GREENHOUSE GAS EMISSIONS AND STOCK RETURNS

ASSESSING EMISSION TYPE, FIRM SIZE, AND REGIONAL DIFFERENCES

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Abstract:

This paper investigates the relationship between greenhouse gas (GHG) emissions and stock returns, addressing the ongoing debate over the existence of a carbon premium, namely, whether investors demand higher returns for holding fossil fuel-intensive stocks. Although research on this topic is expanding, results remain inconclusive, often due to variations in methodological approaches. First, we contribute to the existing literature by examining the baseline relationship between GHG emissions and stock returns, and by comparing vendor-estimated and reported GHG emissions. Second, we extend the literature by assessing the moderating effects of firm size and exploring regional differences between the U.S. and Europe based on the constructed models. Our findings support the evidence of a carbon premium for both reported and vendor-estimated emissions; however, the relationship remains sensitive to research design choices. We observe that firm size moderates the relationship, while evidence from the European sample is less statistically significant compared to that of the U.S.

Keywords:

Greenhouse Gas Emissions; Emission Types; Stock Returns; Firm Size; Regional Differences

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1. Introduction

The main purpose of our paper is to investigate the relationship between greenhouse gas emissions (GHG) and stock returns. The extent to which investors incorporate GHG emissions when pricing stocks has become a prominent topic which attracts growing attention. This growing interest can, in part, be attributed to major regulatory developments, most notably the Paris Agreement, which aims to limit global warming to well below 2°C above pre-industrial levels (United Nations Climate Change, n.d). In the wake of the Paris Agreement, engagement from institutional investors to reduce carbon emissions has gained momentum. For example, the United Nations' Net-Zero Asset Owner Alliance, founded in 2019, is a member-led initiative of institutional investors committed to achieving net-zero GHG emissions across their investment portfolios by 2050 (United Nations Environment Programme, n.d). Initiatives such as this, along with attention from policymakers – including the Paris Agreement and the legally binding emissions targets introduced by the EU in the Fit for 55 climate law package (European Council, 2025) – motivate research into whether the transition toward a carbon-neutral economy is reflected in the cross-sectional pattern of stock returns, and whether there exists a carbon risk premium associated with fossil fuel-intensive firms. However, despite the growing body of research, no definitive conclusion has emerged, as the evidence points to mixed, and sometimes contradictory results.

According to Aswani, Raghunandan, and Rajgopal (2024), prevailing literature on the topic presents two economic arguments as to why fossil fuel-intensive firms would earn a premium: (i) the risk-driven argument and (ii) the investor-preference argument. From the risk-driven perspective, the hypothesis is that fossil fuel-intensive firms are subject to greater risk, and investors therefore demand higher returns for investing in such firms. Aswani et al. (2024) emphasizes regulatory risks, being defined as changes in environmental regulation. First, it is unclear how fossil fuel-intensive firms will adapt to such regulatory changes. For example, Bolton and Kacperczyk (2021) argue that firms reliant on fossil fuels are more exposed to technological risks posed by cheaper renewable energy. This would be especially true if they are unable to switch easily to such alternatives. In theory, this could also be mandated by future regulations, further affecting the relative competitiveness of such firms. Second, Aswani et al. (2024) highlights the uncertainty surrounding which specific regulatory changes will be implemented. Finally, Bolton and Kacperczyk (2021) point out that firms reliant on fossil fuels are more exposed to volatile commodity prices. Theoretically, these risks and uncertainties should lead investors to demand higher returns for investing in such firms. Supporting this view, Pastor, Stambaugh, and Taylor (2021) find that fossil fuel-intensive firms face a higher cost of debt and equity capital. Similarly, Chava (2010), with a broader environmental focus, finds similar results for firms associated with environmental concerns. Furthermore, Hengge, Panizza, and Varghese (2023) examine the effects of policy changes, showing that policies that increase carbon prices raise the cost of equity for firms reliant on fossil fuels. Taken together, these studies reinforce the validity of the risk-driven perspective.

As for the investor-preference perspective, Aswani et al. (2024) argues that investors might treat fossil fuel-intensive stocks like "sin" stocks due to evolving societal norms. Globally, as of 2022, 30.3 trillion USD is invested in sustainable assets, with a 20% increase in non-U.S. markets since 2020, lending weight to the evolution of such norms (Global Sustainable Investment Alliance, 2025). Returning to the proposed "sin" stock treatment, Hong and Kacperczyk (2009) conclude that "sin" stocks have higher returns due to investor neglect. This is explained by the fact that when investors avoid a group of stocks, the resulting decline in demand depresses prices, thereby increasing expected returns. Furthermore, Pedersen, Fitzgibbons, and Pomorski (2021) find that even a modest dispersion to ESG preferences can result in under-pricing. If such occurs in practice, it strengthens the argument presented by Aswani et al. (2024).

With this background, we explore the risk-driven perspective in further detail. An influential paper taking this perspective is "Do investors care about carbon risk?" by Bolton and Kacperczyk (2021). For unscaled Scope 1, Scope 2, and Scope 3 emissions, they find a significant and positive relationship with stock returns. Here, a classification of the different types of emissions is warranted: Scope 1 emissions refer to GHG emissions from sources directly controlled by a company; Scope 2 emissions are indirect GHG emissions, including those from the consumption of electricity, heating, and cooling; and Scope 3 emissions encompass GHG emissions arising from upstream and downstream activities across the value chain (McKinsey & Company, 2024). The evidence documented by Bolton and Kacperczyk (2021) is termed a carbon risk premium, meaning that investors demand higher returns for firms with higher levels of GHG emissions. For the same emission categories, they also find that the growth in annual GHG emissions is positive and significant. Finally, they test the significance of emission intensity, defined as the ratio of the emissions measure of interest to the company's total revenue. In doing so, Bolton and Kacperczyk (2021) fail to find significant results, suggesting that such measures are not correlated with stock returns. They offer three potential explanations for these findings: First, they argue that regulations are more likely to target unscaled emissions, since climate goals are typically framed in absolute rather than relative terms. Second, renewables might first displace fossil fuels where returns to scale are the highest. This implies that large emitters could face greater pressure to adapt, as their total emissions make them targets for change. Third, they argue that emission intensity variables, being ratios, might introduce noise into the model. The study is later extended to a global setting, where similar results are observed (Bolton and Kacperczyk, 2023).

Aswani et al. (2024) critique these findings, arguing that the results presented by Bolton and Kacperczyk (2021, 2023) should be interpreted with caution. First, they criticize the use of vendor-estimated GHG emissions, arguing that these differ systematically from reported emissions. This criticism is raised because Bolton and Kacperczyk (2021) utilize a combination of both. Using only reported emissions, Aswani et al. (2024) find little evidence of a significant relationship between GHG emissions and stock returns. In contrast, when using vendor-estimated emissions, the results are similar to those reported by Bolton and Kacperczyk (2021). Second, Aswani et al. (2024) criticize the lack of focus on emission intensity, arguing that conclusions based on unscaled emissions are misaligned with societal objectives. For example, they suggest that a carbon tax would likely scale with firm size, making emission intensity a more appropriate measure for drawing such conclusions.

In response to these critiques, Bolton and Kacperczyk (2024) provide several counterarguments. Regarding estimated versus reported GHG emissions, they find a robust relationship even when using reported emissions. Furthermore, they observe that the magnitude of the carbon premium has increased over time. If reported emissions grows in availability, as discussed by Aswani et al. (2024), the growth in magnitude appears inconsistent with the claims of insignificance. In addition, Bolton and Kacperczyk (2024) show that the carbon premium based on reported emissions is smaller than that based on vendor-estimated emissions. They argue that this is consistent with empirical expectations, as reported emissions reduce investor uncertainty. In their response, Bolton and Kacperczyk (2024) expand on, and to some extent repeat, their arguments for not placing greater emphasis on emission intensity. First, they claim that emission intensity may make large firms appear more environmentally friendly, despite their larger environmental impact. Second, they point out that net zero-pledges are typically framed in terms of absolute emissions. Finally, they argue that regulatory actions also tend to target absolute emissions.

Zhang (2023) adds to the discussion by exploring the importance of research design, showing that revenue contemporaneously explain 50% of the variation in U.S. Scope 1 emissions, and 71% of the variation in Scope 2 emissions. Based on this, Zhang (2023) concludes that emissions data contain significant information about firm performance. To account for this, and to avoid a look-ahead bias, a data release lag is incorporated. This is deemed important given the finding that emissions data are typically published with a median lag of 10 months in the U.S. and 12 months internationally. With the lag incorporated, Zhang (2023) finds that unscaled emissions and emissions growth are no longer positively correlated with returns. Unlike previous studies, Zhang (2023) concludes that the carbon premium is a result of strong firm performance during the emission period.

As the discussion above highlights, the evidence on the existence and drivers of a carbon premium remains mixed and inconclusive. Building on this, one of our main objectives is to contribute empirical evidence to this ongoing debate. To do so, we utilize the framework presented by Bolton and Kacperczyk (2021) and, to add further depth, incorporate the key critiques discussed above. This leads to the formulation of our four research questions: (i) Is there a statistically significant and economically meaningful relationship between GHG emissions and stock returns? (ii) Are there differences between using vendor-estimated and reported emissions data? (iii) Does firm size moderate the relationship between GHG emissions and stock returns? (iv) Do the results differ between Europe and the U.S? The first two research questions have been investigated in previous literature, however, the third is an extension. The extension is considered relevant due to the importance indirectly attributed to firm size by Bolton and Kacperczyk (2021). Furthermore, the tests are initially made on the U.S. before being extended to Europe, where we hypothesize that differences in climate policy should yield different results. To exemplify, the EU has maintained relative policy stability, whereas the U.S. has a history of instability, best shown through its inconclusive stance on the Paris Agreement (NRDC, 2025). While the aspects presented by Zhang (2023) are not given equal focus, we incorporate them as robustness checks to strengthen our findings.

In conducting our empirical analysis, we, like Bolton and Kacperczyk (2021), perform ordinary least squares (OLS) regressions. Our baseline model regresses monthly stock returns on three alternative measures of firm-level GHG emissions: (a) the natural logarithm of total emissions, (b) the growth rate in emissions, and (c) emissions intensity. This baseline model is designed to address research question (i). To address research question (ii), we extend the baseline model by adding an interaction term between the emissions variable and a binary dummy variable indicating whether the emissions data were disclosed by the company or estimated by the data vendor. Third, to examine whether the relationship varies with firm size, we switch the disclosure-based interaction with an interaction term based on firm size. This size dummy takes the value zero if the company is classified as a small-to-medium-sized enterprise (SME), defined as being in the bottom 75th percentile of average market capitalization over the sample period, and one if classified as a large-cap enterprise (top 25th percentile). Finally, to answer research question (iv), we compare the results from the U.S. sample with those from the European sample to assess whether the observed relationships differ across the two regions. For all models, the dependent variable is the monthly stock return of firm *i*. We also include a host of control variables that, according to Bolton and Kacperczyk (2021), are commonly used as predictors of stock returns. All data used in constructing the variables and conducting our analysis are sourced from Refinitiv Eikon. After merging the datasets, matching observations, and removing observations with missing values for the dependent variable or key firm-level descriptive variables, our final firm-month panel includes 3,393 firms for the U.S. sample and 2,036 firms for the European sample, covering the period from 2015 to 2024.

Starting with the results obtained for the U.S. sample, we find evidence of a carbon premium related to all categories of unscaled emissions. However, this evidence depends on the inclusion of industry fixed effects; without them, little evidence is found. Using growth in unscaled emissions, we find similar results. However, when including the independent variable lag, as suggested by Zhang (2023), the relationship becomes inconclusive and even indicates insignificance. Regarding emission intensity, we find no evidence of a relationship with stock returns. When using an interaction term for reported emissions, we observe significant results in relation to reported unscaled GHG emissions. Furthermore, the premium is smaller when using reported emissions, providing additional evidence that reported emissions reduce uncertainty for investors. With reported emissions, no significant relationship is observed for emissions growth; however, a significantly different relationship does appear. This may imply that the previously documented significant results are driven by vendor-estimated growth in emissions.

As for the moderating effect of firm size, unscaled GHG emissions remain significant. A statistically significant difference is also observed, indicating that the magnitude of the relationship decreases with firm size. The growth variables remain significant; however, no statistical difference is observed. For the European sample, we observe overall less significant results compared to the U.S. We attribute this to the relatively unstable climate policy environment in the U.S., something briefly mentioned already. The only consistently significant results relate to total GHG emissions, which we attribute to regulatory uncertainties in the value chain and/or greater emphasis on Scope 3 emissions, which are included in total GHG emissions.

