Carbon Returns Across the Globe

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Abstract

Carbon-intensive firms have been underperforming in the U.S. despite their higher carbon transition risk. The brown-minus-green return spread, or carbon return, is zero on average globally but varies significantly across countries with unexpected cash flow shocks and climate taste shifts. The lower carbon return in developed markets reflects stronger growth in climate concerns instead of a lower expected carbon return. Additionally, countries with civil laws, more renewable energy, and tighter climate policies exhibit higher carbon returns. The inference differs from previous studies because I relate stock returns to lagged carbon measures, avoiding the issue of forward-looking bias.

Keywords: climate change, carbon-transition risk, predictability, stock return

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The science broadly agrees that a significant reduction in carbon emissions is required to fight climate change and avoid catastrophic consequences. As such, brown firms face higher carbon transition risk during global decarbonization. However, practitioners and academics heatedly debate whether investors materially care about the carbon risk in their investments. In equilibrium, brown firms are more exposed to the carbon transition risk and should earn higher expected returns, known as the carbon premium. However, green firms can outperform when policy shocks kick in, consumer attention turns, and investor tastes shift in transition to the net-zero economy (Pástor, Stambaugh and Taylor, 2021). Alternatively, if investors do not materially pay attention to carbon footprint, we would not observe significant outperformance by either green or brown firms. In light of the debates and challenges, while over 200 asset managers committed to the Net Zero Asset Management initiative, the largest two asset managers have decided not to divest brown firms.[1]

This study analyzes the carbon return, or the return spread between brown and green stocks, in the U.S. and a broad coverage of international stock markets. As global warming is a global risk and carbon reduction requires global commitment and collaboration, it is crucial to examine international markets to gauge the attitude of international societies. In particular, non-US countries account for 86% of the global carbon dioxide emissions by 2021. International stock markets are also economically important as they represent about 40% of the global market capitalization by December 2022. Statistically, turning to the international stock markets also helps us guard against data snooping bias.

I conduct the analysis in four steps. First, the prior literature has been facing the challenge that due to the gradual release of the carbon data, it is difficult to measure real-time carbon-transition risk for each firm. I provide a first assessment of the release lag and find that the lag is longer than that of typical accounting variables with a median of 10 and 12 months after the fiscal year-end for the U.S. and international samples, respectively. Because carbon emissions grow almost linearly with firm sales, carbon emissions contain substantial information about sales and should be lagged sufficiently to avoid the forward looking bias.

[1] See the statements by Blackrock and Vanguard.

Second, I use the most recent carbon emission data available to investors and show that brown firms measured by the carbon intensity, or emissions per unit of sales, earn lower returns than green firms in the U.S. empirically. The value-weighted return spreads per month are -0.39% and -0.27% for the scope 1 and 2 carbon intensities. The result cannot be explained by factor models and is robust to a battery of robustness checks. The return pattern is more consistent with the transition when climate concern strengthens and generates green outperformance. The excess returns stem mostly from the underperformance of brown firms, consistent with investor divestment. Furthermore, the excess return are mostly driven by cross-industry variations rather than firm-level carbon intensities, suggesting that the carbon transition in capital markets is still unfolding and has significant progress ahead.

Third, I compare to previous studies, in particular Bolton and Kacperczyk (2022) (BK, 2022). Note that the BK analysis uses emissions that are not in the investors' information set. In particular, the emissions are used before the accounting and emission information during the same period is released. As such, the analysis is a "contemporaneous" analysis. To demonstrate the impact of forward-looking bias, I replicate their analysis and find a carbon premium associated with emission growth and total emissions lagged by one month as in BK (2022). Next, I control for the sales and sales growth during the same period of emissions and find that total emissions and emission growth are no longer associated with stock returns. In sum, the alleged carbon premium only sources from the future sales information contained in the carbon data and does not reflect the premium for carbon-transition risk.

Fourth and finally, I turn to the international evidence. There is no robust outperformance by brown or green firms across the globe on average at first glance. However, the carbon returns show a huge dispersion across countries. In particular, the carbon return is lower in more developed markets than in developing markets. The international carbon returns can reflect variations in expected risk premia, but can also reflect various unanticipated in-sample shocks, including cash flow shocks and climate concern shifts.

To assess the possibilities, I start by measuring the cash flow news by calculating carbon returns realized on earnings days, the future sales information, and analysis revision with regard to short-term and long-term growth. The cash flow shocks explain up to 7% of carbon return variations. Then, I measure the climate taste shifts by country-level sustainable flows and surveyed climate concerns and find that the carbon return varies significantly across countries with these unexpected shocks. Specifically, developed countries have experienced stronger growth in climate concerns, generating lower carbon returns. Carbon returns for brown firms remain subdued as investors adapt to the carbon-aware economy. In addition, I investigate the variations in carbon returns after controlling for all in-sample shocks. I find that carbon returns tend to be higher in countries with a civil law legal system and higher fractions of renewable energy. This positive relationship aligns well with the level of climate policy tightness observed in these countries, reflecting compensation for heightened policy risk.

This paper is related to a few strands of the literature. First, this paper contributes to the international and country-level evidence on climate finance. In terms of the research question, the analysis closest to this paper is BK (2022). However, the economic insight differs significantly. BK (2022) interprets the cross-country variations in carbon returns as expected return variations and this paper instead highlights the role of in-sample shocks, such as cash flow and climate-concern shocks. In particular, the lower carbon return in developed markets reflects stronger climate-concern shocks instead of a lower required carbon risk premium. After controlling for climate-concern shocks, most country characteristics no longer drive cross-country carbon return variations. Related, Dyck et al. (2019) and Gibson et al. (2022) study responsible institutional investing around the world. Notably, neither of these studies addresses the pricing implications. Görgen et al. (2020) and Aswani, Raghunandan and Rajgopal (2022) also study international or regional carbon return but do not examine what drives the cross-country variations, which is the focus of this paper.

Second, the literature makes different methodology choices regarding the lags of emission data and concludes differently. For example, Görgen et al. (2020) and BK (2022) study the average global carbon returns but document a carbon premium. In terms of the methodology, these two papers study a contemporaneous relation by relating the emission data before the actual release date and fiscal year-end, to stock returns. This paper shows that the previously documented carbon premium sources from the look-ahead bias contained in emissions. Once the contemporaneous sales information is controlled for, the alleged carbon premium disappears. In the U.S.-focused literature, Chava (2014), Hsu, Li and Tsou (2022), and Bolton and Kacperczyk (2021) (BK, 2021) document a brown premium. In, Park and Monk (2017), Garvey, Iyer and Nash (2018), Duan, Li and Wen (2021), Pástor, Stambaugh and Taylor (2022), and Pedersen, Fitzgibbons and Pomorski (2021) find the outperformance for green firms. By comparing a key methodology choice in previous studies, this paper helps reconcile the seemingly conflicting findings.

Finally, this paper contributes to the literature that analyzes the role of institutional investors and ESG investing. Pástor, Stambaugh and Taylor (2021, 2022) characterize stock returns during the transition and show that green assets can outperform when customers' tastes for green products and investors' tastes shift for green holdings. In addition, Berk and van Binsbergen (2021), van der Beck (2021), Ardia et al. (2022), and Alekseev et al. (2022) study the price implications of institutional investors in the U.S. and Hong, Wang and Yang (2021) study welfare implications. This paper instead turns to the international market and examines the cross-sectional impact across countries. Krueger, Sautner and Starks (2020) document that the average respondent believes that the climate risk is not fully priced in market valuations in a survey of institutional investors, while this paper provides further evidence based on asset prices. Choi, Gao and Jiang (2020) study the short-term price implications when retail investors revise their beliefs about climate change, and this paper examines the longer-term cross-country price impacts of climate-aware investing.

The remainder of the paper proceeds as follows. Section 1 discusses the data and characterizes the information set of investors. Section 2 studies the U.S. evidence. Section 3 benchmarks the analysis against previous studies. Section 4 turns to the international evidence and analyzes what drives the cross-country variations in carbon returns. Finally, section 5 concludes.

1 Methodology and Data

1.1 Data

The data on firm's climate performance source from S&P Trucost, which provides annual information on firm-level carbon emissions in tons of carbon dioxide ($CO2$) equivalent ($tCO2e$). The firm-level stock market and accounting information source from CRSP and Compustat for the U.S. and 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. The Trucost data is matched to the stock-level information by CUSIP, ISIN and SEDOL. Finally, I augment the data by the natural gas price, Brent oil price, and commodity index from FRED at the St. Louis Fed and country-level information extracted from the World Bank, World Risk Poll, and Climate Change Performance Index.

Figure 1 illustrates the protocols for classifying greenhouse gas (GHG) emissions. Scope 1 GHG emissions cover direct emissions from owned or controlled sources by the firm. Scope 2 GHG emissions cover indirect emissions from the generation of purchased electricity, steam, heating, and cooling consumed by the reporting company. Scope 3 GHG emissions include all other indirect emissions that occur in a company's value chain. Because the direct reporting of scope 3 emissions is minimal and the estimation is vendor dependent, I focus on scope 1 and 2 emissions in the analysis.

1.2 Information Observability and Data Release Lag

The literature on carbon and ESG investing has been facing the challenge that due to the gradual release of carbon data, it is difficult to measure real-time emissions for each firm. As such, The literature has made different timing choices. Görgen et al. (2020), BK (2021), and Aswani, Raghunandan and Rajgopal (2022) study the contemporaneous relation between returns and carbon footprint. BK (2022) links monthly stock returns to emissions lagged by one month. Alternatively, Pedersen, Fitzgibbons and Pomorski (2021), Duan, Li and Wen (2021), and Lindsey, Pruitt and Schiller (2021) use a 3-, 6-, and 6-month lag from the fiscal year-end, respectively. For comparison, the accounting variables are often lagged by 6 months from the fiscal year-end following Fama and French (1992). As such, the lags adopted for carbon emissions are often less than those for the accounting variables, which can introduce forward-looking bias for the future accounting information. I now characterize the information set of investors and then dicuss the actual data release lags.

1.2.1 Financial Information Contained in Emissions Data

The generalized methodological approach in constructing emissions data is detailed in the IPCC (2006) "Guidelines for National Greenhouse Gas Inventories" and is described by

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

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 emission factors. In other words, the emissions are derived from the annual reports and more detailed economic activity information. The research process is consistent among the various players in the field, from firms, Carbon Disclosure Project (CDP), to data vendors, including Trucost, MSCI, and etc.

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

$$\begin{aligned} \log \text{Emission}_{it} &= \alpha + \beta \log \text{Sales}_{it} + \varepsilon_{it}, \\ \Delta\text{Emission}_{it} &= \alpha + \beta \Delta\text{Sales}_{it} + \varepsilon_{it}, \end{aligned} \tag{2}$$

where Δ denotes the log change. The regression is at the firm-year level, and the standard errors are doubly clustered at the firm and yearly level. Table 3 presents the results. Column 1 to 2 show that log sales explain as much as 50% and 71% variations in the scope 1 and 2 carbon emissions. The coefficients, in line with the linear assumption of typical AK models, are close to unity, with values of 1.04 for both scope 1 and scope 2. Moreover, these coefficients are statistically indistinguishable from unity at the 1% significance level. As such, the carbon intensity measured as emission per unit of sales well purges the sales information contained in emissions. Columns 3 to 4 further show that the carbon growth is also significantly associated with sales growth with coefficients of 0.86 and 0.89, and the explanatory power ranges from 34% to 35%. As such, total emissions and emission growth contain information about the firms' accounting information over the same period. Sufficient lags in the carbon variables need to be included to ensure that the carbon and associated accounting variables are known before the returns they are used to explain. At the minimum, the lag in carbon variables should be no less than that of the accounting variables.

I further study the information contained in carbon intensities,

$$\text{Intensity}_{it} = \alpha + \beta \cdot \text{Charateristics}_{it} + \varepsilon_{it}, \tag{3}$$

where Intensity_{it} denotes the scope 1 and 2 carbon intensities for firm i at time t, and $\text{Characteristics}_{it}$ denotes the firm-level characteristics during the same period. The characteristics include beta, size, book-to-market, ROA, asset growth, momentum, leverage, log PPE, idiosyncratic volatility, sales growth, and EPS growth. All regressions include time fixed effects.

Columns 1 to 2 in Panel B show that the sales growth no longer contains significant information about carbon intensities. In addition, the carbon intensities are positively related to the market beta, firm size, and idiosyncratic volatility, and negatively related to book-to-market, asset growth, and firm leverage. Together, these firm characteristics and temporal variations account for 11% and 18% of the observed intensity variations. Finally, the media and public recognize the industry aspect of carbon footprint and pay special attention to the transition risk of brown industries. Notably, Sustainability Accounting Standards Board develops industry-level sustainability accounting standards and materiality measures. Column 3 to 4 further include the GICS6 industry fixed effects. The R^2s increase significantly to as high as 78% for scope 1 and 63% for scope 2, emphasizing the substantial impact of industry-specific factors on carbon intensities.

1.2.2 Data Release Lag

S&P Trucost adds a new company-year observation to the database after companies complete their fiscal years and relevant data is publicly disclosed. Trucost then conducts a continuous research process as more coverage is made available. When it comes to 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 by CDP. Subsequently, CDP releases the response data from individual companies on an annual basis in October.

While most databases do not provide the date when the emission data is made available, Trucost updates various environmental variables simultaneously and provides a date when the final data is made available. Two observations arise from the inspection of Trucost release dates. First, Trucost reviewed and updated the data before 2008 in May 2009. As such, all data points before 2008 are backfilled. Second, the data is updated with significant lags compared to other sources of data, such as the accounting variables. Figure 2 plots the histogram of the lag between the fiscal-year end and the date when the carbon data is made available for the fiscal year of 2008 and onward. The 25th percentile of the U.S. distribution is 6 months, the typical lag of 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 75th percentile of 24 months. For the international sample, the 25th, 50th, and 75th percentiles are 7, 12, and 22 months, respectively. The data lag compares favorably with other data vendors. For example, for the July 2021 download of the MSCI ESG data, the coverage for the fiscal year 2020 is 5% that of 2019 for the U.S., 16% for the international sample. In this paper, I use the most recent carbon emissions and accounting data based on their respective data release dates to account for the gradual data release.

