NEWS AND CARBON RETURN PREMIUM

LINKING CLIMATE-CHANGE NEWS AND CARBON RETURN PREMIUM

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News and Carbon Return Premium: Linking climate-change news and carbon return premium

Abstract:

First, we study stock returns and emissions using a panel of publicly listed U.S. firms from 2007 to 2024. We find that stocks of firms with higher emissions intensity (CO_2 emissions scaled by revenue) earn lower returns, consistent with the negative carbon return premium literature. This result is robust when testing various model specifications. We also tested carbon premium based on various other emission variables such as emission levels and emission growth rate and found no robust significant results. Furthermore, we estimate monthly carbon premium for the period 2010 to 2024 to examine whether carbon premium can be explained by traditional risk factors. We find that the negative premium cannot be explained by the Fama–French five-factor model. Lastly, this study further examines news effects on carbon premium by testing whether climate-change news can predict the carbon premium. We find that climate-change news has a positive effect on carbon return premium, with regulatory risk news having a stronger effect than physical risk news.

Keywords:
Carbon return premium, Carbon risk, Climate change news, Stock returns, Physical risk, Regulatory risk

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1. Introduction

Climate change has become a global issue with widespread effects, including extreme weather, melting glaciers, rising sea levels, and disruptions to ecosystems. This common issue has brought the international community together to act and led to the Paris COP21 agreement in 2015, in which 195 countries committed to limiting global warming to below 2 degrees above pre-industrial levels (UNFCCC, 2015). This symbolic milestone, together with other climate summits and green policy initiatives, has pushed the financial sector to take climate issues more seriously. Many asset managers and companies have committed to limiting corporate carbon emissions. However, it should be noted that in the past few years, this momentum has been called into question. The United States, under the Trump administration, left the Paris Agreement, and the credibility of other countries and companies has been questioned as part of greenwashing campaigns. Northvolt's recent bankruptcy in Sweden and the retreat of automakers from EV investments (e.g., Volkswagen) are further warning signs, highlighting the challenges of the green transition. This is also relevant for firms with high levels of CO_2 emissions, as they are most exposed to climate policy regulation and shifting investor preferences. We consider these developments by using data for a more recent period that covers growing skepticism about the green transition and policy changes under the Trump administration. This is done by testing stock returns for 2662 unique publicly listed U.S. firms, up to 2024.

Although there is skepticism, the green transition still ranks high on the agenda for countries, consumers, companies, and asset managers. At recent climate summits such as COP30, many countries have pledged new climate actions, and the overall goal remains to move toward a low-carbon economy to curb global warming. In practice, this is driven by commitments like the European Climate Law, which requires a reduction in net emissions by 55% from 1990 levels by 2030 and climate neutrality by 2050. As the world aims to transition toward a low-carbon emission economy, industries are changing, and capital is shifting. For investors, climate change introduces a new form of risk, driven by evolving regulation and technological innovation that increasingly disfavor firms seen as contributing to it. Therefore, financial markets face the question of whether carbon risk is priced in the market or not, and how to hedge against it. Central banks and regulators classify climate change as a physical and transition risk that can threaten financial stability (NGFS, 2019). The Financial Stability Board similarly warns that climate-related physical and transition risks can be amplified by the financial system and increase vulnerabilities to financial stability (FSB, 2025).

As governments respond to climate change by regulating policies, introducing carbon pricing, and requiring mandatory emissions disclosure, companies with high carbon emissions face increased exposure to transition risk (Hambel and van der Ploeg, 2025). Climate change also creates physical risk, as more frequent floods, storms, heatwaves, and wildfires can damage assets, disrupt production, and infrastructure in exposed regions. Empirical studies show that such events affect both cash flows and asset prices, indicating that physical climate risk is economically relevant for investors (Bernstein, Gustafson, and Lewis, 2019; Baldauf, Garlappi, and Yannelis, 2020; Bakkensen and Barrage, 2022). These regulatory and physical risks, together with the rapid growth of sustainable investing and net-zero commitments, raise the question of how capital markets price high-emission companies relative to low-emission firms, and whether climate concerns are accurately reflected in their valuations. Relevant studies find that climate change is an increasingly important source of risk for investors, with rising disclosure demands among institutional investors (Ilhan, Krueger, and Sautner, 2023). According to a survey of institutional investors, the average investor thinks equity valuations do not fully reflect climate risks and considers high-emission firms to be overvalued (Krueger, Sautner, and Starks, 2020).

The literature is ambiguous about how this carbon risk is priced. Some previous literature finds that firms with higher carbon emissions have higher expected returns, where this carbon return premium reflects that investors demand compensation for holding stocks exposed to future regulation or reputational risk (Bolton and Kacperczyk 2021; 2023). Related work also finds that high-emission firms have greater tail risk, as reflected in option prices (Ilhan, Sautner, and Vilkov, 2021). On the other hand, some studies find the opposite, where firms with lower carbon emissions have higher expected returns, suggesting a carbon discount for investing in low-emission firms (Crosignani, Osambela, and Pritsker, 2025; Garvey, Iyer, and Nash, 2018). This is supported by Zhang (2025), who finds that with correct lagging and scaling of the carbon emissions, the realized carbon return is significantly negative in the U.S. in recent years. The conflicting findings on the carbon premium highlight the importance of using correct methodology and that results should be interpreted cautiously before drawing conclusions.

The first objective of this study is therefore to investigate the carbon premium with stock return and emissions. Our work replicates the methodology of Bolton and Kacperczyk (2021) to estimate the carbon risk premium. This is done with the correct lagging and model specifications to avoid look-ahead bias, according to Zhang (2025). To remedy high skewness, we use the log of carbon intensity. Another key difference is that we have a more recent timeframe and merged CRSP-Compustat financial information for U.S. stock returns, with carbon emission data available from LSEG (scope 1-3). Like Zhang (2025), we find a negative carbon premium. The carbon premium is considered the return difference between high- and low-emission firms, and we cannot explain it by the Fama–French five-factor model. This result is robust when testing various model specifications, using both monthly and annual data.

While the pricing of carbon risk has been well documented, less is known about how this premium responds to the changing intensity of climate-change news. Financial markets rely on the media. Whether through traditional outlets or other platforms, the media provides investors with information that can impact their views on investments and influence their trading decisions. In recent years, media attention to climate change has fluctuated with significant events such as the Paris Agreement 2015, IPCC reports, and international climate summits (UNFCCC, 2015). Periods of intense coverage may increase the salience of climate risk among investors, thereby affecting the valuation of high-emission firms. The paper Hedging Climate Change News (Engle, Giglio, Kelly, Lee, and Stroebel, 2020) supports this by showing that climate-change news affects stock returns. However, existing research in this area has primarily examined how climate-related media attention affects stock returns in general, rather than the carbon premium specifically. As a result, it remains unclear whether the pricing of carbon risk varies with the intensity of climate-related news. Firms with stronger environmental performance may be viewed by institutional investors as better prepared for the transition to a low-emission economy (Krueger et al., 2020). If investors become more concerned about carbon risk in periods when climate change receives more attention, the carbon premium may increase.

The second objective of this paper is therefore to extend the analysis by investigating how the intensity of climate-change news affects the carbon risk premium of firms. This is done by using climate-change news based on the Media Climate Change Concerns (MCCC) Ardia, Bluteau, Boudt, and Inghelbrecht (2023) and New York Times (NYT) indices provided by Engle's V-Lab team at NYU Stern. In line with previous literature, the study analyzes the effect of different climate-change news themes. It mainly focuses on the impact of climate-change news to investigate whether news intensity increases or decreases the carbon premium. We find that climate-change news has a positive effect on the carbon premium, consistent with the idea that investors demand greater compensation for holding carbon-intensive firms during periods of high climate news intensity. We also differentiate between physical risk and regulatory risk and show that regulatory news has a stronger impact on the carbon premium. Thus, our study contributes to the literature on whether and how carbon risk is priced, and how climate-change news influences this pricing.

The remainder of the paper proceeds as follows: Section 2 describes the theoretical context and adjacent literature. Section 3 describes the data, limitations, and variables. Section 4 presents methodology and empirical findings. Section 5 concludes with a summary of the main insights.

2. Literature Review

The link between stock returns and carbon emissions has become a central topic in recent finance research. A well-known contribution in this area is Bolton and Kacperczyk (2021), who show that U.S. firms with higher total carbon emissions earn higher average returns. The results suggest a carbon premium associated with both the level and the year-to-year change in emissions (scopes 1–3), after controlling for factors such as market risk, size, value, profitability, investment, and momentum. They find that a one-standard-deviation increase in carbon emissions equals roughly 0.3–0.5% higher monthly returns in the U.S. market. The authors explain this as a premium for carbon risk, interpreting it as compensation investors require for exposure to transition and regulatory risks. They also find that institutional investors with sustainability mandates systematically underweight high-emission firms with high emission intensity (scope 1), particularly in salient high-emission industries such as oil and gas.

In their follow-up paper, Bolton and Kacperczyk (2023) extend the analysis to more than 14,000 firms across 77 countries. They again find that higher emission levels and emission growth are associated with higher expected returns, indicating that carbon-transition risk is priced globally, not only in the U.S. The magnitude of this premium varies across countries and is stronger in economies with lower economic development, greater reliance on fossil fuels, and less inclusive political systems. They also document that the carbon premium increases after the 2015 Paris Agreement, consistent with rising investor awareness of transition risk, particularly in countries that adopt more ambitious climate policies.

