2.71 | 2.19 | 0.99 | 3.04 | 2.27 |
| Scope 2 Intensity | 0.94 | 2.71 | 1.40 | 0.94 | 2.92 | 1.49 |
| Scope 1 ΔEmissions | −0.05 | 0.04 | 0.48 | −0.06 | 0.02 | 0.53 |
| Scope 2 ΔEmissions | −0.10 | 0.06 | 0.56 | −0.09 | 0.04 | 0.54 |
| Scope 1 Log Emissions | 0.98 | 10.08 | 3.06 | 0.98 | 10.14 | 2.93 |
| Scope 2 Log Emissions | 0.97 | 10.08 | 2.53 | 0.97 | 10.02 | 2.29 |
| Log Sales | 0.98 | 7.47 | 1.97 | 0.98 | 6.33 | 2.01 |
| Beta | 0.87 | 1.23 | 0.63 | 0.87 | 1.06 | 0.48 |
| Size | 1.01 | 7.97 | 1.68 | 0.98 | 6.45 | 1.78 |
| Book-to-Market | 0.85 | −0.88 | 0.94 | 0.82 | −0.52 | 0.9 |
| ROA | 0.72 | 0.00 | 0.15 | 0.7 | 0.02 | 0.13 |
| Asset Growth | 0.10 | 0.12 | 0.36 | 0.08 | 0.14 | 0.4 |
| Momentum | 0.00 | 0.16 | 0.50 | 0.10 | 0.15 | 0.53 |
| Log PPE | 0.06 | 4.84 | 3.81 | 0.74 | 3.47 | 4.01 |
| Leverage | 0.74 | 3.90 | 4.05 | 0.14 | 1.67 | 4.98 |
| IVol (×100) | 0.68 | 1.97 | 1.51 | 0.49 | 2.08 | 1.36 |
| ΔSales | −0.04 | 0.05 | 0.36 | −0.08 | 0.08 | 0.42 |
| ΔEPS | −0.28 | 0.10 | 2.37 | −0.29 | 0.03 | 1.58 |
| Natural Gas Exposure | 0.75 | 0.02 | 0.09 | 0.75 | 0.16 | 0.29 |
| Oil Exposure | 0.78 | 0.22 | 0.24 | 0.78 | 0.01 | 0.11 |
| Commodity Exposure | 0.75 | 2.63 | 2.88 | 0.75 | 1.67 | 2.48 |

### *C. Information Observability and Data Release Lag*

A key empirical challenge in carbon and ESG investing is real-time measurement of emissions known to investors due to the gradual release of carbon data. As such, the literature has made various timing choices. Görgen et al. (2020), BK (2021), and Aswani, Raghunandan, and Rajgopal (2024) study the contemporaneous relation between returns and carbon footprint. BK (2023) links monthly stock returns to emissions lagged by one month. Pedersen, Fitzgibbons, and Pomorski (2021), Duan, Li, and Wen (2023), and Lindsey, Pruitt, and Schiller (2021) instead use a three-, six-, and six-month lag from the fiscal year-end, respectively. For comparison, accounting variables are often lagged by six months from the fiscal year-end in these papers following Fama and

French (1992). As such, the lags adopted for carbon emissions are often less than those for accounting variables, which can introduce forward-looking bias for future accounting information. I now analyze the actual data release lags and characterize investors' information set.

### C.1. Data Release Lag

S&P Trucost adds a new company-year observation to the database after companies complete their fiscal year and the relevant data are publicly disclosed. For firm-disclosed carbon emissions, the Carbon Disclosure Project (CDP) serves as the primary source. Participating companies submit underlying data for year $t$ to the CDP disclosure system, which often opens in April in year $t+1$ and closes in September, allowing for the computation of overall scores. Subsequently, CDP releases response data from individual companies on an annual basis in October. Trucost updates its database as soon as CDP releases these data on an ongoing basis as more information is made available and provides its emission estimates.

Two observations arise from the inspection of the Trucost release dates. First, Trucost reviewed and updated all pre-2008 data in May 2009. As such, all data points before 2008 are backfilled. I therefore exclude all emissions data prior to 2008. Second, emission data are updated with significant lags compared to other types of data, such as accounting variables. Figure 1 plots the histogram of lags between the fiscal year-end and data release date for the 2008 fiscal year and onward. The 25$^{\text{th}}$ percentile of the U.S. distribution is six months from the fiscal year-end, the typical lag adopted for accounting variables, and the median is 10 months primarily influenced by the October public releases by CDP. The distribution has a long right tail, with the 75$^{\text{th}}$ percentile equal to 24 months. For the international sample, 25$^{\text{th}}$, 50$^{\text{th}}$, and 75$^{\text{th}}$ percentiles are seven, 12, and 22 months, respectively. The data lag compares favorably with other data vendors. For example, for the July 2021 download of MSCI ESG data, coverage for fiscal year 2020 is 5% that for the United States and 16% that for the international sample in 2019.

### C.2. Financial Information Contained in Emissions Data

The generalized methodological approach for constructing emissions data is detailed in International Panel of Climate Change's "2006 Guidelines for National Greenhouse Gas Inventories" (Eggleston et al., 2006) and can be described by

$$Emissions = Activity\ Data \times Emission\ Factor. \tag{1}$$

The input economic activity data for different vendors and estimation procedures can range from readily available, aggregate company activity data from companies' annual reports, with default emission factors to more detailed and granular activity data, including a wider range of process parameters and

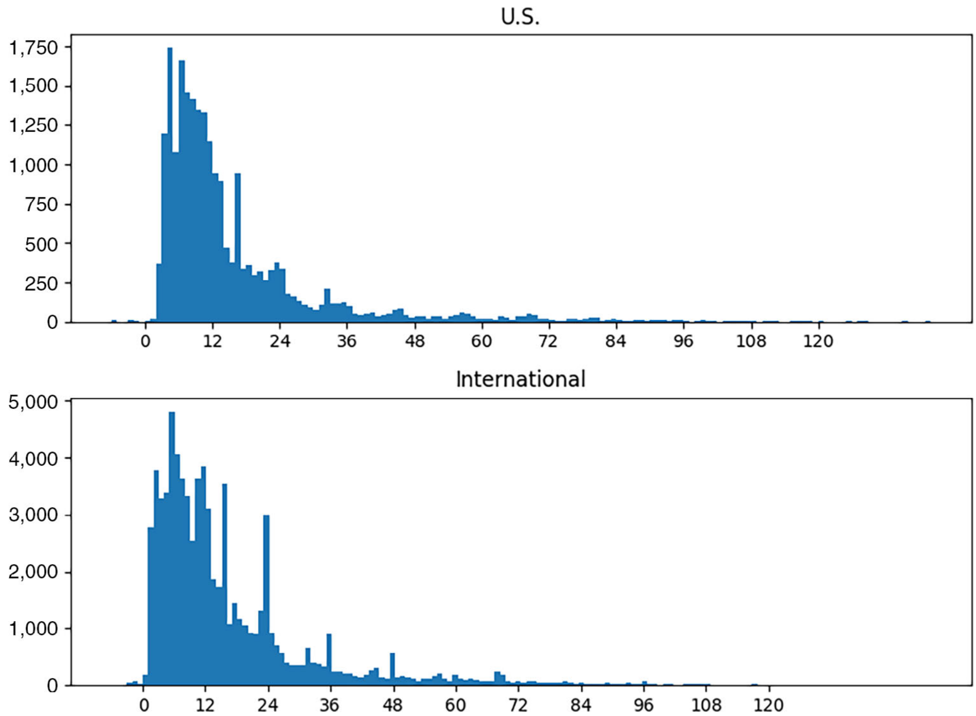


**Figure 1. Data release lags**. This figure plots the frequency tabulation of reporting lags for carbon emissions for the U.S. and international samples from the end of emission fiscal year. (Color figure can be viewed at wileyonlinelibrary.com)

emission factors. In other words, emissions are often derived from accounting information. The research process is consistent for emissions reported by firms through CDP and emissions estimated by data vendors such as Trucost and MSCI.

I now analyze the financial information contained in carbon data. First, I regress log carbon emissions (growth) on log sales (growth) over the same year,

$$\begin{aligned} \log Emission_{it} &= \alpha + \beta \log Sales_{it} + \varepsilon_{it}, \\ \Delta Emission_{it} &= \alpha + \beta \Delta Sales_{it} + \varepsilon_{it}, \end{aligned} \tag{2}$$

where $\Delta$ denotes the log change. The regression is conducted at the firm-year level, and standard errors are double-clustered at firm and year levels. Table III presents results for the U.S. and global samples, respectively. Panel A shows that emissions grow nearly linearly with firm sales. The coefficients are statistically indistinguishable from unity at the 1% significance level for both the U.S. and global sample, in line with the linear assumption that emissions are proportional to output as in Hong, Wang, and Yang (2021) among others. For example, scope 1 coefficients are 1.04 and 1.01 in the U.S. and global samples, respectively. In terms of economic magnitude, sales explain as much

**Table III**
## Scales of Carbon Emissions

This table studies the scale and determinants of carbon emissions. Panel A regresses scope 1 and 2 log emissions and emissions growth on log sales and sales growth for the U.S. and global sample. Panel B regresses carbon intensity on various contemporaneous characteristics over the same fiscal year. I report $t$-statistics in parentheses below the coefficients. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. The sample period is 2007 to 2020.