1.3 Sample and Summary Statistics

The final sample is the intersection between monthly stock return data and annual carbon emissions data, ensuring that the carbon data is available before the stock return is known. The matched sample covers the returns from June 2009 to December 2021. The main measure of the carbon-transition risk is carbon intensities, that is, carbon emissions scaled by the year-end sales. To benchmark against the literature, I also construct measures of the emission growth, or the year-on-year (log) growth of emissions, and (log) total emissions. If the latest carbon data for the latest fiscal year is not released yet, I fill in the missing variables, emissions, growth, or carbon intensities, with the latest available number. For the international sample, I follow Hou, Karolyi and Kho (2011) to screen the international stock returns to minimize the impact of outliers.

Table 1 presents the distribution of headquarter countries and regions of firms as well as the summary statistics of average firm-level carbon intensity.[2] The U.S. firms represent most observations in the sample (22.8%), followed by Japan (13.6%) and China (8.3%). All nominal variables are denominated in U.S. dollars.

The main measure of the carbon-transition risk is the carbon intensity. I make the choice for a few reasons. First, because carbon emissions scale with the magnitude of firms' operations, it is more reasonable and informative to compare the intensity across firms. Second, investors almost exclusively focus on carbon intensity when discussing net-zero investment. As such, one can expect the carbon intensity to be associated with the stock returns if investors care about carbon risk (see Blackrock's statement). Third, policy regulations, such as cap-and-trade or carbon taxes, focus on the total emissions, would have less impact on larger firms, conditional on the same amount of carbon emissions.

Table 2 presents the summary statistics of firm-level carbon measures and controls for the U.S., which is the main sample that I benchmark against existing studies. For the carbon performance, the scope 1 and 2 carbon intensity both have a mean of 2.71 and the scope 1 intensity has a higher standard deviation, 2.19, than that of the scope 2 (1.4). The carbon

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

intensities are persistent, with annual autocorrelations of 0.99 and 0.93 for the scope 1 and 2 measures, respectively. The controls include the exposures to the natural gas, oil, and commodity returns estimated over a 60-month rolling window, 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 the Fama-French 3-factor model, ROA, asset growth, leverage, log PPE, sales growth and EPS growth. I winsorize all controls at 1% and 99% of the distribution.

2 The U.S. Evidence

2.1 Baseline Analysis

The baseline empirical analysis conducts portfolio sorts using proxies of firms' carbon-transition risk. At month t, I adopt the point-in-time carbon emission data to calculate the carbon measures. Then I sort the stocks into tercile portfolios.[3] Thus, the low portfolio contains firms with the lowest carbon footprint and the high portfolio contains firms with the highest carbon footprint. After forming the three portfolios, I calculate the value-weighted monthly returns on these portfolios at time $t + 1$. To examine the relation between the carbon footprint and returns, I also form a high-minus-low portfolio that takes a long position in the high-carbon portfolio and a short position in the low-carbon portfolio.

I first study the relationship between carbon intensities and stock returns in the U.S. Panel A of Table 4 presents the monthly average returns from the portfolio sorts for scope 1 and 2 carbon intensities, respectively. The carbon intensities can help predict the stock returns in the cross-section. For scope 1 carbon intensities, portfolio L to portfolio 2 earns similar average returns from 1.44% to 1.51%, and the most carbon-intensive portfolio (H) earns a much lower return of 1.04% per month. The high-minus-low portfolio generates a significant excess return of -0.39% per month. The negative excess return is consistent with investment managers divesting from the brown firms (BK, 2021). The pattern is similar for

[3] While the carbon emission data is inherently an annual series, the portfolios are updated monthly as new data becomes available.

scope 2 carbon intensities. The tercile-sorted portfolios earn a return of 1.51%, 1.31%, and 1.24% per month, respectively. The high-minus-low portfolio generates a significant excess return of -0.27% per month.

Figure 3 plots the cumulative and rolling returns of a strategy that longs the high portfolio and shorts the low portfolio. Over the sample period, the portfolio loses as much as 50% of its initial value, suggesting a cumulative and 12-month rolling return of 100% for the green-minus-brown (low-minus-high) portfolio over the sample period. Overall, the result shows that the most carbon-intensive stocks have been underperforming the less carbon-intensive ones. The cross-sectional return pattern is the opposite of equilibrium pricing and is more consistent with the pattern during the transition period.

I further conduct portfolio sorts for emission growth and total emissions. The long-short spreads between the high and low portfolios are small and insignificant. In sum, carbon intensity is negatively associated with excess returns in the U.S., especially for the most carbon-intensive firms. In contrast, the total carbon emissions and emission growth do not explain subsequent stock returns, suggesting that investors do not consider these variables as measures of carbon-transition risk.

2.2 Asset Pricing Factor Analysis

This section investigates whether the variation in average returns of the carbon intensity-sorted portfolios can be explained by existing risk factors. In particular, firms can adopt a less cost-efficient but green business model or use carbon offsets to lower emissions, which also reduces firms' profitability (Garvey, Iyer and Nash, 2018; Hsu, Li and Tsou, 2022). To account for this endogenous choice, I use the FF6 factor models (Fama and French, 2018), which includes the profitability factor together with the market, size, value, asset growth, and momentum factors.

Panel B in Table 4 presents the results. Panel B.1 shows that the intensity-sorted long-short portfolio loads strongly positively on the profitability factor, consistent with the conjecture above. After adjusting for the factor exposure, more carbon-intensive stocks earn significantly lower alphas than less carbon-intensive ones. The portfolios sorted by the 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 less carbon-intensive portfolio (L) underperforms, the high carbon-intensive one (H) outperforms, and the underperformance driven by brown firms accounts for more of the excess returns. The long-short portfolio alphas sorted by scope 2 carbon intensities are -0.34% (t-statistics = -2.40). Because the carbon return can comove with various energy price movements, I further control the oil, natural gas, and commodity index price movements in the Internet Appendix and again find significantly negative risk-adjusted returns.

Panel B.2 to 3 further presents the factor-adjusted returns for the portfolios sorted by emission growth and total emissions. The FF6-adjusted HML carbon alphas are significantly negative for total emissions, similar to the intensity-sorted portfolios. On the other hand, the emission growth sorts do not generate significant alphas. In short, the carbon intensity contains explanatory power for future stock returns and alphas, while the total carbon emissions and carbon emission growth do not provide consistent predictability.

2.3 Robustness

This section now conducts a few robustness analyses regarding carbon intensities. First, more than half of the scope 1 and 2 emissions are estimated by Trucost instead of reported by the firms. Note that the estimated carbon emissions data can be subject to revisions by the data vendor. However, the data reported by firms are immune to vendor estimation and revisions. Indeed, Busch et al. (2018) find that the reported scope 1 and 2 emissions are almost the same across data providers. I now study the subsample in which the emissions are reported by firms only. Panel A, Table 5 reports raw returns of the sorted portfolios and return spreads. The return spreads are -0.39% and -0.27% for scope 1 and 2 carbon intensities, respectively, and the FF6-adjusted alphas are -0.40% and -0.34%. In sum, there is a strong green return associated with the reported emission intensities and the results are similar to the baseline. Related, the estimation process can differ across different vendors, leading to variations in the timing of data releases to investors. I hence conduct the robustness analysis, in which I use the year t emission data in October year t+1. The results are similar to the baseline and are reported in the Internet Appendix.

Panel B considers alternative measures of carbon intensities. First, I consider the carbon intensity measured as emissions divided by end-of-year market equity as in Ilhan, Sautner and Vilkov (2021) and find significantly negative carbon returns and alphas consistent with the baseline. Second, I consider the year-on-year changes in the carbon intensity (ΔIntensity). The high-minus-low return spreads in sorted portfolios are again negative, consistent with the baseline.

Furthermore, I analyze the carbon return within different firm size groups. In Panel C, the results reveal negative raw return spreads and alphas across all size groups. The findings are particularly pronounced for large and mid-cap stocks, while they are less significant for microcaps. This suggests that during the transition, the market has primarily focused on larger stocks, indicating that smaller stocks are still in the early stages of incorporating the transition.

Finally, to examine the relationship between stock returns and carbon intensities, I conduct a regression analysis using the following model:

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

The regression is at the firm-month level and controls for the time-fixed effect. The standard errors are doubly clustered at the firm and monthly levels. Weighted least squares regression is utilized to avoid excessive influence from small stocks. I standardize the carbon measures to have zero mean and unit variance throughout the regressions such that the coefficients can be interpreted as the change in monthly stock returns for a one-standard-deviation increase in the carbon footprint. The control variables encompass a comprehensive list of firm characteristics that are shown to be related to stock returns, including the exposures to oil, natural gas, and the commodity index, beta, size, book-to-market, ROA, asset growth, momentum, leverage, log PPE, sales growth, and EPS growth.

Columns 1 to 2 in Panel D report the results. Similar to the sorting-based evidence, more carbon-intensive stocks are associated with lower future excess returns. A one-standard-deviation increases in the carbon intensity is associated with a 0.19% and 0.21% decrease in scope 1 and 2 monthly returns, respectively. For the controls, stocks more exposed to the oil and natural gas price fluctuations tend to be browner and earn a lower excess return in the sample, similar to the carbon intensity.

Motivated by the focus of public attention on the industry-level carbon intensities, columns 3 and 4 further include the industry-fixed effects. While the carbon intensities are again negatively associated with stock returns, the coefficients are halved relative to the specification without industry fixed effects, and the effect is largely insignificant. The results suggest that the predictability mainly comes from cross-industry variations and I analyze the industry decomposition below.

2.4 Cross-Industry vs Within-Industry Variations

The literature heatedly debates whether the carbon or green premium sources more from cross-industry or within-industry variations. For example, Choi, Gao and Jiang (2020) and Ilhan, Sautner and Vilkov (2021) highlight the role of industry-level carbon footprint, and most ESG vendors provide industry-neutral firm-level measures. However, BK emphasizes the within-industry firm-level measures, and Sautner et al. (2023) find some pricing evidence for both. I now compare the importance of the industry-level and firm-level carbon intensities.

Specifically, I conduct the portfolio sorts using the industry-level carbon intensities and within-industry firm-level residuals, respectively. The industry-level carbon intensity is calculated as the log ratio of total carbon emissions to total sales in each industry. The within-industry firm-level residual is the difference between firm-level and industry-level carbon intensity. Table 2 presents the corresponding summary statistics. The standard deviations of the cross-industry and within-industry scope 1 carbon intensities are 2.15 and 1.31, respectively. These values indicate a pronounced industry structure in scope 1 intensities.

In the case of scope 2 intensities, the standard deviations are more comparable for both cross-industry and within-industry measurements, with values of 0.99 and 1.05, respectively.

Panel A of Table 6 finds that brown firms earn lower alphas than others on average when sorted by industry-level carbon intensities. The scope 1 and 2 alphas are -0.42% and -0.34%, respectively, comparable to the baseline alphas. The Internet Appendix further presents the results of industry-level portfolio sorting and finds similar results. Next, Panel B conducts stock portfolio sorting with within-industry firm-level carbon intensities. The long-short carbon return is consistently negative across carbon categories and for both raw returns and alphas but tends to be insignificant. Overall, the predictability stems mostly from the industry-level information. This is consistent with investors divest brown industries. There is some suggestive evidence that investors also pay attention to firm-level carbon-transition risk but yet to fully price in this finer risk.

3 Information Observability and Carbon Return

The results up until now find that investors pay attention to the carbon-transition risk proxied by the carbon intensities and carbon-intensive firms earn lower returns in the sample. In contrast, total emissions and emission growth do not correlate with future stock returns. The results differ from previous studies. In particular, BK (2022) documents that total emissions and emission growth are associated with higher excess returns, or carbon premium, in the U.S. and globally. This section first replicates the analysis in previous studies and then shows that the forward-looking bias contained in the analysis overstates the carbon premium in data.

3.1 The Role of Future Sales Information

As is documented in section 1.2, the carbon information is made available to investors with significant lags. For year t, the carbon emission data is only available for 50% firms by October year t+1. In the BK analysis, stock returns are related to emissions that are lagged by one month. This means that the analysis utilizes carbon variables that are not yet available to investors at the time. Specifically, the carbon variables are used before the release of accounting information for the same period.

It's important to note that while carbon intensity tends to be persistent, sales can vary and experience significant growth over time. In fact, sales play a crucial role as the primary input in estimating emissions. As a result, the emissions for year t contain substantial accounting information about the company. Therefore, the alleged carbon premium observed in stock returns could potentially stem from future sales information that is not yet available to investors, rather than being solely attributed to true carbon risk.

It is possible to speculate that investors may develop expectations regarding carbon emissions as the fiscal year progresses. However, it is reasonable to assume that investors can also form equally accurate expectations about firm sales during the same time period. The accuracy of emission estimates that investors can formulate before firms release their information is dependent on the accuracy of their sales estimates. Therefore, it is crucial to control for firm sales during the same period as carbon emissions and ensure that the relationship between returns and emissions genuinely originates from the carbon-transition risk rather than forward-looking sales information.

I start by replicating the relation between stock returns and one-month-lagged emission growth using nonparametric portfolio sorts. Table 7 presents the results. The emission 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 BK (2022).

To gauge the impact of future sales information on estimated carbon returns, I now conduct double sorts with sales and carbon 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 sale growth tercile. The sales and emission growth are measured over the same period. The results show that the sales growth sorts generate large positive excess returns from 0.91% to 1.09%, but the emission growth sorts no longer generate consistent return spreads. The spreads are small and largely insignificant. In short, the alleged carbon premium associated with emission growth in previous studies does not represent compensation for higher carbon-transition risk and instead is driven by using future sales information contained in emission data.

For the portfolio sorts with total emissions, there is no significant raw return or alpha spreads in the sorted portfolios. I show in the next section that the regression analysis well replicates the positive relation between stock returns and emissions, but the predictability again sources from the forward-looking bias.