The empirical insights highlight the need to situate our findings within the broader academic debate, prompting a closer examination of other related literature. Starting with studies that claim an outperformance of more sustainable firms, Görgen, Jacob, Nerlinger, Riordan, Rohleder, and Wilkens (2017) constructs a "brown-minus-green" portfolio, designed to mimic a factor related to carbon risk, finding a negative realized return for this portfolio. Similarly, In, Park, and Monk (2017) find substantial outperformance of "green" stocks over the period 2009 to 2015. Pastor, Stambaugh, and Taylor (2022) gives an explanation, arguing that "green" assets can experience higher returns when investor demand shifts in favour of sustainability, resulting in temporary outperformance. However, when controlling for such demand shifts, Pastor et al. (2022) find that "brown" stocks outperform. Pedersen et al. (2021) show that ESG characteristics can be a positive return predictor if they lead to higher future profits and are not fully priced by the stock market. However, when such characteristics are fully priced in, ESG factors can become a negative return predictor. Hong, Li, and Xu (2019) add to the discussion on market efficiency, showing that forecasted environmental trends in the food industry, an industry sensitive to climate disruptions, can forecast stock returns. In an efficient market, such predictability would not exist. Taken together, most of the cited studies point to the conclusion that fossil fuel-intensive stocks tend to outperform, with observed underperformance largely attributed to various market inefficiencies.

Another important consideration is whether investors genuinely incorporate carbon emissions into their decision-making. Gibson, Glossner, Kreuger, Matos, and Steffen (2022) find that U.S. based signatories to the Principles for Responsible Investment exhibit little to no improvement in their ESG scores. Zhang (2022) notes that the two largest asset managers, BlackRock and Vanguard, have not divested "brown" stocks. Anderson, Bolton, and Samama (2014), focusing on U.S. institutional investors, find that many are unaware of climate risks or their portfolio's carbon footprint, which they attribute to the polarized climate debate in the U.S. Taken together, the evidence remains inconclusive regarding the extent to which investors consider GHG emissions in their decision-making.

2. Data

2.1 Data collection

The main source used to obtain the data for our study is Refinitiv Eikon, a comprehensive database covering over 99% of global market capitalization and spanning more than 25 years of data (LSEG, n.d). We follow the same data collection procedure for both the U.S. and Europe, filtering for public companies listed on U.S. exchanges for the former and European exchanges for the latter. The variables selected to conduct our research include (i) monthly stock price data; (ii) firm-level emissions data; (iii) other financial data, including company betas; (iv) various accounting data, such as the book value of equity; and (v) descriptive firm-level data, such as company identifier, Global Industry Classification Standard (GICS) code, and absolute fiscal year.

Although the universe of companies listed on both U.S. and European exchanges is large, both reported and estimated emissions data remain relatively scarce. Therefore, to arrive at our initial samples, we apply a variety of filters. Specifically, we only retain companies with emissions data available for Scope 1, Scope 2, and total GHG emissions in any of the past eight fiscal years. This produces a sample of 3,413 public companies for the U.S. and 2,120 for Europe. Importantly, we filter based on the presence of *any* emissions data over the period rather than *all*, to avoid an overly restrictive criterion that would significantly reduce the number of companies.

We collect emissions and accounting data based on each company's relative fiscal year, which introduces an important caveat: the most recent data available for different variables may come from different fiscal years. For instance, a firm's latest accounting data might be from fiscal year 2023, while its most recent emissions data could be from 2022. Similarly, the most recent fiscal year available differs across firms – for one company it may be 2023, while for another it is 2022. To address these discrepancies both within and across firms, we match emissions and accounting data using the company identifier and absolute fiscal year. While both emissions and accounting data are obtained on a fiscal year basis, Refinitiv Eikon calculates the company betas over the calendar year. Therefore, betas are aligned with the other annual variables using the company identifier and by matching the calendar year of the former with the absolute fiscal year of the latter, producing a firm-year panel.

However, because we follow the methodology outlined by Bolton and Kacperczyk (2021), where the dependent variable is tested at the firm-month level, we align the annual variables with monthly stock price data accordingly. Specifically, they are matched based on calendar year, such that data for a given year is assigned to all monthly stock price observations within the same calendar year (January through December). Because we obtain stock price data for the period from January 2015 to March 2025, all firm-year observations that cannot be matched within this period are excluded from the final panel. Similarly, stock price observations that cannot be matched with annual variables are also removed from the samples.

Following the construction of the firm-month panel, and after calculating and winsorizing the selected variables, we remove all observations with missing values for the dependent variable, company identifier, or GICS industry code. The final panel consists of 3,393 firms in 74 different industries in the U.S. sample, and 2,036 firms in 73 different industries across 23 countries in the European sample, covering the period from 2015 to 2024. Summary statistics are reported in Panel A and Panel B of Table 1 for the U.S. and European samples, respectively. Note that the number of observations is reported based on the frequency of each variable. That is, the counts for emissions, accounting, and beta variables reflect annual observations – even though, in the firm-month panel used for the empirical tests, each of these variables appears approximately 12 times per year, once for each month within the corresponding calendar year.

Table 1. Summary statistics (U.S. and European samples)

This table presents summary statistics for the variables used in the empirical analysis for the U.S. (Panel A) and European (Panel B) samples. When applicable, the winsorization cutoffs are indicated next to each variable. Note that the number of observations is reported based on the frequency of each variable. Annual variables (all except RETURN, MOMENTUM, and VOLATILITY) are counted once per year, even though they appear roughly 12 times per year in the firm-month panel used for the empirical analysis.

Panel A: U.S.				
Variable	**N**	**Mean**	**Median**	**SD**
Dependent Variable				
(1) RETURN in %	272,276	0.82	0.42	(14.52)
Independent Variables				
(2) LOG SCOPE 1	20,449	8.98	8.79	(3.10)

(3) LOG SCOPE 2	20,449	9.51	9.58	(2.50)
(4) LOG GHG TOT	20,446	12.57	12.69	(2.87)
(5) SCOPE 1 GR (winsorized at 2.5%)	15,502	0.25	0.03	(1.01)
(6) SCOPE 2 GR (winsorized at 2.5%)	15,502	0.10	0.01	(0.55)
(7) GHG TOT GR (winsorized at 2.5%)	15,495	0.25	0.08	(0.72)
(8) SCOPE 1 INTENSITY (tons of emissions/USDm)/100 (winsorized at 2.5%)	18,388	0.90	0.10	(2.49)
(9) SCOPE 2 INTENSITY (tons of emissions/USDm)/100 (winsorized at 2.5%)	18,388	0.32	0.18	(0.41)
(10) GHG TOT INTENSITY (tons of emissions/USDm)/100 (winsorized at 2.5%)	18,387	7.51	1.84	(14.78)
Control Variables				
(11) LOG SIZE	21,415	7.48	7.42	(1.96)
(12) B/M (winsorized at 2.5%)	21,415	0.55	0.43	(0.50)
(13) LEVERAGE (winsorized at 2.5%)	23,464	0.25	0.21	(0.23)
(14) CAPEX/ASSETS (winsorized at 2.5%)	22,566	0.03	0.02	(0.04)
(15) LOG PPE	22,826	5.25	5.34	(2.53)
(16) ROE in % (winsorized at 2.5%)	22,183	-2.97	7.95	(44.35)
(17) REVENUE GR (winsorized at 0.5%)	16,287	0.06	0.02	(0.42)
(18) EPS GR (winsorized at 0.5%)	18,149	0.03	0.00	(0.28)
(19) BETA	22,367	1.17	1.11	(0.68)
(20) MOMENTUM (winsorized at 0.5%)	246,287	0.12	0.02	(0.62)
(21) VOLATILITY (winsorized at 0.5%)	244,367	0.13	0.11	(0.09)

Panel B: Europe

Variable	**N**	**Mean**	**Median**	**SD**
Dependent Variable				
(1) RETURN in %	181,611	0.71	0.40	(11.62)
Independent Variables				
(2) LOG SCOPE 1	12,009	9.20	9.03	(3.22)
(3) LOG SCOPE 2	12,009	9.34	9.37	(2.64)
(4) LOG GHG TOT	12,008	13.11	13.05	(2.79)
(5) SCOPE 1 GR (winsorized at 2.5%)	9,720	0.07	-0.01	(0.55)
(6) SCOPE 2 GR (winsorized at 2.5%)	9,720	0.01	-0.04	(0.48)
(7) GHG TOT GR (winsorized at 2.5%)	9,719	0.24	0.04	(0.82)
(8) SCOPE 1 INTENSITY (tons of emissions/USDm)/100 (winsorized at 2.5%)	11,254	0.85	0.08	(2.17)
(9) SCOPE 2 INTENSITY (tons of emissions/USDm)/100 (winsorized at 2.5%)	11,254	0.29	0.11	(0.49)
(10) GHG TOT INTENSITY (tons of emissions/USDm)/100 (winsorized at 2.5%)	11,253	8.58	2.80	(14.86)
Control Variables				
(11) LOG SIZE	15,072	7.24	7.13	(1.81)
(12) B/M (winsorized at 2.5%)	15,072	0.71	0.53	(0.61)
(13) LEVERAGE (winsorized at 2.5%)	15,450	0.24	0.22	(0.17)
(14) CAPEX/ASSETS (winsorized at 2.5%)	14,917	0.04	0.03	(0.04)
(15) LOG PPE	15,224	5.14	5.28	(2.58)
(16) ROE in % (winsorized at 2.5%)	15,264	9.08	10.57	(17.85)

(17) REVENUE GR (winsorized at 0.5%)	12,340	0.07	0.03	(0.44)
(18) EPS GR (winsorized at 0.5%)	13,063	0.01	0.00	(0.19)
(19) BETA	14,937	0.96	0.91	(0.54)
(20) MOMENTUM (winsorized at 0.5%)	162,490	0.09	0.02	(0.47)
(21) VOLATILITY (winsorized at 0.5%)	161,965	0.10	0.09	(0.05)

2.2 Independent variables

Refinitiv Eikon gathers or estimates firm-level emissions data following the Greenhouse Gas Protocol. For our study, the emissions data obtained are Scope 1, Scope 2, Scope 3, and total GHG emissions. For Scope 1 and Scope 2 emissions, the data vendor specifies the method used to derive each value: (i) a reported value disclosed by the company; (ii) a reported value adjusted through winsorization; (iii) an extrapolated value based on historical data; or (iv) an estimated value derived from a model combining input-output analysis, sector medians, and linear regressions (LSEG, 2025). Because methods (ii) through (iv) are affected by the subjectivity of the vendor, they are treated as estimated values in our research.

As for Scope 3 emissions, the methodology used by Refinitiv Eikon to obtain these values is not disclosed and is therefore assumed to be estimated in all cases. Even when Scope 3 values are not estimated by the data vendor, they are likely estimated by the companies themselves, given the inherent complexity of accurate measurement (PwC, n.d.) This complexity stems from the need to estimate emissions from both upstream and downstream activities across the entire value chain. Not only is the estimation process itself complicated and ambiguous; its precision is also likely to vary across companies and industries. That is, due to the possibility that firms and their suppliers differ in the sophistication of their emissions tracking, the resulting measures may be inaccurate which raises concerns about the reliability of the Scope 3 data. Naturally, since total GHG emissions encompass Scope 3 emissions, similar concerns apply. However, because total GHG emissions also include Scope 1 and Scope 2, whose measurement methods are known, using total GHG emissions arguably reduces potential measurement error bias. For this reason, and in contrast to much of the prior literature, we use total GHG emissions instead of Scope 3 alone in our analysis. Nevertheless, we place greater emphasis on Scope 1 and Scope 2 emissions, as their values are easier to measure and the method of obtaining them is disclosed by Refinitiv Eikon.

We use the data on Scope 1, Scope 2, and total GHG emissions to construct our set of independent variables, largely in line with those employed by Bolton and Kacperczyk (2021). The total emissions variables – LOG SCOPE 1, LOG SCOPE 2, and LOG GHG TOT – represent the natural logarithm of firm *i*'s Scope 1, Scope 2, and total GHG emissions at the end of year *t*, measured in tons of GHG emissions. The growth variables – SCOPE 1 GR, SCOPE 2 GR, and GHG TOT GR – are defined as the annual growth rate in firm *i*'s emissions between year *t* and *t–1*. The emissions intensity variables – SCOPE 1/REVENUE, SCOPE 2/REVENUE, and GHG TOT/REVENUE – are calculated as the ratio of firm *i*'s emissions in tons to its revenue in millions of USD at the end of year *t*, divided by 100 to facilitate interpretation of the regression coefficients. The emissions growth rate and emissions intensity variables are all winsorized at the 2.5% level to mitigate the influence of outliers.

Comparing the summary statistics presented in Table 1 for our U.S. sample (Panel A) with those of Bolton and Kacperczyk (2021), we find a lower average for Scope 1 and Scope 2, both in terms of emissions levels and emissions intensity. For example, in their sample, the average firm emits 192 tons of Scope 1 emissions per USD million in revenue, while in our sample, only 90 tons are emitted for the same amount of revenue. This difference may have two possible explanations: (i) the cross-section of U.S. companies in our sample differs from theirs; and/or (ii) companies may have reduced their Scope 1 and Scope 2 emissions over time and become more efficient in their use of GHG emissions to generate revenue. On the other hand, what warrants highlighting is the summary statistic for GHG TOT INTENSITY in our sample, as it appears high: firms emit, on average, roughly 750 tons of total GHG emissions per USD million in revenue. However, the median GHG TOT INTENSITY in our sample is close to the mean Scope 3 intensity reported by Bolton and Kacperczyk (2021), which suggests that many firms in our sample are relatively more efficient, given that total GHG emissions include Scope 1, Scope 2, and Scope 3. That said, the high standard deviation of GHG TOT INTENSITY among U.S. firms indicates that further winsorization could be warranted. Even so, with a 2.5% winsorization already applied, the mean remains large. We refrain from applying a higher threshold, as increasing the winsorization to 5% does not materially alter the summary statistics nor our empirical analysis. As seen in Panel B of Table 1, similar results can be found for Europe.