Panel A: Emissions and Sales

| | U.S. | | | | Global | | | |
|---|---|---|---|---|---|---|---|---|
| | Log Emissions | | ΔEmissions | | Log Emissions | | ΔEmissions | |
| | Scope 1 | 2 | 1 | 2 | 1 | 2 | 1 | 2 |
| Log Sales | 1.04*** | 1.04*** | | | 1.01*** | 0.97*** | | |
| | (44.51) | (78.79) | | | (55.21) | (74.03) | | |
| ΔSales | | | 0.86*** | 0.89*** | | | 0.74*** | 0.72*** |
| | | | (29.56) | (35.73) | | | (29.12) | (27.59) |
| Industry FE | N | N | N | N | N | N | N | N |
| Time FE | Y | Y | Y | Y | Y | Y | Y | Y |
| Country FE | N | N | N | N | Y | Y | Y | Y |
| $R^2$ | 0.50 | 0.71 | 0.34 | 0.35 | 0.49 | 0.66 | 0.18 | 0.18 |
| Observations | 21,783 | 21,783 | 19,219 | 19,219 | 92,790 | 92,790 | 84,247 | 84,247 |

Panel B: Carbon Intensity and Firm Characteristics

| | U.S. | | | | Global | | | |
|---|---|---|---|---|---|---|---|---|
| | Scope 1 | 2 | 1 | 2 | 1 | 2 | 1 | 2 |
| Beta | −0.19 | 0.38*** | −0.05** | 0.04*** | −0.12** | 0.19*** | 0.01 | 0.05*** |
| | (−1.65) | (9.71) | (−2.48) | (3.07) | (−2.90) | (5.38) | (0.68) | (3.11) |
| Size | 0.08*** | 0.04*** | −0.09*** | 0.02*** | 0.02* | −0.03*** | −0.05*** | 0.02*** |
| | (4.87) | (6.74) | (−15.74) | (3.21) | (2.16) | (−8.21) | (−7.02) | (6.10) |
| Book-to-Market | −0.03 | −0.34*** | 0.03* | 0.01 | 0.21*** | −0.05*** | 0.10*** | 0.04*** |
| | (−0.90) | (−8.81) | (1.96) | (0.41) | (7.29) | (−3.21) | (8.18) | (5.24) |
| ROA | −0.13 | 0.51*** | −0.07 | −0.08** | −0.22 | 0.11 | 0.05 | −0.14*** |
| | (−0.54) | (4.01) | (−1.36) | (−2.92) | (−1.02) | (1.52) | (1.37) | (−3.34) |
| Asset Growth | −0.30*** | −0.23*** | −0.00 | −0.06** | −0.23*** | −0.11*** | −0.02 | −0.04* |
| | (−7.20) | (−7.80) | (−0.18) | (−2.75) | (−4.44) | (−6.03) | (−0.93) | (−2.04) |
| Momentum | −0.10 | −0.20*** | 0.03 | −0.01 | 0.06 | −0.03 | 0.08*** | 0.03 |
| | (−1.38) | (−4.18) | (1.62) | (−0.56) | (0.84) | (−0.53) | (3.87) | (1.28) |
| Leverage | −0.15*** | −0.10*** | −0.01*** | −0.00 | −0.18*** | −0.12*** | −0.01*** | −0.01*** |
| | (−36.12) | (−28.45) | (−3.83) | (−1.75) | (−39.18) | (−32.28) | (−3.13) | (−4.51) |
| Log PPE | −0.01 | 0.00 | 0.00 | 0.01** | −0.05*** | −0.03*** | −0.01*** | −0.01** |
| | (−1.03) | (0.62) | (0.51) | (2.19) | (−8.16) | (−5.88) | (−6.74) | (−2.36) |
| IVol (×100) | 0.19*** | 0.17*** | 0.01 | 0.03*** | 0.13*** | 0.07*** | 0.01 | 0.03*** |
| | (5.68) | (10.70) | (1.42) | (6.86) | (5.45) | (7.28) | (1.68) | (3.45) |
| ΔSales | 0.15 | 0.16** | 0.35*** | 0.28*** | 0.22** | 0.20*** | 0.26*** | 0.23*** |
| | (1.49) | (2.55) | (3.55) | (3.24) | (2.42) | (4.47) | (4.39) | (3.89) |
| ΔEPS | −0.04** | −0.02* | −0.01 | −0.00 | −0.02* | −0.01 | −0.01** | −0.00 |
| | (−2.48) | (−1.79) | (−0.76) | (−0.12) | (−2.05) | (−1.56) | (−2.21) | (−0.64) |

(*Continued*)

**Table III**—*Continued*

| Panel B: Carbon Intensity and Firm Characteristics | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | U.S. | | | | Global | | | |
| | Scope 1 | 2 | 1 | 2 | 1 | 2 | 1 | 2 |
| Oil Exposure | −0.16 | −0.04 | 0.02 | 0.04 | −0.02 | 0.08 | 0.02 | 0.07* |
| | (−0.85) | (−0.63) | (0.23) | (0.60) | (−0.11) | (1.04) | (0.28) | (2.02) |
| Natural Gas Exposure | 2.18*** | 0.43** | 0.08 | −0.10 | 0.57 | 0.05 | 0.18* | 0.23*** |
| | (3.51) | (2.43) | (1.05) | (−1.58) | (1.49) | (0.31) | (1.83) | (4.51) |
| Commodity Exposure | 0.11*** | 0.05*** | 0.02*** | 0.01* | 0.08*** | 0.02* | 0.01 | −0.01 |
| | (8.39) | (4.64) | (4.78) | (1.89) | (6.66) | (2.13) | (1.30) | (−1.32) |
| Industry FE | N | N | Y | Y | N | N | Y | Y |
| Time FE | Y | Y | Y | Y | Y | Y | Y | Y |
| Country FE | N | N | N | N | Y | Y | Y | Y |
| $R^2$ | 0.14 | 0.19 | 0.78 | 0.63 | 0.14 | 0.14 | 0.69 | 0.53 |
| Observations | 18,573 | 18,573 | 18,572 | 18,572 | 80,987 | 80,987 | 80,987 | 80,987 |

as 71% of the variation in U.S. emissions and 66% of the variation in global emissions.[4] As such, sales are the most important determinant of emissions.

Emissions growth is significantly associated with sales growth, with coefficients of 0.86 and 0.89 in the U.S. sample and 0.74 and 0.72 in the global sample. In terms of the $R^2$s, sales growth alone can explain up to 35% and 18% emissions growth variation in the U.S. and global sample, implying correlations with emissions growth of 0.59 and 0.42. For comparison, BK (2021, table 7) and BK (2023, table 4) find that various lagged firm characteristics together with additional industry fixed effects can explain less than 15% and 6% of the variation in the United States and globally. In short, contemporaneous firm performance, as measured by sales and sales growth, explains more of the variation in emissions and emissions growth than do lagged characteristics combined. Moreover, sufficient lags in emissions and emissions growth need to be included such that emission data are known at the time of the return analysis to avoid forward-looking bias. At the minimum, the lag of carbon variables should be no less than that of accounting variables.

I further study the information contained in carbon intensity,

$$Intensity_{it} = \alpha + \beta \cdot Characteristics_{it} + \varepsilon_{it}, \tag{3}$$

where $Intensity_{it}$ denotes scope 1 and 2 log carbon intensities available to investors at time $t$, and $Characteristics_{it}$ denotes firm-level characteristics available to investors at time $t$. The characteristics include beta, size, book-to-market, ROA, asset growth, momentum, leverage, log PPE, idiosyncratic volatility, sales growth, EPS growth, and exposures to commodity factors.

[4] For comparison, table 4 of BK (2023) can explain only up to 54% of the variation of the same dependent variable using various lagged firm characteristics with the same fixed effects in the global sample.

Panel B shows that carbon intensity is associated with several firm-level characteristics. In particular, brown firms tend to have higher market beta, leverage, and more exposure to natural gas and commodity fluctuations but have lower asset growth and idiosyncratic volatility. Together, these firm characteristics and temporal variation account for 14% and 19% of the variation in intensity in the United States and globally.

Finally, the media and public recognize the industry aspect of carbon footprints and pay special attention to the transition risk of brown industries. For instance, the Sustainability Accounting Standards Board has developed industry-level sustainability accounting standards and materiality measures. As such, columns 3 to 4 of Panel B further include GICS6 industry fixed effects. The $R^2$s increase significantly to as high as 78% and 63% for scope 1 and 2 in the United States and 69% and 53% globally. These results show that industry variation drives most of the variation in carbon intensity.