3.2 Regression Analysis

This section conducts regression analysis as in BK (2022) in the more updated sample,

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

The regression is at the firm-month level, controlling for time- and industry-fixed effects. $Carbon_{i\tau}$ represents one-month lagged (log) emission growth or (log) emissions. The controls include a comprehensive list of firm characteristics that are shown to predict stock returns, including the beta, size, book-to-market, ROA, asset growth, momentum, leverage, log PPE, and idiosyncratic volatility. I include the industry-fixed effects because BK (2022) finds that the carbon premium strengthens in this case. The carbon measures are standardized to have zero mean and unit variance such that the coefficients can be interpreted as the change in monthly stock returns for a one-standard-deviation increase in the carbon footprint.

Table 8 shows that the analysis well replicates the results of BK (2022). Both emissions and emission growth are significantly associated with higher stock returns contemporaneously. For example, a one-standard-deviation increase in total emissions is associated with 0.19% and 0.23% increase in monthly U.S. stock returns. The coefficients are comparable to 0.21% and 0.17% excess returns per unit of standard deviation in the U.S. in Tables 6 of BK (2022).

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

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

In particular, $\mathbf{Sales}_{i\tau}$ denotes log sales and sales growth during the same emission period. Table 8 shows that future sales and sales growth are strongly associated with higher excess returns. However, carbon emissions and emission growth no longer contain consistent additional information about returns once the sales information is controlled for. Instead, the carbon return estimates tend to be negative, contradicting the carbon premium observed in BK (2022).

Finally, it is worth noting that BK (2022) conducts robustness analysis using alternative lags in the global sample. I replicate the analysis and present the carbon coefficients in Figure 4. The emission variables are associated with higher stock returns ("Baseline") when the lag is no more than six months but not beyond, consistent with Table 8 in BK (2021) and Table 6 in BK (2022). After controlling for sales information as in equation (6), the carbon coefficient ("Controlled") dramatically decreases and becomes consistently negative across different lags. The coefficient bias introduced by the forward-looking bias is particularly prominent in contemporaneous analysis or when shorter lags are used. Supplementary findings in the Internet Appendix demonstrate that the results hold true for U.S. stocks as well. In sum, the alleged positive carbon return documented in previous studies comes from the forward-looking bias introduced by using future sales information instead of a carbon risk premium.

4 International Evidence

This section now turns to international markets and studies whether global investors materially care about carbon-transition risk. Foreign countries produce the majority of carbon emissions, and international stock markets represent a significant fraction of the global market capitalization. The international analysis also helps provide out-of-sample evidence and guards against potential data snooping bias.

4.1 Average International Carbon Return

I conduct the portfolio sorting using carbon intensities as in the baseline analysis for each country. The U.S. evidence shows that the carbon returns load on various risk factors. I now 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 long-short carbon return and $factors_{it}$ denotes the FF6 factors for each region or country, including the U.S., North America excluding the U.S., Europe, Japan, Asia Pacific excluding Japan, and other countries as emerging markets. This approach allows the factor returns or loading to vary across countries and imperfectly integrated international markets (Fama and French, 2017).

To test the average international carbon return, I pool the country-level carbon returns together and regress on a constant using ordinary least squares and weighted least squares weighted by the market capitalization of each country. Table 9 (Column "All") presents the results. The average carbon return and alpha are close to zero and less negative compared to the baseline U.S. estimates. For example, the value-weighted alphas are -0.14% and -0.16% for scope 1 and 2, respectively, compared to -0.40% and -0.34% in the U.S.

Alternatively, I conduct the weighted least squares regression analysis for international stocks as in equation (4) and control for the country-fixed effect in addition to the time-fixed effect. Panel C again finds a negative relation between the returns and carbon intensities, consistent with the value-weighted alphas. A one-standard-deviation increase in scope 1 intensity is associated with a 0.10% decrease in monthly global stock returns, about half the U.S. coefficient. For scope 2, the coefficient is negative (-0.05), but small and insignificant. In short, the negative carbon return strongly exists in the U.S. stock market, but the evidence is weaker globally on average.

4.2 Geographic Dispersion

I now turn to the geographic dispersion in carbon returns. Figure 5 plots the country-level carbon alphas and shows that the portfolio alphas vary substantially across countries. Visually, carbon returns tend to be lower in more developed markets and higher in less developed markets. For example, the U.S. has negative carbon alphas (-0.4% and -0.34%), and China has positive alphas instead (0.53% and 0.23%).

Formally, I first split the international sample into groups of countries. I start with G7 (excluding the U.S.) and Australia, which contain the developed countries most comparable to the U.S. Table 9 shows that the value-weighted carbon alphas are -0.33% and -0.25% for scope 1 and 2, respectively, and are more comparable to the U.S. estimates (-0.4% and -0.34%). Second, I split the international sample into the developed and emerging markets (DM and EM) and find more negative carbon returns in the DM countries. The value-weighted carbon alphas for the DM countries are -0.28% and -0.26% for scope 1 and 2, respectively. In contrast, the carbon alphas for the EM countries are positive, 0.20% and 0.06%. The regression analysis provides similar evidence. The coefficients for more developed countries are significantly negative, -0.19% and -0.08% for G7+AUS, and are more comparable to the U.S. estimates (-0.19% and -0.21%). The coefficients are statistically indifferent from zero for EM countries.

4.3 What Drives Carbon Return Variations?

The previous analysis shows that the evidence of negative carbon return is weak on average globally and varies significantly across countries. For example, the carbon return tends to be lower in more developed countries. A few possible interpretations follow. First, carbon return variations are driven by in-sample cash flow shocks across countries unrelated to carbon-transition risk or climate concerns. Second, shifts in investor preference have differed widely across countries during the global green transition, generating cross-country variations in carbon returns. Finally, the carbon return variations reflect variations in the carbon risk premium in equilibrium. The following sections now evaluate each of the possibilities.

4.3.1 Cash Flow Shocks

I first study the impact of in-sample cash flow shocks. These shocks can represent country-specific shocks, such as strong economic growth and demand in a country that have boosted the brown firms' sales and returns in this country accordingly. The shocks also account for global shocks that systematically affect firm-level earnings, such as oil price fluctuations. In particular, these shocks impact returns through firm cash flows, as such measuring the firms' cash flow and earnings day returns can also help capture these macroeconomic shocks.

I construct a few cash flow measures. The first measure is carbon returns on earnings days because most new earnings-related information arrives on earnings days. Specifically, I calculate the long-short spread in earnings day carbon returns in the sorted portfolios. The earnings day return incorporates the impact of information arrival in the current period. Investors accordingly update their beliefs and further adjust the prices. Second, I measure the long-short spread in future sales growth for next year. The sales growth information is not in the investors' information set. However, it is plausible that investors can collect information as the current quarter proceeds and form updated beliefs. Third, I capture investor belief updates directly by measuring the long-short spread in consensus analyst revisions of the one-year-ahead EPS forecasts and long-term growth forecasts. These variables measure the short-term and long-term cash flow news perceived by the public. Finally, I explicitly account for the exposure of stocks to energy price fluctuations by estimating the exposure to oil, natural gas, and commodity price fluctuations by running a rolling 60-month regression.

I examine the relation between abnormal carbon returns and in-sample cash flow shocks in the following regression

$$r_{it}^s = a + \kappa \cdot \mathrm{Y}_{it} + \nu_t + e_{it}, \tag{8}$$

where abnormal carbon return $r_{it}^s = \alpha + \varepsilon_{it}$ is calculated from equation (7) and is unaffected by country-level market return variations. Y_{it} denotes contemporaneous cash flow shocks or earnings news. In addition, the regression includes monthly fixed effects, such that the regression is more of a cross-sectional analysis and focuses on cross-country variations in carbon returns. The coefficient κ can be interpreted as the increase in the carbon return associated with positive cash flow news. The standard errors are clustered at the monthly level.

Column 1 and 5 in Panel A, Table 10 present the results for scope 1 and 2 carbon intensities, respectively. The earnings shock, captured by contemporaneous earnings day returns, emerges as the most significant driver of carbon return variations. One percent increase in the earnings day returns leads to 0.78 and 0.70 percent increases in scope 1 and 2 carbon returns, respectively. The result suggests that most earnings day returns do not revert and contribute significantly to country-level carbon returns. Positive cash flow news measured by the other direct measures are all associated with higher carbon returns, and the effect is most significant for consensus forecast revisions for the one-year-ahead EPS. The impact of exposures to energy price shocks is largely absorbed by direct cash flow measures. Collectively, the various cash flow news sources account for up to 7% of the variations observed in carbon returns.

4.3.2 Sustainable Flow and Climate Concern

In this section, I construct two measures of climate-concern or taste shifts. First, investors' demand for green assets can increase and drive up green asset prices. I measure the shift by the country-level sustainable investor flows each quarter scaled by the end-of-quarter market capitalization.[4] The sustainable flow is highly correlated with log GDP per capita, with a coefficient of 0.47.

Second, during the transition, consumers' demands for green products strengthen, driving up green firms' profits and thus their stock prices. I proxy the cumulative shift in consumer demand by the level of climate concerns from the Lloyd's Register Foundation (2020)'s 2019 World Risk Poll. The survey asks whether the interviewees perceive climate change as a very serious threat, a somewhat serious threat, or not a threat at all. The climate concern is calculated as the total fraction who answer a "very serious" and "somewhat serious" threat.

[4]The data is 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.

Because climate change only started concerning the public in recent years, the measure proxies for the cumulative increase in climate concern. The climate concern is also highly correlated with the log GDP per capita, with a coefficient of 0.43.

I examine the relation between abnormal carbon return r^s_{it} and climate concern shocks after controlling for cash flow shocks Y_{it} in a regression similar to equation (8),

$$r^s_{it} = a + b \cdot \mathrm{X}_{it-1} + \kappa \cdot \mathrm{Y}_{it} + \nu_t + e_{it}, \tag{9}$$

where the new variable X_{it-1} denotes lagged country characteristics, such as log GDP per capita or sustainable flow, or a snapshot of country characteristics. The variables Xs are standardized to have zero mean and unit variance, allowing the coefficient b to be interpreted as the increase in the carbon return associated with a one-standard-deviation increase in X.

Panel A, Table 10 presents the results. Column 2 shows that the carbon return is significantly negatively correlated with the log GDP per capita, confirming the earlier analysis. Furthermore, the carbon return is significantly negatively associated with sustainable flows and climate concerns. A one-standard-deviation increase in the sustainable flow is associated with a decrease of 0.1% and 0.15% in the average monthly carbon return. A one-standard-deviation increase in the climate concern is associated with a monthly return decrease of 0.11% and 0.15%. The magnitudes are economically large enough to explain the negative carbon return in DM countries and zero or slightly positive returns in EM countries. In sum, the shifts in investor and consumer preference drive sizable carbon return variations across countries.

4.3.3 Additional Country-Level Characteristics

This section further studies the impact of additional country characteristics as in equation (8). In the analysis, I control for all in-sample cash flow and climate concern shocks studied above. All country characteristics are standardized, except for the dummy variables. It is natural to expect that countries with tighter climate policies can carry higher expected carbon returns. However, climate policies are subject to change, and investors expect most policies to come into shape in the future years.[5]

First, I measure the current policy tightness using the policy score in Climate Change Performance Index. Panel B shows that countries with more stringent climate policies have higher carbon returns in general. A one-standard-deviation increase in the climate policy tightness is associated with an increase of 0.13% in the scope 1 carbon return. However, the effect is only marginally significant, suggesting limited information contained in current policies.

Next, I examine additional characteristics that are associated with policy tightness and can provide insights into future policy developments. Civil law countries often have robust investor protection mechanisms, prioritize shareholder rights, and promote environmentally friendly corporate practices. Similarly, countries with a higher proportion of renewable energy tend to enforce more environmentally friendly policies while discouraging the use of fossil fuels. Notably, the civil law dummy and fraction of renewable energy exhibit correlations of 0.58 and 0.47, respectively, with policy tightness, suggesting an inclination towards implementing stricter policies now and in the future.

Panel B shows countries with a civil law system and a higher fraction of renewable energy yield significantly higher carbon returns. On average, the carbon return is 0.55% higher for scope 1 and 0.41% higher for scope 2 in civil law countries. A one-standard-deviation increase in the fraction of renewable energy is associated with an increase of 0.20% and 0.16% in the scope 1 and 2 carbon returns, respectively. The finding reflects investors' demand for higher premiums for brown firms in these countries due to the anticipation of higher policy risk.

Finally, I study the carbon dependence of the country by measuring the sales fraction of brown industries (energy, materials, and utilities) and find little impact on carbon returns. This is consistent with the fact that the climate policies or willingness to commit to net zero are largely independent of the industry structure. For example, the U.S. is ranked at the bottom for climate policies while both EU countries and China both rank at the top.

[5] The 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.

5 Conclusion

The practitioners and academics heatedly debate whether investors materially care about the carbon risk in their investments. This paper finds that more carbon-intensive firms underperform in the U.S. in recent years, while there is no excess return associated with total carbon emissions and emission growth. The carbon premium documented in previous studies stems from the forward-looking bias instead of a true risk premium. International evidence on carbon or green premium is also largely absent. Further analysis shows that cash flow shocks, shifts in investor preferences, and climate concerns are important drivers of the cross-country carbon return variations. In summary, the global transition towards full carbon awareness is well underway, signaling a significant shift in addressing climate change. Nonetheless, additional research is necessary to enhance our understanding and refine the impact of these transitions on stock prices. Exploring this relationship will provide valuable insights for sustainable investing and aid asset managers in striking a balance between making an impact and fiduciary duty.