A growing literature reaches different conclusions about how emission levels and emission intensity are reflected in expected stock returns. As summarized by Crosignani, Osambela, and Pritsker (2025), the literature remains divided, with conflicting results on whether carbon emissions are priced in equity markets. Depending on the empirical approach and model specification, some studies find a positive relation, consistent with a carbon premium for high-emission firms. In contrast, others document a negative relation, suggesting a carbon discount (Table 1). According to Crosignani et al. (2025), this is due to different methodologies, such as using realized instead of expected emissions and the sensitivity of the results to “super emitters”. Moreover, variation in data vendors, sample composition, and treatment of salient industries are mentioned as other possible reasons for the ambiguous results.

Table 1

Studies running stock return regressions on emission variables.
Table 1 summarizes the results of prominent papers on the link between carbon emissions and stock returns, showing whether each paper finds a positive, negative, or no relation (Crosignani et al., 2025). It also notes key differences across studies, including when emissions are measured (contemporaneous or lagged timing), which years are covered in the data sample, and whether emissions are total or scaled by firm size (emissions level or intensity). These choices, together with the study's control variables, help explain why results differ.

Paper	Timing	Data	Emission variable	Relation
Bolton and Kacperczyk (2021)	Contemporaneous	2005–2017	Emissions level	Positive
Bolton and Kacperczyk (2023)	Lagged	2005–2018	Emissions level	Positive
Lioui and Mis`ra (2023)	Lagged	2009–2024	Emissions intensity	Positive
Garvey et al. (2018)	Lagged	2011–2015	Emissions intensity	Negative
Zhang (2025)	Lagged	2009–2021	Emissions intensity	Negative
Pedersen et al. (2021)	Lagged	2009–2019	Emissions intensity	Negative
Aswani et al. (2024)	Contemporaneous	2005–2019	Emissions intensity	None

Building on earlier studies that document a carbon premium, Zhang (2025) revisits the pricing of carbon transition risk. The paper starts from the theoretical view that high-emission firms should be more exposed to transition risk and therefore earn higher expected returns in equilibrium. Zhang shows that this result mainly comes from using forward-looking emissions data with current sales and profits. To avoid this, the study logs carbon emissions intensity and lags firm-level emissions by ten months before forming portfolios, so that the measures take into consideration the time it takes to inform investors before returns are realized. When emissions are lagged to reflect what investors knew at the time, the U.S. carbon premium over 2009–2021 is significantly negative. The study documents value-weighted carbon spreads of roughly -0.39% and -0.27% per month for Scope 1 and Scope 1–2 intensities, and these results are robust to standard factor adjustments. Zhang argues that what previous literature, such as Bolton and Kacperczyk (2021; 2023), interpreted as a carbon premium reflects the use of forward-looking emissions measures that already account for a company's strong performance. When emissions are lagged to match the information available to investors, recent returns look more like a carbon discount, with brown firms underperforming green firms, consistent with the shift toward a carbon-aware pricing equilibrium.

As listed in Table 1, several other studies examine how carbon emissions relate to stock returns while controlling standard risk factors (Lioui and Misra, 2023; Garvey, Iyer, and Nash, 2018; Pedersen, Fitzgibbons, and Pomorski, 2021; Aswani, Raghunandan, and Rajgopal, 2024). These papers mainly differ in timing, data, emission variable and approach, resulting in different contributions. Garvey et al. (2018) study a global MSCI World universe, use carbon intensity emissions measured before returns, and find a negative relation where firms with lower intensity earn higher returns. This is supported by Pedersen et al. (2021), who also find a negative relation when analyzing the S&P 500. Lioui and Misra (2023) instead focus on factor construction for U.S. firms with data from Trucost. They find that a value-weighted carbon factor gives a negative carbon premium, while a carbon-weighted factor gives a positive carbon premium. After robustness checks, they found out that value weighted is not robust while carbon weighted remains robust. Further, they show that carbon intensity is not robust, but emission levels are robust. Their finding was that previous carbon premium calculations included size premium and when they constructed a model that hedged against that size premium, carbon premium became significant, robust and positive, based on emission levels. The authors mean that these implementation differences can explain prior disagreement and suggest that future studies should be based on emission levels and implement a correct approach to hedge against size for reliable and consistent results. On the contrary, Aswani et al. (2024) argue for emissions intensity as the appropriate measurement choice to compute carbon premium for firms, since when analyzing U.S. firms by using firm-disclosed data and emissions intensity, they find that carbon emissions intensity has no relation to stock returns. The study means that the previously documented positive carbon premium can be driven by vendor-estimated, unscaled emissions that are highly correlated with firm size. Taken together, these papers emphasize how sensitive results are to choices such as scaling of emissions and lagging of data. This has been taken into consideration in our study when running stock return regressions on emissions, so we have reliable data according to the latest research insights when testing news effects on carbon premium.

Furthermore, Engle et al. (2020) show that climate-change news shocks are priced in equity markets by constructing climate-news indices and hedge portfolios designed to offset this risk. Using articles from the Wall Street Journal (WSJ), they build a Climate Change News Index (CCNI) that measures the intensity of climate-related news in major financial newspapers. By building climate change hedge portfolios, they find that negative climate news is related to lower market returns and that some portfolios serve as hedges against this risk. Similarly, Campos-Martins and Hendry (2023) study the global effects of climate-change news on financial markets. The study demonstrates that climate change news increases volatility as concerns rise about the energy transition, especially oil and gas share prices. The authors build on Engle et al. (2020) by extending their WSJ-based climate-news indices and denoting them CC+ and CC-, which capture positive and negative climate-change news, respectively. They show that negative climate-news shocks (CC–) amplify volatility across oil and gas stocks, while positive climate-news shocks (CC+) have a stabilizing effect.

To summarize, these studies show that carbon emissions can be a priced risk factor and that climate-change news affects both stock returns and oil market volatility. However, previous studies find both positive and negative relations between emissions and stock returns consistent with either a carbon premium or a carbon discount. Furthermore, it remains unclear whether the carbon risk premium varies during periods when climate risk becomes more salient due to climate-change news. This thesis addresses this gap by combining time series of carbon premium with time-varying measures of climate-news intensity, including the NYT index and the MCCC index. The analysis investigates whether the carbon risk premium strengthens or weakens in response to changes in climate-news intensity. Our work makes two main contributions. First, it replicates the empirical framework of Bolton and Kacperczyk (2021) and extends it to a more recent period (up to 2024) while continuing to focus on U.S publicly listed firms. We also use correct specifications according to recent advancements in the field by removing super emitter, removing salient industries, lagging emissions, match frequency of emission data and stock return data (Crosignani et al., 2025; Zhang, 2025). Secondly, it links the carbon risk premium literature (Bolton and Kacperczyk, 2021) with research on climate change news (Engle et al., 2020; Campos-Martins and Hendry, 2023) by running regressions on the carbon premium and news with controls.

3. Data Collection

Our primary database covers the period 2002–2024 and is built by matching U.S. stock market data from WRDS CRSP–Compustat with firm-level carbon emissions data from LSEG. We include both active and inactive firms to avoid bias towards companies that survive and remain listed. LSEG provides carbon emission data for 3,903 unique firms. After matching this to CRSP–Compustat, our final merged data contains 2,662 unique firms. The number of unique firms and observations varies across years, as illustrated in Table 2, with more firms reporting their emissions and more data available as years pass. The sample increases over time from 12 firms and 18 observations in 2002 to more than 2,000 firms and over 20,000 observations in 2020. Although we have lost approximately 30% of firms in our merging process, our sample remains large enough to provide accurate results. The loss mainly reflects data quality issues in the raw LSEG output and the inability to match some firms in LSEG to CRSP–Compustat due to the non-existence of data, timing issues, and missing identifiers. We decided to keep a clean, consistent data sample rather than include observations with unclear identifiers or duplicates. We further merge this database based on date with the Fama-French Five-Factors, the MCCC index, and the NYT climate-news index.

Table 2

Unique firms and observations per year.
Table 2 reports the number of distinct firms and the corresponding total number of firm-year observations in our sample for each calendar year from 2002 to 2024. *Unique firms* are identified using the CRSP permanent identifier (PERMNO). *Total observations* denote the number of observations for the specific *Year* with data for the variables used in the main regressions.

Year	Unique firms	Total observations
2002	12	18
2003	16	149
2004	25	223
2005	52	318
2006	75	666
2007	98	919
2008	130	1,134
2009	191	1,561
2010	220	2,334
2011	236	2,532
2012	248	2,753
2013	254	2,761
2014	276	2,957
2015	965	4,619
2016	1,344	12,476
2017	1,613	16,752
2018	1,743	19,909
2019	1,923	21,381
2020	2,106	23,485
2021	2,289	25,665
2022	2,460	26,978
2023	2,393	26,733
2024	1,926	20,311

3.1 Stock Sample

To examine the carbon premium, we start from a panel of publicly listed U.S. firms in the merged CRSP–Compustat database for the period 2002–2024. This span includes several major climate-policy milestones, such as the 2015 Paris Agreement, that may have affected the premium. From CRSP we use monthly total returns, market capitalization, and security identifiers. Compustat gives us annual accounting variables such as total assets, common equity, net income, property, plant, and equipment, capital expenditures, revenues, and earnings per share. The merged CRSP–Compustat data is retrieved from WRDS, where we set the lag parameter to 0, since we introduce our own lags later. We restrict attention to U.S. firms, set the currency to USD, and include both active and inactive securities.