## II. U.S. and Global Carbon Returns

### *A. U.S. Baseline Analysis*

The baseline empirical analysis conducts portfolio sorts using proxies for firms' carbon transition risk. For each month $t$, I use point-in-time carbon emission data available to investors to calculate carbon measures. I then sort stocks into tercile portfolios.[5] Thus, portfolio L contains firms with the lowest carbon footprint and portfolio H contains firms with the highest carbon footprint. After forming the three portfolios, I calculate value-weighted monthly returns on the portfolios at time $t+1$. To examine the relationship between carbon footprint and returns, I also form a high-minus-low portfolio that takes a long position in brown portfolio H and a short position in green portfolio L.

I first examine the relationship between carbon intensity and stock returns in the United States. Panel A of Table IV presents monthly average returns from portfolio sorts using scope 1 and 2 carbon intensities, respectively. Carbon intensity can predict stock returns in the cross-section. Portfolio L and M earn similar average returns of 1.44% and 1.51%, while the most carbon-intensive portfolio (H) earns a much lower return of 1.04% per month. The high-minus-low portfolio generates a significantly negative excess return of $-0.39\%$ per month, which is consistent with investment managers divesting from brown firms (BK, 2021). The pattern is similar for scope 2 carbon intensities, with the tercile-sorted portfolios earning returns of 1.51%, 1.31%, and 1.24% per month, respectively, and the high-minus-low portfolio generating a significant excess return of $-0.27\%$ per month.

I next examine whether the negative carbon return can be explained by existing risk factors. Carbon intensity might be correlated with a firm's profitability and investment decisions and, therefore, might be correlated with risk

[5] Although emission data are inherently an annual series, portfolios are updated monthly as new data become available.

**Table IV**

**Carbon Sorted U.S. Portfolios**

This table presents monthly value-weighted raw returns of carbon footprint-sorted portfolios. Sorting variables are carbon intensity, emissions growth, and total emissions, respectively. I report $t$-statistics in parentheses below the coefficients. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. The sample period is 2009:06 to 2021:12.

| Panel A: Intensity | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Scope 1 | | | | Scope 2 | | | |
| | L | M | H | H-L | L | M | H | H-L |
| Raw Return | 1.44*** | 1.51*** | 1.04*** | −0.39** | 1.51*** | 1.31*** | 1.24*** | −0.27* |
| | (4.03) | (4.51) | (3.00) | (−2.47) | (4.26) | (3.88) | (3.62) | (−1.87) |
| $\alpha$ | 0.15** | 0.11 | −0.24** | −0.40** | 0.21*** | 0.01 | −0.13 | −0.34** |
| | (2.16) | (1.39) | (−2.34) | (−2.51) | (2.68) | (0.11) | (−1.57) | (−2.40) |
| MKT | 1.04*** | 0.99*** | 0.96*** | −0.09** | 1.02*** | 1.00*** | 0.98*** | −0.04 |
| | (57.81) | (50.48) | (36.23) | (−2.15) | (51.67) | (67.89) | (47.18) | (−1.17) |
| SMB | −0.16*** | 0.07* | 0.06 | 0.22*** | −0.08** | −0.08*** | 0.08** | 0.15** |
| | (−5.20) | (1.95) | (1.35) | (3.22) | (−2.20) | (−3.15) | (2.12) | (2.46) |
| HML | 0.12*** | −0.19*** | 0.05 | −0.07 | 0.09*** | −0.05* | −0.03 | −0.12* |
| | (3.76) | (−5.38) | (1.04) | (−1.00) | (2.65) | (−1.73) | (−0.81) | (−1.94) |
| RMW | −0.20*** | 0.14*** | 0.13** | 0.33*** | −0.08* | −0.07** | 0.20*** | 0.28*** |
| | (−5.07) | (3.33) | (2.31) | (3.79) | (−1.95) | (−2.06) | (4.36) | (3.62) |
| CMA | −0.13** | 0.23*** | 0.19*** | 0.32*** | −0.14*** | 0.03 | 0.29*** | 0.43*** |
| | (−2.59) | (4.26) | (2.63) | (2.89) | (−2.63) | (0.83) | (4.99) | (4.37) |
| MOM | −0.02 | 0.03 | −0.05 | −0.03 | −0.00 | −0.04* | 0.01 | 0.01 |
| | (−0.73) | (1.22) | (−1.54) | (−0.69) | (−0.06) | (−1.95) | (0.29) | (0.20) |
| $R^2$ | 0.97 | 0.96 | 0.93 | 0.19 | 0.96 | 0.98 | 0.95 | 0.21 |
| Observations | 151 | 151 | 151 | 151 | 151 | 151 | 151 | 151 |
| **Panel B: ΔEmissions** | | | | | | | | |
| Raw Return | 1.29*** | 1.26*** | 1.49*** | 0.20 | 1.31*** | 1.31*** | 1.41*** | 0.10 |
| | (3.95) | (3.65) | (4.04) | (1.37) | (3.80) | (3.89) | (3.90) | (0.68) |
| $\alpha$ | 0.06 | −0.02 | 0.04 | −0.02 | 0.07 | 0.03 | −0.01 | −0.08 |
| | (0.91) | (−0.34) | (0.44) | (−0.17) | (0.89) | (0.46) | (−0.16) | (−0.57) |
| **Panel C: Emissions** | | | | | | | | |
| Raw Return | 1.62*** | 1.41*** | 1.28*** | −0.34* | 1.39*** | 1.50*** | 1.30*** | −0.09 |
| | (4.03) | (3.70) | (4.02) | (−1.77) | (3.61) | (4.14) | (3.86) | (−0.42) |
| $\alpha$ | 0.36*** | 0.11 | −0.06 | −0.42*** | 0.28** | 0.23** | −0.05 | −0.33** |
| | (3.74) | (1.34) | (−1.13) | (−3.30) | (2.07) | (2.39) | (−1.30) | (−2.17) |

factors commonly used in the literature. I use the FF6 factor model (Fama and French, 2018), which includes profitability and asset growth factors together with market, size, value, and momentum factors.

The intensity-sorted long-short portfolio loads strongly positively on profitability and asset growth factors. After adjusting for factor exposure, more carbon-intensive stocks earn significantly lower alphas than less

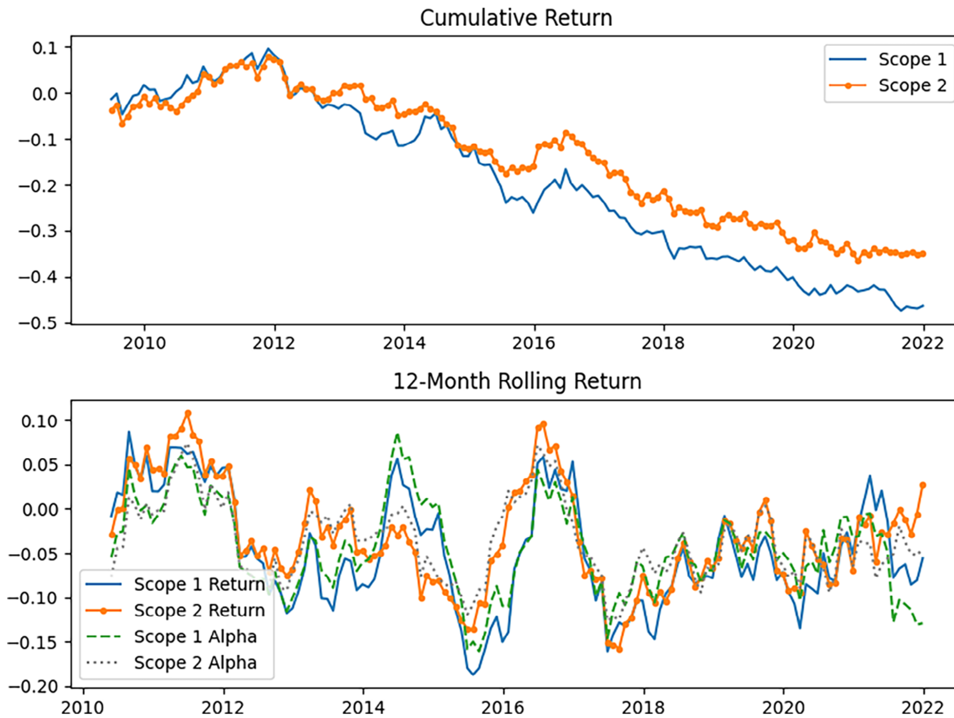


**Figure 2. U.S. carbon return**. This figure plots U.S. carbon return spreads between high- and low-carbon intensity portfolios. Panel A plots cumulative returns, and Panel B plots 12-month rolling returns and FF6 factor-adjusted alphas. (Color figure can be viewed at wileyonlinelibrary.com)

carbon-intensive stocks. Portfolios sorted by scope 1 carbon intensities earn abnormal returns of 0.15%, 0.11%, and −0.24% per month, and the long-short alpha is −0.40% and significantly negative. The long-short portfolio alphas sorted by scope 2 carbon intensity are −0.34% ($t$-statistics = −2.40).