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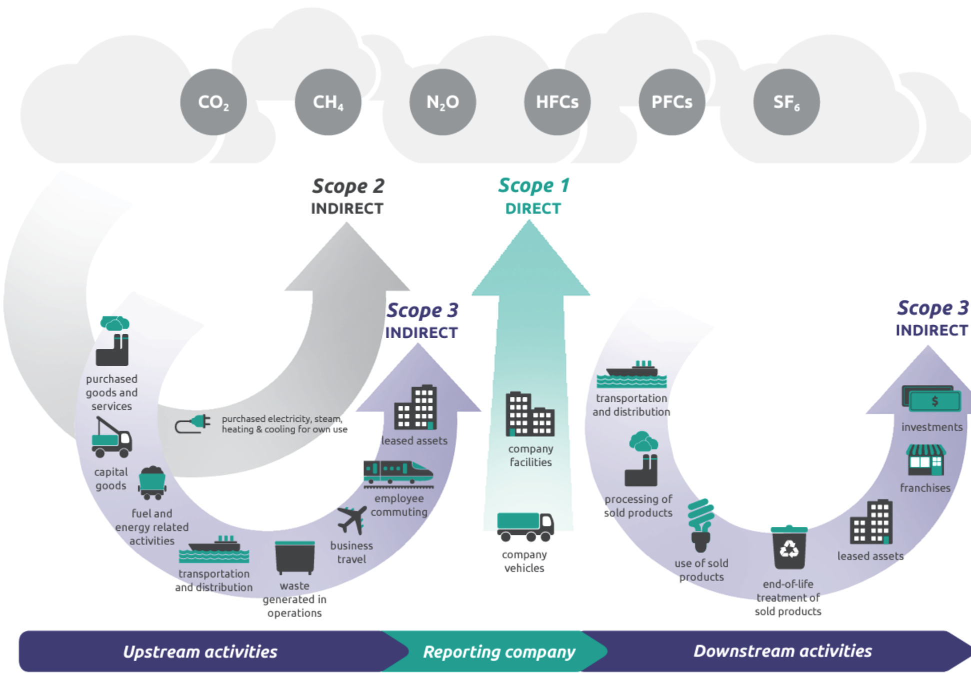
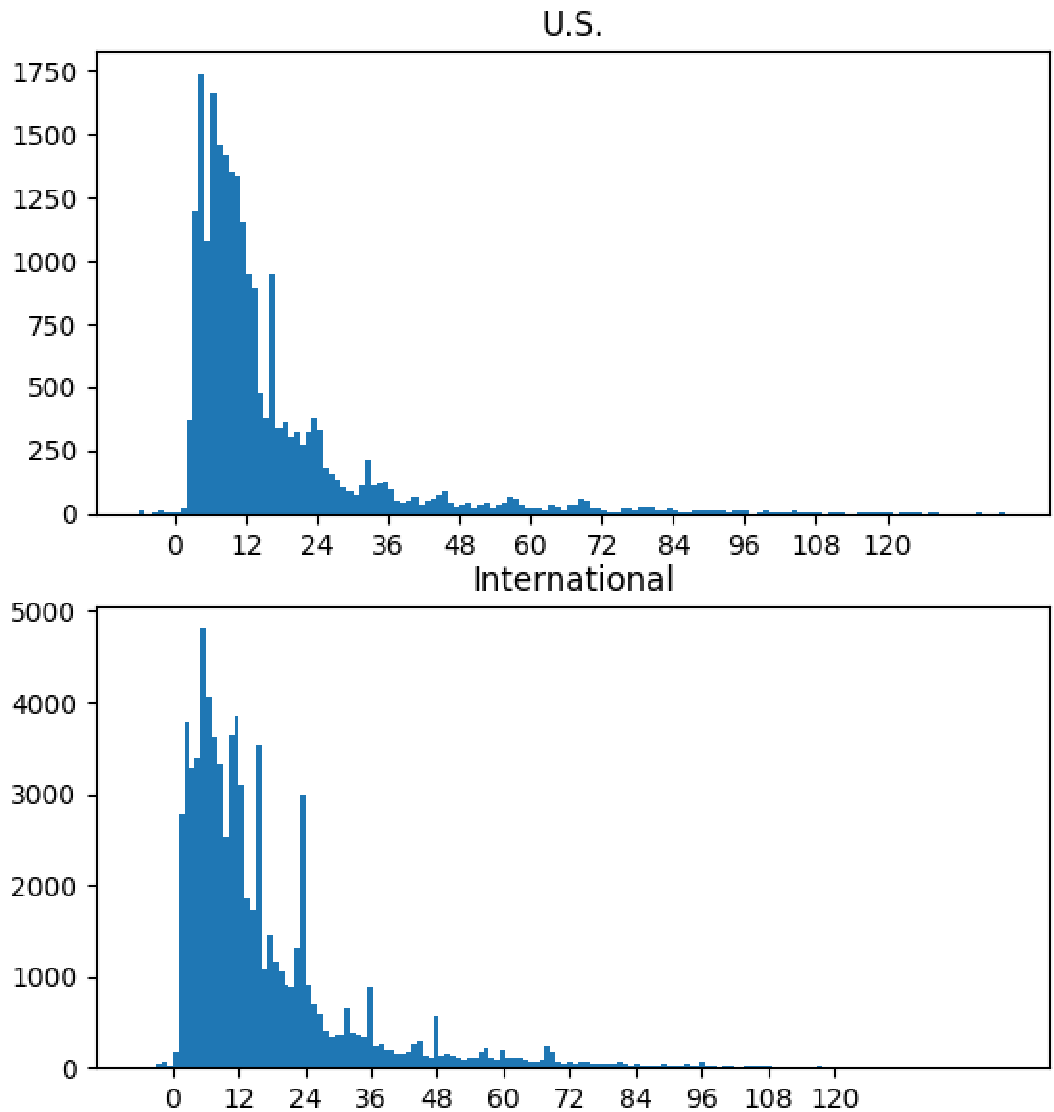
Figure 1: GHG Protocol Scopes and Emissions Across the Value Chain



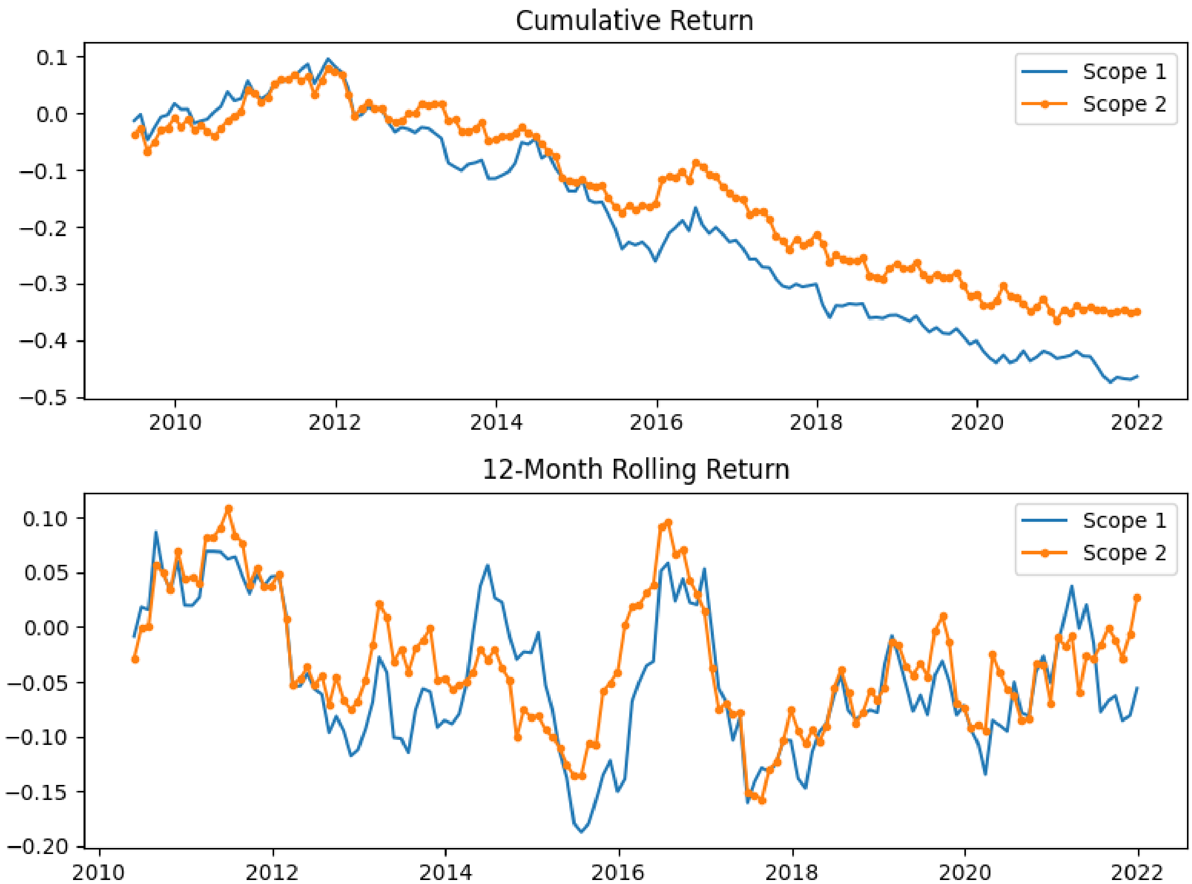
Source: WRI/WBCSD Corporate Value Chain Accounting and Reporting Standard.

Figure 2: Reporting Lags



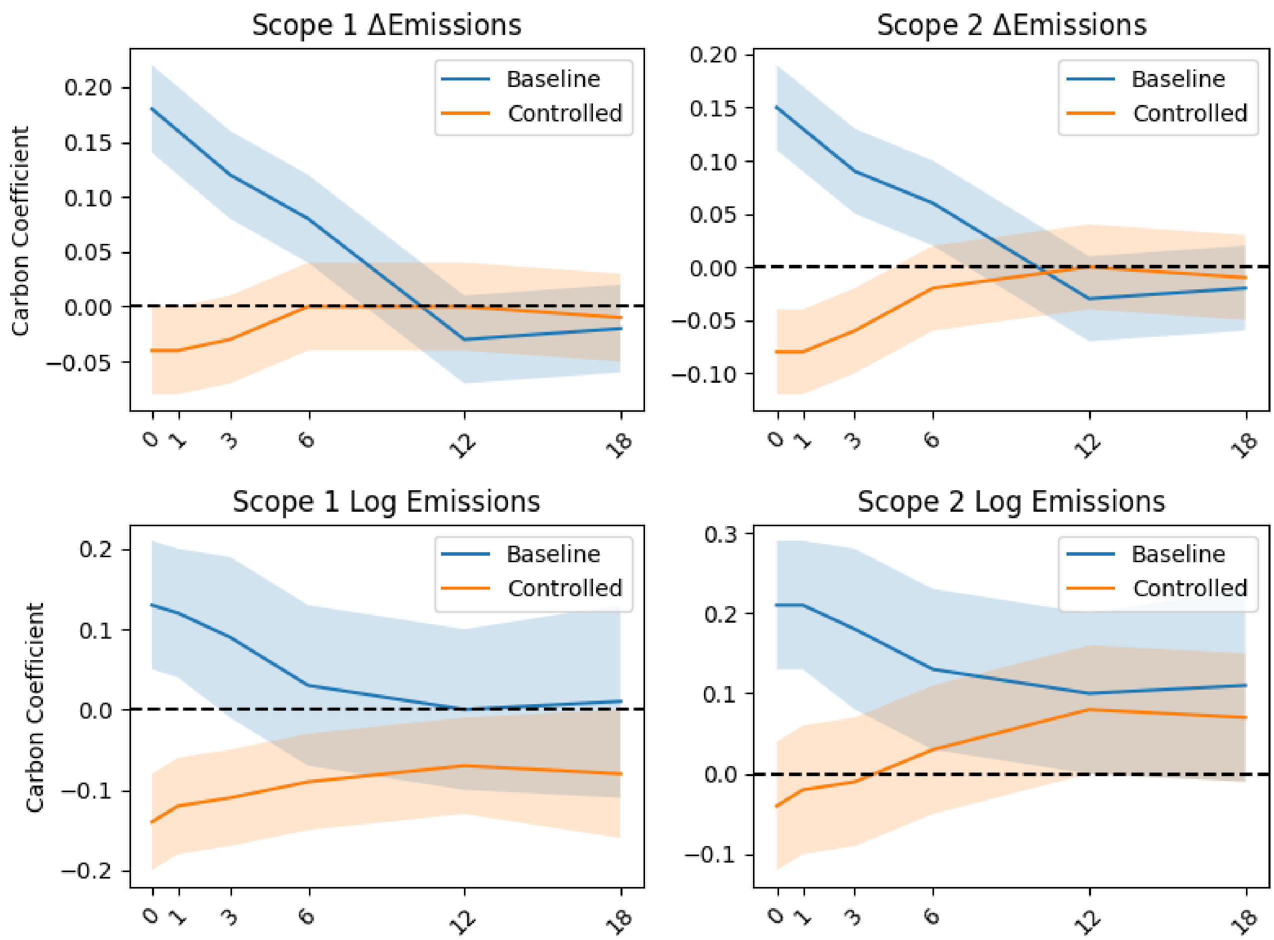
Notes: This figure plots the frequency tabulation of reporting lags for scope 1 carbon emissions for the U.S. and international samples.