For the main tests with annual regressions, we compound monthly returns to get a panel of annual stock returns. We compute a yearly return only when all 12 monthly returns for that year are available to avoid inaccurate and artificial annual stock returns. Firm identifiers are harmonized across datasets using CUSIP8 codes as the main identifier. To focus on U.S. common equity and avoid duplicates, we further restrict the sample to securities with CUSIPs ending in "10", which correspond to common shares. The CRSP–Compustat also had a fiscal-year-end inconsistency since it reports two sets of fundamentals that map to the same return date but have slightly different dates. In these cases, the underlying fundamentals are identical, and only the date differs. We keep the observation with the most common reporting date for that firm and drop the duplicates.

3.2 Carbon Emissions

Firm-level carbon emissions (Scopes 1-3) are from LSEG ESG, the only emissions provider we had access to. LSEG reports two main emissions fields for each scope: "Scope Combined (Reported or Estimated) Total" and "CO2 Equivalent Emissions". For each scope, our primary measure is the "Scope Combined (Reported or Estimated) Total" series. When this measure is missing, we fill it with the corresponding "CO2 Equivalent Emissions" series for the same scope. This gives us a more complete emissions sample without changing the underlying scale. We follow the Greenhouse Gas Protocol definitions of the three scopes. Scope 1 includes direct emissions from the firm's own operations, such as fuel burned on-site or process emissions from production. Scope 2 includes indirect emissions from purchased electricity, steam, heating, and cooling. Scope 3 contains other indirect emissions along the value chain, such as emissions from suppliers, transport, and the use or disposal of the firm's products.

We then create several firm-year variables. For each firm and year, we compute combined measures for Scope 1+2, Scope 2+3, and Scope 1+2+3. For the regression, we use the log of total emissions, emissions growth rates (y-o-y), carbon intensity, and the log of carbon intensity. The log of carbon intensity is used because the raw intensity measure is highly skewed, while its logarithm has a more regular distribution (Appendix D). Furthermore, emission variables are lagged by 10 months to avoid look-ahead bias, as recommended by Zhang (2025).

Furthermore, data cleaning for carbon emissions from LSEG was challenging as we had to retrieve a very large database, which required API code. Using API code, there were no columns for date, and CUSIPs were only reported in the first row. We therefore forward-fill CUSIP and ISIN within each firm. Emission observations were recorded at different dates during the year since LSEG reports the date the emission first became available in the system, which may not match the fiscal year-end. Without data standardization in LSEG, there was a problem with duplicates. For example, dates were in the following format: 1/1/2023 and the next one 31/12/2023, which caused problems, as 1/1/2023 should technically have belonged to 31/12/2022. We therefore standardized the dates to the nearest December, except for some special instruments that had a different pattern.

3.3 Climate-news Measures

We test the relationship between climate-news intensity and the carbon premium using the Media Climate Change Concerns (MCCC) index and a New York Times (NYT) climate-news series. The MCCC index, built by Ardia, Bluteau, Boudt, and Inghelbrecht (2023), is a measure of climate change concern constructed from articles on climate change in major U.S. newspapers. Each article receives a "concern score" that combines the perceived level of climate risk and the article's tone, and these scores are aggregated into an overall index and several thematic subindices. We use the aggregate index as a broad measure of climate-news intensity and exploit the thematic breakdown to distinguish between news related to physical risks (e.g., extreme weather and natural disasters) and regulatory or transition risks (e.g., climate policy, regulation, and carbon pricing). This allows us to examine whether different types of climate-related news are linked to the carbon premium in different ways.

The New York Times (NYT) climate-news series was provided directly by Professor Engle's V-Lab team at NYU Stern. The unpublished dataset contains two weekly indices, derived from NYT articles via LexisNexis. As a first step, they filtered out articles from certain sections that they deemed irrelevant, such as fashion and sports. The NYT Cosine Similarity Index applies the Engle et al. (2020) methodology to New York Times articles by comparing their content to a fixed climate-change vocabulary, yielding a weekly measure of climate news intensity. This uses essentially the same methodology as the original WSJ Index, where they compute the cosine similarity between a given week's worth of NYT articles with a corpus of text known to be related to climate change. This is the same corpus as was used for the WSJ News Index. Prior to computing cosine similarity, they perform standard text cleaning steps, including stemming, the removal of stop words, and bigram tokenization. The NYT Tag Index, Professor Engle's preferred measure, is simply the ratio of articles with either the "Climate Change" or "Global Warming" subject tag assigned by LexisNexis. This is divided by the total number of articles in the sample. In our empirical analysis, we only use the NYT Tag Index and aggregate it from weekly to monthly frequency to match our return and emissions data. Both the MCCC indices and the NYT Tag Index are then merged with our firm-level panel by date.

3.4 Data Merging

The merged stock-emissions panel is obtained by matching CRSP–Compustat data with LSEG data using security identifiers. Our primary matching key is CUSIP8, but for a small number of firms in LSEG (18 in total), CUSIP is missing. For these firms, we matched them using their ticker symbols and set a similarity score of 1. The result of the merging process was 2662 unique firms out of 3903 unique firms in the LSEG database. We could not match 31.57% of the firms in the LSEG database, primarily due to data quality issues. Two main problems were that, firstly, some firms in the LSEG database did not exist in the CRSP-COMPUSTAT merged database. Secondly, some firms were missing CUSIP identifiers. Thirdly, we suspect it may be a timing quality issue, as we had to standardize the reporting date for LSEG to merge it with CRSP-COMPUSTAT without creating duplicates. Although we lost some firms, our sample database is still large enough that we can be confident in our results.

3.5 Control Variable Winsorization

To control for standard firm characteristics that may be related to both emissions and expected returns, we follow Bolton and Kacperczyk (2021) and include size (log market capitalization), book-to-market, return on equity, leverage, investment-to-assets, log PPE, sales growth, EPS growth, return volatility, market beta, and momentum (past 12-month return excluding the most recent month). However, many of these variables are prone to extreme outliers.

To eliminate outliers and remedy skewness of data and remove the outliers, we apply winsorization in line with Bolton and Kacperczyk's (2021) approach. Book-to-market, leverage, investment-to-assets, and return on equity are winsorized at the 2.5th and 97.5th percentiles of their cross-sectional distributions. Volatility, sales growth, EPS growth, and momentum are winsorized at the 0.5th and 99.5th percentiles. We apply the same logic to the emission-based variables. Emission growth rates and emission intensities (based on both revenues and assets, as well as their logarithms) are winsorized at the 2.5 percent tails. Before winsorization. These steps are taken to ensure that a small number of extreme observations do not drive our results, as emphasized in previous literature (Crosignani et al., 2025; Zhang, 2025).

3.6 Fama-French Five-Factor and Other Control Variables

In line with Bolton and Kacperczyk (2021), we merge our firm-level panel with Fama–French five-factor data from the Fama–French U.S. data library to test whether traditional risk factors can explain the carbon premium. The dataset includes the market excess return (Rm–Rf), the size factor (SMB), the value factor (HML), the profitability factor (RMW), the investment factor (CMA), and the risk-free rate. We get monthly factor returns from Kenneth French's online data library, and these are merged with our stock return data by calendar month. For annual regressions, we convert monthly factor returns to annual returns by compounding over the 12 months of each year, using the same approach as for stock returns.

In addition to the Fama–French factors, we add other control variables. We use the U.S. economic policy uncertainty index from the Federal Reserve Bank of St. Louis (series USEPUINDXD). We also use the CBOE Volatility Index from FRED (series VIXCLS) as a measure of aggregate stock market uncertainty. Finally, we use the U.S. West Texas Intermediate (WTI) crude oil spot price obtained from the U.S. Energy Information Administration (EIA). These macro controls are used at a monthly frequency and are merged with our data by calendar month.

3.7 Industries

We use Global Industry Classification Standard (GICS) to identify which industry each firm belongs to and to create industry fixed effects for our regression. We first use the first 6 digits of GICS to classify firms into 74 industries. Since our sample lacks within-industry variation (low number of firms in some industries), we check robustness using the first 4 digits of GICS to classify firms into 25 main industry groups, allowing for more within-industry variation.

3.8 Super Emitters and Salient Industries

We define super emitters as firms with total emissions (*Scope 1+2+3*) exceeding 1 million tons. In our sample, we identified 23 super emitters and removed them from our main regression. We deemed Energy, Transportation, and Utilities as salient industries. As a result, we identified 193 firms in salient industries and removed them from our main regression.