Furthermore, we assess the correlations among emission levels and emission intensity variables in the U.S. sample. As reported in Table A1 (Panel A), all these relationships are found to be positive, which is expected. We find that firms that emit more Scope 1 emissions also tend to emit more Scope 2 emissions. Similarly, the correlations with total GHG emissions are strong and positive, which makes sense since GHG total encompasses both Scope 1 and Scope 2 (and Scope 3). When assessing the correlations between emission levels and emission intensities, the relationships remain positive but are lower in magnitude. Nevertheless, this indicates that firms with higher absolute emissions also tend to have higher emissions intensity, although the relationship is weaker. Panel B of Table A1 further presents the serial correlation results for the independent variables in our U.S. sample. We observe that the coefficients for all emission levels and emission intensities are statistically significant at the 1% level, meaning that these variables are persistent over time. Hence, this indicates that firms with high emissions or high emission intensities in one period are likely to exhibit similar levels in the following period. In contrast, we find no evidence of serial correlation for emission growth, suggesting that changes in emissions are not persistent over time. Although we do not tabulate the results for our European sample in terms of correlations and serial correlations, the findings are largely consistent with those for the U.S., with the exception that the serial correlation for the growth in emissions variables is negative and statistically significant at the 1% level. While small in magnitude, the negative direction of the coefficients suggests that increases in emissions growth are followed by decreases in the next period.

Finally, when examining emissions levels across industries, the five largest emitters in the U.S., on average over the entire sample period, are: electrical utilities (551010), multi-utilities (551030), machinery (201050), oil, gas and consumable fuels (101020), and airlines (203020), in that order. In Europe, the five largest emitters on average are: multi-utilities (551030), automobiles (251020), electrical utilities (551010), banks (401010), and oil, gas and consumable fuels (101020). As for the smallest emitters in the U.S., these are biotechnology (352010), health care technology (351030), pharmaceuticals (352020), software (451030), and health care equipment and supplies (351010). Similar patterns are observed in Europe, with biotechnology (352010) as the smallest emitter, followed by interactive media and services (502030), software (451030), and office real estate investment trusts (601040) (S&P Global, 2018, and S&P Dow Jones Indices, 2023). Additional statistics on the largest and smallest emitters, based on industry averages for Scope 1, Scope 2, and total GHG emissions, are provided in Table A2 for the U.S. sample and Table A3 for the European sample (Appendix).

2.3 Dependent variable

The dependent variable of interest in our study is RETURN, defined as the monthly stock return of firm *i* in month *t,* expressed as a percentage. We calculate the monthly stock return as the percentage change in the stock's closing price between month *t-1* and *t.* Furthermore, to remain consistent with Bolton and Kacperczyk (2021) and to limit the impact of outliers, we remove all return observations exceeding 100%. As presented in the summary statistics in Table 1, the average monthly stock return for U.S. firms over the sample period is 0.82%. In Europe, the mean monthly stock return for company *i* is found to be 0.71%.

2.4 Control variables

When performing our analysis of the relationship between stock returns and emissions, a variety of control variables are employed. Following Bolton and Kacperczyk (2021), these are: LOG SIZE, defined as the natural logarithm of firm *i*'s market capitalization in millions of USD at the end of year *t*, calculated as the company's number of shares outstanding multiplied by its closing stock price at the end of the firm's fiscal year; B/M, defined as the ratio of the company's book value of equity to its market capitalization at the end of year *t*; LEVERAGE, defined as the ratio of company *i*'s book value of debt to its book value of assets at the end of year *t*; CAPEX/ASSETS, defined as the ratio of firm *i*'s capital expenditures to its book value of assets at the end of year *t*; LOG PPE, defined as the natural logarithm of company *i*'s book value of property, plant, and equipment in millions of USD at the end of year *t*; ROE, defined as the ratio of company *i*'s net income after taxes to its book value of equity at the end of year *t*; REVENUE GR, defined as the annual change in company *i*'s revenue in millions of USD normalized over its market capitalization in millions of USD at the end of year *t*; EPS GR, defined as the annual change in firm *i*'s earnings per share normalized over its closing price at the end of year *t*, calculated as the difference between the ratio of net income after taxes to the number of shares outstanding, and then divided by the stock's closing price; BETA, defined as the one-year CAPM beta at the end of year *t;* MOMENTUM, defined as the 12-month cumulative return of firm *i* over the past 12 months excluding month *t*; VOLATILITY , defined as the standard deviation of firm *i*'s monthly returns over the past 12 months excluding month *t*. Note that B/M, LEVERAGE, CAPEX/ASSETS, and ROE are winsorized at 2.5%, and REVENUE GR, EPS GR, MOMENTUM, and VOLATILITY are winsorized at 0.5% to mitigate the effect of outliers.

Looking at the summary statistics for the U.S. sample, the only control variable worth highlighting is ROE, which has a mean of approximately -3% even after winsorization. A closer (not tabulated) examination of our data shows that this is primarily driven by the large and negative ROEs observed in the biotechnology industry (GICS: 351020), which also accounts for a significant share of the observations in our sample. Negative ROE is common in this industry and has been documented in prior research (Damodaran, 2025). Therefore, we consider this finding reasonable given the distribution of our sample and take no further action.

In contrast to Bolton and Kacperczyk (2021) and Aswani et al. (2024), we do not include the Herfindahl-Hirschman Index (HHI) as a control variable in our study. The HHI measures a firm's size relative to its industry and serves as an indicator of market concentration and competitiveness (Bromberg, 2024). This variable is not directly available in Refinitiv Eikon or in any other data source to which we have access. Manually calculating the HHI based on our sample would likely distort the metric and make it unrepresentative of actual market conditions, as our dataset does not include the full universe of firms within each industry. Therefore, we exclude the HHI from our analysis, while acknowledging this as a potential limitation, as the omission of market concentration may exclude an important firm-specific dimension.

3. Methodology

Our empirical analysis is designed to investigate whether there exists a statistically significant and economically meaningful relationship between stock returns and firm-level GHG emissions. To conduct this research, we first specify an OLS regression model. Further, we extend this model by testing for heterogeneous effects in two ways: we investigate whether the relationship between the dependent and independent variables varies depending on whether the emissions data for Scope 1 and Scope 2 emissions were disclosed by the company or estimated by the data vendor; and we test whether the relationship is moderated by the size of the firm. In the OLS regression models employed, the emissions variables of interest alternate between the total level, growth, and intensity of Scope 1, Scope 2, and total GHG emissions. For each variable, we perform listwise deletion of the independent and control variables used in the particular model tested. The rationale for conducting listwise deletion separately in this way is to avoid unnecessarily losing observations that could have been used, given that the missing values vary depending on the variables tested. The summary statistics for the final samples used for each independent variable are presented in Table A4 for the U.S. sample and Table A5 for the European sample (Appendix).

To assess the robustness of our baseline model, we test for heteroskedasticity using the Breusch-Pagan test. As the null hypothesis of homoskedasticity is rejected at the 1% significance level, we conclude that heteroskedasticity is present in our data. To mitigate this, we cluster standard errors at the firm and year levels across all models, which provides robust inference despite heteroskedasticity. The use of clustered standard errors is further motivated by the previously discussed serial correlation, as evidenced in Table A1 (Panel B). Furthermore, we test for multicollinearity by calculating the Variance Inflation Factors (VIF) for all our models. We find that the interaction term in the total emissions level models exceeds the VIF threshold of five, indicating potential multicollinearity concerns in our data. Therefore, to address this, we mean-center the continuous variables used in the interaction term (i.e., the natural logarithm of the emissions variables). Next, because our firm-month panel also comprises variables calculated at the annual level that are held constant over the 12-month window, we use year-month fixed effects. For all our models, we conduct the empirical analysis both without and with industry fixed effects, where the fixed effects are based on the six-digit GICS code. This is because of structural differences in emissions data across industries; for example, as previously seen in Table A2, the multi-utilities industry has substantially higher levels of emissions compared to the biotechnology industry. Finally, for Europe, we include country fixed effects to account for structural differences across countries.

The following equations specify the models underlying our OLS regression analysis:

$$RETURN_{\{it\}} = \alpha + \beta_1 \cdot Emissions_{\{it\}} + \beta_2 \cdot Controls_{\{i,t-1\}} + \gamma_t + \varepsilon_{\{it\}} \tag{1}$$

Equation (1) tests the relationship between stock returns and GHG emissions. RETURN, as previously defined, represents the percentage return of stock *i* in month *t*. The emissions variable alternates between the natural logarithm of GHG emission levels, GHG emissions growth, and GHG emissions intensity, depending on the independent variable of interest. Specifically, we estimate separate model specifications for each of these emissions measures. In each case, the emissions variable replaces the generic "Emissions" term in Equation (1), and all emissions variables are measured at time *t*, thereby capturing contemporaneous effects. The generic "Controls" term refers to a vector containing all control variables defined in the previous section. All control variables are measured at time *t–1*, except for REVENUE GR and EPS GR, which are measured at time *t* to remain consistent with the methodology employed by Bolton and Kacperczyk (2021). As these two variables may have a nontrivial contemporaneous relationship with emissions at time *t*, they are included in the model at the same point in time as the emissions variable. Note that VOLATILITY and MOMENTUM are lagged by construction, as they are calculated excluding month *t*. γ_t refers to year-month fixed effects. We test each model both with and without industry fixed effects. For Europe, we include country fixed effects for all models.

$$\begin{aligned} RETURN_{\{it\}} = {} & \alpha + \beta_1 \cdot Emissions_{\{it\}} + \beta_2 \cdot Estimated(Dummy)_{\{it\}} + \beta_3 \\ & \cdot \left(Emissions_{\{it\}} \times Estimated(Dummy)_{\{it\}}\right) + \beta_4 \\ & \cdot Controls_{\{i,t-1\}} + \gamma_t + \varepsilon_{\{it\}} \end{aligned} \tag{2}$$

Equation (2) tests whether the relationship between stock returns and GHG emissions differs depending on whether the emissions data were disclosed by the company or estimated by Refinitiv Eikon. In addition to the variables defined in Equation (1), Equation (2) includes a disclosure method dummy variable and an interaction term. The dummy variable takes the value 0 if the emissions data were disclosed by the company, and 1 if the data were estimated by the data vendor. Because Refinitiv Eikon only discloses the methodology employed to obtain emissions data for Scope 1 and Scope 2, these models are limited to those two emission scopes.

$$RETURN_{\{it\}} = \alpha + \beta_1 \cdot Emissions_{\{it\}} + \beta_2 \cdot Large\ Cap(Dummy)_{\{it\}} + \beta_3 \cdot \left(Emissions_{\{it\}} \times Large\ Cap(Dummy)_{\{it\}}\right) + \beta_4 \cdot Controls_{\{i,t-1\}} + \gamma_t + \varepsilon_{\{it\}} \quad (3)$$

Finally, Equation (3) tests whether the relationship between stock returns and GHG emissions is moderated by firm size. In addition to the variables defined in Equation (1), Equation (3) includes a size dummy variable and an interaction term. The dummy variable takes the value 0 if the firm is classified as an SME, defined as having an average market capitalization in the bottom 75th percentile over the sample period. It takes the value 1 if the firm is classified as large, defined as having an average market capitalization in the top 25th percentile over the sample period.

4. Results

4.1 GHG emissions in the U.S.

Table 2 presents the results from estimating the OLS regression models specified in Equation (1) for the U.S. sample. Panel A displays the findings for the relationship between monthly stock returns and the level of GHG emissions. Specifically, columns (1) and (2) report the results for total Scope 1 emissions, columns (3) and (4) for total Scope 2 emissions, and columns (5) and (6) for total GHG emissions. We find that when excluding industry fixed effects, only LOG SCOPE 2 is statistically significant at the 1% level. When introducing industry fixed effects, LOG SCOPE 1, LOG SCOPE 2, and LOG GHG TOT all become statistically significant at the 1% level. These findings are also economically significant: For example, a one-standard-deviation change in LOG SCOPE 1 is associated with a 52.8 bps (coefficient times standard deviation) change in monthly stock returns, corresponding to an annualized effect of approximately 6.3%.

Based on the presented results, we find evidence of a carbon premium linked to unscaled GHG emissions. However, compared to Bolton and Kacperczyk (2021), some key differences are observed. When including industry fixed effects, as noted above, the positive relationship is highly significant. However, when excluding industry fixed effects, the results become inconclusive, with only one emissions variable remaining significant. This contrasts with Bolton and Kacperczyk (2021), who observe a significant relationship both with and without the inclusion of industry fixed effects. That said, our findings are consistent with prior research in showing that the relationship between emissions and returns strengthens when accounting for industry-specific effects. For example, our results seem to align with those of Aswani et al. (2024), who find that all three emissions variables are statistically significant, conditional on controlling for both firm size and industry fixed effects. This highlights the importance of research design choices in drawing conclusions. Given that emissions levels appear to vary substantially across industries, we argue that including such controls is relevant. Furthermore, we observe that including industry fixed effects increases the explanatory power of the model, as the R-squared increases from 0.212 to 0.214, indicating that additional variability in stock returns is explained. With the inclusion of industry fixed effects, our results for the levels of GHG emissions support the carbon premium claim made by Bolton and Kacperczyk (2021). Consistent with their conclusions, we also find evidence that the carbon premium has increased over time. Specifically, we observe larger regression coefficients for the statistically significant variables compared to those reported by Bolton and Kacperczyk (2021), which we attribute to using a more recent dataset.