Figure 3: U.S. Carbon Return



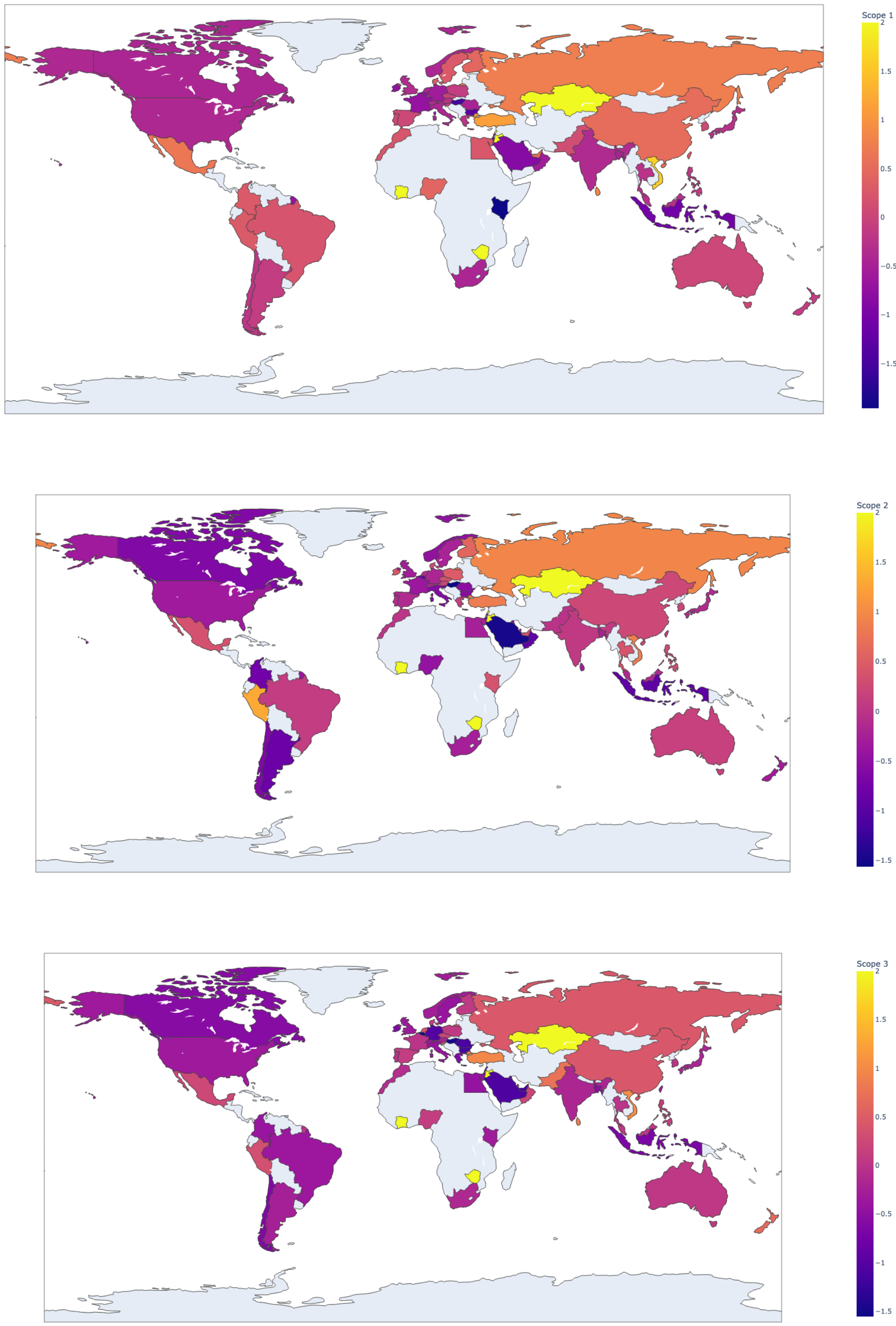
Notes: This figure plots the cumulative and 12-month rolling U.S. return spreads between the high- and low-carbon intensity portfolios.

Figure 4: Global Carbon Returns and Lags



Notes: This figure ("Baseline") first plots the baseline coefficients in BK (2021, 2022) by regressing global stock returns on x-month lagged emission growth and log emissions. Controls include beta, size, book-to-market, ROA, asset growth, momentum, leverage, log PPE, ROA, and idiosyncratic volatility. The orange line in the figure ("Controlled") further plots the corresponding coefficients after controlling for the forward-looking sales information during the same period of emissions (log sales and sales growth). The regressions include industry and time-fixed effects. The standard errors are double clustered at the firm and time level, and the shaded area denotes the 95% confidence intervals. The sample period is 2009:06 to 2021:12.

Figure 5: Country-Level Alphas



Notes: This figure plots the FF6-adjusted return spreads in percentage points between the high and low carbon intensity portfolios for each country.

Table 1: Summary Statistics by Country

			Carbon Intensity		
Country	Observations	Min Year	Scope 1	Scope 2	Scope 3
ARE	1,899	2009	2.37	2.72	4.19
ARG	1,097	2009	3.60	2.85	4.71
AUS	31,817	2009	3.20	3.33	4.61
AUT	3,427	2009	3.45	2.87	4.70
BEL	5,019	2009	2.97	2.90	4.51
BGD	427	2015	3.47	3.06	5.02
BGR	266	2015	3.33	3.16	4.44
BHR	291	2015	0.19	1.42	3.32
BMU	28	2019	-0.16	0.10	3.17
BRA	7,834	2009	3.13	2.30	4.72
BWA	17	2020	-0.55	-0.30	2.78
CAN	24,264	2009	3.50	3.13	4.57
CHE	15,528	2009	2.28	2.38	4.68
CHL	4,055	2009	3.46	2.20	4.24
CHN	56,034	2009	3.68	3.21	4.97
CIV	169	2015	2.36	2.75	4.90
COL	1,033	2009	3.94	1.88	4.74
CYP	32	2019	0.04	1.06	2.91
CZE	862	2009	2.75	2.38	4.68
DEU	18,753	2009	2.83	2.85	4.73
DNK	4,047	2009	2.82	2.39	4.88
EGY	3,454	2009	3.52	3.04	4.81
ESP	6,842	2009	2.72	2.46	4.60
EST	129	2015	4.10	3.39	4.18
FIN	5,250	2009	2.87	2.89	5.05
FRA	22,018	2009	2.54	2.52	4.59
GBR	52,609	2009	2.44	2.67	4.51
GHA	128	2015	3.49	3.39	6.37
GRC	2,602	2009	3.41	2.94	4.77
HKG	43,381	2009	3.35	3.24	4.79
HRV	237	2009	2.65	3.39	4.18
HUN	468	2009	2.34	2.42	4.00
IDN	8,352	2009	3.53	2.98	4.74
IND	30,181	2009	3.54	2.81	4.90
IRL	1,567	2009	3.82	3.17	5.25
ISR	7,171	2009	2.60	2.78	4.25
ITA	8,573	2009	2.88	2.62	4.72
JAM	44	2018	-0.14	1.23	3.42
JOR	386	2015	1.84	2.37	4.06
JPN	131,104	2009	3.01	3.06	4.91
KAZ	157	2014	1.09	0.85	3.15
KEN	823	2012	2.44	1.41	3.86

KOR	53,121	2009	3.29	3.12	5.10
KWT	1,163	2009	1.62	2.31	3.82
LBN	219	2015	0.74	2.24	2.86
LKA	582	2009	2.54	2.88	4.43
LTU	158	2015	2.07	3.21	4.10
LUX	166	2013	-0.90	1.40	2.79
MAR	1,385	2009	4.27	3.74	5.06
MEX	5,181	2009	3.20	3.27	4.90
MUS	96	2015	-0.08	1.08	2.70
MYS	13,941	2009	3.58	2.96	4.89
NAM	83	2015	2.64	3.79	3.63
NGA	1,643	2011	2.68	2.36	4.74
NLD	4,990	2009	2.51	2.43	4.59
NOR	6,558	2009	3.29	2.25	4.86
NZL	2,846	2009	3.05	2.38	4.51
OMN	777	2010	2.11	1.85	3.75
PAK	4,247	2009	4.36	2.84	5.07
PER	1,629	2009	4.14	3.72	4.82
PHL	4,693	2009	3.87	3.10	4.66
POL	5,615	2009	3.08	2.79	4.54
PRT	1,831	2009	3.23	2.88	4.59
QAT	1,918	2014	2.90	2.48	4.12
ROU	338	2014	3.14	1.39	4.65
RUS	3,896	2009	4.94	2.92	4.90
SAU	2,439	2018	3.64	3.30	4.86
SGP	9,681	2009	3.13	3.24	4.47
SRB	12	2015	-0.15	-0.32	2.70
SVN	404	2009	2.41	2.93	4.15
SWE	9,282	2009	2.02	2.47	4.56
THA	8,462	2009	3.31	2.89	4.66
TUN	162	2015	-0.27	-0.19	2.88
TUR	7,146	2009	3.78	3.12	4.92
TWN	47,442	2009	3.31	3.28	5.09
UKR	84	2015	4.53	3.48	4.73
USA	211,470	2009	2.71	2.71	4.60
VNM	1,107	2012	3.22	2.64	4.91
ZAF	12,857	2009	2.96	3.88	4.65
ZWE	169	2016	4.09	3.89	5.89

Notes: This table presents the sample frequency and average scope 1, 2, and 3 firm-level carbon intensities by country.

Table 2: Summary Statistics for the U.S. Sample

	AR	Mean	SD	P50	P25	P75
Scope 1 Intensity	0.99	2.71	2.19	2.71	1.40	3.61
Scope 2 Intensity	0.93	2.71	1.40	2.82	2.04	3.65
Scope 1 ΔEmissions	0.00	0.04	0.48	0.03	-0.06	0.14
Scope 2 ΔEmissions	0.00	0.06	0.56	0.03	-0.06	0.16
Scope 1 Emissions	0.98	10.08	3.06	10.16	8.07	11.91
Scope 2 Emissions	0.97	10.08	2.53	10.30	8.64	11.74
Scope 1 Industry Intensity	0.99	2.96	2.15	2.73	1.50	3.93
Scope 2 Industry Intensity	0.98	3.05	0.99	2.98	2.43	3.66
Scope 1 Within-Industry Intensity	0.98	-0.27	1.31	-0.08	-0.70	0.46
Scope 2 Within-Industry Intensity	0.92	-0.35	1.05	-0.23	-0.87	0.24
Log Sales	0.98	7.47	1.97	7.62	6.39	8.74
Natural Gas Exposure	0.75	0.02	0.09	0.02	-0.02	0.06
Oil Exposure	0.78	0.22	0.24	0.19	0.08	0.32
Commodity Exposure	0.75	2.63	2.88	2.09	0.84	3.87
Beta	0.87	1.23	0.63	1.15	0.81	1.55
Size	1.01	7.97	1.68	8.01	6.83	9.15
Book-to-Market	0.85	-0.88	0.94	-0.76	-1.40	-0.25
ROA	0.72	0.00	0.15	0.03	0.00	0.07
Asset Growth	0.10	0.12	0.36	0.05	-0.02	0.14
Momentum	0.00	0.16	0.50	0.10	-0.11	0.33
Log PPE	0.06	4.84	3.81	5.50	4.24	6.19
Leverage	0.74	3.90	4.05	2.32	1.76	4.01
IVol (×100)	0.68	1.97	1.51	1.51	1.01	2.39
ΔSales	-0.04	0.05	0.36	0.05	-0.03	0.13
ΔEPS	-0.28	0.10	2.37	0.13	-0.55	0.82

Notes: This table reports summary statistics of the variables in the analysis. The carbon intensity is calculated as the log ratio of the total carbon emissions to the year-end sales; Δ emission is the log emission growth. Sector intensity is the value-weighted carbon intensity, and the within-sector intensity is the difference between the firm-level and sector-level mean intensity. The autocorrelations (AR) are calculated at the annual frequency. The exposure to natural gas, oil, and commodity is the loading of the stock return on corresponding commodity returns over a 60-month rolling window. Size is the log year-end market equity; beta is estimated over a 60-month rolling window; the (log) book-to-market ratio is the log of the book value of equity divided by the market value of equity; ROA is the net income scaled by total assets; asset growth is the percentage change of total assets; momentum is the 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 the idiosyncratic volatility from the Fama-French 3-factor model; and ΔSales and ΔEPS are the log four-quarter sales and EPS growth.

Table 3: Scales of Carbon Emissions

	Panel A: Emissions and Sales			
	Log Emissions		ΔEmissions	
	Scope 1	2	1	2
Log Sales	1.04***	1.04***		
	(44.51)	(78.79)		
ΔSales			0.86***	0.89***
			(29.56)	(35.73)
Time FE	Y	Y	Y	Y
R^2	0.50	0.71	0.34	0.35
Observations	21783	21783	19219	19219
	Panel B: Variations in Intensity			
	Scope 1	2	1	2
Beta	0.05	0.48***	-0.01	0.08***
	(0.48)	(12.33)	(-0.51)	(6.73)
Size	0.07***	0.04***	-0.09***	0.02***
	(4.17)	(6.07)	(-16.56)	(3.08)
Book-to-Market	-0.01	-0.33***	0.03*	0.01
	(-0.17)	(-8.56)	(1.98)	(0.45)
ROA	-0.15	0.51***	-0.08	-0.08**
	(-0.57)	(3.99)	(-1.39)	(-2.96)
Asset Growth	-0.28***	-0.22***	-0.00	-0.06**
	(-4.98)	(-7.54)	(-0.06)	(-2.76)
Momentum	-0.08	-0.19***	0.03	-0.01
	(-0.74)	(-3.35)	(1.66)	(-0.39)
Leverage	-0.15***	-0.10***	-0.01***	-0.00
	(-41.58)	(-28.91)	(-3.81)	(-1.62)
Log PPE	-0.01	0.00	0.00	0.01**
	(-1.22)	(0.63)	(0.55)	(2.27)
IVol	0.22***	0.18***	0.02*	0.04***
	(5.88)	(9.73)	(2.17)	(6.78)
Sales Growth	0.16	0.17**	0.35***	0.28***
	(1.31)	(2.31)	(3.49)	(3.17)
EPS Growth	-0.04*	-0.02	-0.01	-0.00
	(-2.03)	(-1.67)	(-0.70)	(-0.09)
Industry FE	N	N	Y	Y
Time FE	Y	Y	Y	Y
R^2	0.11	0.18	0.78	0.63
Observations	18576	18576	18575	18575

Note: This table studies the scale and determinants of carbon emissions. Panel A regresses scope 1 and 2 log carbon emissions and emission growth on log sales and sales growth. Panel B regresses the carbon intensity on various contemporaneous characteristics over the fiscal year. All regressions control for time-fixed effects and the standard errors are double clustered at the firm and time level. The t-statistics are reported in the parenthesis below the coefficients. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively. The sample period is 2007 to 2020.

Table 4: Carbon Sorted U.S. Portfolios

	Scope 1				Scope 2			
	L	2	H	H-L	L	2	H	H-L
Panel A: Raw Returns								
Intensity	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)
ΔEmissions	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)
Emissions	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)
Panel B: Alphas								
Panel B.1: Carbon Intensity								
α	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.2: ΔEmissions								
α	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 B.3: Emissions								
α	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)

Notes: This table presents monthly value-weighted raw returns of the carbon footprint-sorted portfolios. The sorting variables are carbon intensity, log emission growth, and total emissions, respectively. The t-statistics are reported in the parenthesis below the coefficients. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively. The sample period is 2009:06 to 2021:12.