Table 3

Summary statistics.
Table 3 reports summary statistics (averages, medians, and standard deviations) for the variables used in the main regressions in the sample period of 2002–2024. Panel A reports the *Emission variables*, including log levels, growth rates, and intensity measures of firm-level CO_2 emissions across Scopes 1, 2, 3, and their combinations; emission growth rates and intensity measures are winsorized at the tails as explained in the table to mitigate the influence of outliers. Panel B reports the *Cross-sectional return variables*. *AnnualRet* is the annual stock return; *Annual ExcessRet* is the annual stock return in excess of the risk-free rate LOGSIZE is the natural logarithm of market capitalization (in USD million); *B/M* is the book value of equity divided by market value of equity; *ROE* is the return on equity; *LEVERAGE* is the book value of leverage defined as the book value of debt divided by the book value of assets; *INVEST/A* is capital expenditures divided by the book value of assets; *LOGPPE* is the natural logarithm of plant, property, and equipment (in USD million); *BETA* is the *CAPM* beta calculated over the one-year period; *VOLAT* is the stock return volatility calculated over the one-year year; *MOMENTUM* is the cumulative stock return over the past 12 months (excluding the most recent month). All cross-sectional variables are winsorized at the percentiles reported in the table to reduce the impact of outliers. Panel C reports the time-series variables. *Annual MKTRF*, *SMB*, *HML*, *UMD*, *RMW*, and *CMA* are the annual returns on the market, size, value, momentum, profitability, and investment factor-mimicking portfolios from the Fama–French U.S. data library, obtained by compounding monthly factor returns within each calendar year; *Annual RF* is the annual risk-free rate. Panel D reports the *Control variables for news regressions*, including an *Oil Price Shock* measure, the *VIX* index capturing stock market volatility, a *US Policy Uncertainty* index, a *Carbon Tax News Index,* and an *Aggregate News Index* (see Section 3.3 and Section 3.5 for further explanations). Asterisks denote statistical significance (* p<0.05, ** p<0.01, *** p<0.001).

Variables	Mean	Median	Std. Dev.
Panel A: Emission variables			
Log Carbon Emissions Scope 1 (tons CO_2e)	9.48	9.17	3.12
Log Carbon Emissions Scope 2 (tons CO_2e)	10.03	10.04	2.45
Log Carbon Emissions Scope 3 (tons CO_2e)	12.91	12.98	2.63
Log Carbon Emissions Scope 1+2 (tons CO_2e)	13.19	13.21	2.58
Growth Rate in Carbon Emissions Scope 1 (winsorized at 2.5%)	0.10	0.02	0.48
Growth Rate in Carbon Emissions Scope 2 (winsorized at 2.5%)	0.06	0.00	0.38
Growth Rate in Carbon Emissions Scope 3 (winsorized at 2.5%)	0.21	0.09	0.78
Growth Rate in Carbon Emissions Scope 1+2+3 (winsorized at 2.5%)	0.28	0.07	0.57
Carbon Intensity Scope 1 (tons CO_2/USD m.) (winsorized at 2.5%)	95.28	7.55	290.67
Carbon Intensity Scope 2 (tons CO_2/USD m.) (winsorized at 2.5%)	31.33	16.97	39.43
Carbon Intensity Scope 3 (tons CO_2/USD m.) (winsorized at 2.5%)	935.57	258.76	1413.77
Carbon Intensity Scope 1+2+3 (tons CO_2/USD m.) (winsorized at 2.5%)	1088.07	322.48	1582.45
Log Carbon Intensity Scope 1(winsorized at 1%)	2.21	2.02	2.11
Log Carbon Intensity Scope 2 (winsorized at 1%)	2.77	2.83	1.28
Log Carbon Intensity Scope 3 (winsorized at 1%)	5.72	5.56	1.69
Log Carbon Intensity Scope 1+2+3 (winsorized at 1%)	6.00	5.78	1.50
Panel B: Cross-sectional return variables			
AnnualRet	0.15	0.09	0.57
Annual ExcessRet	0.14	0.08	0.57
ROE (winsorized at 2.5%)	0.07	0.10	0.34
LOGSIZE	8.07	8.00	1.85
B/M (winsorized at 2.5%)	0.47	0.39	0.37
LEVERAGE (winsorized at 2.5%)	0.27	0.25	0.21
INVEST/A (winsorized at 2.5%)	0.03	0.02	0.21
LOGPPE	5.83	5.80	2.38
SALESGR (winsorized at 0.5%)	0.03	0.02	0.25
EPSGR (winsorized at 0.5%)	0.00	0.00	0.14
VOALT (winsorized at 0.5%)	0.11	0.09	0.07
BETA	1.11	1.02	1.05
MOMENTUM (winsorized at 0.5%)	0.14	0.08	0.50
Panel C: Time-series variables			
Annual MKTRF	0.13	0.21	0.16
Annual SMB	-0.02	-0.04	0.05

Annual HML	0.00	-0.08	0.19
Annual UMD	0.01	-0.01	0.14
Annual RMW	0.05	0.04	0.08
Annual CMA	0.01	-0.03	0.13
Annual RF	0.02	0.01	0.02
Panel D: Control variables for news regression			
Oil Price Shock	-0.00	0.01	0.11
VIX	18.14	16.70	6.34
US Policy Uncertainty	161.89	149.13	67.06
NYT Tag Index	1.20	1.10	0.46
Aggregate News Index	1.53	1.45	0.59

4. Results and Methodology

In this section, we present our methodology and empirical results. We begin by estimating annual cross-sectional regressions to get the carbon return premium across different emissions measures and scopes. We then test whether well-known risk factors can explain this carbon premium. Finally, we investigate the effects of climate-related news on the carbon return premium and whether these effects differ between physical and regulatory risk.

4.1 Annual Cross-sectional Regression for Carbon Return Premium

We start with Bolton and Kacperczyk (2021) as our baseline model, which we later adjust to match advancements in the field. The baseline model is the following:

$$RET_{i,t} = \alpha_0 + \alpha_1 \log (TOT\ Emissions_{i,t}) + \alpha_2^{\top} Controls_{i,t-1} + \mu_t + \varepsilon_{i,t}, \quad (1)$$

where, $RET_{i,t}$ denotes the annual excess return of firm *i* in month *t*, and *Emission* is a generic term representing each of our emissions variables and scopes (*Scope 1*, *Scope 2,* and *Scope 3*). The vector of control variables includes firm-level characteristics known to predict returns: *LOGSIZE, B/M, ROE, LEVERAGE, MOMENTUM, INVEST/A, HHI, LOGPPE, BETA, VOLAT, SALESGR,* and *EPSGR* (explained in Table 3). They also include fixed effects, and cluster standard errors at both the firm and year levels. Their coefficient of interest is α_1.

Our empirical framework follows Bolton and Kacperczyk (2021) from which we adopt the same set of control variables. The only variable we exclude is the Herfindahl–Hirschman Index (*HHI*) of business segment concentration, as data limitations prevent us from constructing it. However, our model differs from Bolton and Kacperczyk (2021) in three important ways: we lag emissions, we match the frequency of emissions and returns, and we use excess returns. These choices reflect recent methodological advancements and follow Crosignani et al. (2025), who show that these specifications are necessary for obtaining unbiased and consistent estimates of β. Emissions must be lagged to address measurement error and omitted-variable concerns, and we apply a 10-month lag based on Zhang (2025), who finds that the median reporting delay for emissions data is approximately 10 months. Using identical frequencies for emissions and returns addresses the same econometric concerns. Excess returns are used to control the risk-free rate. These choices also align with guidance from recent climate-finance research on the correct specification for estimating the carbon return premium.

Specifically, there are two main econometric issues with regard to unmatched frequency and no lagging of emissions. First, measurement error: investors may receive emissions-related information more frequently than annual disclosures, leading to measurement error when annual emissions are used at a monthly frequency and biasing estimates of β toward zero. Second, omitted variable bias: emissions for year t are not known to investors during year t, but they are correlated with the information investors learn throughout the year. This correlation between reported emissions and intra-year innovations in emissions introduces omitted-variable bias, again biasing β downward.

We also exclude super-emitters and salient industries from our main specifications. As robustness checks, we estimate models in which both are included, models in which only one is excluded, and a specification that uses monthly excess returns and monthly emissions data. We include industry fixed effects because emissions tend to cluster substantially within specific industries. To test whether firm-level variation in emissions is driven by industry-level factors, we incorporate industry fixed effects based on CRSP GICS codes. We estimate models using both 6-digit GICS industries and 4-digit GICS industry groups. Using 6-digit codes yields insufficient within-industry variation due to small sample sizes in specific industries, whereas the 4-digit specification increases the number of observations per industry and provides a more reliable estimation while serving as a robustness check. We first studied the carbon return premium in annual cross-sectional regressions by estimating the following pooled OLS regression separately for each of the four emissions measures *Log emissions, Growth in emissions*, *Log emissions intensity (revenue)*, and *Emissions intensity (revenue)*. Within each category, we run separate regressions for each emissions scope (*Scope 1, Scope 2, Scope 3, Scope 1+2, Scope 2+3*, and *Scope 1+2+3*):

$$AExRet_{i,t} = \alpha + \beta \cdot Emission_{\,i,t-1} + \gamma \cdot Controls_{\,i,t-1} + Industry\ FE + \mu_t + \varepsilon_{i,t}, \qquad (2)$$

where, $AExRet_{i,t}$ denotes the annual excess return of firm *i* in year *t*, and Emission is a generic term representing each of our emissions variables and scopes. The vector of control variables includes firm-level characteristics known to predict returns: *LOGSIZE, B/M, ROE, LEVERAGE, MOMENTUM, INVEST/A, LOGPPE, BETA, VOLAT, SALESGR*, and *EPSGR*. Our regressions include year and industry fixed effects, and we cluster standard errors at both the firm and year levels. Our coefficient of interest is *β,* which captures the carbon return premium for the relevant emissions measure.