Furthermore, Panel B presents the results for GHG emissions growth. Here, we find that when excluding industry fixed effects, SCOPE 1 GR and GHG TOT GR are significant at the 5% level, while SCOPE 2 GR is significant at the 1% level. When including industry fixed effects, SCOPE 1 GR remains significant at the 5% level, and both SCOPE 2 GR and GHG TOT GR are significant at the 1% level. The results obtained are similar to Bolton and Kacperczyk (2021) in terms of statistical significance. We find that all emission growth variables are significant, and that this remains with, and without, the inclusion of industry fixed effects. However, again, the statistical significance increases when including such. Taken together, this points to the conclusion that growth in emissions is positive correlated with stock returns.

However, Zhang (2023) argues that the relationship between emissions and stock returns could be overstated if emissions are measured contemporaneously, since emissions levels and growth are highly correlated with firm-specific variables such as revenue growth. To address this concern, Zhang (2023) suggests lagging the emissions variables to better isolate their independent effect on returns. As a robustness check, we apply this lag structure and report the results in Table A6 (Appendix). In Panel A, we find that the significance level drops to 10% for LOG SCOPE 1 and to 5% for LOG GHG TOT, while LOG SCOPE 2 remains significant at the 1% level, all with industry fixed effects included. Without industry fixed effects, LOG SCOPE 2 is significant at the 5% level. Additionally, the R-squared of the models increases to 0.22, indicating a slight improvement in explanatory power. Although the statistical significance for LOG SCOPE 1 and LOG SCOPE 2 weakens, we conclude that the results remain robust to this alternative specification. In terms of emissions growth the results incorporating the lag are reported in Panel B of Table A6. Here, when excluding industry fixed effects, we find that only SCOPE 1 GROWTH and SCOPE 2 GROWTH remain significant, both at the 10% level. Interestingly, the coefficients of these variables turn negative, which is consistent with the findings of Zhang (2023). This suggests that when controlling for firm-specific variables in the same period and avoiding potential look-ahead bias, the previously observed positive relationship between emissions growth and stock returns weakens or even disappears.

Finally, Panel C of Table 2 reports the results for GHG emissions intensity. Across all specifications, the relationship between emissions intensity and stock returns is statistically insignificant, both with and without industry fixed effects. This finding is consistent with previous literature, notably Bolton and Kacperczyk (2021, 2023) and Aswani et al. (2024). Since this finding is well-established in the literature and the underlying explanations have been discussed, we do not provide further interpretations. Taken together, this does, however, imply that the critique related to the emissions intensity variable, presented by Aswani et al. (2024), remains relevant.

Table 2: Stock returns and GHG emissions (U.S. baseline)

The table presents the results of the pooled OLS regressions models estimating the relationship between stock returns and GHG emissions for the U.S. sample. Panel A reports the results for the total level of GHG emissions, Panel B reports the results for the growth in GHG emissions, and finally, Panel C the results for GHG emissions intensity. Columns (1), (3), and (5) do not include industry fixed effects, while columns (2), (4), and (6) introduce industry fixed effects. The standard errors are two-way clustered at the firm and year level, and year-month fixed effects are included for all models.

Panel A: Effect of Total Emissions on Returns						
Variable	(1)	(2)	(3)	(4)	(5)	(6)
LOG SCOPE 1	0.052	0.165***				
	(0.059)	(0.035)				
LOG SCOPE 2			0.161***	0.223***		
			(0.034)	(0.034)		

LOG GHG TOT					0.128	0.326***
					(0.066)	(0.047)
LOG $SIZE_{t-1}$	-0.168*	-0.319***	-0.200**	-0.352***	-0.222*	-0.457***
	(0.083)	(0.060)	(0.080)	(0.055)	(0.102)	(0.071)
B/M_{t-1}	0.005	0.091	0.027	0.072	-0.105	-0.075
	(0.274)	(0.183)	(0.289)	(0.194)	(0.252)	(0.176)
$LEVERAGE_{t-1}$	-0.200	-0.125	-0.240	-0.115	-0.242	-0.319
	(0.328)	(0.286)	(0.328)	(0.283)	(0.337)	(0.271)
$CAPEX/ASSETS_{t-1}$	-1.712	-1.191	-1.038	-0.830	-1.410	-0.651
	(2.291)	(2.743)	(2.166)	(2.730)	(2.116)	(2.677)
ROE_{t-1}	0.011**	0.010**	0.010**	0.010**	0.010**	0.010**
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
LOG PPE_{t-1}	0.024	0.110	-0.026	0.093	-0.008	0.062
	(0.074)	(0.060)	(0.111)	(0.065)	(0.079)	(0.059)
$BETA_{t-1}$	0.403*	0.350**	0.384*	0.347**	0.377*	0.330**
	(0.174)	(0.129)	(0.165)	(0.127)	(0.165)	(0.123)
REVENUE GR	1.584***	1.590***	1.550***	1.570***	1.533***	1.518***
	(0.219)	(0.227)	(0.225)	(0.227)	(0.227)	(0.241)
EPS GR	2.927***	2.828***	2.880***	2.799***	2.859***	2.755***
	(0.571)	(0.592)	(0.596)	(0.607)	(0.570)	(0.593)
MOMENTUM	0.179	0.112	0.171	0.111	0.166	0.091
	(0.325)	(0.349)	(0.334)	(0.352)	(0.321)	(0.345)
VOLATILITY	-2.121	-1.708	-1.934	-1.618	-1.950	-1.504
	(2.811)	(2.816)	(2.816)	(2.852)	(2.708)	(2.761)
Observations	148,436	148,436	148,436	148,436	148,412	148,412
R-squared	0.212	0.214	0.212	0.214	0.212	0.214
Year/Month F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Industry F.E.	No	Yes	No	Yes	No	Yes

Panel B: Effect of Emissions Growth on Returns

Variable	(1)	(2)	(3)	(4)	(5)	(6)
SCOPE 1 GR	0.154**	0.178**				
	(0.053)	(0.058)				
SCOPE 2 GR			0.455***	0.488***		
			(0.085)	(0.098)		
GHG TOT GR					0.302**	0.323***
					(0.101)	(0.085)
LOG $SIZE_{t-1}$	-0.126	-0.241**	-0.130	-0.244**	-0.130	-0.249**
	(0.103)	(0.080)	(0.103)	(0.080)	(0.103)	(0.080)
B/M_{t-1}	0.063	0.167	0.077	0.188	0.085	0.176
	(0.264)	(0.160)	(0.268)	(0.166)	(0.260)	(0.158)
$LEVERAGE_{t-1}$	-0.230	-0.030	-0.225	-0.014	-0.247	-0.045
	(0.373)	(0.295)	(0.366)	(0.293)	(0.376)	(0.293)
$CAPEX/ASSETS_{t-1}$	-1.471	-1.398	-1.794	-1.697	-1.434	-1.419
	(1.692)	(2.261)	(1.710)	(2.276)	(1.690)	(2.257)
ROE_{t-1}	0.013**	0.013**	0.014**	0.014**	0.014**	0.014***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)

LOG PPE_{t-1}	0.065	0.196**	0.071	0.203**	0.067	0.201**
	(0.117)	(0.077)	(0.117)	(0.078)	(0.117)	(0.077)
$BETA_{t-1}$	0.412*	0.371*	0.408*	0.364*	0.410*	0.371*
	(0.199)	(0.152)	(0.198)	(0.151)	(0.201)	(0.155)
REVENUE GR	1.499***	1.511***	1.432***	1.443***	1.445***	1.456***
	(0.243)	(0.239)	(0.248)	(0.246)	(0.249)	(0.244)
EPS GR	3.325***	3.269***	3.322***	3.261***	3.324***	3.263***
	(0.595)	(0.604)	(0.588)	(0.600)	(0.594)	(0.604)
MOMENTUM	0.097	0.036	0.082	0.020	0.086	0.025
	(0.323)	(0.347)	(0.323)	(0.348)	(0.327)	(0.348)
VOLATILITY	-0.738	-0.514	-0.772	-0.525	-0.735	-0.506
	(2.879)	(2.900)	(2.861)	(2.886)	(2.840)	(2.872)
Observations	140,161	140,161	140,161	140,161	140,137	140,137
R-squared	0.219	0.220	0.219	0.220	0.219	0.220
Year/Month F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Industry F.E.	No	Yes	No	Yes	No	Yes

Panel C: Effect of Emissions Intensity on Returns

Variable	(1)	(2)	(3)	(4)	(5)	(6)
SCOPE 1 INTENSITY	-0.028	-0.036				
	(0.044)	(0.036)				
SCOPE 2 INTENSITY			-0.188	-0.176		
			(0.130)	(0.104)		
GHG TOT INTENSITY					-0.003	-0.001
					(0.012)	(0.008)
LOG $SIZE_{t-1}$	-0.165*	-0.276***	-0.178*	-0.279***	-0.162	-0.273***
	(0.080)	(0.058)	(0.078)	(0.061)	(0.085)	(0.065)
B/M_{t-1}	0.045	0.147	0.015	0.142	0.047	0.145
	(0.256)	(0.187)	(0.284)	(0.187)	(0.227)	(0.182)
$LEVERAGE_{t-1}$	-0.198	0.070	-0.207	0.050	-0.206	0.056
	(0.326)	(0.276)	(0.324)	(0.275)	(0.321)	(0.274)
$CAPEX/ASSETS_{t-1}$	-1.201	-1.332	-1.334	-1.371	-1.237	-1.386
	(2.394)	(2.722)	(2.147)	(2.695)	(2.706)	(2.721)
ROE_{t-1}	0.011**	0.011**	0.011**	0.011**	0.011**	0.011**
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
LOG PPE_{t-1}	0.072	0.194**	0.079	0.195**	0.069	0.191**
	(0.100)	(0.070)	(0.105)	(0.073)	(0.097)	(0.072)
$BETA_{t-1}$	0.409*	0.368**	0.412*	0.369**	0.415*	0.369**
	(0.174)	(0.132)	(0.175)	(0.131)	(0.177)	(0.131)
REVENUE GR	1.623***	1.645***	1.612***	1.643***	1.623***	1.649***
	(0.228)	(0.225)	(0.233)	(0.230)	(0.226)	(0.227)
EPS GR	2.958***	2.887***	2.951***	2.888***	2.960***	2.890***
	(0.585)	(0.605)	(0.589)	(0.602)	(0.577)	(0.598)
MOMENTUM	0.187	0.131	0.186	0.130	0.186	0.131

	(0.336)	(0.360)	(0.335)	(0.359)	(0.336)	(0.360)
VOLATILITY	-2.076	-1.911	-2.091	-1.919	-2.079	-1.940
	(2.906)	(2.935)	(2.830)	(2.900)	(2.955)	(2.926)
Observations	148,304	148,304	148,304	148,304	148,304	148,304
R-squared	0.212	0.213	0.212	0.213	0.212	0.213
Year/Month F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Industry F.E.	No	Yes	No	Yes	No	Yes

*Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$*

4.2 Reported versus estimated GHG emissions in the U.S.

Table 3 presents the results from estimating the models specified in Equation (2) for the U.S. sample. As previously noted, since Refinitiv Eikon only discloses the methodology used to derive emissions values for Scope 1 and Scope 2 emissions, this analysis is limited to these two categories. While Aswani et al. (2024) extend their analysis to include Scope 3 emissions, we argue that it is conceptually less meaningful to distinguish between “reported” and “estimated” Scope 3 emissions. This is because, even when companies disclose Scope 3 emissions, these figures are typically based on estimation models due to the inherent complexity of measuring such emissions accurately across the value chain. As a result, the distinction between “reported” and “estimated” in this context might simply reflect who performed the estimation – whether the company or the data vendor.

That said, Panel A reports our findings on the relationship between stock returns and Scope 1 and Scope 2 emissions, specifically examining how these relationships vary depending on whether the emissions data were disclosed by the company or estimated by the data vendor, respectively. Columns (1) and (2) relate to total level of Scope 1 emissions, while columns (3) and (4) relate to total level of Scope 2 emissions. Because this empirical analysis is conducted in response to prior literature (e.g., Aswani et al., 2024) arguing that the results found in the previous section may be explained by the presence of vendor-estimated emissions values, the primary coefficients of interest are those for LOG SCOPE 1 (REPORTED) and LOG SCOPE 2 (REPORTED). This is because the dummy variable in these respective models takes the value zero when the emissions data are directly disclosed by the company. Examining these results first, we observe that, when including industry fixed effects, both LOG SCOPE 1 (REPORTED) and LOG SCOPE 2 (REPORTED) are statistically significant at the 5% and 1% levels, respectively. Without industry fixed effects, LOG SCOPE 1 (REPORTED) is not statistically significant, while LOG SCOPE 2 (REPORTED) remains marginally significant at the 10% level. These results are largely consistent with those presented for the full U.S. sample in Panel A of Table 2, suggesting that the relationship holds even when focusing exclusively on reported emissions. The interaction terms, LOG SCOPE 1 × ESTIMATED and LOG SCOPE 2 × ESTIMATED, when excluding industry fixed effects, are statistically significant and positive at the 10% and 5% level respectively. Including industry fixed effects, the interaction terms, LOG SCOPE 1 x ESTIMATED and LOG SCOPE 2 x ESTIMATED, are positive and significant at the 5% and 1% level respectively. Hence, like Aswani et al. (2024), we observe a significant difference in the relationship depending on whether the emissions are reported or estimated by the data vendor. Bolton and Kacperczyk (2024) argue that the fact that the carbon premium is lower when firms report their emissions is a consequence of the reduced uncertainty resulting from such action. That is, with reported GHG emissions, investors do not need to assess the validity of the carbon emissions in the same way as they would for vendor-estimated data. Nevertheless, we conclude that the relationship between stock returns and reported Scope 1 and Scope 2 emissions are statistically significant when including industry fixed effects, supporting the robustness of the results found in the previous section.