Table 5: Robustness Analysis

	Raw Return		Alpha	
Panel A: Firm-Reported Emissions Only				
	Scope 1	2	1	2
Reported Only	-0.39**	-0.27*	-0.40**	-0.34**
	(-2.47)	(-1.87)	(-2.51)	(-2.40)
Panel B: Alternative Measures				
Emission/Market Equity	-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)
Panel D: Regression Analysis				
	Scope 1	2	1	2
Scope 1	-0.19**		-0.13	
	(-2.52)		(-1.04)	
Scope 2		-0.21**		-0.06
		(-2.46)		(-0.80)
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)
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)
Sales Growth	-0.55	-0.52	-0.72	-0.72*
	(-1.19)	(-1.12)	(-1.65)	(-1.66)
EPS Growth	-0.01	-0.01	-0.00	-0.01
	(-0.57)	(-0.49)	(-0.24)	(-0.32)
Industry FE	N	N	Y	Y
Time FE	Y	Y	Y	Y
R^2	0.27	0.27	0.27	0.27
Observations	206025	206025	206025	206025

Notes: This table conducts various robustness tests. Panel A focuses on the sample with the emissions reported by the firm only. Panel B and C present return spreads of the tercile portfolios sorted by emissions scaled by year-end market equity and year-on-year change in carbon intensity, respectively. Panel C conducts weighted least square regressions of stock returns on lagged carbon intensities, controlling for a number of firm characteristics, including the exposures to various commodities, beta, size, book-to-market, ROA, asset growth, momentum, leverage, log PPE, sales growth, and EPS growth. The regression controls for the time-fixed effects. The standard errors are doubly clustered at the firm and monthly level, accordingly. The t-statistics are reported in the parenthesis below the coefficients. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively. The sample period is 2009:06 to 2021:12.

Table 6: Industry-level and Within-industry Sorted U.S. Portfolios

	Panel A: Industry-level Intensity							
	Scope 1				Scope 2			
	L	2	H	H-L	L	2	H	H-L
Raw Return	1.45***	1.48***	1.08***	-0.37**	1.43***	1.40***	1.19***	-0.24
	(4.06)	(4.50)	(3.00)	(-2.17)	(3.89)	(4.32)	(3.37)	(-1.40)
α	0.16**	0.13*	-0.26**	-0.42**	0.16*	0.07	-0.18*	-0.34*
	(1.98)	(1.69)	(-2.28)	(-2.39)	(1.74)	(0.95)	(-1.82)	(-1.97)
	Panel B: Within-Industry Firm-level Intensity							
Raw Return	1.44***	1.30***	1.27***	-0.17	1.45***	1.35***	1.28***	-0.18
	(4.02)	(3.88)	(3.68)	(-1.44)	(4.16)	(4.03)	(3.69)	(-1.54)
α	0.06	-0.02	0.03	-0.03	0.11	0.02	-0.02	-0.12
	(0.86)	(-0.30)	(0.44)	(-0.25)	(1.27)	(0.40)	(-0.29)	(-1.04)

Notes: This table presents monthly raw returns and alphas of carbon-sorted portfolios, based on the industry-level carbon intensities and within-industry firm-level carbon intensities. The alphas are obtained by regressing raw returns on FF6 factors. The t-statistics are reported in the parenthesis below the coefficients. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively. The sample period is 2009:06 to 2021:12.

Table 7: Contemporaneously Sorted U.S. Portfolios

	Panel A: Emission Growth Sorted Portfolios							
	Scope 1				Scope 2			
	A.1 Contemporaneous Return Relation							
	L	2	H	H-L	L	2	H	H-L
ΔEmissions	0.89***	0.91***	1.30***	0.41***	0.78**	0.93***	1.38***	0.60***
	(2.83)	(3.28)	(4.15)	(2.91)	(2.50)	(3.39)	(4.40)	(4.44)
α	-0.02	0.08	0.37***	0.39***	-0.11	0.10	0.43***	0.54***
	(-0.19)	(1.27)	(4.81)	(2.97)	(-1.37)	(1.59)	(4.62)	(4.66)
	A.2 Controlling for Future Sales Growth							
	L	2	H	$HML_{\Delta Sales}$	L	2	H	$HML_{\Delta Sales}$
Portfolio L	0.50	1.15***	1.44***	0.95***	0.43	1.06***	1.34***	0.91***
	(1.33)	(3.93)	(4.73)	(3.97)	(1.21)	(3.66)	(4.28)	(3.86)
2	0.49	0.92***	1.57***	1.08***	0.47	1.01***	1.56***	1.09***
	(1.34)	(3.39)	(4.65)	(4.29)	(1.27)	(3.84)	(4.60)	(4.56)
H	0.63*	1.00***	1.59***	0.96***	0.55	1.02***	1.75***	1.19***
	(1.72)	(3.65)	(4.18)	(3.26)	(1.53)	(3.57)	(4.61)	(3.86)
$HML_{\Delta Emissions}$	0.14	-0.15	0.15		0.12	-0.04	0.40**	
	(0.65)	(-1.13)	(0.75)		(0.64)	(-0.30)	(1.98)	
α	0.06	-0.18	0.14		0.03	-0.07	0.49**	
	(0.27)	(-1.30)	(0.67)		(0.14)	(-0.53)	(2.38)	
	Panel B: Total Emission Sorted Portfolios							
	B.1 Contemporaneous Return Relation							
Emissions	1.19***	1.04***	1.02***	-0.17	1.15***	1.18***	0.98***	-0.18
	(3.32)	(3.09)	(3.80)	(-0.96)	(3.55)	(3.63)	(3.44)	(-1.28)
α	0.31***	0.17**	0.13*	-0.18	0.32***	0.24***	0.09**	-0.22**
	(3.33)	(2.10)	(1.81)	(-1.43)	(3.10)	(3.29)	(2.23)	(-2.11)
	B.2 Controlling for Future Sales Growth							
	L	2	H	$HML_{\Delta Sales}$	L	2	H	$HML_{\Delta Sales}$
Portfolio L	0.73*	1.01***	1.64***	0.92***	0.63*	0.96***	1.56***	0.93***
	(1.82)	(3.00)	(4.47)	(4.05)	(1.80)	(3.25)	(4.17)	(3.94)
M	0.58	1.07***	1.65***	1.06***	0.70*	1.03***	1.66***	0.96***
	(1.38)	(3.48)	(4.65)	(3.82)	(1.90)	(3.40)	(4.58)	(4.27)
H	0.54*	1.03***	1.50***	0.95***	0.42	1.05***	1.49***	1.07***
	(1.66)	(4.14)	(4.58)	(3.85)	(1.18)	(4.02)	(4.62)	(4.39)
α	-0.31	0.00	-0.16		-0.38**	0.05	-0.14	
	(-1.45)	(0.03)	(-0.70)		(-2.15)	(0.32)	(-0.59)	

Notes: This table shows monthly value-weighted U.S. portfolio returns sorted by one-month lagged emission growth and total emissions. Panel A presents the portfolio returns sorted by carbon variables, and Panel B presents the portfolio returns double-sorted by sales growth and carbon variables sequentially. The t-statistics are reported in the parenthesis below the coefficients. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively. The sample period is 2009:06 to 2021:12.

Table 8: Carbon Returns, Emissions, and Forward-Looking Sales Information

	Scope 1	2	1	2	1	2	1	2
ΔEmissions$_\tau$	0.24***	0.21***	0.01	-0.05*				
	(5.96)	(4.53)	(0.15)	(-1.71)				
Log Emissions$_\tau$					0.19*	0.23**	-0.06	-0.02
					(1.84)	(2.38)	(-0.91)	(-0.37)
ΔSales$_\tau$			1.10***	1.19***			1.08***	1.08***
			(4.78)	(5.39)			(6.37)	(6.36)
Log Sales$_\tau$			0.14*	0.14*			0.16**	0.15*
			(1.71)	(1.70)			(2.08)	(1.81)
Beta	0.07	0.07	0.08	0.08	0.03	0.03	0.04	0.04
	(0.49)	(0.52)	(0.54)	(0.54)	(0.24)	(0.23)	(0.29)	(0.29)
Size	-0.01	-0.01	-0.14	-0.14	-0.15*	-0.19**	-0.21*	-0.21*
	(-0.11)	(-0.14)	(-1.14)	(-1.14)	(-1.72)	(-2.01)	(-1.82)	(-1.81)
Book-to-Market	0.05	0.04	-0.00	-0.00	-0.01	-0.03	0.02	0.02
	(0.34)	(0.30)	(-0.00)	(-0.00)	(-0.08)	(-0.22)	(0.13)	(0.12)
Leverage	0.03	0.02	0.01	0.01	0.01	0.01	0.01	0.01
	(1.42)	(1.41)	(0.79)	(0.79)	(0.86)	(0.66)	(0.79)	(0.78)
Momentum	0.30	0.31	0.21	0.21	0.27	0.27	0.18	0.17
	(1.06)	(1.07)	(0.72)	(0.71)	(1.05)	(1.05)	(0.68)	(0.68)
Asset Growth	-0.13	-0.12	-0.24*	-0.23*	-0.08	-0.07	-0.23*	-0.23*
	(-0.98)	(-0.92)	(-1.72)	(-1.71)	(-0.64)	(-0.56)	(-1.76)	(-1.77)
Log PPE	-0.00	-0.00	-0.00	-0.00	0.01	0.01	0.01	0.01
	(-0.10)	(-0.08)	(-0.16)	(-0.17)	(0.73)	(0.73)	(0.68)	(0.68)
ROA	-0.01	-0.02	-0.06	-0.06	-0.58	-0.63	-0.31	-0.30
	(-0.01)	(-0.04)	(-0.09)	(-0.10)	(-0.94)	(-1.04)	(-0.49)	(-0.49)
IVol	0.25*	0.25*	0.27*	0.27*	0.25*	0.24*	0.28**	0.28**
	(1.69)	(1.69)	(1.87)	(1.87)	(1.83)	(1.82)	(2.03)	(2.03)
Industry FE	Y	Y	Y	Y	Y	Y	Y	Y
Time FE	Y	Y	Y	Y	Y	Y	Y	Y
R^2	0.18	0.18	0.18	0.18	0.17	0.17	0.17	0.17
Observations	224392	224392	223903	223903	252949	252949	251480	251480

Notes: This table first replicates the results of regressing stock returns on one-month lagged carbon emissions and emission growth as in BK (2022) and then controls for the forward-looking sales information measured over the same emission period. Controls include beta, size, book-to-market, ROA, asset growth, momentum, leverage, log PPE, ROA and idiosyncratic volatility. The standard errors are double clustered the firm and time level. The t-statistics are reported in the parenthesis below the coefficients. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively. The sample period is 2009:06 to 2021:12.

Table 9: International Carbon Returns

	Panel A: Country-Level Raw Returns							
	Equal-Weighted				Value-Weighted			
	All	G7 + AUS	DM	EM	All	G7 + AUS	DM	EM
Scope 1	0.00	-0.25**	-0.07	0.05	-0.03	-0.23***	-0.15**	0.23***
	(0.07)	(-2.34)	(-0.92)	(0.54)	(-0.81)	(-2.77)	(-2.56)	(3.94)
Scope 2	0.02	-0.15	-0.00	0.04	-0.05	-0.15*	-0.13**	0.12**
	(0.35)	(-1.58)	(-0.02)	(0.40)	(-1.30)	(-1.84)	(-2.27)	(1.97)
	Panel B: Country-Level Carbon Alphas							
Scope 1	-0.05	-0.36***	-0.25***	0.08	-0.14***	-0.33***	-0.28***	0.20***
	(-0.73)	(-3.81)	(-3.30)	(0.86)	(-3.75)	(-4.20)	(-5.38)	(3.55)
Scope 2	0.00	-0.26***	-0.13*	0.09	-0.16***	-0.25***	-0.26***	0.06
	(0.07)	(-2.94)	(-1.79)	(0.97)	(-4.34)	(-3.29)	(-5.01)	(0.99)
	Panel C: Stock-Level Regression Analysis							
	All		G7 + AUS		DM		EM	
Scope 1	-0.10***		-0.19***		-0.10***		-0.07	
	(-2.90)		(-4.13)		(-2.77)		(-1.40)	
Scope 2		-0.05		-0.08*		-0.09**		0.03
		(-1.59)		(-1.68)		(-2.49)		(0.36)
Controls	Y	Y	Y	Y	Y	Y	Y	Y
Country FE	Y	Y	Y	Y	Y	Y	Y	Y
Time FE	Y	Y	Y	Y	Y	Y	Y	Y
R^2	0.23	0.23	0.28	0.28	0.27	0.27	0.21	0.21
Observations	700230	700230	280796	280796	402653	402653	297577	297577

Note: This table presents results of the international (excluding the U.S.) carbon returns. Panel A and B present raw and FF6 factor-adjusted international excess returns weighting the countries equally or by the total market capitalization. Panel C conducts the weighted least square regression of stock returns on lagged carbon intensities in various international samples. The controls include a number of firm characteristics, including oil exposure, natural gas exposure, commodity exposure, beta, size, book-to-market, ROA, asset growth, momentum, leverage, log PPE, sales growth, and EPS growth. The regression controls for the time and country fixed effects. The standard errors are doubly clustered at the firm and monthly level, accordingly. The t-statistics are reported in the parenthesis below the coefficients. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively. The sample period is 2009:06 to 2021:12.