In our main annual regression, all control variables except *BETA*, *VOLAT*, and *MOMENTUM* are lagged by 6 months, following Fama, as these accounting fundamentals become available to investors then. *BETA*, *VOLAT*, and *MOMENTUM* are lagged by 1 month, as this information is continuously available to investors each month. We take means of these control variables each year so we can use them in annual frequency and avoid bias when the fiscal year end of companies differs, while years in our regression are based on calendar date. In comparison with Bolton and Kacperczyk (2021), we include one additional emissions variable, the logarithm of carbon intensity. We do so because Zhang (2025) deems it relevant and because our skewness tests show that raw carbon intensities are highly skewed.

Table 4 reports the results for all model specifications and robustness checks of the annual regression. In Panel A (log emissions) and Panel B (growth in emissions) of Table 4, the estimated coefficients are generally statistically insignificant across Scope 1–3 and their combinations. By contrast, Panel C shows that the coefficient on log carbon intensity is negative and statistically significant for the scopes. For instance, the coefficient on log carbon intensity for *Scope 1+2+3* with *6-digit industry FE* in Panel C is negative and significant with an approximate value of -0.0079 and a standard error of roughly 0.0015. These results are economically significant and suggest a negative carbon premium. Using the coefficients from the baseline *6-digit industry FE* specification in Panel C Table 4, and the standard deviations in Panel A Table 3, we can calculate that a one-standard-deviation increase in log carbon intensity for *Scope 1+2+3* reduces annual excess returns by about 1.2 percentage points, meaning roughly 10 basis points per month.

When we look at emissions intensity (revenue) in levels in Panel D of Table 4, the evidence is much weaker. Only the coefficient for Scope 2 is statistically different from zero, and even that effect is very small. For all the other scopes, the coefficients are near zero. While we also see in the robustness checks, and when changing the industry fixed effects, that some other variables sometimes become significant and negative, those effects are not robust. Comparing Panels C and D of Table 4, we conclude that log-transforming carbon intensity is important for capturing the carbon return premium. Since emissions are concentrated in specific industries, we also compare the specification without industry fixed effects to the models with 4-digit and 6-digit GICS fixed effects in Panel C of Table 4. Adding industry fixed effects increases the absolute value of the log-intensity coefficient for *Scope 2* by roughly 80% and for *Scope 1+2* by roughly 50%, while changes for the other scopes are modest. This shows that controlling industry effects strengthens the economic importance of the carbon premium. The reason why the log of carbon intensity of scope 3 is nan in our table is due to insufficient within-industry variation when using 6-digit code (fewer companies reported scope 3 than scope 1 or 2)

When experimenting with model specification by changing the lag structure of emissions and controls and altering the definitions of how *BETA*, *VOLAT*, and *MOMENTUM* are calculated, we find that the estimated carbon premium and its significance vary substantially by these choices, while the sign remains negative. We therefore conclude that the results depend heavily on the lag structure and the exact definitions of the control variables. We defined lags and control variables to the best of our knowledge and according to recent research papers to be as accurate as possible. During the model's experimentation, *Scope 2* for *Log Carbon intensity (revenue)* was constantly showing a negative significance coefficient. We interpret this as weak evidence that investors care particularly about *Scope 2* emissions, how a company sources its energy, and whether it uses green energy, and that *Scope 2* is the most important aspect since it is the most robust.

Since we need a monthly time series of the carbon premium to study the effect of news in Section 4.3, we also run an additional regression using monthly excess returns instead of annual excess returns. To retain consistency with previous findings and to match the frequency of emissions with stock returns, we assume that firms' emissions and revenues are distributed equally across the 12 calendar months and that firms operate at a maximum capacity over the year. In this monthly regression, we use monthly market capitalization from CRSP (lagged by 1 month), treat the remaining controls as in the annual specification except the controls that depend on market capitalization, and continue to lag emissions by 10 months. We also include year-month fixed effects together with 6-digit industry fixed effects.

Table 5 summarizes the results of this monthly regression. The results of this monthly regression are consistent with the annual regressions: the coefficient on the log of carbon intensity remains economically significant and negative for all scopes except *Scope 1* (see Panel C in Table 5). Panels A and B (*Log emissions* and *Growth in Emissions*) show insignificant coefficients for all scopes, while Panel D reports *Emissions intensity (revenue)* in levels and finds only a small and weakly significant negative coefficient for *Scope 2*. Overall, the monthly regressions confirm that the most robust evidence for a carbon return premium is linked to the log of carbon intensity, and that the main findings are not driven by the choice of annual versus monthly frequency. While we tried to mitigate the effects of measurement error and omitted-variable bias by assuming monthly emissions, we see that the *R-squared* values in Table 5 are lower than in Table 4, and the results are less significant in Panel C. This reflects more severe measurement-error and omitted-variable concerns at the monthly frequency, arising from limitations in our data, as we do not have access to monthly emissions data, and our sample lacks observations in certain industries. Nevertheless, Table 5 still shows a negative carbon premium, with *Scope 2* and combined-scopes coefficients remaining economically meaningful for *Log emissions intensity (revenue)* in Panel C.

Thus, we conclude that the log of carbon intensity is the most robust and relevant variable for estimating the carbon premium. Adding industry fixed effects strengthens the results. Comparing the robust sample, we can see that removing super emitters and salient industries also strengthens the coefficient's absolute value. Since *Scope 2* even appears as significant without taking the log, and due to our previous explanation for when we were experimenting with model specification, we see it as the most important scope. Carbon premium with regard to carbon emission levels and growth rates shows no robust significant results in our analysis, and we deem them irrelevant for our further analysis.

Table 4

Carbon emissions and annual stock returns.
Table 4 reports results from pooled cross-section regressions of firms' annual excess stock returns (*Annual ExcessRet*) on lagged carbon-emissions measures and control variables. The sample period is 2007–2024. Emissions are lagged by 10 months, accounting controls by 6 months, and *VOLAT/BETA/MOMENTUM* controls by 1 month, as described in Section 4.1. Regressions include year and industry fixed effects, and standard errors are clustered by firm and year (in parenthesis). Panel A reports results for the *Log Emissions*, Panel B for the *Growth in emissions*, Panel C for the *Log emissions intensity (revenue)*, and Panel D for *Emissions intensity (revenue)*. Within each panel, columns report results *for Scope 1, Scope 2, Scope 3, Scope 1+2, Scope 2+3,* and *Scope 1+2+3.* Rows report the baseline *6-digit industry FE* specification, the *4-digit industry FE,* and the *No industry FE,* along with robustness checks that exclude or include super emitters and salient industries (*Robust 1, Robust 2, and Robust 3)*. Asterisks denote statistical significance (* p<0.05, ** p<0.01, *** p<0.001).