Furthermore, Panel B of Table 3 reports the results on the relationship between stock returns and growth in Scope 1 and Scope 2 emissions, examining how these relationships vary depending on whether the emissions data were disclosed or estimated, respectively. As shown in the table, emissions growth reported directly by the company is not statistically significant for either SCOPE 1 GR (REPORTED) or SCOPE 2 GR (REPORTED). However, the interaction term SCOPE 1 GR × ESTIMATED is significant at the 10% level without industry fixed effects and at the 5% level with industry fixed effects, suggesting that the relationship differs depending on the disclosure method. Similarly, SCOPE 2 GR × ESTIMATED is significant at the 1% level both with and without industry fixed effects. Notably, all interaction coefficients are positive, indicating that vendor-estimated emissions growth is associated with a stronger positive relationship with stock returns compared to reported data. Comparing these findings to those in the previous section, the results suggest that the previously observed significant relationships could be driven by the presence of vendor-estimated data, rather than by company-reported emissions values.

Finally, Panel C of Table 3 reports the results on the relationship between stock returns and Scope 1 and Scope 2 emissions intensities, examining how these relationships vary depending on whether the emissions data were disclosed estimated, respectively. Among the reported variables, only SCOPE 2 INTENSITY (REPORTED) shows a negative and statistically significant relationship with stock returns, at the 5% level without industry fixed effects and at the 10% level with industry fixed effects. The interaction terms for both Scope 1 and Scope 2 are not statistically significant, indicating no meaningful difference between reported and vendor-estimated emissions intensities in how they relate to stock returns. These results differ from the baseline model in the previous section, where all emissions intensity variables are statistically insignificant. Taken together, we interpret these coefficients with caution and refrain from drawing definitive conclusions. This is due to inconsistencies with the baseline findings, the lack of any significant difference between estimated and reported values, and the possibility that the statistical significance observed here may reflect noise inherent to the emissions intensity variable, as suggested by Bolton and Kacperczyk (2021).

Table 3. Stock returns and GHG emissions by reporting method (U.S. sample)

This table presents the results of pooled OLS regression models estimating the relationship between stock returns and GHG emissions (Scope 1 and Scope 2) based on the reporting method (estimated versus reported) for the U.S sample. Panel A reports the results for the total level of GHG emissions, Panel B for GHG emissions growth, and Panel C for GHG emissions intensity. The models include an interaction term between the emissions variable and a dummy variable indicating whether the emissions are estimated or reported. Columns (1), (3), and (5) exclude industry fixed effects, while Columns (2), (4), and (6) include industry fixed effects. All models include year-month fixed effects, and standard errors are two-way clustered at the firm and year levels. The set of control variables is described in the Data and Methodology section; their coefficients are not displayed in this table.

Panel A: Effect of Total Emissions on Returns by Method

Variable	(1)	(2)	(3)	(4)
LOG SCOPE 1 (REPORTED)	0.002	0.135**		
	(0.071)	(0.043)		
SCOPE 1 ESTIMATED (DUMMY)	-0.363*	-0.533***		
	(0.154)	(0.141)		
LOG SCOPE 1 × ESTIMATED	0.095*	0.074**		
	(0.046)	(0.030)		
LOG SCOPE 2 (REPORTED)			0.069*	0.151***

Variable	(1)	(2)	(3)	(4)
			(0.035)	(0.027)
SCOPE 2 ESTIMATED (DUMMY)			-0.414**	-0.556**
			(0.140)	(0.152)
LOG SCOPE 2 × ESTIMATED			0.143**	0.132***
			(0.054)	(0.033)
Observations	148,436	148,436	148,436	148,436
R-squared	0.212	0.214	0.212	0.214
Controls	Yes	Yes	Yes	Yes
Year/Month F.E.	Yes	Yes	Yes	Yes
Industry F.E.	No	Yes	No	Yes

Panel B: Effect of Emissions Growth on Returns by Method

Variable	(1)	(2)	(3)	(4)
SCOPE 1 GR (REPORTED)	-0.038	-0.045		
	(0.095)	(0.086)		
SCOPE 1 GR ESTIMATED (DUMMY)	-0.278	-0.386*		
	(0.217)	(0.175)		
SCOPE 1 GR × ESTIMATED	0.275*	0.320**		
	(0.130)	(0.104)		
SCOPE 2 GR (REPORTED)			0.074	0.092
			(0.110)	(0.118)
SCOPE 2 GR ESTIMATED (DUMMY)			-0.316	-0.387*
			(0.204)	(0.195)
SCOPE 2 GR × ESTIMATED			0.600***	0.626***
			(0.134)	(0.115)
Observations	140,161	140,161	140,161	140,161
R-squared	0.219	0.220	0.219	0.221
Controls	Yes	Yes	Yes	Yes
Year/Month F.E.	Yes	Yes	Yes	Yes
Industry F.E.	No	Yes	No	Yes

Panel C: Effect of Emissions Intensity on Returns by Method

Variable	(1)	(2)	(3)	(4)
SCOPE 1 INTENSITY (REPORTED)	-0.031	-0.033		
	(0.040)	(0.036)		
SCOPE 1 INTENSITY ESTIMATED (DUMMY)	-0.319	-0.413**		
	(0.188)	(0.154)		

SCOPE 1 INTENSITY × ESTIMATED	-0.005	0.001		
	(0.021)	(0.012)		
SCOPE 2 INTENSITY (REPORTED)			-0.299**	-0.199*
			(0.103)	(0.087)
SCOPE 2 INTENSITY ESTIMATED (DUMMY)			-0.391	-0.431*
			(0.213)	(0.185)
SCOPE 2 INTENSITY × ESTIMATED			0.212	0.143
			(0.170)	(0.123)
Observations	148,304	148,304	148,304	148,304
R-squared	0.212	0.213	0.212	0.213
Controls	Yes	Yes	Yes	Yes
Year/Month F.E.	Yes	Yes	Yes	Yes
Industry F.E.	No	Yes	No	Yes

*Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$*

4.3 SMEs versus large-cap firms in the U.S.

Table 4 presents the results from estimating the OLS regression models specified in equation (3) for the U.S. sample. Panel A reports our findings on the relationship between stock returns and Scope 1, Scope 2, and total GHG emissions, specifically examining how these relationships vary depending on whether the firm is classified as an SME or large-cap firm. Columns (1) and (2) relate to total Scope 1 emissions, columns (3) and (4) to total Scope 2 emissions, and columns (5) and (6) to total GHG emissions. When including industry fixed effects, LOG SCOPE 1 (SMEs) is significant at the 1% level. LOG SCOPE 2 (SMEs) is significant at the 1% level both with and without industry fixed effects. Finally, LOG GHG TOT (SMEs) is significant at the at the 5% level without industry fixed effects and at the 1% level with industry fixed effects. The interaction terms LOG SCOPE 1 x LARGE CAP and LOG GHG TOT x LARGE CAP are significant at the 1% level both with and without, industry fixed effects. For LOG SCOPE 2 x LARGE CAP, when excluding industry fixed effects, the interaction is significant at the 5% level, and at the 1% level when including industry fixed effects. Taken together, the interaction terms indicate a significantly different effect for large-cap firms.

The findings in Panel A suggest that the relationship between GHG emissions and stock returns is moderated by firm size. Specifically, the coefficient of the interaction terms is found to be negative. One possible explanation is that large-cap firms possess more resources, which may enable them to better adapt to, for example, environmental regulation. As a result, investors could perceive these firms as more resilient, lowering their relative risk. Klein and Mikaelson (n.d) lend weight to this view, arguing that small- and medium-sized firms may lack the organizational and financial capacity to respond effectively on their own. However, the specific mechanism underlying this relationship remain unclear, warranting further research.

Next, Panel B reports our findings on the relationship between stock returns and growth in Scope 1, Scope 2, and total GHG emissions, specifically examining how these relationships vary depending on whether the firm is classified as an SME or large-cap firm. Here, we find that, without industry fixed effects, SCOPE 1 GR (SMEs), is significant at the 5% level. Including industry fixed effects, SCOPE 1 GR (SMEs) is significant at the 1% level. SCOPE 2 GR (SMEs) is significant at the 1% level both with and without industry fixed effects. Finally, GHG TOT GR (SMEs) is significant at the 5% level both with and without industry fixed effects. Here, no interaction term is significant, indicating no significant difference between SMEs and large-cap firms. This suggests that the implications presented in the baseline model for the growth variables remain unchanged in this specification.

Finally, Panel C report our findings on the relationship between stock returns and Scope 1, Scope 2, and total GHG emissions intensities, specifically examining how these vary depending on whether the firm is classified as an SME or large-cap firm. Here only two significant results are found. When excluding industry fixed effects, the interaction term SCOPE 2 INTENSITY x LARGE CAP is significant at the 1% level. When including industry fixed effects, the same interaction term is significant at the 5% level. The interaction term indicates a significant difference between SMEs and large-cap firms; however, no significant relationship is observed for SMEs themselves. Considering the earlier findings on Scope 2 intensity, one could further investigate whether large-cap firms with reported emissions are driving the previous results. However, conducting such a focused test falls outside the scope of our analysis. Therefore, based on the mixed evidence presented, we conclude that the results for this variable remain inconclusive.

Table 4. Stock returns and GHG emissions by firm size (U.S. sample)

This table presents the results of pooled OLS regression models estimating the relationship between stock returns and GHG emissions by firm size for the U.S. sample. Panel A reports the results for the total level of GHG emissions, Panel B for GHG emissions growth, and Panel C for GHG emissions intensity. The models include an interaction term between the emissions variables and a dummy variable indicating whether the firm is classified as a large-cap firm or an SME. Columns (1), (3), and (5) exclude industry fixed effects, while Columns (2), (4), and (6) include industry fixed effects. All models include year-month fixed effects, and standard errors are two-way clustered at the firm and year levels. The set of control variables is described in the Data and Methodology section; however, only the coefficient for LOG SIZE is displayed in the table, while the remaining control coefficients are omitted for brevity.

Panel A: Effect of Total Emissions on Returns by Firm Size

Variable	(1)	(2)	(3)	(4)	(5)	(6)
LOG SCOPE 1 (SMEs)	0.100	0.216***				
	(0.063)	(0.039)				
LOG SCOPE 2 (SMEs)			0.203***	0.276***		
			(0.043)	(0.035)		
LOG GHG TOT (SMEs)					0.163**	0.365***
					(0.065)	(0.049)
LARGE CAP (DUMMY)	1.478***	1.471***	1.512***	1.512***	1.517***	1.488***
	(0.261)	(0.243)	(0.285)	(0.258)	(0.249)	(0.226)
LOG SCOPE 1 × LARGE CAP	-0.122***	-0.115***				
	(0.028)	(0.026)				
LOG SCOPE 2 × LARGE CAP			-0.145**	-0.152***		
			(0.046)	(0.038)		
LOG GHG TOT × LARGE CAP					-0.146***	-0.140***
					(0.036)	(0.024)
LOG $SIZE_{t-1}$	-0.445***	-0.598***	-0.475***	-0.625***	-0.487***	-0.720***

	(0.095)	(0.071)	(0.089)	(0.063)	(0.102)	(0.067)
Observations	148,436	148,436	148,436	148,436	148,412	148,412
R-squared	0.213	0.214	0.213	0.214	0.213	0.215
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year/Month F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Industry F.E.	No	Yes	No	Yes	No	Yes
Panel B: Effect of Emissions Growth on Returns by Firm Size						
Variable	(1)	(2)	(3)	(4)	(5)	(6)
SCOPE 1 GR (SMEs)	0.146**	0.172***				
	(0.048)	(0.042)				
SCOPE 2 GR (SMEs)			0.436***	0.478***		
			(0.094)	(0.092)		
GHG TOT GR (SMEs)					0.275**	0.303**
					(0.106)	(0.098)
LARGE CAP (DUMMY)	1.251***	1.219***	1.260***	1.231***	1.227***	1.197***
	(0.260)	(0.225)	(0.262)	(0.230)	(0.266)	(0.236)
SCOPE 1 GR × LARGE CAP	0.052	0.036				
	(0.201)	(0.169)				
SCOPE 2 GR × LARGE CAP			0.144	0.090		
			(0.316)	(0.275)		
GHG TOT GR × LARGE CAP					0.057	0.028
					(0.191)	(0.172)
LOG SIZE$_{t-1}$	-0.383**	-0.485***	-0.390**	-0.491***	-0.383**	-0.490***
	(0.123)	(0.099)	(0.122)	(0.098)	(0.122)	(0.098)
Observations	140,161	140,161	140,161	140,161	140,137	140,137
R-squared	0.219	0.221	0.220	0.221	0.220	0.221
Other controls	Yes	Yes	Yes	Yes	Yes	Yes
Year/Month F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Industry F.E.	No	Yes	No	Yes	No	Yes
Panel C: Effect of Emissions Intensity on Returns by Firm Size						
Variable	(1)	(2)	(3)	(4)	(5)	(6)
SCOPE 1 INTENSITY (SMEs)	-0.016	-0.017				
	(0.058)	(0.044)				
SCOPE 2 INTENSITY (SMEs)			-0.095	-0.042		
			(0.150)	(0.129)		
GHG TOT INTENSITY (SMEs)					-0.003	0.000
					(0.014)	(0.010)