Table 10: Carbon Return Variations

	Panel A: In-Sample Shocks							
	Scope 1				Scope 2			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
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	0.78***	0.79***	0.77***	0.78***	0.70***	0.71***	0.69***	0.71***
	(8.63)	(8.62)	(8.53)	(8.46)	(6.46)	(6.42)	(6.41)	(6.39)
ΔSales_{t+1}	0.48	0.49	0.27	0.53	0.43	0.44	0.24	0.47
	(1.40)	(1.41)	(0.80)	(1.47)	(1.19)	(1.23)	(0.68)	(1.28)
$\Delta E_t[\text{EPS}_{t+1}]$	4.07***	3.87***	3.65***	3.98***	4.72***	4.68***	3.94***	4.71***
	(3.21)	(3.10)	(2.88)	(3.15)	(3.61)	(3.56)	(3.15)	(3.45)
$\Delta E_t[\text{LTG}]$	0.19	0.16	0.15	0.17	0.18	0.14	0.12	0.22
	(0.83)	(0.71)	(0.66)	(0.73)	(0.62)	(0.51)	(0.41)	(0.76)
Oil Exposure	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01
	(-1.39)	(-1.29)	(-1.24)	(-1.41)	(-1.44)	(-1.47)	(-1.51)	(-1.48)
Natural Gas Exposure	-0.02	-0.02	-0.02	-0.02	-0.02	-0.02	-0.03	-0.01
	(-1.28)	(-1.12)	(-1.61)	(-1.34)	(-1.17)	(-1.11)	(-1.63)	(-0.88)
Commodity Exposure	-0.00	-0.00	0.00	-0.00	-0.00	-0.00	-0.00	-0.00
	(-0.48)	(-0.45)	(0.79)	(-0.85)	(-0.71)	(-0.57)	(-0.16)	(-0.97)
Time FE	Y	Y	Y	Y	Y	Y	Y	Y
R^2	0.07	0.07	0.07	0.07	0.06	0.06	0.06	0.06
Observations	7535	7325	6571	7045	7535	7325	6571	7045
	Panel B: Additional Country Characteristics							
Policy	0.13**				0.10			
	(2.12)				(1.33)			
1(Civil Law)		0.55***				0.41**		
		(3.38)				(2.52)		
% Renewable Energy			0.20**				0.16**	
			(2.60)				(2.08)	
% Brown Sales				-0.05				0.06
				(-0.51)				(0.54)
Controls	Y	Y	Y	Y	Y	Y	Y	Y
Time FE	Y	Y	Y	Y	Y	Y	Y	Y
R^2	0.12	0.08	0.08	0.08	0.09	0.07	0.06	0.06
Observations	4376	6033	6033	6033	4376	6033	6033	6033

Notes: This table studies the variations of 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 the standard errors are clustered at the monthly level. The t-statistics are reported in the parenthesis below the coefficients. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively. The sample period is 2009:06 to 2021:12.

Internet Appendix to
"Carbon Returns Across the Globe"

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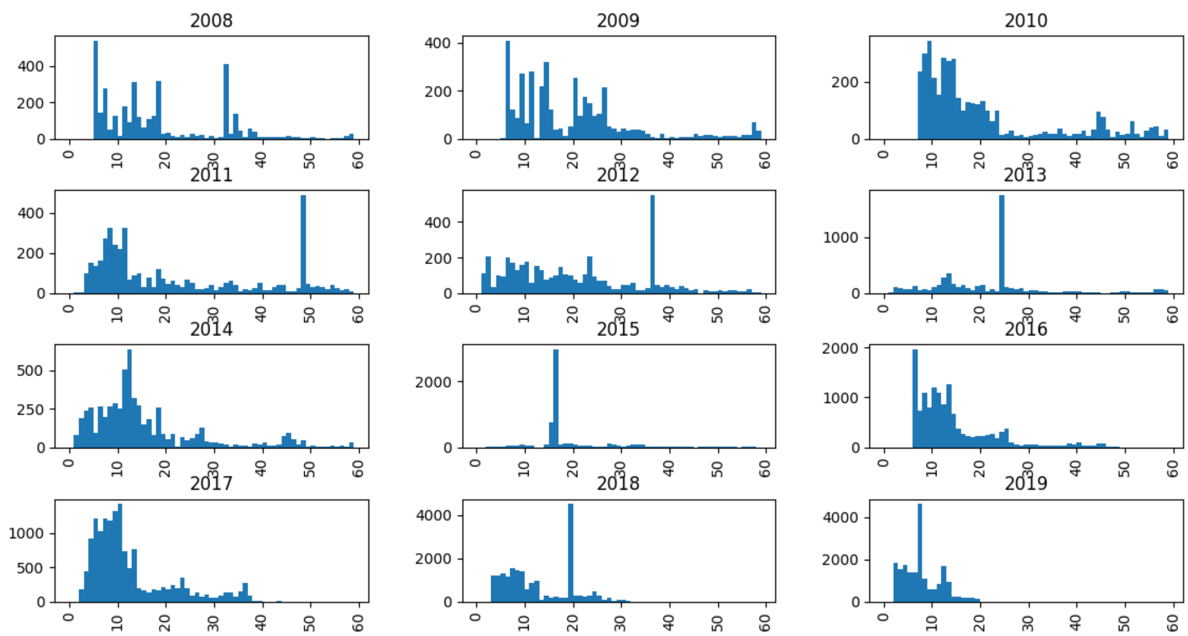
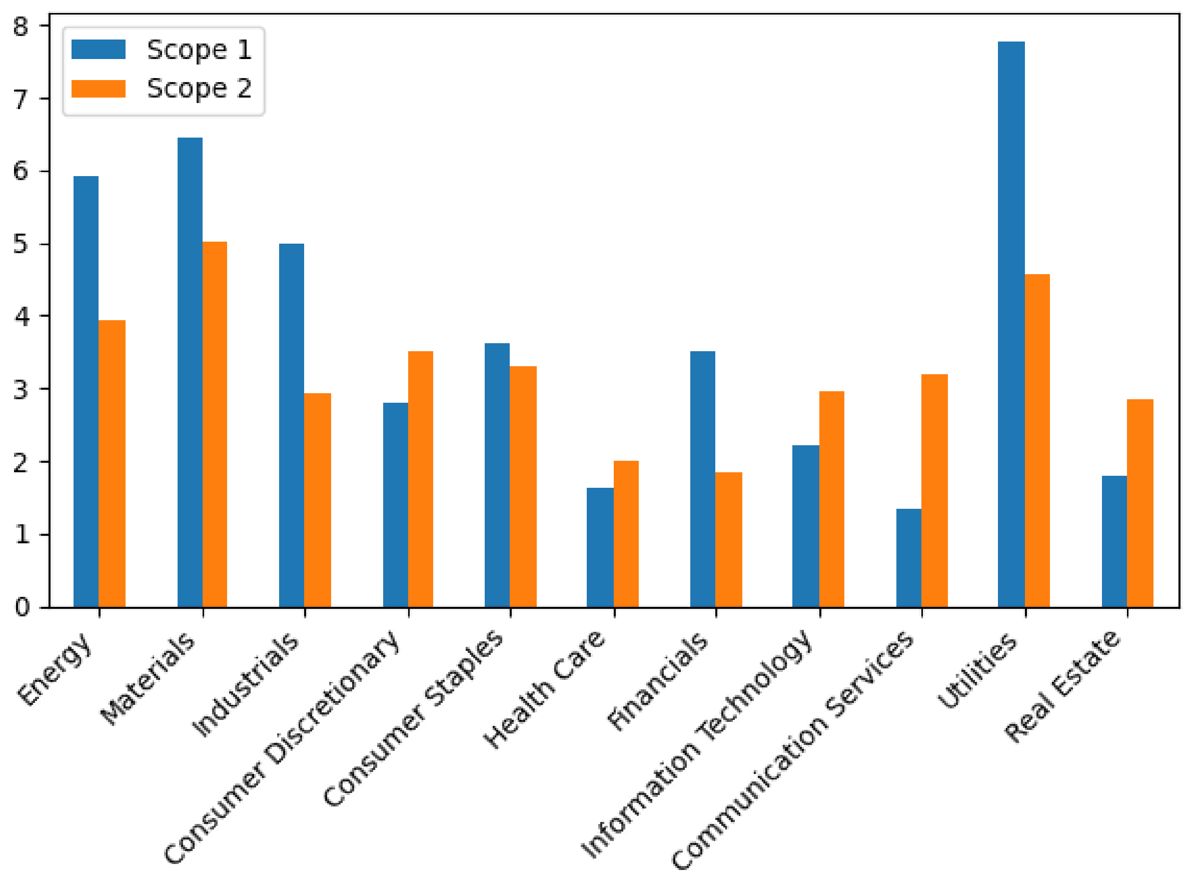
This document contains the supplementary results for the paper "Carbon Returns Across the Globe".

Figure IA.1: Reporting Lags By Year



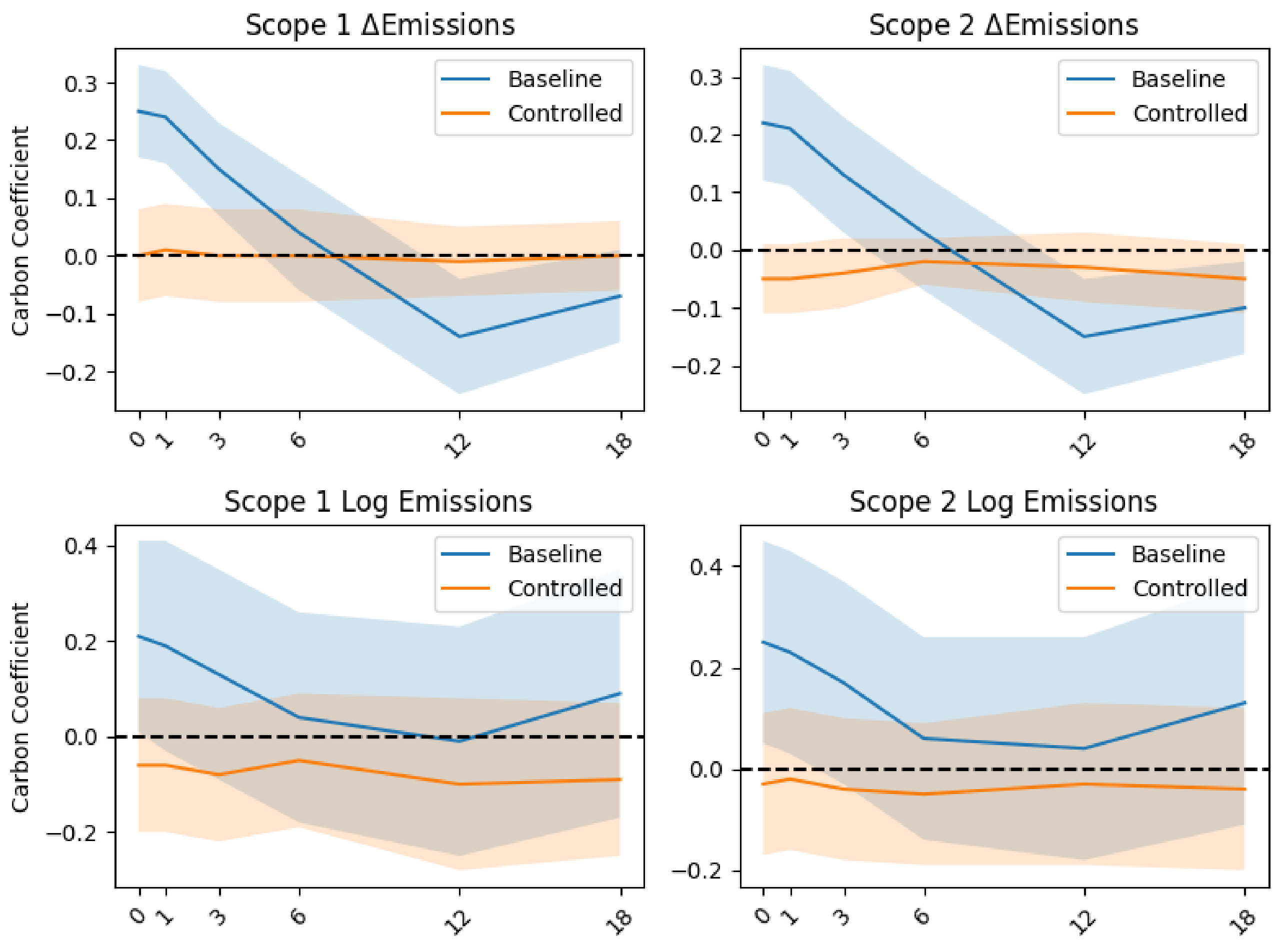
Notes: This figure plots the tabulation of the U.S. reporting lags for scope 1 carbon emissions by year.

Figure IA.2: Carbon Intensity Across Industries



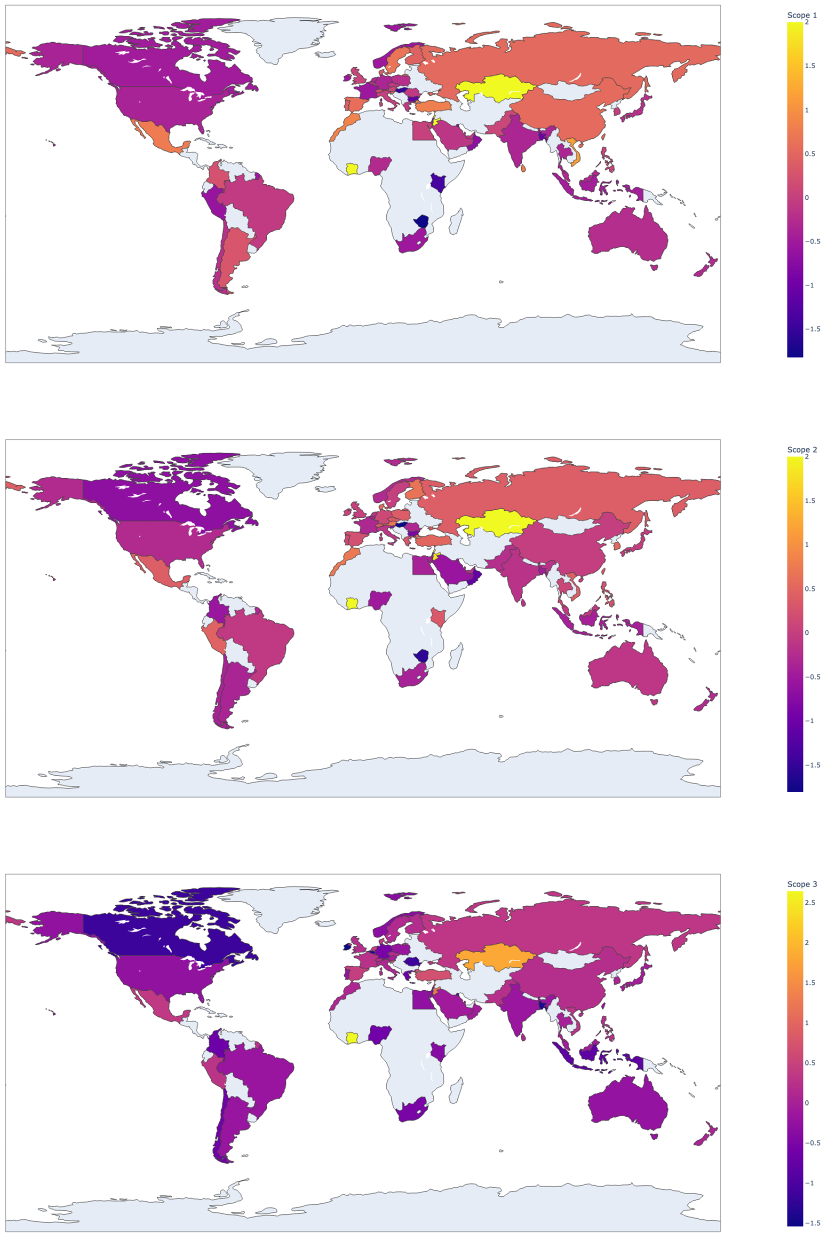
Notes: This figure plots U.S. industry-level log carbon intensities for the scope 1 and 2 in 2019.