Figure 2 plots the cumulative return, rolling return, and rolling alpha of a strategy that longs the high carbon-intensity portfolio and shorts the low carbon-intensity portfolio. Over the sample period, the high-minus-low portfolio loses as much as 50% of its initial value, suggesting a cumulative return of 100% for the green-minus-brown portfolio. Because the carbon return can move together with various energy price movements, I further control for oil, natural gas, and commodity index price movements in the Internet Appendix and again find significantly negative risk-adjusted returns.[6] In sum, brown firms have underperformed green firms in the United States. The return pattern contrasts with the idea that brown firms earn a risk premium in equilibrium and is more consistent with the pattern during transition.

[6] The Internet Appendix is available in the online version of this article on *The Journal of Finance* website.

Table IV, Panels B and C, repeats the analysis for portfolios sorted by emissions growth and total emissions. The evidence suggests that investors do not consider these variables as measures of carbon transition risk. The FF6-adjusted high-minus-low carbon alphas are significantly negative for total emissions but insignificant for emissions growth. In sum, carbon intensity is negatively associated with future stock returns and alphas, while total emissions and emissions growth do not have consistent predictability.

### B. Robustness Tests

In this section, I conduct several robustness analyses regarding carbon intensities. First, note that more than half of the data on emissions are estimated by Trucost rather than reported by firms. While estimated carbon emissions data can be subject to revisions by the data vendor, data reported by firms are immune to vendor estimation and revisions. Indeed, Busch et al. (2022) find that firm-reported scope 1 and 2 emissions are almost the same across data providers. Accordingly, I study the subsample in which emissions are reported by firms only. Table V, Panel A, reports raw returns of sorted portfolios and return spreads. Return spreads are −0.39% and −0.27% for scope 1 and 2 carbon intensities, respectively, and FF6-adjusted alphas are −0.40% and −0.34%. These results point to a strong green return associated with reported emission intensities, with results similar to the baseline. Related, the estimation process can differ across different vendors, leading to differences in the timing of data releases to investors. I hence conduct robustness analysis, in which I use year $t$ emission data in October year $t+1$. Results are again similar to the baseline and are reported in the Internet Appendix.

Table V, Panel B, considers two alternative measures of carbon transition risk. I first use emissions divided by end-of-year market equity as in Ilhan, Sautner, and Vilkov (2021). I find significantly negative carbon returns and alphas consistent with the baseline. I next use year-over-year changes in carbon intensity ($\Delta Intensity$), measuring the extent to which carbon transition risk has got better or worse. The high-minus-low return spreads in sorted portfolios are again negative, consistent with the baseline results. Panel C of Table V analyzes carbon returns within different firm size groups. The results reveal negative return spreads across all size groups, with the pattern most significant for larger stocks.

Finally, I conduct regression analysis using the model,

$$r_{it} = \alpha + \beta Intensity_{it-1} + \gamma Controls_{it-1} + \nu_t + \varepsilon_{it}. \tag{4}$$

The regression is run at the firm-month level and controls for time fixed effect. Standard errors are double-clustered at firm and month levels. Here I use weighted least squares regression to avoid excessive influence from small stocks. I standardize carbon measures to have zero mean and unit variance throughout these regressions, so the coefficients can be interpreted as the change in monthly stock returns in response to a one-standard-deviation

**Table V**

**Robustness Analysis**

This table conducts various robustness tests of U.S. carbon returns. Panel A focuses on the sample with emissions reported by firms only. Panel B presents return spreads of tercile portfolios sorted by emissions scaled by year-end market equity and year-over-year change in carbon intensity, respectively. Panel C presents return spreads by size group of stocks. I report $t$-statistics in parentheses below the coefficients. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. The sample period is 2009:06 to 2021:12.

| | Raw Return | | Alpha | |
|---|---|---|---|---|
| | Scope 1 | 2 | 1 | 2 |
| **Panel A: Firm-Reported Emissions Only** | | | | |
| Reported Only | −0.37** | −0.26* | −0.39** | −0.34** |
| | (−2.20) | (−1.79) | (−2.28) | (−2.41) |
| **Panel B: Alternative Measures** | | | | |
| Emission/ME | −0.42** | −0.24 | −0.39** | −0.35** |
| | (−2.25) | (−1.41) | (−2.37) | (−2.52) |
| ΔIntensity | −0.26** | −0.14 | −0.22** | −0.07 |
| | (−2.47) | (−1.28) | (−1.98) | (−0.63) |
| **Panel C: By Size Group** | | | | |
| Large | −0.42** | −0.25* | −0.42*** | −0.29** |
| | (−2.55) | (−1.71) | (−2.62) | (−1.98) |
| Mid | −0.13 | −0.17 | −0.34 | −0.60*** |
| | (−0.53) | (−0.74) | (−1.36) | (−2.95) |
| Small | −0.68 | 0.23 | −1.18* | −0.20 |
| | (−1.14) | (0.38) | (−1.87) | (−0.31) |

increase in carbon footprint. Control variables include various firm characteristics that are shown to be related to stock returns, including beta, size, book-to-market, ROA, asset growth, momentum, leverage, log PPE, sales growth, EPS growth, and exposures to oil, natural gas, and commodity index.

Columns 1 to 2 of Table VI report the results. Similar to the sorting-based evidence, more carbon-intensive stocks are associated with lower future excess returns. In particular, a one-standard-deviation increase in scope 1 and 2 (log) carbon intensity is associated with a 0.19% and 0.21% decrease in monthly return, respectively. Turning to the controls, stocks more exposed to oil and natural gas price fluctuations tend to be browner and earn a lower excess return in-sample, similar to carbon intensity.

Finally, the literature heatedly debates whether carbon returns are driven more by cross-industry or within-industry variation. For example, Choi, Gao, and Jiang (2020) and Ilhan, Sautner, and Vilkov (2021) highlight the role of the industry-level carbon footprint. While BK emphasizes within-industry firm-level measures, Sautner et al. (2023) find some pricing evidence for both.

**Table VI**
**Regression Analysis**

This table conducts weighted least square regressions of U.S. stock returns on lagged carbon intensities controlling for a number of firm characteristics. The regression includes time-fixed effects. Standard errors are double-clustered at firm and monthly levels, accordingly. I report $t$-statistics in parentheses below the coefficients. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. The sample period is 2009:06 to 2021:12.

| | (1)<br>Scope 1 | (2)<br>2 | (3)<br>1 | (4)<br>2 |
|---|---|---|---|---|
| Scope 1 | −0.19** | | −0.13 | |
| | (−2.52) | | (−1.04) | |
| Scope 2 | | −0.21** | | −0.06 |
| | | (−2.46) | | (−0.80) |
| Beta | 0.31 | 0.40 | 0.09 | 0.11 |
| | (1.11) | (1.43) | (0.43) | (0.51) |
| Size | −0.08 | −0.06 | −0.11 | −0.10 |
| | (−0.95) | (−0.69) | (−1.40) | (−1.25) |
| Book-to-Market | −0.32** | −0.35** | −0.30* | −0.30* |
| | (−2.05) | (−2.14) | (−1.66) | (−1.66) |
| ROA | 0.60 | 0.78 | −0.87 | −0.78 |
| | (0.44) | (0.60) | (−0.75) | (−0.64) |
| Asset Growth | −0.08 | −0.07 | −0.02 | −0.03 |
| | (−0.37) | (−0.36) | (−0.12) | (−0.15) |
| Momentum | −0.03 | −0.04 | −0.37 | −0.37 |
| | (−0.06) | (−0.09) | (−0.86) | (−0.85) |
| Leverage | −0.03 | −0.03 | −0.02 | −0.02 |
| | (−1.39) | (−1.24) | (−1.12) | (−1.09) |
| Log PPE | 0.04* | 0.04** | 0.04* | 0.04* |
| | (1.92) | (1.99) | (1.78) | (1.81) |
| IVol ($\times$100) | −0.07 | −0.08 | −0.12 | −0.12 |
| | (−0.43) | (−0.46) | (−0.71) | (−0.70) |
| $\Delta$Sales | −0.55 | −0.52 | −0.72 | −0.72* |
| | (−1.19) | (−1.12) | (−1.65) | (−1.66) |
| $\Delta$EPS | −0.01 | −0.01 | −0.00 | −0.01 |
| | (−0.57) | (−0.49) | (−0.24) | (−0.32) |
| Oil Exposure | −1.10* | −1.08** | −1.38** | −1.36** |
| | (−1.92) | (−1.99) | (−2.49) | (−2.48) |
| Natural Gas Exposure | −2.02** | −2.15** | −1.75* | −1.82* |
| | (−1.98) | (−2.04) | (−1.71) | (−1.73) |
| Commodity Exposure | 0.10* | 0.09 | 0.16** | 0.16** |
| | (1.68) | (1.57) | (2.23) | (2.19) |
| Industry FE | N | N | Y | Y |
| Time FE | Y | Y | Y | Y |
| $R^2$ | 0.27 | 0.27 | 0.27 | 0.27 |
| Observations | 206,025 | 206,025 | 206,025 | 206,025 |

Columns 3 and 4 examine the evidence when including industry fixed effects. Although carbon intensities are still negatively associated with stock returns, the coefficients are −0.13% and −0.06%, smaller in magnitude than the specification without industry-fixed effects. The evidence suggests that industry