Variables	Scope 1	Scope 2	Scope 3	Scope 1+2	Scope 2+3	Scope 1+2+3
Panel A: Log emissions						
6-digit industry FE	-0.0023	-0.0031	0.0030	-0.0030	0.0037	0.0037
	(0.0024)	(0.0019)	(0.0027)	(0.0042)	(0.0028)	(0.0031)
4-digit industry FE	-0.0036***	-0.0044	0.0020	-0.0057	0.0023	0.0020
	(0.0009)	(nan)	(0.0030)	(0.0037)	(0.0030)	(0.0034)
No industry FE	-0.0041	-0.0010	-0.0019	-0.0034	-0.0023	-0.0028
	(0.0027)	(0.0010)	(0.0023)	(0.0034)	(0.0027)	(0.0030)
Robust 1: Super emitters removed, salient industries kept	0.0006	0.0002	0.0040	0.0019	0.0051	0.0056
	(0.0050)	(0.0031)	(0.0046)	(0.0072)	(0.0055)	(0.0058)
Robust 2: Both included	0.0012	0.0012	0.0040	0.0027	0.0052	0.0057
	(0.0049)	(0.0032)	(0.0048)	(0.0071)	(0.0059)	(0.0061)
Robust 3: Salient industries removed, Super emitters kept	-0.0021	-0.0027	0.0029	-0.0027	0.0036	0.0036
	(0.0025)	(0.0018)	(0.0034)	(0.0042)	(0.0034)	(0.0036)
Observations (6-digit)	11,286	11,283	11,176	11,282	11,166	11,165
Observations (4-digit)	11,286	11,283	11,176	11,282	11,166	11,165
Observations (No industry FE)	11,286	11,283	11,176	11,282	11,166	11,165
Observations (Robust 1)	12,286	12,270	12,147	12,269	12,134	12,133
Observations (Robust 2)	12,936	12,881	12,460	12,884	12,441	12,439
Observations (Robust 3)	11,697	11,695	11,339	11,690	11,327	11,325
R-squared (6-digit)	0.29	0.29	0.29	0.29	0.29	0.29
R-squared (4-digit)	0.28	0.28	0.28	0.28	0.28	0.28
R-squared (No industry FE)	0.28	0.28	0.28	0.28	0.28	0.28
R-squared (Robust 1)	0.28	0.28	0.28	0.28	0.28	0.28
R-squared (Robust 2)	0.28	0.28	0.29	0.28	0.29	0.29
R-squared (Robust 3)	0.28	0.28	0.28	0.28	0.28	0.28
Panel B: Growth in emissions						
6-digit industry FE	-0.0193	-0.0209	-0.0057	-0.0279	-0.0108	-0.0143
	(0.0142)	(0.0255)	(0.0086)	(0.0306)	(0.0129)	(0.0151)
4-digit industry FE	-0.0191	-0.0208	-0.0036	-0.0274	-0.0081	-0.0113
	(0.0131)	(0.0259)	(0.0084)	(0.0307)	(0.0124)	(0.0147)
No industry FE	-0.0232**	-0.0233	-0.0018	-0.0317	-0.0059	-0.0087
	(0.0111)	(0.0244)	(0.0083)	(0.0289)	(0.0123)	(0.0146)
Robust 1: Super emitters removed, salient industries kept	-0.0207	-0.0251	-0.0066	-0.0316	-0.0125	-0.0169
	(0.0139)	(0.0226)	(0.0097)	(0.0264)	(0.0138)	(0.0160)
Robust 2: Both included	-0.0189	-0.0263	-0.0045	-0.0308	-0.0096	-0.0132
	(0.0141)	(0.0225)	(0.0096)	(0.0264)	(0.0137)	(0.0158)
Robust 3: Salient industries removed, Super emitters kept	-0.0186	-0.0222	-0.0031	-0.0286	-0.0071	-0.0101
	(0.0142)	(0.0253)	(0.0088)	(0.0306)	(0.0130)	(0.0151)
Observations (6-digit)	11,059	11,051	10,804	11,046	10,776	10,774
Observations (4-digit)	11,059	11,051	10,804	11,046	10,776	10,774
Observations (No industry FE)	11,059	11,051	10,804	11,046	10,776	10,774
Observations (Robust 1)	12,050	12,009	11,728	12,003	11,696	11,694
Observations (Robust 2)	12,678	12,581	12,011	12,580	11,971	11,969
Observations (Robust 3)	11,449	11,438	10,950	11,429	10,918	10,916
R-squared (6-digit)	0.28	0.28	0.28	0.28	0.28	0.28
R-squared (4-digit)	0.28	0.28	0.28	0.28	0.28	0.28
R-squared (No industry FE)	0.27	0.27	0.27	0.27	0.27	0.27
R-squared (Robust 1)	0.28	0.28	0.28	0.28	0.28	0.28
R-squared (Robust 2)	0.28	0.28	0.28	0.28	0.28	0.28
R-squared (Robust 3)	0.28	0.28	0.28	0.28	0.28	0.28

Variables	Scope 1	Scope 2	Scope 3	Scope 1+2	Scope 2+3	Scope 1+2+3
Panel C: Log emissions intensity (revenue)						
6-digit industry FE	-0.0100*** (0.0024)	-0.0188*** (0.0051)		-0.0175*** (0.0053)	-0.0077*** (0.0006)	-0.0079*** (0.0015)
4-digit industry FE	-0.0102*** (0.0010)	-0.0180*** (0.0050)	-0.0061*** (0.0009)	-0.0184*** (0.0049)	-0.0083*** (0.0013)	-0.0091*** (0.0024)
No industry FE	-0.0083*** (0.0031)	-0.0100*** (0.0038)	-0.0077** (0.0034)	-0.0116*** (0.0042)	-0.0091** (0.0041)	-0.0097** (0.0042)
Robust 1: Super emitters removed, salient industries kept	-0.0077** (0.0033)	-0.0156*** (0.0053)	-0.0060*** (0.0012)	-0.0128*** (0.0049)	-0.0080*** (0.0014)	-0.0079*** (0.0022)
Robust 2: Both included	-0.0072** (0.0033)	-0.0144*** (0.0047)	-0.0056*** (0.0020)	-0.0123*** (0.0047)	-0.0076*** (0.0022)	-0.0075*** (0.0027)
Robust 3: Salient industries removed, Super emitters kept	-0.0095*** (0.0025)	-0.0177*** (0.0047)	-0.0050*** (0.0010)	-0.0168*** (0.0050)	-0.0071*** (0.0010)	-0.0073*** (0.0018)
Observations (6-digit)	11,286	11,283		11,282	11,166	11,165
Observations (4-digit)	11,286	11,283	11,176	11,282	11,166	11,165
Observations (No industry FE)	11,286	11,283	11,176	11,282	11,166	11,165
Observations (Robust 1)	12,285	12,269	12,147	12,268	12,134	12,133
Observations (Robust 2)	12,934	12,879	12,460	12,882	12,441	12,439
Observations (Robust 3)	11,696	11,694	11,339	11,689	11,327	11,325
R-squared (6-digit)	0.29	0.29		0.29	0.29	0.29
R-squared (4-digit)	0.28	0.28	0.28	0.28	0.28	0.28
R-squared (No industry FE)	0.28	0.28	0.28	0.28	0.28	0.28
R-squared (Robust 1)	0.28	0.28	0.28	0.28	0.28	0.28
R-squared (Robust 2)	0.29	0.29	0.29	0.29	0.29	0.29
R-squared (Robust 3)	0.28	0.28	0.28	0.28	0.28	0.28
Panel D: Emissions intensity (revenue)						
6-digit industry FE	-0.0000 (0.0000)	-0.0004*** (0.0001)	-0.0000 (0.0000)	-0.0000 (0.0000)	-0.0000 (0.0000)	-0.0000 (0.0000)
4-digit industry FE	-0.0000 (0.0000)	-0.0004*** (0.0001)	-0.0000* (0.0000)	-0.0000 (0.0000)	-0.0000** (0.0000)	-0.0000*** (0.0000)
No industry FE	-0.0000 (0.0000)	-0.0002 (0.0001)	-0.0000* (0.0000)	-0.0000 (0.0000)	-0.0000** (0.0000)	-0.0000** (0.0000)
Robust 1: Super emitters removed, salient industries kept	0.0000 (0.0000)	-0.0003*** (0.0001)	-0.0000** (0.0000)	0.0000 (0.0000)	-0.0000** (0.0000)	-0.0000 (0.0000)
Robust 2: Both included	0.0000 (0.0000)	-0.0003*** (0.0000)	-0.0000 (0.0000)	0.0000 (0.0000)	-0.0000 (0.0000)	-0.0000 (0.0000)
Robust 3: Salient industries removed, Super emitters kept	-0.0000 (0.0000)	-0.0004*** (0.0001)	-0.0000 (0.0000)	-0.0000 (0.0000)	-0.0000 (0.0000)	-0.0000 (0.0000)
Observations (6-digit)	11,286	11,283	11,176	11,282	11,166	11,165
Observations (4-digit)	11,286	11,283	11,176	11,282	11,166	11,165
Observations (No industry FE)	11,286	11,283	11,176	11,282	11,166	11,165
Observations (Robust 1)	12,285	12,269	12,147	12,268	12,134	12,133
Observations (Robust 2)	12,934	12,879	12,460	12,882	12,441	12,439
Observations (Robust 3)	11,696	11,694	11,339	11,689	11,327	11,325
R-squared (6-digit)	0.29	0.29	0.29	0.29	0.29	0.29
R-squared (4-digit)	0.28	0.28	0.28	0.28	0.28	0.28
R-squared (No industry FE)	0.28	0.28	0.28	0.28	0.28	0.28
R-squared (Robust 1)	0.28	0.28	0.28	0.28	0.28	0.28
R-squared (Robust 2)	0.28	0.29	0.29	0.28	0.29	0.29
R-squared (Robust 3)	0.28	0.28	0.28	0.28	0.28	0.28

Table 5

Carbon emissions and monthly stock returns.
Table 5 reports results from pooled cross-section regressions of firms' monthly excess stock returns on lagged carbon-emissions measures and control variables. The sample period is 2007–2024. Emissions are lagged by 10 months, accounting controls by 6 months, and *VOLAT/BETA/MOMENTUM* controls by 1 month. Regressions include year-month and 6-digit industry fixed effects, and standard errors are clustered by firm and year-month. Panel A reports results for the *Log Emissions*, Panel B for the monthly *Growth in emissions*, Panel C for the *Log emissions intensity (revenue),* and Panel D for *Emissions intensity (revenue)*. Within each panel, columns report results *for Scope 1, Scope 2, Scope 3, Scope 1+2, Scope 2+3*, and *Scope 1+2+3*. Rows report the coefficient on the emissions variable for the baseline *6-digit industry FE* specification. Asterisks denote statistical significance (* p<0.05, ** p<0.01, *** p<0.001).