Figure IA.3: U.S. Carbon Returns and Forward-Looking Sales Information



Notes: This figure ("Baseline") first plots the baseline coefficients in BK (2021, 2022) by regressing U.S. stock returns on x-month lagged emission growth and log emissions. Controls include beta, size, book-to-market, ROA, asset growth, momentum, leverage, log PPE, ROA, and idiosyncratic volatility. The orange line in the figure ("Controlled") further plots the corresponding coefficients after controlling for the forward-looking sales information during the same period of emissions (log sales and sales growth). The regressions include industry and time-fixed effects. The standard errors are double clustered at the firm and time level, and the shaded area denotes the 95% confidence intervals. The sample period is 2009:06 to 2021:12.

Figure IA.4: Country-Level Raw Returns



Notes: This figure plots the raw return spreads between high and low-carbon-intensity portfolios for each country. The raw returns are in percentage points.

Table IA.1: Controlling for Commodity Exposures: Carbon Intensity-Sorted Portfolios

	Scope 1				Scope 2			
	L	2	H	H-L	L	2	H	H-L
α	0.17**	0.10	-0.28***	-0.45***	0.24***	0.00	-0.17**	-0.41***
	(2.45)	(1.31)	(-2.68)	(-2.87)	(3.19)	(0.01)	(-2.08)	(-3.04)
MKT	1.05***	0.99***	0.94***	-0.11***	1.02***	1.01***	0.98***	-0.04
	(55.50)	(46.24)	(33.99)	(-2.62)	(50.64)	(62.97)	(45.59)	(-1.23)
SMB	-0.14***	0.07**	0.03	0.17**	-0.04	-0.08***	0.05	0.09
	(-4.49)	(2.04)	(0.62)	(2.44)	(-1.35)	(-3.09)	(1.30)	(1.53)
HML	0.13***	-0.20***	0.05	-0.08	0.08**	-0.04	-0.02	-0.10
	(3.96)	(-5.51)	(1.00)	(-1.13)	(2.22)	(-1.36)	(-0.58)	(-1.60)
RMW	-0.18***	0.15***	0.11*	0.29***	-0.06	-0.07**	0.17***	0.23***
	(-4.72)	(3.38)	(1.87)	(3.37)	(-1.38)	(-2.12)	(3.90)	(3.11)
CMA	-0.13***	0.25***	0.18**	0.32***	-0.12**	0.02	0.27***	0.39***
	(-2.65)	(4.41)	(2.52)	(2.86)	(-2.24)	(0.58)	(4.78)	(4.12)
MOM	-0.01	0.03	-0.06*	-0.05	0.00	-0.03*	0.00	-0.00
	(-0.47)	(1.24)	(-1.80)	(-0.98)	(0.17)	(-1.88)	(0.08)	(-0.04)
Natural Gas	-0.68*	-0.46	1.01*	1.69*	-1.06**	-0.02	0.86*	1.92**
	(-1.74)	(-1.06)	(1.78)	(1.96)	(-2.57)	(-0.07)	(1.95)	(2.61)
Oil	0.28	0.73	-1.61	-1.89	2.82***	-0.96	-2.61***	-5.43***
	(0.32)	(0.75)	(-1.26)	(-0.98)	(3.05)	(-1.31)	(-2.66)	(-3.31)
Commodity	-17.38**	3.93	26.07**	43.44**	-20.15**	1.40	25.53***	45.68***
	(-2.03)	(0.41)	(2.08)	(2.29)	(-2.21)	(0.19)	(2.64)	(2.82)
R^2	0.97	0.96	0.93	0.25	0.97	0.98	0.96	0.33
Observations	151	151	151	151	151	151	151	151

Notes: This table presents monthly alphas of the intensity-sorted portfolios after controlling for FF6 and commodity factors. The t-statistics are reported in the parenthesis below the coefficients. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively. The sample period is 2009:06 to 2021:12.

Table IA.2: Alternative Lags: 10 Month

	Scope 1				Scope 2			
Raw Return	1.47***	1.38***	1.04***	-0.43***	1.48***	1.34***	1.19***	-0.29**
	(4.12)	(4.33)	(3.07)	(-2.64)	(4.19)	(4.01)	(3.60)	(-2.03)
α	0.18**	0.08	-0.25**	-0.43***	0.21***	0.04	-0.11	-0.32**
	(2.58)	(1.08)	(-2.46)	(-2.71)	(2.65)	(0.65)	(-1.33)	(-2.25)

Notes: This table presents monthly value-weighted returns of the carbon-sorted portfolios. The sorting variables are the scope 1 and 2 intensities lagged by 10 months from the fiscal year-end, that is, to use year t emissions in October year t+1. The t-statistics are reported in the parenthesis below the coefficients. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively. The sample period is 2009:11 to 2021:12.

Table IA.3: Contemporaneously Sorted International Portfolios

	Panel A: Carbon Sorted Portfolios							
	Scope 1				Scope 2			
	L	2	H	H-L	L	2	H	H-L
ΔEmissions	0.68**	0.85***	1.08***	0.40***	0.64*	0.91***	1.05***	0.41***
	(2.01)	(2.70)	(3.13)	(3.59)	(1.85)	(2.89)	(3.08)	(3.56)
Emissions	0.95**	0.90***	0.84***	-0.11	0.94***	0.91***	0.85**	-0.09
	(2.59)	(2.65)	(2.61)	(-0.93)	(2.70)	(2.70)	(2.59)	(-0.90)
	Panel B: ΔSales-and-Emission Sorted Portfolios							
	B.1. ΔEmissions							
	L	2	H	$\text{HML}_{\Delta Sales}$	L	2	H	$\text{HML}_{\Delta Sales}$
Portfolio L	0.40	0.81**	1.18***	0.78***	0.41	0.71**	1.19***	0.79***
	(1.09)	(2.54)	(3.58)	(5.32)	(1.11)	(2.14)	(3.56)	(5.46)
2	0.48	0.90***	1.24***	0.76***	0.54	0.84***	1.19***	0.65***
	(1.41)	(3.05)	(3.76)	(4.79)	(1.60)	(2.81)	(3.77)	(3.87)
H	0.56	0.87**	1.30***	0.74***	0.47	0.98***	1.37***	0.90***
	(1.57)	(2.53)	(3.53)	(3.61)	(1.31)	(3.05)	(3.67)	(4.09)
$\text{HML}_{\Delta Emissions}$	0.17	0.06	0.12		0.06	0.26**	0.18	
	(1.51)	(0.50)	(0.74)		(0.52)	(2.37)	(1.03)	
	B.2. Total Emissions							
Portfolio L	0.41	0.87***	1.48***	1.07***	0.38	0.93***	1.53***	1.16***
	(1.12)	(2.60)	(4.05)	(6.71)	(1.08)	(2.98)	(4.28)	(8.35)
2	0.50	0.88***	1.34***	0.83***	0.44	0.85***	1.40***	0.96***
	(1.37)	(2.84)	(4.13)	(4.19)	(1.30)	(2.73)	(4.25)	(6.47)
H	0.47	0.88***	1.19***	0.72***	0.49	0.87***	1.19***	0.70***
	(1.36)	(2.79)	(3.48)	(4.30)	(1.38)	(2.73)	(3.54)	(3.99)
$HML_{Emissions}$	0.06	0.01	-0.29*		0.12	-0.06	-0.34**	
	(0.39)	(0.10)	(-1.70)		(0.85)	(-0.50)	(-2.06)	

Notes: This table shows monthly value-weighted global portfolio returns sorted by one-month lagged emission growth and total emissions. Panel A presents the portfolio returns sorted by carbon variables, and Panel B presents the portfolio returns double-sorted by sales growth and carbon variables sequentially. The t-statistics are reported in the parenthesis below the coefficients. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively. The sample period is 2009:06 to 2021:12.

Table IA.4: Carbon Returns, Emissions, and Sales: International Evidence

	Panel A: With Industry FE							
	Scope 1	2	1	2	1	2	1	2
ΔEmissions$_\tau$	0.16***	0.13***	-0.04**	-0.08***				
	(8.32)	(6.42)	(-1.99)	(-4.47)				
Log Emissions$_\tau$					0.12***	0.21***	-0.12***	-0.02
					(2.65)	(4.68)	(-3.68)	(-0.65)
ΔSales$_\tau$			1.67***	1.72***			1.42***	1.42***
			(11.02)	(11.28)			(11.18)	(11.19)
Log Sales$_\tau$			0.15***	0.15***			0.19***	0.16***
			(3.39)	(3.38)			(4.37)	(3.46)
Additional Controls	Y	Y	Y	Y	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y	Y	Y	Y	Y
Time FE	Y	Y	Y	Y	Y	Y	Y	Y
R^2	0.18	0.18	0.17	0.17	0.17	0.17	0.17	0.17
Observations	1011679	1011679	869416	869416	1119066	1119066	959759	959759
	Panel A: Without Industry FE							
	Scope 1	2	1	2	1	2	1	2
ΔEmissions$_\tau$	0.16***	0.13***	-0.04**	-0.08***				
	(8.01)	(6.20)	(-2.12)	(-4.31)				
Log Emissions$_\tau$					0.03	0.13***	-0.11**	-0.02
					(0.66)	(2.68)	(-2.02)	(-0.41)
ΔSales$_\tau$			1.67***	1.71***			1.42***	1.42***
			(11.01)	(11.23)			(11.35)	(11.35)
Log Sales$_\tau$			0.13***	0.13***			0.17***	0.14***
			(3.32)	(3.30)			(4.06)	(3.07)
Additional Controls	Y	Y	Y	Y	Y	Y	Y	Y
Industry FE	N	N	N	N	N	N	N	N
Time FE	Y	Y	Y	Y	Y	Y	Y	Y
R^2	0.18	0.18	0.17	0.17	0.17	0.17	0.16	0.16
Observations	1011679	1011679	869416	869416	1119066	1119066	959759	959759

Notes: This table first replicates the results of regressing global stock returns on one-month-lagged carbon emissions and emission growth as in BK (2022) and then controls for the forward-looking sales information contained in the emissions. Controls include beta, size, book-to-market, ROA, asset growth, momentum, leverage, log PPE, ROA, and idiosyncratic volatility. The standard errors are double clustered at the firm and time level. The t-statistics are reported in the parenthesis below the coefficients. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively. The sample period is 2009:06 to 2021:12.

Table IA.5: FF49 Sorted U.S. Portfolios

	Panel A: Industry-level Intensity							
	Scope 1				Scope 2			
	L	2	H	H-L	L	2	H	H-L
Raw Return	1.43***	1.50***	1.10***	-0.33**	1.32***	1.47***	1.23***	-0.09
	(4.06)	(4.43)	(3.10)	(-2.01)	(3.61)	(4.49)	(3.35)	(-0.53)
Alpha	0.18**	0.09	-0.20*	-0.37**	0.13	0.13	-0.22**	-0.35**
	(2.30)	(1.08)	(-1.76)	(-2.20)	(1.35)	(1.54)	(-2.29)	(-2.12)
	Panel B: Industry-Level Analysis							
Raw Return	1.50***	1.49***	1.10***	-0.40**	1.43***	1.44***	1.22***	-0.21
	(4.16)	(3.96)	(2.66)	(-2.23)	(4.07)	(3.92)	(2.81)	(-1.07)
α	0.16**	0.11	-0.27	-0.43**	0.16*	0.06	-0.22	-0.38*
	(2.29)	(1.05)	(-1.63)	(-2.38)	(1.92)	(0.59)	(-1.24)	(-1.92)
	Panel C: Within-Industry Firm-level Intensity							
Raw Return	1.40***	1.35***	1.31***	-0.09	1.50***	1.30***	1.31***	-0.19
	(3.92)	(3.87)	(3.97)	(-0.86)	(4.30)	(3.92)	(3.77)	(-1.65)
Alpha	0.03	0.04	0.02	-0.00	0.13	0.03	-0.02	-0.15
	(0.40)	(0.67)	(0.36)	(-0.04)	(1.58)	(0.51)	(-0.36)	(-1.30)

Notes: This table presents monthly raw returns and FF6 alphas of industry-level and firm-level sorted portfolios. The industries are defined by the FF49 industries. Panel A conducts individual stock sorts using the industry-level carbon intensities, Panel B conducts industry sorts using industry-level carbon intensities, and Panel C conducts individual stock sorts the within-industry firm-level carbon intensities. The t-statistics are reported in the parenthesis below the coefficients. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively. The sample period is 2009:06 to 2021:12.

Table IA.6: Carbon Returns and Climate News Shocks

	Scope 1			Scope 2		
ΔClimate Concerns (same month)	0.53		6.23	-1.86		3.43
	(0.06)		(0.66)	(-0.18)		(0.33)
ΔClimate Concerns (prev. month)		-26.64***	-24.85**		-22.74**	-23.10**
		(-2.92)	(-2.50)		(-2.24)	(-2.08)
R^2	0.00	0.06	0.04	0.00	0.03	0.03
Observations	144	145	144	144	145	144

Notes: This table regresses the carbon intensity-sorted industry returns on climate news shocks. The robust t-statistics are reported in the parenthesis below the coefficients. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively. The sample period is 2009:06 to 2021:05. The climate news shocks are calculated following Pastor, Stambaugh, and Taylor (2022) and build on climate news constructed by Ardia et al. (2022).