**Table VII**

**Carbon Sorted Global Portfolios**

This table reports value-weighted returns of country-neutral carbon-sorted global portfolios. Alphas are obtained by regressing raw returns on DM FF6 factors. I report $t$-statistics in parentheses below the coefficients. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. The sample period is 2009:06 to 2021:12.

| | Scope 1 | | | | Scope 2 | | | |
|---|---|---|---|---|---|---|---|---|
| | L | M | H | H-L | L | M | H | H-L |
| **Panel A: Intensity** | | | | | | | | |
| Raw Return | 0.90*** | 0.84*** | 0.90*** | −0.01 | 0.90*** | 0.82*** | 0.93*** | 0.01 |
| | (10.61) | (9.70) | (10.58) | (−0.20) | (10.66) | (9.60) | (10.74) | (0.08) |
| $\alpha$ | 0.06 | −0.07 | −0.05 | −0.06 | 0.05 | −0.06 | −0.03 | −0.03 |
| | (0.74) | (−0.88) | (−0.61) | (−0.74) | (0.62) | (−0.75) | (−0.41) | (−0.43) |
| **Panel B: ΔEmissions** | | | | | | | | |
| Raw Return | 0.90*** | 0.88*** | 0.84*** | −0.07 | 0.85*** | 0.90*** | 0.88*** | 0.02 |
| | (10.46) | (10.35) | (9.86) | (−1.13) | (10.11) | (10.39) | (10.29) | (0.25) |
| $\alpha$ | 0.01 | 0.00 | −0.10 | −0.08 | −0.02 | 0.00 | −0.06 | 0.00 |
| | (0.16) | (0.03) | (−1.25) | (−1.22) | (−0.25) | (0.02) | (−0.74) | (0.00) |
| **Panel C: Emissions** | | | | | | | | |
| Raw Return | 0.93*** | 0.88*** | 0.84*** | −0.12* | 0.95*** | 0.91*** | 0.78*** | −0.20*** |
| | (10.82) | (10.42) | (10.04) | (−1.77) | (10.98) | (10.60) | (9.61) | (−3.06) |
| $\alpha$ | 0.07 | 0.01 | −0.09 | −0.11 | 0.06 | 0.00 | −0.11 | −0.15** |
| | (0.83) | (0.11) | (−1.16) | (−1.44) | (0.76) | (0.03) | (−1.51) | (−2.07) |

variation explains most of the variation in carbon intensity and, correspondingly, accounts for the majority of negative carbon returns. Thus, investors are attentive to both cross-industry and within-industry carbon transition risk, with cross-industry variation carrying more significance.

### *C. Global Carbon Returns*

In this section, I now study average carbon returns in global markets. Specifically, I sort stocks into terciles using firm-level carbon intensity in each country. The final portfolio consists of all stocks in the same tercile across countries, including the United States. I adjust for raw returns with developed market (DM) FF6 factors. Table VII presents the results. Average carbon excess return and alpha are negative but statistically indistinguishable from zero. Value-weighted alphas are −0.06% and −0.03% for scope 1 and 2 intensity, respectively, compared to −0.40% and −0.34% in the United States. Return spreads generated by emissions growth and total emissions again tend to be negative, but mostly small and insignificant. In short, carbon returns are negative in the United States but insignificant globally. I explore cross-country variation in carbon returns in more detail in Section IV.

## III. Information Observability and Carbon Returns

The results above show that, in recent years, carbon-intensive firms earn lower returns than green firms in the United States and brown and green firms yield similar returns globally. In contrast, total emissions and emissions growth do not correlate with future stock returns. These results differ from previous studies. In particular, BK (2021, 2023) document a carbon premium associated with total emissions and emissions growth both in the United States and globally. In this section, I first replicate their analysis. I then show that forward-looking information contained in their emissions data overstates their estimated ex ante carbon premium in returns.

### *A. The Role of Future Sales Information*

As I document in Section I.C, emissions are tightly linked to firm sales. Consequently, strong firm performance can simultaneously lead to higher emissions and higher stock returns. BK (2021, 2023) relate stock returns to contemporaneous emissions and emissions lagged by one month before accounting and emission information for the emitting period is released. As such, the analysis is effectively contemporaneous, and the documented carbon premium could stem from future sales information contained in emissions.

It is reasonable to speculate, as BK argues, that investors can develop expectations regarding carbon emissions as the fiscal year progresses. However, it is also reasonable to expect that investors can form equally accurate expectations about firm sales during the same period. The accuracy of emission estimates that investors can formulate depends on the accuracy of their sales estimates. It, therefore, continues to be crucial to control for firm performance during the emitting period to avoid forward-looking bias (or, look-ahead bias).

I start by studying the relation between U.S. stock returns and contemporaneous emission variables as in BK (2021) but using nonparametric portfolio sorts as in the baseline analysis. Table VIII presents portfolio returns. First, portfolio sorts with contemporaneous carbon intensity do not generate significant long-short excess returns, consistent with BK. Carbon intensity information is not available to investors contemporaneously and thus is not reflected in stock returns.

Second, emissions growth-sorted portfolios exhibit significantly positive high-minus-low carbon returns of 0.41% per month for scope 1 and as much as 0.6% for scope 2, consistent with the positive carbon returns in BK (2021). To gauge the impact of future sales information on estimated carbon returns, I conduct double sorts with sales and emission information. The analysis first sorts stocks into tercile portfolios by sales growth and then sequentially sorts stocks by carbon variables into tercile portfolios within each sales-growth tercile. Sales and carbon variables are measured over the same period. After

**Table VIII**

**Contemporaneous Carbon-Sorted U.S. Portfolios**

This table reports monthly value-weighted U.S. portfolio returns sorted by contemporaneous carbon variables. Panel A presents portfolio returns sorted by carbon variables, and Panel B presents portfolio returns double-sorted first by sales growth and then by carbon variables sequentially. I report $t$-statistics in parentheses below the coefficients. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. The sample period is 2009:06 to 2021:12.

Panel A: Contemporaneous Return

| | Scope 1 | | | | Scope 2 | | | |
|---|---|---|---|---|---|---|---|---|
| | L | M | H | H-L | L | M | H | H-L |
| Intensity | 1.03*** | 1.01*** | 0.98*** | −0.05 | 1.08*** | 0.95*** | 1.03*** | −0.04 |
| | (3.15) | (3.71) | (3.20) | (−0.29) | (3.43) | (3.24) | (3.40) | (−0.28) |
| ΔEmissions | 0.82*** | 0.93*** | 1.30*** | 0.47*** | 0.74** | 0.97*** | 1.32*** | 0.58*** |
| | (2.61) | (3.37) | (4.11) | (3.25) | (2.36) | (3.53) | (4.18) | (4.34) |
| Emissions | 1.13*** | 1.01*** | 0.99*** | −0.14 | 1.10*** | 1.16*** | 0.95*** | −0.16 |
| | (3.10) | (2.99) | (3.69) | (−0.75) | (3.37) | (3.56) | (3.31) | (−1.13) |

Panel B: Controlling for Future Sales Growth

| | Scope 1 | | | | Scope 2 | | | |
|---|---|---|---|---|---|---|---|---|
| | L | M | H | H-L | L | M | H | H-L |
| | | | | B.1 Intensity | | | | |
| ΔSales L | −0.04 | 0.13 | −0.11 | −0.07 | −0.01 | −0.07 | −0.13 | −0.12 |
| | (−0.10) | (0.36) | (−0.31) | (−0.42) | (−0.01) | (−0.17) | (−0.37) | (−0.71) |
| 2 | 0.95*** | 0.91*** | 0.74** | −0.21 | 0.80*** | 0.97*** | 0.87*** | 0.07 |
| | (3.20) | (3.15) | (2.57) | (−1.43) | (2.75) | (3.37) | (3.02) | (0.50) |
| H | 1.71*** | 1.49*** | 1.72*** | 0.01 | 1.63*** | 1.47*** | 1.80*** | 0.18 |
| | (5.52) | (4.54) | (4.31) | (0.04) | (5.26) | (4.04) | (4.64) | (0.81) |
| | | | | B.2 ΔEmissions | | | | |
| ΔSales L | 0.04 | −0.05 | 0.01 | −0.03 | 0.17 | −0.00 | −0.08 | −0.25 |
| | (0.10) | (−0.12) | (0.04) | (−0.11) | (0.45) | (−0.01) | (−0.24) | (−1.31) |
| 2 | 0.75** | 0.75** | 0.99*** | 0.24 | 0.80** | 0.81*** | 0.91*** | 0.12 |
| | (2.15) | (2.36) | (3.70) | (1.25) | (2.58) | (2.64) | (3.24) | (0.81) |
| H | 1.56*** | 1.72*** | 1.66*** | 0.10 | 1.52*** | 1.84*** | 1.62*** | 0.10 |
| | (4.05) | (4.71) | (5.00) | (0.42) | (4.08) | (4.95) | (4.91) | (0.46) |
| | | | | B.3 Emissions | | | | |
| ΔSales L | 0.09 | 0.13 | 0.12 | 0.03 | 0.20 | 0.07 | 0.06 | −0.14 |
| | (0.22) | (0.38) | (0.35) | (0.11) | (0.52) | (0.21) | (0.17) | (−0.73) |
| 2 | 0.92*** | 1.02*** | 1.02*** | 0.10 | 0.88*** | 1.08*** | 0.97*** | 0.08 |
| | (3.06) | (3.74) | (3.77) | (0.57) | (3.16) | (3.80) | (3.42) | (0.49) |
| H | 1.76*** | 1.78*** | 1.50*** | −0.26 | 1.74*** | 1.67*** | 1.73*** | −0.02 |
| | (4.92) | (5.62) | (4.07) | (−0.91) | (5.16) | (4.73) | (5.13) | (−0.06) |

controlling for sales growth, emissions growth sorts no longer generate significant return spreads. For example, scope 1 carbon returns are small and insignificant within each sales growth tercile (−0.03%, 0.24%, and 0.10%). In other words, the carbon premium associated with contemporaneous emissions growth does not represent compensation for higher carbon transition risk but instead arises from forward-looking sales information. U.S. portfolio alphas and portfolio sorts, based on all global stocks, presented in the Internet Appendix yield similar results. Finally, for portfolio sorts with total emissions, in general, there is no evidence of a significant long-short return spread.