Variables	Scope 1	Scope 2	Scope 3	Scope 1+2	Scope 2+3	Scope 1+2+3
Panel A: Log emissions						
6-digit industry FE	-0.0001 (0.0006)	-0.0003 (0.0008)	-0.0003 (0.0008)	-0.0002 (0.0008)	-0.0002 (0.0009)	-0.0001 (0.0009)
Observations	80,091	80,116	79,678	80,093	79,628	79,618
R-squared	0.003	0.003	0.003	0.003	0.003	0.003
Panel B: Growth in emissions						
6-digit industry FE	-0.0019 (0.0012)	-0.0006 (0.0017)	-0.0010 (0.0009)	-0.0015 (0.0017)	-0.0013 (0.0012)	-0.0013 (0.0013)
Observations	75,427	75,465	74,519	75,409	74,387	74,365
R-squared	0.004	0.004	0.004	0.004	0.004	0.004
Panel C: Log emissions intensity						
6-digit industry FE	-0.0007 (0.0005)	-0.0016** (0.0007)	-0.0020** (0.0008)	-0.0016** (0.0007)	-0.0023** (0.0010)	-0.0023** (0.0010)
Observations	80,073	80,098	79,660	80,075	79,610	79,600
R-squared	0.003	0.003	0.004	0.003	0.004	0.004
Panel D: Emissions intensity						
6-digit industry FE	0.0000 (0.0000)	-0.0000* (0.0000)	-0.0000* (0.0000)	-0.0000 (0.0000)	-0.0000** (0.0000)	-0.0000* (0.0000)
Observations	80,073	80,098	79,660	80,075	79,610	79,600
R-squared	0.003	0.003	0.003	0.003	0.003	0.003

4.2 Carbon Return Premium and Traditional Risk Factors

The next step is to assess whether traditional Fama–French risk factors can account for the carbon premium. Following the asset-pricing approach of Bolton and Kacperczyk (2021), we estimate a model that includes only the Fama–French factor series, as these are the only factors available to us. Since the previous section establishes the presence, significance, and robustness of a carbon premium based on log of carbon intensity, we focus on this measure and run cross-sectional Fama–MacBeth regressions to obtain a monthly time series of the carbon premium:

$$\beta_t = c_0 + cF_t + \varepsilon_t, \qquad (3)$$

where β_t represents the carbon return premium estimated each month from the cross-sectional Fama–MacBeth procedure. *Ft* is the vector of monthly Fama–French factor returns *(SMB, HML, UMD/MOMENTUM, RMW,* and *CMA)*. These factors are widely used in the asset-pricing literature, and there are economic grounds for expecting potential linkages to our carbon factor. Consistent with Bolton and Kacperczyk (2021), we include *SMB* and *HML*; the investment factor *CMA* helps capture cross-firm differences in investment behavior; and the market and momentum factors serve as standard controls in time-series regressions. Standard errors are computed using the Newey–West adjustment with 12 lags to correct for autocorrelation. Our main parameter of interest is c_0, which captures the residual carbon premium after controlling for risk and style factors.

The results in Table 6 show that the log of carbon intensity for *Scope 1+2+3*, as well as for *Scope 3* alone, gives a statistically significant negative intercept for *Five-factor regressions with 6-digit industry FE*. This implies that the traditional Fama–French factors cannot fully explain the negative carbon premiums, and carbon premiums remain economically and statistically meaningful, even after accounting for those factors. Although other scopes cannot be explained by traditional risk factors, their interceptions lack significance. The *R-squared* is also very low, which means the regression explains almost no variation in the sample, supporting that the carbon premium cannot be explained by traditional risk factors. In Table 6, the results provide the strongest and most reliable estimate of the carbon premium.

The time-series analysis indicates that the carbon premium associated with the log of carbon intensity for *Scope 1+2+3* and *Scope 3* is not captured by established risk factors. This finding supports the conclusion from Section 3.2 that carbon emissions contain independent information relevant for explaining the cross-section of average returns.

Table 6

Carbon premium and Fama–French factors.
Table 6 reports time-series regressions of the monthly carbon premium on Fama–French five factors. The sample period is 2010–2024 at a monthly frequency. The dependent variable is the monthly carbon premium estimated for each emissions scope from cross-sectional regressions using log carbon emissions intensity and 6-digit GICS industry fixed effects. Columns show results for *Scope 1*, *Scope 2*, *Scope 3*, *Scope 1+2*, and *Scope 1+2+3*. For each scope, the carbon premium is regressed on the market excess return (*MKTRF*), size (*SMB*), value (*HML*), profitability (*RMW*), investment (*CMA*), and momentum (*UMD*) factors. Standard errors adjusted for autocorrelation with 12 lags using Newey-West test. The *Intercept* captures the residual carbon premium after controlling for the risk factors. Asterisks denote statistical significance (* $p<0.05$, ** $p<0.01$, *** $p<0.001$).

Variables	Scope 1	Scope 2	Scope 3	Scope 1+2	Scope 1+2+3
Five-factor regressions with 6-digit industry FE					
Intercept	-0.0063	0.0003	-0.0040*	-0.0001	-0.0110**
	(0.0044)	(0.0027)	(0.0021)	(0.0027)	(0.0051)
MKTRF	-0.0166	0.4403	0.0081	0.5385	-0.0301
	(0.0350)	(0.3898)	(0.0493)	(0.4522)	(0.1078)
SMB	0.0152	0.8072	0.1191	0.5403	0.0274
	(0.0487)	(0.7404)	(0.1111)	(0.5202)	(0.1848)
HML	0.0560	-0.8246	0.0703	-0.7516	0.0637
	(0.0964)	(0.7515)	(0.0531)	(0.6811)	(0.1039)
RMW	0.1032	0.3756	0.0611	0.2383	-0.0566
	(0.0629)	(0.3620)	(0.1406)	(0.2768)	(0.1972)
CMA	-0.1249	0.9315	0.0520	1.0136	-0.0816
	(0.1160)	(0.8419)	(0.0859)	(0.8915)	(0.2381)
UMD	-0.0020	0.2353	-0.0596	0.2398	0.0358
	(0.0249)	(0.2238)	(0.0757)	(0.2156)	(0.1325)
Observations	174	174	171	174	171
R-squared	0.00	0.05	0.01	0.07	0.00

4.3 Carbon Return Premium and News

In the final step, we examine whether climate change news helps explain the time variation in the carbon premium. To do this, we estimate a series of time-series regressions for the monthly carbon premium and compute standard errors using Newey–West HAC(12) corrections.

We start with a baseline model in which the monthly carbon premium, *a1_monthly(t)*, is regressed solely on lagged climate news:

$$a1\_monthly_t = \alpha + \beta \cdot News_{t-1} + \varepsilon. \quad (4)$$

Next, we incorporate persistence in the carbon premium by adding its lagged value as an additional regressor:

$$a1\_monthly_t = \alpha + \varphi \cdot a1\_monthly_{t-1} + \beta \cdot News_{t-1} + \varepsilon. \quad (5)$$

We then expand the specification by adding macroeconomic control variables that may influence climate- and market-related conditions, including oil prices, policy uncertainty, and volatility indices. This produces the "Full (Macro)" specification:

$$a1\_monthly_t = \alpha + \varphi \cdot a1\_monthly_{t-1} + \beta \cdot News_{t-1} + \gamma \cdot Controls_{t-1} + \varepsilon. \quad (6)$$

Finally, to ensure that the effect of climate news is not confounded by standard priced risk factors, we add the Fama–French factors to obtain the "Full (Macro + Five Factors)" model:

$$a1\_monthly_t = \alpha + \varphi \cdot a1\_monthly_{t-1} + \beta \cdot News_{t-1} + \gamma \cdot Controls_{t-1} + \delta \cdot F_{t-1} + \varepsilon, \quad (7)$$

where *a1_monthly* is the carbon premium obtained from the cross-sectional Fama–MacBeth regressions in our monthly model. *News* refers to the different climate-news indices used in the analysis (see Section 3.3). The control variables include oil prices, *VIXCLS*, and the U.S. policy uncertainty index (see Section 3.6), while F_{t-1} denotes the five standard Fama–French factors. The main coefficient of interest is β, which captures the sensitivity of the carbon premium to climate-news intensity.

Table 7 presents the estimates. These four specifications allow us to observe how the explanatory power of climate news evolves as we progressively add more controls including, macroeconomic conditions, and traditional risk factors, and serve as robustness. As reported in Table 7, adding more controls and Fama–French factors increase the economic significance of the results, and the coefficients remain positive. This pattern indicates that the carbon premium rises when there is heightened market awareness of climate-related news.

Both the NYT Tag Index and the Aggregate MCCC index show positive and statistically significant relationships with the carbon premium in all specifications. Although the Aggregate MCCC index is our main news measure because it is directly comparable to the thematic news categories, we confirm robustness using the Tag Index, which yields similarly significant results.

We also examine different lag structures for the news indices, and the lag analysis further supports these findings. We examine one-, two-, and three-month lags to account for the time investors may need to absorb climate information. For both the *Aggregate* index and the *Tag Index*, coefficients increase with longer lags, and significance improves in the full model with Fama–French factors. The three-month lag consistently yields the highest coefficients, lowest p-values, and the highest *R-squared* values. We therefore conclude that the full model with factors and a three-month lag (*Full+5F L3*) is the most accurate and robust, indicating that climate news takes approximately three months to be fully reflected in market prices and carbon return premium.