LARGE CAP (DUMMY)	1.378***	1.347***	1.419***	1.405***	1.391***	1.361***
	(0.260)	(0.232)	(0.287)	(0.257)	(0.240)	(0.213)
SCOPE 1 INTENSITY × LARGE CAP	-0.033	-0.041				
	(0.033)	(0.030)				
SCOPE 2 INTENSITY × LARGE CAP			-0.249***	-0.312**		
			(0.064)	(0.100)		
GHG TOT INTENSITY × LARGE CAP					-0.005	-0.006
					(0.007)	(0.005)
LOG $SIZE_{t-1}$	-0.432***	-0.530***	-0.444***	-0.532***	-0.430***	-0.526***
	(0.091)	(0.067)	(0.089)	(0.068)	(0.092)	(0.069)
Observations	148,304	148,304	148,304	148,304	148,304	148,304
R-squared	0.213	0.214	0.213	0.214	0.213	0.214
Other controls	Yes	Yes	Yes	Yes	Yes	Yes
Year/Month F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Industry F.E.	No	Yes	No	Yes	No	Yes

*Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$*

4.4 European results

Tables 5, 6, and 7 present the results from estimating the OLS regression models specified in equations (1), (2), and (3) for the European sample. The structure of the results follows the same format as previously presented for the U.S. sample. Here, rather than discussing each result in isolation as done previously, we interpret them collectively to draw broader conclusions. This follows the intent of looking at differences between Europe and the U.S.

Table 5 presents the results from estimating the OLS regression models specified in equation (1), following the same panel and column structure as the U.S. results. Here, when industry fixed effects are included, LOG GHG TOT is significant at the 5% level. Furthermore, GHG TOT GR is significant at the 1% level, both with and without industry fixed effects. Table 6 presents the results from estimating the OLS regression models specified in equation (2), following the same panel and column structure as the U.S. results. Both with and without industry fixed effects, the interaction term SCOPE 1 GR x ESTIMATED is significant at the 10% level, Similarly, both with and without industry fixed effects, the interaction term SCOPE 2 GR x ESTIMATED is significant at the 1% level. Table 7 presents the results from estimating the OLS regression models specified in equation (3), following the same panel and column structure as the U.S. results. With industry fixed effects, LOG GHG TOT (SMEs) is significant at the 1% level. Furthermore, the interaction term LOG GHG TOT x LARGE CAP, when including industry fixed effects, is significant at the 10% level. GHG TOT GR both with and without industry fixed effects is significant at the 1% level. When excluding industry effects, the interaction term GHG TOT GR x LARGE CAP is significant at the 10% level. Finally, when including such, this interaction term is significant at the 5% level.

Based on these results, there are two particularly interesting mechanisms observed. First, compared to the U.S., the results are overall less significant for the European dataset. Second, the only emissions category consistently found to be significant relate to total GHG emissions. Starting with overall results, we believe that the relative insignificance observed in Europe might be attributed to a key factor. Specifically, as previously discussed, the risk-driven perspective emphasizes regulatory risks, including potential changes to the regulatory environment. This suggests that firms operating in different countries are subject to varying levels of regulatory uncertainty. Such differences in uncertainty are particularly evident when comparing the U.S. and European regulatory environments, potentially explaining the results observed.

In Europe, the future regulatory landscape regarding climate policy appears relatively stable. The EU, acting as a proxy for Europe, has set a legally binding target of becoming climate neutral by 2050, with emissions reductions of at least 55% compared to 1990 levels by 2030 (European Commission, n.d.). While political shifts could potentially challenge this trajectory, for example, as noted by Kate Abnett (2024), who suggests that a more right-leaning EU might make it harder to sustain the current agenda, others are less worried. In the same article, Bas Eickhout (2024), head of the European parliament's Greens group states, "I don't think that we'll be rolling back on (climate) policies," suggesting that the current trajectory is likely to hold. As such, European companies face relatively low uncertainty in this regard. In contrast, the U.S. regulatory environment is considerably more uncertain. Eccles (2024) cites a poll by Pew Research Center showing that 78% of Democrats view climate change as a major threat, compared to only 23% of Republicans. The U.S. has also demonstrated a history of inconsistent climate policy, having initially joined the Paris agreement in 2016, withdrawn under President Trump in 2020, rejoined under President Biden in 2021, and announced another withdrawal in 2025 under President Trump (NRDC, 2025). Consequently, even if a concrete long-term plan were introduced, it could be subject to dramatic change within a short period, creating uncertainty. A plausible explanation for the more significant relationship observed in the U.S. is the greater uncertainty, and thus higher risk, associated with future regulatory changes. It is important to note that this remains a theoretical interpretation, and future research could explore these findings in more depth.

As for the second finding, the significant results mainly relate to total GHG emissions in the European sample. Since Scope 1 and Scope 2 emissions are found to be insignificant, this suggests that Scope 3 emissions could be driving the observed effects. While European firms face less uncertainty in their direct operations due to stable regulations, this does not necessarily apply to Scope 3 emissions, which may fall outside the EU's jurisdiction. This could imply that regulatory uncertainty in other parts of the value chain indirectly influences the returns demanded by investors. This interpretation can be supported by the high level of global value chain participation among European firms. According to the European Commission (2025), such participation reached 37.9% in 2022, exceeding both China and the U.S.

Another explanation could be that increased attention is being placed on Scope 3 emissions because emissions directly controlled by firms are already subject to regulations. This perspective is reflected in the EU's Fit for 55 climate law package, which includes the Carbon Border Adjustment Mechanism (CBAM), designed to prevent emission reductions within the EU from being offset by increased emissions abroad (European Council, 2025). As a result, Scope 3 emissions become an increasingly important metric for assessing corporate sustainability. For example, Amundi (Le Berthe, Nguiakam, Jouanneau, McDougall, and Elbaz, 2022), a major European institutional investor, actively engages with companies to improve Scope 3 disclosure and promote emission reductions, adding to this viewpoint.

Table 5. Stock returns and GHG emissions (Europe baseline)

The table presents the results of the pooled OLS regressions models estimating the relationship between stock returns and GHG emissions for the European sample. Panel A reports the results for the total level of GHG emissions; Panel B reports the results for the growth in GHG emissions; and finally, Panel C the results for GHG emissions intensity. Columns (1), (3), and (5) do not include industry fixed effects, while columns (2), (4), and (6) introduce industry fixed effects. The standard errors are two-way clustered at the firm and year level, and year-month and country fixed effects are included for all models. The set of control variables is described in the Data and Methodology section; their coefficients are not displayed in this table.

Panel A: Effect of Total Emissions on Returns

Variable	(1)	(2)	(3)	(4)	(5)	(6)
LOG SCOPE 1	-0.017	0.010				
	(0.029)	(0.038)				
LOG SCOPE 2			0.001	0.035		
			(0.027)	(0.019)		
LOG GHG TOT					0.015	0.075**
					(0.026)	(0.023)
Observations	113,709	113,709	113,709	113,709	113,709	113,709
R-squared	0.316	0.317	0.316	0.317	0.316	0.317
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year/Month F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Industry F.E.	No	Yes	No	Yes	No	Yes
Country F.E.	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Effect of Emissions Growth on Returns

Variable	(1)	(2)	(3)	(4)	(5)	(6)
SCOPE 1 GR	0.094	0.089				
	(0.066)	(0.069)				
SCOPE 2 GR			0.140	0.125		
			(0.119)	(0.108)		
GHG TOT GR					0.166***	0.143***
					(0.044)	(0.037)
Observations	101,416	101,416	101,416	101,416	101,416	101,416
R-squared	0.318	0.320	0.318	0.320	0.318	0.320
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year/Month F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Industry F.E.	No	Yes	No	Yes	No	Yes
Country F.E.	Yes	Yes	Yes	Yes	Yes	Yes

Panel C: Effect of Emissions Intensity on Returns

Variable	(1)	(2)	(3)	(4)	(5)	(6)
SCOPE 1 INTENSITY	-0.002	-0.016				
	(0.018)	(0.024)				
SCOPE 2 INTENSITY			-0.048	-0.040		
			(0.095)	(0.071)		
GHG TOT INTENSITY					0.000	0.000
					(0.002)	(0.002)
Observations	113,553	113,553	113,553	113,553	113,553	113,553
R-squared	0.316	0.317	0.316	0.317	0.316	0.317
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year/Month F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Industry F.E.	No	Yes	No	Yes	No	Yes
Country F.E.	Yes	Yes	Yes	Yes	Yes	Yes

*Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$*

Table 6. Stock returns and GHG emissions by reporting method (European sample)
This table presents the results of pooled OLS regression models estimating the relationship between stock returns and GHG emissions (Scope 1 and Scope 2) based on the reporting method (estimated versus reported) for the European sample. Panel A reports the results for the total level of GHG emissions, Panel B for GHG emissions growth, and Panel C for GHG emissions intensity. The models include an interaction term between the emissions variable and a dummy variable indicating whether the emissions are estimated or reported. Columns (1), (3), and (5) exclude industry fixed effects, while Columns (2), (4), and (6) include industry fixed effects. All models include year-month and country fixed effects, and standard errors are two-way clustered at the firm and year levels. The set of control variables is described in the Data and Methodology section; their coefficients are not displayed in this table.

Panel A: Effect of Total Emissions on Returns by Method

Variable	(1)	(2)	(3)	(4)
LOG SCOPE 1 (REPORTED)	-0.023	0.006		
	(0.024)	(0.032)		
SCOPE 1 ESTIMATED (DUMMY)	0.135	0.058		
	(0.079)	(0.069)		
LOG SCOPE 1 × ESTIMATED	0.019	0.013		
	(0.032)	(0.023)		
LOG SCOPE 2 (REPORTED)			0.000	0.033
			(0.028)	(0.024)
SCOPE 2 ESTIMATED (DUMMY)			0.126**	0.104*
			(0.047)	(0.053)
LOG SCOPE 2 × ESTIMATED			0.010	0.006
			(0.027)	(0.024)
Observations	113,709	113,709	113,709	113,709
R-squared	0.316	0.317	0.316	0.317
Controls	Yes	Yes	Yes	Yes
Year/Month F.E.	Yes	Yes	Yes	Yes
Industry F.E.	No	Yes	No	Yes
Country F.E.	Yes	Yes	Yes	Yes

Panel B: Effect of Emissions Growth on Returns by Method

Variable	(1)	(2)	(3)	(4)
SCOPE 1 GR (REPORTED)	0.010	-0.002		
	(0.093)	(0.093)		
SCOPE 1 GR ESTIMATED (DUMMY)	0.033	-0.037		
	(0.113)	(0.081)		
SCOPE 1 GR × ESTIMATED	0.318*	0.345*		
	(0.163)	(0.156)		
SCOPE 2 GR (REPORTED)			0.004	-0.013
			(0.099)	(0.085)

SCOPE 2 GR ESTIMATED (DUMMY)			0.036	0.028
			(0.086)	(0.080)
SCOPE 2 GR × ESTIMATED			0.528***	0.531***
			(0.115)	(0.142)
Observations	101,416	101,416	101,416	101,416
R-squared	0.318	0.320	0.318	0.320
Controls	Yes	Yes	Yes	Yes
Year/Month F.E.	Yes	Yes	Yes	Yes
Industry F.E.	No	Yes	No	Yes
Country F.E.	Yes	Yes	Yes	Yes
Panel C: Effect of Emissions Intensity on Returns by Method				
Variable	(1)	(2)	(3)	(4)
SCOPE 1 INTENSITY (REPORTED)	-0.011	-0.021		
	(0.019)	(0.019)		
SCOPE 1 INTENSITY ESTIMATED (DUMMY)	0.097	0.042		
	(0.114)	(0.077)		
SCOPE 1 INTENSITY × ESTIMATED	0.022	0.012		
	(0.038)	(0.028)		
SCOPE 2 INTENSITY (REPORTED)			-0.072	-0.048
			(0.117)	(0.101)
SCOPE 2 INTENSITY ESTIMATED (DUMMY)			0.099	0.104
			(0.064)	(0.064)
SCOPE 2 INTENSITY × ESTIMATED			0.074	-0.006
			(0.073)	(0.103)
Observations	113,553	113,553	113,553	113,553
R-squared	0.316	0.317	0.316	0.317
Controls	Yes	Yes	Yes	Yes
Year/Month F.E.	Yes	Yes	Yes	Yes
Industry F.E.	No	Yes	No	Yes
Country F.E.	Yes	Yes	Yes	Yes

Notes: $^{*} p < 0.1$, $^{**} p < 0.05$, $^{***} p < 0.01$

Table 7. Stock returns and GHG emissions by firm size (European sample)

This table presents the results of pooled OLS regression models estimating the relationship between stock returns and GHG emissions by firm size for the European sample. Panel A reports the results for the total level of GHG emissions, Panel B for GHG emissions growth, and Panel C for GHG emissions intensity. The models include an interaction term between the emissions variables and a dummy variable indicating whether the firm is classified as a large-cap firm or an SME. Columns (1), (3), and (5) exclude industry fixed effects, while Columns (2), (4), and (6) include industry fixed effects. All models include year-month and country fixed effects, and standard errors are two-way clustered at the firm and year levels. The set of control variables is described in the Data and Methodology section; however, only the coefficient for LOG SIZE is displayed in the table, while the remaining control coefficients are omitted for brevity.