### *B. Regression Analysis*

In this section, I conduct the regression analysis as in BK (2021, 2023) using an updated sample and focus on emissions growth and total emissions, which BK finds a significant carbon premium for. Specifically, I run the following regression

$$r_{it} = \alpha + \beta Carbon_{i\tau} + \gamma Controls_{it-1} + \delta_k + \nu_t + \varepsilon_{it}. \tag{5}$$

The regression is conducted at the firm-month level, controlling for time and industry fixed effects. The main independent variable, $Carbon_{i\tau}$, represents contemporaneous (log) emissions growth or (log) emissions. Controls are the same as in the baseline regression (4). In addition, I include industry fixed effects because BK finds that the estimated carbon premium strengthens using this specification. Carbon measures are standardized to have zero mean and unit variance.

Table IX presents results for U.S. stocks and finds that both emissions and emissions growth are significantly associated with higher contemporaneous stock returns as in BK (2021). For example, a one-standard-deviation increase in total emissions is associated with an increase in monthly stock returns, 0.19% and 0.23%, respectively. The coefficients are comparable to 0.23% and 0.14% excess returns per unit of standard deviation in table 8 of BK (2021).

Next, I control for sales information during the same period of carbon emissions,

$$r_{it} = \alpha + \beta Carbon_{i\tau} + \beta \mathbf{Sales}_{i\tau} + \gamma Controls_{it-1} + \nu_t + \varepsilon_{it}, \tag{6}$$

where $\mathbf{Sales}_{i\tau}$ denotes log sales and sales growth during the same emission period. Table IX shows that forward-looking sales and sales growth information is strongly associated with higher stock returns. However, carbon emissions and emissions growth are no longer positively associated with returns once sales information is controlled for. Instead, carbon return estimates tend to be negative, more consistent with my baseline result.

Finally, I study the global evidence. BK (2023) studies the relationship between stock returns and emissions lagged by one month and longer lags using regression (5). I conduct the same analysis and present the carbon coefficients in Figure 3. Emission variables are associated with higher stock returns ("Baseline") contemporaneously and when the lag is no more than six months from the start of the fiscal year but not beyond, consistent with table 6 in BK (2023). However, after controlling for sales information as in

**Table IX**

## U.S. Stock Returns and Contemporaneous Emissions

This table first regresses U.S. stock returns on contemporaneous emissions and emissions growth and then controls for sales and sales growth over the same emitting period. The carbon variables are standardized to have zero mean and unit variance. Standard errors are double clustered firm and time levels. I report $t$-statistics in parentheses below the coefficients. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. The sample period is 2009:06 to 2021:12.

| | Scope 1 | 2 | 1 | 2 | 1 | 2 | 1 | 2 |
|---|---|---|---|---|---|---|---|---|
| $\Delta$Emissions$_\tau$ | 0.28*** | 0.24*** | 0.01 | −0.04 | | | | |
| | (5.98) | (4.79) | (0.19) | (−1.52) | | | | |
| Log Emissions$_\tau$ | | | | | 0.22** | 0.24** | −0.11 | −0.11* |
| | | | | | (2.06) | (2.36) | (−1.50) | (−1.68) |
| $\Delta$Sales | | | 1.43*** | 1.50*** | | | 1.30*** | 1.29*** |
| | | | (5.51) | (5.96) | | | (6.45) | (6.44) |
| Log Sales | | | 0.16* | 0.16* | | | 0.22*** | 0.23*** |
| | | | (1.93) | (1.93) | | | (2.61) | (2.66) |
| Oil Exposure | 0.05 | 0.05 | 0.05 | 0.05 | −0.17 | −0.17 | −0.13 | −0.13 |
| | (0.15) | (0.14) | (0.15) | (0.15) | (−0.48) | (−0.49) | (−0.38) | (−0.38) |
| Natural Gas Exposure | −0.56 | −0.56 | −0.57 | −0.57 | −0.86 | −0.84 | −0.87 | −0.88 |
| | (−0.69) | (−0.69) | (−0.70) | (−0.70) | (−1.22) | (−1.19) | (−1.25) | (−1.25) |
| Commodity Exposure | 0.00 | 0.00 | 0.00 | 0.00 | 0.03 | 0.03 | 0.03 | 0.03 |
| | (0.07) | (0.08) | (0.03) | (0.03) | (0.78) | (0.75) | (0.65) | (0.66) |
| Beta | 0.08 | 0.09 | 0.08 | 0.08 | 0.03 | 0.03 | 0.02 | 0.02 |
| | (0.61) | (0.64) | (0.60) | (0.60) | (0.23) | (0.22) | (0.12) | (0.13) |
| Size | 0.01 | 0.01 | −0.15 | −0.15 | −0.14 | −0.18* | −0.26* | −0.26* |
| | (0.18) | (0.15) | (−1.13) | (−1.13) | (−1.47) | (−1.70) | (−1.93) | (−1.90) |
| Book-to-Market | 0.05 | 0.04 | 0.03 | 0.03 | 0.00 | −0.01 | 0.04 | 0.04 |
| | (0.38) | (0.35) | (0.22) | (0.22) | (0.02) | (−0.10) | (0.30) | (0.30) |
| ROA | 0.09 | 0.07 | 0.15 | 0.15 | 0.02 | −0.03 | 0.20 | 0.20 |
| | (0.13) | (0.10) | (0.23) | (0.23) | (0.04) | (−0.04) | (0.34) | (0.33) |
| Asset Growth | 0.04 | 0.05 | −0.08 | −0.08 | 0.04 | 0.05 | −0.15 | −0.15 |
| | (0.32) | (0.36) | (−0.65) | (−0.64) | (0.27) | (0.36) | (−1.08) | (−1.08) |
| Momentum | 0.22 | 0.22 | 0.07 | 0.07 | 0.21 | 0.21 | 0.05 | 0.05 |
| | (0.87) | (0.88) | (0.29) | (0.29) | (0.86) | (0.85) | (0.23) | (0.22) |
| Leverage | 0.02 | 0.02 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 |
| | (1.12) | (1.10) | (0.69) | (0.69) | (0.57) | (0.41) | (0.57) | (0.56) |
| Log PPE | 0.00 | 0.00 | 0.00 | 0.00 | 0.01 | 0.01 | 0.01 | 0.01 |
| | (0.10) | (0.13) | (0.01) | (0.01) | (0.98) | (0.98) | (0.86) | (0.85) |
| IVol | 0.23 | 0.23 | 0.25* | 0.25* | 0.24* | 0.24* | 0.26* | 0.26* |
| | (1.64) | (1.65) | (1.78) | (1.78) | (1.79) | (1.77) | (1.92) | (1.93) |
| Sales Growth | −0.51** | −0.51** | −0.63*** | −0.63*** | −0.42*** | −0.42*** | −0.55*** | −0.55*** |
| | (−2.57) | (−2.54) | (−3.09) | (−3.08) | (−2.63) | (−2.65) | (−3.06) | (−3.06) |
| EPS Growth | −0.05** | −0.05** | −0.05** | −0.05** | −0.05** | −0.05* | −0.05* | −0.05* |
| | (−2.18) | (−2.16) | (−2.05) | (−2.05) | (−1.99) | (−1.95) | (−1.92) | (−1.93) |
| Industry FE | Y | Y | Y | Y | Y | Y | Y | Y |
| Time FE | Y | Y | Y | Y | Y | Y | Y | Y |
| $R^2$ | 0.20 | 0.20 | 0.20 | 0.20 | 0.19 | 0.19 | 0.19 | 0.19 |
| Observations | 218,874 | 218,874 | 218,507 | 218,507 | 243,666 | 243,666 | 243,234 | 243,234 |

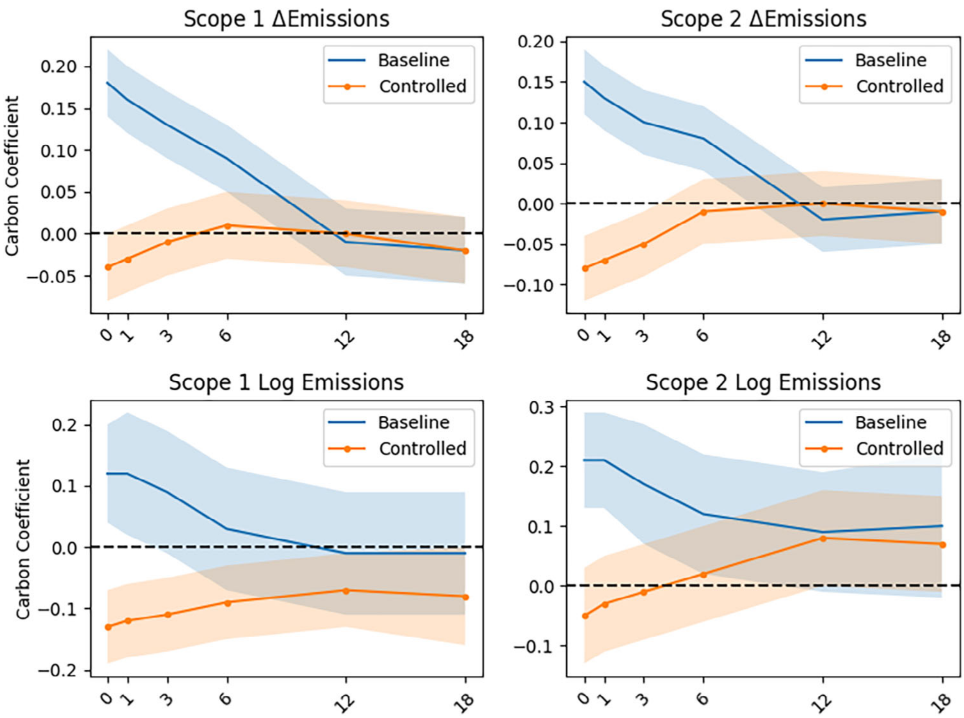


**Figure 3. Global carbon returns and alternative lags**. This figure ("Baseline") first plots the carbon coefficients by regressing global stock returns on x-month lagged emissions growth and log emissions from the fiscal year start, controlling for firm characteristics, including beta, size, book-to-market, ROA, asset growth, momentum, leverage, log PPE, IVol, sales growth, EPS growth, and oil, natural gas, and commodity exposures as well as country, industry, and time fixed effects. The orange line in the figure ("Controlled") further plots the corresponding coefficients after further controlling for log sales and sales growth during the same period of emissions. The regressions include industry and time-fixed effects. Standard errors are double clustered at firm and time levels, and the shaded area denotes the 95% confidence intervals. The sample period is 2009:06 to 2021:12. (Color figure can be viewed at wileyonlinelibrary.com)

equation (6), the carbon coefficient ("Controlled") decreases dramatically and becomes consistently negative across different lags. The difference between baseline and controlled coefficients is particularly large with the lag being shorter, suggesting that the coefficient bias introduced by forward-looking bias is particularly prominent in contemporaneous analysis or when shorter lags are used. The Internet Appendix plots comparable U.S. coefficients and shows that the results are unchanged.

In summary, the positive relation between stock returns and contemporaneous emissions in prior studies comes from strong forward-looking firm performance rather than a risk premium in ex ante expected returns. Lagging emission data sufficiently can address forward-looking bias and avoid incorrect inference.

## IV. Cross-Country Variation in Carbon Returns

In this section, I now turn to country-level evidence beyond average global carbon returns and study what drives differences in carbon returns. As global warming is a global risk and carbon reduction requires global commitment and collaboration, it is useful to examine international markets to gauge the attitude of individual countries.

### A. Geographic Dispersion

Here, I conduct portfolio sorts using carbon intensity as in baseline analysis for each country and then adjust for risk factors by running a time-series regression for each country

$$r_{it} = \alpha_i + \beta_i factors_{it} + \varepsilon_{it}, \tag{7}$$

where $r_{it}$ is the value-weighted long-short carbon return in country $i$ and $factors_{it}$ denotes FF6 factors for each region or country, including the United States, North America excluding the United States, Europe, Japan, the Asia Pacific excluding Japan, and other countries as emerging markets. This approach allows for imperfectly integrated international markets in which factor returns and factor loadings vary across countries (Fama and French, 2017).

I examine whether carbon returns display geographic dispersion. I start with the G7 and Australia, which contain the United States and developed countries most comparable to the United States. Panel A, Table X shows that carbon alphas, value-weighted across countries, are −0.44% and −0.4% for scope 1 and 2, respectively, and are more comparable to the U.S. estimates (−0.4% and −0.34%). I next split the international sample into developed and emerging markets (DM and EM) and find more negative carbon returns in DM countries. Value-weighted carbon alphas for DMs are −0.4% and −0.33% for scopes 1 and 2, respectively. In particular, the United States has negative carbon alphas (−0.4% and −0.34%), and while China has positive alphas instead (0.53% and 0.23%). In contrast, carbon alphas for EMs are positive at 0.2% and 0.06%. Panel B shows that carbon alphas, equally weighted across countries, reveal a similar picture.

Alternatively, I conduct weighted least squares regression analysis for global stocks as in equation (4) with the same set of firm-level control variables. Here I control for country fixed effect in addition to time fixed effect. The results in Panel C provide similar evidence. Coefficients for more developed countries are significantly negative at −0.19% and −0.15% for G7+AUS and are more comparable to U.S. estimates (−0.19% and −0.21%). For EM countries, the coefficients are statistically indistinguishable from zero.

### B. What Drives Carbon Return Variation?

The previous analysis shows that carbon returns vary significantly across countries and are lower in more developed countries. A few possible

**Table X**

**Country-Level Carbon Returns**

Note: This table studies geographic variation in country-level carbon returns. Panel A presents average raw carbon returns and corresponding FF6 factor-adjusted alphas, value weighted by country-level market capitalization or equally. Panel B presents the carbon returns, equal weighted across countries. Panel C conducts a weighted least square regression of stock returns on lagged carbon intensities. The controls include various firm characteristics, including beta, size, book-to-market, ROA, asset growth, momentum, leverage, log PPE, IVol, sales growth, EPS growth, and oil, natural gas, and commodity exposures. The regression controls for time and country fixed effects. Standard errors are double-clustered at firm and monthly levels, accordingly. I report $t$-statistics in parentheses below the coefficients. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. The sample period is 2009:06 to 2021:12.

| | Scope 1 | | | Scope 2 | | |
|---|---|---|---|---|---|---|
| | G7 + AUS | DM | EM | G7 + AUS | DM | EM |
| **Panel A: Value-Weighted Sorting** | | | | | | |
| Raw Return | −0.38*** | −0.32*** | 0.23*** | −0.25*** | −0.22*** | 0.12** |
| | (−5.84) | (−6.95) | (3.94) | (−4.11) | (−5.16) | (1.97) |
| $\alpha$ | −0.44*** | −0.40*** | 0.20*** | −0.34*** | −0.33*** | 0.06 |
| | (−7.24) | (−9.52) | (3.55) | (−6.10) | (−8.36) | (0.99) |
| **Panel B: Equal-Weighted Sorting** | | | | | | |
| Raw Return | −0.27*** | −0.09 | 0.05 | −0.17* | −0.01 | 0.04 |
| | (−2.81) | (−1.14) | (0.54) | (−1.92) | (−0.18) | (0.40) |
| $\alpha$ | −0.37*** | −0.26*** | 0.08 | −0.27*** | −0.14** | 0.09 |
| | (−4.32) | (−3.54) | (0.86) | (−3.41) | (−2.00) | (0.97) |
| **Panel C: Stock-Level Regression Analysis** | | | | | | |
| Scope 1 | −0.19*** | −0.15*** | −0.07 | | | |
| | (−3.28) | (−2.97) | (−1.40) | | | |
| Scope 2 | | | | −0.15** | −0.14*** | 0.03 |
| | | | | (−2.42) | (−2.70) | (0.36) |
| Controls | Y | Y | Y | Y | Y | Y |
| Country FE | Y | Y | Y | Y | Y | Y |
| Time FE | Y | Y | Y | Y | Y | Y |
| $R^2$ | 0.26 | 0.25 | 0.21 | 0.26 | 0.25 | 0.21 |
| Observations | 486,821 | 608,678 | 297,577 | 486,821 | 608,678 | 297,577 |

interpretations follow. First, shifts in investor preferences have differed widely across countries during the transition, generating cross-country differences in carbon returns. Second, carbon return variation reflects differences in the carbon risk premium in equilibrium. Third, carbon return variation is driven by in-sample cash flow shocks unrelated to carbon transition risk or climate concerns.