Panel A: Effect of Total Emissions on Returns by Firm Size						
Variable	(1)	(2)	(3)	(4)	(5)	(6)
LOG SCOPE 1 (SMEs)	-0.007	0.021				
	(0.042)	(0.047)				
LOG SCOPE 2 (SMEs)			0.008	0.037		
			(0.033)	(0.023)		
LOG GHG TOT (SMEs)					0.029	0.089***
					(0.027)	(0.020)
LARGE CAP (DUMMY)	1.008***	1.079***	1.022***	1.078***	1.043***	1.110***
	(0.148)	(0.150)	(0.151)	(0.151)	(0.148)	(0.152)
LOG SCOPE 1 × LARGE CAP	-0.015	-0.035				
	(0.035)	(0.027)				
LOG SCOPE 2 × LARGE CAP			-0.024	-0.035		
			(0.032)	(0.021)		
LOG GHG TOT × LARGE CAP					-0.038	-0.057*
					(0.033)	(0.026)
LOG $SIZE_{t-1}$	-0.295**	-0.316**	-0.296**	-0.323**	-0.304**	-0.360**
	(0.109)	(0.097)	(0.108)	(0.103)	(0.112)	(0.109)
Observations	113,709	113,709	113,709	113,709	113,709	113,709
R-squared	0.316	0.318	0.316	0.318	0.316	0.318
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year/Month F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Industry F.E.	No	Yes	No	Yes	No	Yes
Country F.E.	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Effect of Emissions Growth on Returns by Firm Size						
	(1)	(2)	(3)	(4)	(5)	(6)
SCOPE 1 GR (SMEs)	0.113	0.114				
	(0.065)	(0.066)				
SCOPE 2 GR (SMEs)			0.150	0.144		
			(0.113)	(0.112)		
GHG TOT GR (SMEs)					0.209***	0.194***
					(0.047)	(0.042)

LARGE CAP (DUMMY)	0.837***	0.889***	0.833***	0.883***	0.870***	0.927***
	(0.141)	(0.130)	(0.140)	(0.132)	(0.147)	(0.136)
SCOPE 1 GR × LARGE CAP	-0.040	-0.067				
	(0.109)	(0.097)				
SCOPE 2 GR × LARGE CAP			-0.008	-0.054		
			(0.087)	(0.079)		
GHG TOT GR × LARGE CAP					-0.116*	-0.141**
					(0.051)	(0.048)
LOG SIZE$_{t-1}$	-0.249*	-0.263*	-0.250*	-0.262*	-0.253*	-0.267*
	(0.122)	(0.119)	(0.123)	(0.120)	(0.124)	(0.120)
Observations	101,416	101,416	101,416	101,416	101,416	101,416
R-squared	0.319	0.320	0.319	0.320	0.319	0.320
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year/Month F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Industry F.E.	No	Yes	No	Yes	No	Yes
Country F.E.	Yes	Yes	Yes	Yes	Yes	Yes

Panel C: Effect of Emissions Intensity on Returns by Firm Size

	(1)	(2)	(3)	(4)	(5)	(6)
SCOPE 1 INTENSITY (SMEs)	0.011	-0.003				
	(0.027)	(0.027)				
SCOPE 2 INTENSITY (SMEs)			-0.049	-0.076		
			(0.096)	(0.061)		
GHG TOT INTENSITY (SMEs)					0.002	0.001
					(0.004)	(0.003)
LARGE CAP (DUMMY)	1.016***	1.065***	0.988***	1.006***	1.017***	1.063***
	(0.177)	(0.165)	(0.176)	(0.161)	(0.193)	(0.179)
SCOPE 1 INTENSITY × LARGE CAP	-0.021	-0.023				
	(0.034)	(0.030)				
SCOPE 2 INTENSITY × LARGE CAP			0.026	0.125		
			(0.061)	(0.065)		
GHG TOT INTENSITY × LARGE CAP					-0.002	-0.002
					(0.005)	(0.004)
LOG SIZE$_{t-1}$	-0.296**	-0.313**	-0.297**	-0.311**	-0.296**	-0.312**
	(0.112)	(0.104)	(0.111)	(0.105)	(0.110)	(0.104)

Observations	113,553	113,553	113,553	113,553	113,553	113,553
R-squared	0.316	0.318	0.316	0.318	0.316	0.318
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year/Month F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Industry F.E.	No	Yes	No	Yes	No	Yes
Country F.E.	Yes	Yes	Yes	Yes	Yes	Yes

Notes: $*p < 0.1$, $**p < 0.05$, $***p < 0.01$

5. Conclusion

Our study provides empirical evidence of a significant relationship between GHG emissions and stock returns. Unscaled GHG emissions are significant across all scopes when industry fixed effects are included, and this relationship remains robust with the introduction of lag in the independent variables. However, the evidence regarding unscaled GHG emissions growth remains inconclusive, particularly as the results are affected by the inclusion of lagged independent variables. Furthermore, when using reported unscaled GHG emissions, a significant relationship is observed. In this case, we find evidence of a lower magnitude premium, which aligns with previous empirical findings. Firm size moderates the relationship when unscaled GHG emissions are used, with larger firms earning a lower premium. Finally, we find evidence of a generally weaker relationship within the European sample, which we attribute to differences in climate policy stability.

Overall, this paper contributes to the literature by offering new insights into how GHG emissions influence stock returns, as well as providing further empirical evidence to previous results. While some relationships remain inconclusive, our results broadly concludes that a carbon, or greenhouse gas, premium exist. With that said, future research could explore several aspects. First, a more thorough investigation relating policy differences between the U.S. and Europe to the observed regional differences is warranted. Second, emission intensity continues to remain insignificant, however, future research could explore new proxies for such, as suggested by Aswani et al. (2024). Finally, the concrete mechanism underlying the observed moderating effect of firm size remain inconclusive, warranting further research.

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Appendix A

Table A1. Cross-correlations and serial correlations (U.S. sample)

This table presents the cross-correlations and serial correlations among the independent variables in the U.S. sample. Specifically, Panel A reports the cross-correlations among emission levels and intensity variables, while Panel B reports the serial correlations for each independent variable. The number of observations in Panel B reflects annual observations.

Panel A: Correlation matrix

	(1)	(2)	(3)	(4)	(5)	(6)
LOG SCOPE 1	1					
LOG SCOPE 2	0.825	1				
LOG GHG TOT	0.755	0.754	1			
SCOPE 1 INTENSITY	0.555	0.205	0.358	1		
SCOPE 2 INTENSITY	0.34	0.426	0.19	0.342	1	
GHG TOT INTENSITY	0.437	0.212	0.517	0.603	0.252	1

Panel B: Serial correlation

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
LOG SCOPE 1_{t-1}	0.962***								
	(0.008)								
LOG SCOPE 2_{t-1}		0.956***							
		(0.005)							
LOG GHG TOT_{t-1}			0.971***						
			(0.004)						
SCOPE 1 GR_{t-1}				0.007					
				(0.016)					
SCOPE 2 GR_{t-1}					-0.001				
					(0.025)				
GHG TOT GR_{t-1}						0.013			
						(0.015)			
SCOPE 1 $INTENSITY_{t-1}$							0.934***		
							(0.020)		
SCOPE 2 $INTENSITY_{t-1}$								0.874***	
								(0.016)	

GHG TOT $INTENSITY_{t-1}$									0.933***
									(0.025)
Observations	16,959	16,959	16,956	12,431	12,431	12,425	15,186	15,186	15,185
R-squared	0.935	0.921	0.951	0.033	0.006	0.009	0.926	0.813	0.888
Time F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A2. Average largest and smallest 10 emitters by industry (U.S. sample)

This table presents the average largest and smallest emission levels by GICS industry code for the U.S. sample, separately for Scope 1, Scope 2, and total GHG emissions. Panel A reports the top 10 industries with the highest average emissions for each emissions variable, while Panel B reports the bottom 10 industries with the lowest average emissions. Emissions are reported as the natural logarithm of the emission level, averaged over the sample period.

Panel A: Largest emissions (avg.)

GICS	LOG SCOPE 1	GICS	LOG SCOPE 2	GICS	LOG GHG TOT
551010	15.899	201050	13.345	551010	16.972
551030	15.645	151030	12.926	551030	16.877
203020	15.363	151010	12.334	201050	16.411
201050	14.094	301010	12.288	101020	16.104
101020	13.652	151040	12.199	203020	15.612
151020	13.458	151020	12.143	551020	15.155
151040	13.232	151050	12.055	151030	14.926
203030	13.017	551030	12.043	151040	14.857
551020	12.836	303010	11.987	101010	14.821
151010	12.809	551010	11.822	203010	14.797

Panel B: Smallest emissions (avg.)

GICS	LOG SCOPE 1	GICS	LOG SCOPE 2	GICS	LOG GHG TOT
352010	5.703	352010	6.042	352010	7.775
451030	6.319	402040	7.512	351030	9.298
402040	6.661	203030	7.555	352020	9.665
351030	6.693	352020	7.823	451030	10.121
401010	6.709	401010	7.833	351010	10.187
402030	6.960	351030	8.030	601010	10.714
601025	7.062	403010	8.225	352030	10.917
403010	7.242	351010	8.431	202020	11.092
451020	7.349	451030	8.462	602010	11.168
601010	7.406	402030	8.666	502010	11.225

Table A3. Average largest and smallest 10 emitters by industry (European sample)

This table presents the average largest and smallest emission levels by GICS industry code for the European sample, separately for Scope 1, Scope 2, and total GHG emissions. Panel A reports the top 10 industries with the highest average emissions for each emissions variable, while Panel B reports the bottom 10 industries with the lowest average emissions. Emissions are reported as the natural logarithm of the emission level, averaged over the sample period.

Panel A: Largest Emissions (avg.)

GICS	LOG SCOPE 1	GICS	LOG SCOPE 2	GICS	LOG GHG TOT
203020	15.107	551030	12.370	551030	16.479
151020	14.460	551010	12.366	251020	16.328
551030	14.370	151040	12.342	551010	16.096
551010	14.305	151020	12.199	401010	16.075
101020	13.545	151010	12.153	101020	16.026
203030	13.288	303010	12.043	101010	15.657
551020	12.974	251020	12.010	551020	15.657
151040	12.820	551040	11.814	303010	15.644
151050	12.605	151030	11.765	203020	15.633
151010	12.376	302030	11.713	151020	15.505

Panel B: Smallest Emissions (avg.)

GICS	LOG SCOPE 1	GICS	LOG SCOPE 2	GICS	LOG GHG TOT
502030	5.345	502030	6.208	352010	8.347
451030	5.735	352010	6.249	502030	9.067
402030	5.792	601050	6.414	451030	9.634
352010	6.048	601025	6.621	351030	9.955
601050	6.058	402020	6.628	601040	10.088
452020	6.099	402030	6.695	601050	10.113
601025	6.113	451030	6.877	601080	10.230
402020	6.148	452020	7.019	253020	10.375
601080	6.303	402010	7.136	601060	10.409
351030	6.501	252020	7.358	402020	10.747

Table A4. Summary statistics by model specification (U.S. sample)

This table presents summary statistics for the variables used in the different model specifications for the U.S. sample. Each column corresponds to one of the model setups reported in the empirical analysis, covering total emissions, emissions growth, and emissions intensity. For each model, the table reports the mean and standard deviation (in parentheses) of the variables used. Observations are reported monthly based on the firm-month panel used in the pooled OLS regressions.