I construct two measures of changes in climate concern or climate tastes. First, I measure investors' demand for green assets as country-level sustainable investor flows each quarter scaled by end-of-quarter market capitalization.[7] Second, I proxy for the cumulative shift in consumer demand using the level of climate concerns from the Lloyd's Register Foundation (2020) 2019 World Risk Poll. The survey asks whether interviewees perceive climate change as a very serious threat, a somewhat serious threat, or not a threat at all. The climate concern equals the total fraction who answer a "very serious" and "somewhat serious" threat. Because climate change only started concerning the public in recent years, the measure proxies for cumulative increase in climate concern. Both sustainable flow and climate concern are highly correlated with log GDP per capita, with coefficients of 0.47 and 0.43.

Next, I study additional country characteristics that can correlate with the country's required carbon premium. I measure current policy tightness using the policy score in the Climate Change Performance Index. However, existing climate policies are still in the preliminary stage, and investors expect most policies to come into shape in future years.[8] I thus consider additional socioeconomic conditions. The first measure is the fraction of renewable energy because countries with a higher proportion of renewable energy tend to enforce more environmentally friendly policies while discouraging the use of fossil fuels. The second measure is a civil law dummy because civil law countries tend to promote environmentally friendly corporate practices and civil law firms are more responsive to CSR shocks (Liang and Renneboog, 2017). Empirically, the fraction of renewable energy and civil law dummy exhibit correlations with climate policy tightness of 0.47 and 0.58, respectively, suggesting an inclination toward implementing stricter climate policies.

Finally, I construct several cash flow shock measures. The first cash flow measure is carbon returns on earnings days because most new earnings-related information arrives on earnings days. Earnings day returns incorporate the impact of information arrival in the current period, and investors accordingly update their beliefs and adjust stock prices. Second, I capture investor belief updates directly by measuring long-short spread in consensus analyst revisions of one-year-ahead EPS forecasts and long-term growth forecasts. I also measure the long-short spread in sales growth next year to be conservative. In addition, I explicitly account for the exposure of stocks to energy price fluctuations by estimating exposures to oil, natural gas, and commodity price fluctuations by using a rolling 60-month regression.

I examine the relation between abnormal carbon returns $r^s_{it}$ and climate concern shocks using the specification,

$$r^s_{it} = a + b \cdot X_{it-1} + \kappa \cdot Y_{it} + \nu_t + e_{it}, \tag{8}$$

[7] Data are obtained from the report "Passive Sustainable Funds: The Global Landscape 2020" published by Morningstar. The data on active sustainable flows are available for a subset of countries from 2016 onward. Active and passive sustainable flows are highly correlated, with a coefficient of 0.93.

[8] Detailed climate policies are yet to be fleshed out in most countries, leaving much room for policy uncertainty, and adding to the transition risk of brown firms. By 2021, a total of 131 countries have committed to reducing net carbon emissions to zero, but just six have enshrined that commitment in law.

**Table XI**

## Carbon Return Variation

This table reports variation in carbon returns. Panel A regresses country-level carbon returns on cash flow shocks and climate taste shifts. Panel B studies additional country characteristics while controlling for all measures in Panel A. These characteristics are standardized to have zero mean and unit variance unless it is a dummy variable. The regressions include time-fixed effects and standard errors are clustered at the monthly level. I report $t$-statistics in parentheses below the coefficients. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. The sample period is 2009:06 to 2021:12.

Panel A: In-Sample Shocks

| | Scope 1 | | | Scope 2 | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| GDP Per Capita | −0.18** | | | −0.17** | | |
| | (−2.41) | | | (−2.35) | | |
| Sustainable Flow | | −0.10 | | | −0.15** | |
| | | (−1.37) | | | (−2.11) | |
| Climate Concern | | | −0.11* | | | −0.15** |
| | | | (−1.68) | | | (−2.26) |
| Earnings Day Ret | 0.79*** | 0.77*** | 0.78*** | 0.71*** | 0.69*** | 0.71*** |
| | (8.62) | (8.53) | (8.46) | (6.42) | (6.41) | (6.39) |
| $E_t[\Delta \text{EPS}_{t+1}]$ | 3.87*** | 3.65*** | 3.98*** | 4.68*** | 3.94*** | 4.71*** |
| | (3.10) | (2.88) | (3.15) | (3.56) | (3.15) | (3.45) |
| $E_t[\Delta \text{LTG}]$ | 0.16 | 0.15 | 0.17 | 0.14 | 0.12 | 0.22 |
| | (0.71) | (0.66) | (0.73) | (0.51) | (0.41) | (0.76) |
| $\Delta \text{Sales}_{t+1}$ | 0.49 | 0.27 | 0.53 | 0.44 | 0.24 | 0.47 |
| | (1.41) | (0.80) | (1.47) | (1.23) | (0.68) | (1.28) |
| Oil Exposure | −0.01 | −0.01 | −0.01 | −0.01 | −0.01 | −0.01 |
| | (−1.29) | (−1.24) | (−1.41) | (−1.47) | (−1.51) | (−1.48) |
| Natural Gas Exposure | −0.02 | −0.02 | −0.02 | −0.02 | −0.03 | −0.01 |
| | (−1.12) | (−1.61) | (−1.34) | (−1.11) | (−1.63) | (−0.88) |
| Commodity Exposure | −0.00 | 0.00 | −0.00 | −0.00 | −0.00 | −0.00 |
| | (−0.45) | (0.79) | (−0.85) | (−0.57) | (−0.16) | (−0.97) |
| Time FE | Y | Y | Y | Y | Y | Y |
| $R^2$ | 0.07 | 0.07 | 0.07 | 0.06 | 0.06 | 0.06 |
| Observations | 7,325 | 6,571 | 7,045 | 7,325 | 6,571 | 7,045 |

Panel B: Additional Country Characteristics

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Policy | 0.13** | | | 0.10 | | |
| | (2.12) | | | (1.33) | | |
| %Renewable Energy | | 0.20** | | | 0.16** | |
| | | (2.60) | | | (2.08) | |
| 1(Civil Law) | | | 0.55*** | | | 0.41** |
| | | | (3.38) | | | (2.52) |
| Controls | Y | Y | Y | Y | Y | Y |
| Time FE | Y | Y | Y | Y | Y | Y |
| $R^2$ | 0.12 | 0.08 | 0.08 | 0.09 | 0.06 | 0.07 |
| Observations | 4,376 | 6,033 | 6,033 | 4,376 | 6,033 | 6,033 |

where abnormal carbon returns $r^s_{it} = \alpha + \varepsilon_{it}$ are calculated from equation (7) and are unaffected by country-level market returns. $X_{it-1}$ denotes lagged country characteristics, such as log GDP per capita, sustainable investing flows, or a snapshot of country characteristics. $Y_{it}$ denotes contemporaneous cash flow shocks or earnings news. The $X$ variables are standardized to have zero mean and unit variance, allowing the coefficient $b$ to be interpreted as the increase in carbon return associated with a one-standard-deviation increase in $X$, unless $X$ is a dummy variable. Standard errors are clustered at the monthly level.

Table XI, Panel A, presents the results. Carbon returns are significantly negatively correlated with log GDP per capita, sustainable flows, and climate concerns. A one-standard-deviation increase in the sustainable flow is associated with a decrease in scope 1 and 2 carbon returns of 0.1% and 0.15%, respectively. The magnitudes are economically large enough to explain the negative carbon returns in DM countries and the zero or slightly positive returns in EM countries. The evidence suggests that the transition to the equilibrium with carbon-aware investment is underway. Cash flow shocks are positively associated with carbon returns across measures, with earnings-day returns and consensus EPS revisions being the most significant. Collectively, cash flow news accounts for up to 7% of the variation in carbon returns.

Finally, I study the role of country characteristics in equation (8) after controlling for all in-sample climate concerns and cash flow shocks. Table XI, Panel B, shows that countries with more stringent climate policies, more renewable energy, and civil law yield higher carbon returns, consistent with tighter climate policies in these countries. A one-standard-deviation increase in climate policy tightness is associated with an increase in scope 1 carbon returns of 0.13%. This finding reflects investors' demand for a higher carbon premium in these countries due to anticipation of higher policy risk and provides suggestive evidence that carbon transition risk is at least partially priced in global equities.

## V. Conclusion

Practitioners and academics heatedly debate whether investors materially care about carbon transition risk in their investments. Emissions are a weighted sum of firm sales scaled by emission factors and grow almost linearly with firm sales. However, emissions data are released at significant lags relative to accounting variables, including sales. After accounting for the data release lag, more carbon-intensive firms underperform relative to less carbon-intensive firms in the United States in recent years. International evidence on carbon or green premium is largely absent. The carbon premium documented in previous studies stems from forward-looking bias instead of a true risk premium in ex ante expected returns.

Further analysis shows that shifts in investor preferences, policy tightness, and cash flow shocks are factors driving the cross-country carbon return variation. In summary, the global transition toward full carbon awareness seems to be underway. Nonetheless, equilibrium carbon return may remain muted for an extended period as the transition takes place. Additional research is necessary to enhance our understanding and refine the impact of these transitions on asset prices. Exploring this relationship will provide valuable insights for sustainable investing and aid asset managers in striking a balance between positive ESG impact and fiduciary duty.

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## Supporting Information

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

**Appendix S1:** Internet Appendix.
**Replication Code.**