Variable	LOG SCOPE 1	LOG SCOPE 2	LOG GHG TOT	SCOPE 1 GR	SCOPE 2 GR	GHG TOT GR	SCOPE 1 INTENSITY	SCOPE 2 INTENSITY	GHG TOT INTENSITY
RETURN	0.76 (14.57)	0.76 (14.57)	0.76 (14.57)	0.79 (14.25)	0.79 (14.25)	0.79 (14.25)	0.76 (14.56)	0.76 (14.56)	0.76 (14.56)
LOG SCOPE 1	9.21 (3.20)								
LOG SCOPE 2		9.62 (2.53)							
LOG GHG TOT			12.33 (3.00)						
SCOPE 1 GR				0.17 (0.87)					
SCOPE 2 GR					0.09 (0.56)				
GHG TOT GR						0.26 (0.74)			
SCOPE 1 INTENSITY							0.98 (2.60)		
SCOPE 2 INTENSITY								0.33 (0.42)	
GHG TOT INTENSITY									7.74 (15.24)
LOG SIZE	7.77 (1.88)	7.77 (1.88)	7.77 (1.88)	7.86 (1.84)	7.86 (1.84)	7.86 (1.84)	7.76 (1.88)	7.76 (1.88)	7.76 (1.88)
B/M	0.50 (0.45)	0.50 (0.45)	0.50 (0.45)	0.50 (0.45)	0.50 (0.45)	0.50 (0.45)	0.50 (0.45)	0.50 (0.45)	0.50 (0.45)
LEVERAGE	0.25 (0.21)	0.25 (0.21)	0.25 (0.21)	0.26 (0.20)	0.26 (0.20)	0.26 (0.20)	0.25 (0.21)	0.25 (0.21)	0.25 (0.21)
CAPEX/ASSETS	0.04 (0.04)	0.04 (0.04)	0.04 (0.04)	0.04 (0.04)	0.04 (0.04)	0.04 (0.04)	0.04 (0.04)	0.04 (0.04)	0.04 (0.04)
LOG PPE	5.50 (2.51)	5.50 (2.51)	5.50 (2.51)	5.64 (2.45)	5.64 (2.45)	5.64 (2.45)	5.50 (2.52)	5.50 (2.52)	5.50 (2.52)
ROE	-2.24 (43.72)	-2.24 (43.72)	-2.24 (43.72)	-0.62 (42.07)	-0.62 (42.07)	-0.61 (42.06)	-2.23 (43.72)	-2.23 (43.72)	-2.23 (43.72)
REVENUE GR	0.06 (0.36)	0.06 (0.36)	0.06 (0.36)	0.06 (0.36)	0.06 (0.36)	0.06 (0.36)	0.06 (0.36)	0.06 (0.36)	0.06 (0.36)
EPS GR	0.02 (0.23)	0.02 (0.23)	0.02 (0.23)	0.02 (0.22)	0.02 (0.22)	0.02 (0.22)	0.02 (0.23)	0.02 (0.23)	0.02 (0.23)
BETA	1.20 (0.67)	1.20 (0.67)	1.20 (0.67)	1.21 (0.66)	1.21 (0.66)	1.21 (0.66)	1.20 (0.67)	1.20 (0.67)	1.20 (0.67)
MOMENTUM	0.14 (0.64)	0.14 (0.64)	0.14 (0.64)	0.14 (0.63)	0.14 (0.63)	0.14 (0.63)	0.14 (0.64)	0.14 (0.64)	0.14 (0.64)
VOLATILITY	0.13 (0.09)	0.13 (0.09)	0.13 (0.09)	0.13 (0.08)	0.13 (0.08)	0.13 (0.08)	0.13 (0.09)	0.13 (0.09)	0.13 (0.09)
Observations	148,436	148,436	148,412	140,161	140,161	140,137	148,304	148,304	148,304

Table A5. Summary statistics by model specification (European sample)

This table presents summary statistics for the variables used in the different model specifications for the European sample. Each column corresponds to one of the model setups reported in the empirical analysis, covering total emissions, emissions growth, and emissions intensity. For each model, the table reports the mean and standard deviation (in parentheses) of the variables used. Observations are reported monthly based on the firm-month panel used in the pooled OLS regressions.

Variable	LOG SCOPE 1	LOG SCOPE 2	LOG GHG TOT	SCOPE 1 GR	SCOPE 2 GR	GHG TOT GR	SCOPE 1 INTENSITY	SCOPE 2 INTENSITY	GHG TOT INTENSITY
RETURN	0.57 (11.78)	0.57 (11.78)	0.57 (11.78)	0.49 (11.63)	0.49 (11.63)	0.49 (11.63)	0.57 (11.78)	0.57 (11.78)	0.57 (11.78)
LOG SCOPE 1	9.32 (3.24)								
LOG SCOPE 2		9.35 (2.65)							
LOG GHG TOT			12.93 (2.76)						
SCOPE 1 GR				0.06 (0.53)					
SCOPE 2 GR					0.01 (0.47)				
GHG TOT GR						0.25 (0.83)			
SCOPE 1 INTENSITY							0.85 (2.16)		
SCOPE 2 INTENSITY								0.29 (0.48)	
GHG TOT INTENSITY									8.64 (14.89)
LOG SIZE	7.53 (1.71)	7.53 (1.71)	7.53 (1.71)	7.68 (1.69)	7.68 (1.69)	7.68 (1.69)	7.53 (1.71)	7.53 (1.71)	7.53 (1.71)
B/M	0.64 (0.54)	0.64 (0.54)	0.64 (0.54)	0.65 (0.55)	0.65 (0.55)	0.65 (0.55)	0.64 (0.54)	0.64 (0.54)	0.64 (0.54)
LEVERAGE	0.24 (0.16)	0.24 (0.16)	0.24 (0.16)	0.25 (0.16)	0.25 (0.16)	0.25 (0.16)	0.24 (0.16)	0.24 (0.16)	0.24 (0.16)
CAPEX/ASSETS	0.04 (0.03)	0.04 (0.03)	0.04 (0.03)	0.04 (0.03)	0.04 (0.03)	0.04 (0.03)	0.04 (0.03)	0.04 (0.03)	0.04 (0.03)
LOG PPE	5.50 (2.46)	5.50 (2.46)	5.50 (2.46)	5.68 (2.43)	5.68 (2.43)	5.68 (2.43)	5.50 (2.46)	5.50 (2.46)	5.50 (2.46)
ROE	9.75 (17.82)	9.75 (17.82)	9.75 (17.82)	9.81 (17.75)	9.81 (17.75)	9.81 (17.75)	9.75 (17.82)	9.75 (17.82)	9.75 (17.82)
REVENUE GR	0.06 (0.41)	0.06 (0.41)	0.06 (0.41)	0.06 (0.41)	0.06 (0.41)	0.06 (0.41)	0.06 (0.41)	0.06 (0.41)	0.06 (0.41)
EPS GR	0.01 (0.17)	0.01 (0.17)	0.01 (0.17)	0.01 (0.17)	0.01 (0.17)	0.01 (0.17)	0.01 (0.17)	0.01 (0.17)	0.01 (0.17)
BETA	0.96 (0.51)	0.96 (0.51)	0.96 (0.51)	0.99 (0.50)	0.99 (0.50)	0.99 (0.50)	0.96 (0.51)	0.96 (0.51)	0.96 (0.51)
MOMENTUM	0.09 (0.47)	0.09 (0.47)	0.09 (0.47)	0.07 (0.46)	0.07 (0.46)	0.07 (0.46)	0.09 (0.47)	0.09 (0.47)	0.09 (0.47)
VOLATILITY	0.10 (0.05)	0.10 (0.05)	0.10 (0.05)	0.10 (0.05)	0.10 (0.05)	0.10 (0.05)	0.10 (0.05)	0.10 (0.05)	0.10 (0.05)
Observations	113,709	113,709	113,709	101,416	101,416	101,416	113,553	113,553	113,553

Table A6. Stock returns and lagged GHG emissions (U.S. sample)

This table presents the results of pooled OLS regression models estimating the relationship between stock returns and lagged GHG emissions for the U.S. sample. Panel A reports the results for the total level of lagged GHG emissions, and Panel B reports the results for lagged GHG emissions growth. Columns (1), (3), and (5) exclude industry fixed effects, while Columns (2), (4), and (6) include industry fixed effects. All models include year-month fixed effects, and standard errors are two-way clustered at the firm and year levels.

Panel A: Effect of Lagged Total Emissions on Returns

Variable	(1)	(2)	(3)	(4)	(5)	(6)
LOG SCOPE 1_{t-1}	0.055	0.114*				
	(0.084)	(0.058)				
LOG SCOPE 2_{t-1}			0.114**	0.122***		
			(0.034)	(0.033)		
LOG GHG TOT_{t-1}					0.131	0.208**
					(0.102)	(0.080)
LOG $SIZE_{t-1}$	-0.180	-0.306**	-0.200	-0.318**	-0.233	-0.392**
	(0.128)	(0.098)	(0.127)	(0.095)	(0.160)	(0.124)
B/M_{t-1}	0.234	0.232	0.250	0.227	0.112	0.119
	(0.322)	(0.206)	(0.341)	(0.215)	(0.270)	(0.177)
$LEVERAGE_{t-1}$	0.002	0.150	-0.028	0.181	-0.037	0.040
	(0.429)	(0.351)	(0.427)	(0.340)	(0.440)	(0.348)
$CAPEX/ASSETS_{t-1}$	-3.848*	-3.973	-3.279*	-3.833	-3.480*	-3.550
	(1.733)	(2.295)	(1.538)	(2.297)	(1.473)	(2.228)
ROE_{t-1}	0.007***	0.006***	0.007**	0.006**	0.006**	0.005***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
LOG PPE_{t-1}	0.085	0.177**	0.062	0.180*	0.052	0.150**
	(0.086)	(0.065)	(0.134)	(0.077)	(0.088)	(0.062)
$BETA_{t-1}$	0.424*	0.375*	0.415*	0.380**	0.395*	0.366*
	(0.202)	(0.160)	(0.196)	(0.160)	(0.195)	(0.156)
REVENUE GR_{t-1}	0.176	0.153	0.166	0.150	0.131	0.121
	(0.204)	(0.228)	(0.196)	(0.222)	(0.188)	(0.221)
EPS GR_{t-1}	-0.152	-0.046	-0.107	-0.044	-0.125	-0.050
	(0.556)	(0.502)	(0.568)	(0.501)	(0.559)	(0.494)
MOMENTUM	0.400	0.320	0.401	0.323	0.388	0.315
	(0.348)	(0.358)	(0.356)	(0.361)	(0.344)	(0.357)
VOLATILITY	-0.645	-0.205	-0.563	-0.202	-0.488	-0.138
	(2.392)	(2.269)	(2.418)	(2.317)	(2.255)	(2.236)
Observations	129,864	129,864	129,864	129,864	129,852	129,852
R-squared	0.219	0.220	0.219	0.220	0.219	0.220
Year/Month F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Industry F.E.	No	Yes	No	Yes	No	Yes

Panel B: Effect of Lagged Emissions Growth on Returns

Variable	(1)	(2)	(3)	(4)	(5)	(6)
SCOPE 1 $GROWTH_{t-1}$	-0.123*	-0.090				
	(0.059)	(0.060)				
SCOPE 2 $GROWTH_{t-1}$			-0.269*	-0.229		
			(0.123)	(0.141)		

GHG TOTAL GROWTH$_{t-1}$					-0.090	-0.064
					(0.097)	(0.079)
LOG SIZE$_{t-1}$	-0.133	-0.206*	-0.131	-0.205*	-0.134	-0.206*
	(0.135)	(0.100)	(0.133)	(0.098)	(0.132)	(0.099)
B/M$_{t-1}$	0.286	0.305	0.283	0.299	0.279	0.303
	(0.328)	(0.209)	(0.326)	(0.208)	(0.324)	(0.208)
LEVERAGE$_{t-1}$	0.103	0.333	0.107	0.329	0.103	0.330
	(0.451)	(0.326)	(0.442)	(0.323)	(0.454)	(0.328)
CAPEX/ASSETS$_{t-1}$	-4.335**	-5.245*	-4.146**	-5.074*	-4.413**	-5.282*
	(1.558)	(2.335)	(1.531)	(2.248)	(1.524)	(2.318)
ROE$_{t-1}$	0.006**	0.004*	0.006**	0.004*	0.006**	0.004*
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
LOG PPE$_{t-1}$	0.115	0.195	0.112	0.191	0.118	0.196
	(0.163)	(0.116)	(0.160)	(0.113)	(0.161)	(0.115)
BETA$_{t-1}$	0.427*	0.351*	0.430**	0.356**	0.425*	0.349*
	(0.182)	(0.151)	(0.181)	(0.150)	(0.182)	(0.152)
REVENUE GR$_{t-1}$	0.236	0.180	0.264	0.208	0.227	0.171
	(0.213)	(0.228)	(0.195)	(0.207)	(0.216)	(0.222)
EPS GR$_{t-1}$	0.172	0.244	0.190	0.257	0.166	0.242
	(0.570)	(0.529)	(0.572)	(0.531)	(0.574)	(0.531)
MOMENTUM	0.323	0.236	0.325	0.238	0.324	0.236
	(0.391)	(0.395)	(0.393)	(0.395)	(0.391)	(0.395)
VOLATILITY	-0.471	-0.224	-0.461	-0.214	-0.506	-0.248
	(2.694)	(2.733)	(2.690)	(2.715)	(2.689)	(2.738)
Observations	120,895	120,895	120,895	120,895	120,883	120,883
R-squared	0.227	0.229	0.227	0.229	0.227	0.229
Year/Month F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Industry F.E.	No	Yes	No	Yes	No	Yes

Notes: $* p < 0.1$, $** p < 0.05$, $*** p < 0.01$

Appendix B: AI disclosure

AI, and more specifically, ChatGPT-4 has been used for two main purposes. First, it has been used to improve grammar and clarity. Second, it has been used to aid in the development of the code, using it to enhance formatting and resolve issues.