Furthermore, we use the thematic MCCC categories to investigate which types of climate news matter most. Table 8 represents the results, where we categorize each theme into our own categories: *Regulatory risk*, *Physical risk*, *Technology risk*, *Awareness*, and *Other*. Comparing *Regulatory risk* and *Physical risk*, we can see that regulatory risks are more robust and have a stronger impact on carbon premium. News related to *Carbon tax, Climate legislation/regulation*, *Government programs, Legal actions*, and *Political campaign* news produces the most robust and statistically significant effects, generally around 1.5%. These effects also persist with a three-month lag, indicating that regulatory information takes time to be priced in. Only Legal Actions show a stronger response at a two-month lag. In contrast, most *Physical risk* themes exhibit limited robustness. The most significant are *Agricultural shifts, Forests,* and *Marine wildlife*, which have effects of roughly 1% on the carbon premium. For these themes, significance peaks at a two-month lag and declines at a three-month lag, indicating faster market reflection relative to regulatory risks. Overall, *Regulatory risk* has a stronger and more persistent impact on the coefficient than *Physical risk*. We therefore conclude that regulatory risk news is more influential on the carbon return premium, and that investors care more about it than physical risk.

Within the *Other* category, we see that the *Car industry, Airline industry, Cities, Tourism,* and *Corporations/Investments* also have a robust and significant impact on carbon premium, though generally around 1%. This means that their influence is weaker than that of regulatory and physical risks. In the *Awareness* category, *Social events* and *Controversies* that increase climate awareness are also robust and significant, with an effect of about 1%. Notably, *Scientific studies* have the smallest impact in this group. Finally, within the *Technology Risk* category, *Renewable energy* news exhibits a robust effect of approximately 1.5%, whereas news on *Carbon-reduction technologies* shows no significant results.

Overall, the evidence consistently indicates that regulatory risk is the most powerful driver of the carbon return premium, with physical risks, awareness, and industry-specific news also contributing, but to a lesser degree.

Table 7

Climate-change news and the carbon premium.
Table 7 reports time-series regressions of the monthly carbon premium on climate-change news indices over the sample period 2010–2024. The dependent variable is the monthly carbon premium estimated from the regressions based on log carbon emissions intensity for *Scope 1+2+3*. Each row corresponds to a different news index from the MCCC and NYT datasets. The *Tag Index* and *Aggregate* series are overall news measures, while the remaining rows report thematic news. The *Simple* column regresses the carbon premium only on the lagged news index. *AR(1)+News* adds the lagged carbon premium to capture persistence. *Full L1* augments *AR(1)+News* with macroeconomic controls (oil price changes, VIX, and policy uncertainty) and a one-month lag of the news index. *Full L2* is identical to *Full L1* but uses a two-month news lag, while *Full L3* uses a three-month lag. *Full+5F L1–L3* extend the corresponding *Full L1–L3* specifications by including the Fama–French five factors. All regressions include year-month and 6-digit industry fixed effects. Standard errors adjusted for aweutocorrelation with 12 lags using Newey-West test. The last rows report the number of observations and the mean R-squared for each specification. Asterisks denote statistical significance (* p<0.05, ** p<0.01, *** p<0.001).

Variables	Simple	AR(1)+News	Full L1	Full L2	Full L3	Full+5F L1	Full+5F L2	Full+5F L3
News regressions with 6-digit industry FE								
Tag Index	0.5169*	0.4695*	0.4926*	0.4926*	0.6077**	0.4470**	0.4470**	0.5854**
	(0.2839)	(0.2546)	(0.2545)	(0.2545)	(0.3098)	(0.2065)	(0.2065)	(0.2660)
Aggregate	0.0119*	0.0109*	0.0109*	0.0109*	0.0158**	0.0101*	0.0101*	0.0151**
	(0.0071)	(0.0065)	(0.0062)	(0.0062)	(0.0078)	(0.0052)	(0.0052)	(0.0067)
cluster_Business Impact	0.0125*	0.0103	0.0101*	0.0101*	0.0212*	0.0106*	0.0106*	0.0223**
	(0.0075)	(0.0063)	(0.0057)	(0.0057)	(0.0112)	(0.0059)	(0.0059)	(0.0105)
cluster_Environmental Impact	0.0123	0.0115	0.0118	0.0118	0.0159*	0.0113*	0.0113*	0.0148**
	(0.0077)	(0.0073)	(0.0073)	(0.0073)	(0.0081)	(0.0063)	(0.0063)	(0.0069)
cluster_Societal Debate	0.0109*	0.0101*	0.0104*	0.0104*	0.0127**	0.0094**	0.0094**	0.0119**
	(0.0062)	(0.0057)	(0.0055)	(0.0055)	(0.0059)	(0.0046)	(0.0046)	(0.0050)
cluster_Research	0.0103	0.0096	0.0095	0.0095	0.0147*	0.0087	0.0087	0.0135*
	(0.0092)	(0.0085)	(0.0083)	(0.0083)	(0.0087)	(0.0074)	(0.0074)	(0.0079)
Agreements/Actions	0.0097	0.0087	0.0083	0.0083	0.0173**	0.0072	0.0072	0.0166**
	(0.0073)	(0.0065)	(0.0060)	(0.0060)	(0.0087)	(0.0053)	(0.0053)	(0.0078)
Agriculture Shifts	0.0107**	0.0093***	0.0098***	0.0098***	0.0166	0.0085***	0.0085***	0.0161*
	(0.0044)	(0.0035)	(0.0036)	(0.0036)	(0.0105)	(0.0031)	(0.0031)	(0.0092)
Airline Industry	0.0090*	0.0084*	0.0086*	0.0086*	0.0130	0.0084**	0.0084**	0.0130*
	(0.0051)	(0.0046)	(0.0045)	(0.0045)	(0.0080)	(0.0042)	(0.0042)	(0.0074)
Arctic Wildlife	0.0067*	0.0069*	0.0070*	0.0070*	0.0089**	0.0054	0.0054	0.0084**
	(0.0035)	(0.0036)	(0.0036)	(0.0036)	(0.0037)	(0.0037)	(0.0037)	(0.0036)
Car Industry	0.0068*	0.0064*	0.0061*	0.0061*	0.0058*	0.0061*	0.0061*	0.0059*
	(0.0041)	(0.0037)	(0.0034)	(0.0034)	(0.0033)	(0.0034)	(0.0034)	(0.0033)
Carbon Credits Market	0.0131	0.0104	0.0105	0.0105	0.0207	0.0108	0.0108	0.0189*
	(0.0089)	(0.0078)	(0.0079)	(0.0079)	(0.0130)	(0.0075)	(0.0075)	(0.0110)
Carbon Reduction Technologies	0.0052	0.0027	0.0024	0.0024	0.0138	0.0032	0.0032	0.0148*
	(0.0047)	(0.0039)	(0.0037)	(0.0037)	(0.0084)	(0.0036)	(0.0036)	(0.0079)
Carbon Tax	0.0151*	0.0140*	0.0138*	0.0138*	0.0153**	0.0119**	0.0119**	0.0152**
	(0.0083)	(0.0075)	(0.0072)	(0.0072)	(0.0078)	(0.0055)	(0.0055)	(0.0074)
Cities	0.0086*	0.0078*	0.0082*	0.0082*	0.0101**	0.0072*	0.0072*	0.0098**
	(0.0052)	(0.0047)	(0.0047)	(0.0047)	(0.0047)	(0.0039)	(0.0039)	(0.0041)
Climate Legislation/Regulations	0.0108**	0.0096**	0.0094**	0.0094**	0.0081**	0.0076**	0.0076**	0.0069**
	(0.0050)	(0.0041)	(0.0038)	(0.0038)	(0.0035)	(0.0030)	(0.0030)	(0.0032)
Climate Summits	0.0023	0.0019	0.0016	0.0016	0.0068*	0.0021	0.0021	0.0062*
	(0.0017)	(0.0015)	(0.0014)	(0.0014)	(0.0039)	(0.0018)	(0.0018)	(0.0034)
Controversies	0.0134	0.0120*	0.0122*	0.0122*	0.0106***	0.0123*	0.0123*	0.0092**
	(0.0082)	(0.0072)	(0.0071)	(0.0071)	(0.0040)	(0.0066)	(0.0066)	(0.0041)
Corporations/Investments	0.0096**	0.0088**	0.0091**	0.0091**	0.0103**	0.0083**	0.0083**	0.0098**
	(0.0046)	(0.0042)	(0.0042)	(0.0042)	(0.0045)	(0.0037)	(0.0037)	(0.0039)
Ecosystems	0.0143	0.0134	0.0134	0.0134	0.0162*	0.0128	0.0128	0.0148*
	(0.0098)	(0.0095)	(0.0093)	(0.0093)	(0.0086)	(0.0083)	(0.0083)	(0.0078)
Extreme Temperatures	0.0081	0.0078	0.0080	0.0080	0.0108*	0.0058	0.0058	0.0101*
	(0.0065)	(0.0063)	(0.0064)	(0.0064)	(0.0063)	(0.0045)	(0.0045)	(0.0055)
Food Shortage/Poverty	0.0088	0.0081	0.0084	0.0084	0.0091*	0.0078*	0.0078*	0.0083*
	(0.0058)	(0.0053)	(0.0054)	(0.0054)	(0.0053)	(0.0045)	(0.0045)	(0.0046)
Forests	0.0069*	0.0061*	0.0062*	0.0062*	0.0071	0.0059**	0.0059**	0.0064*
	(0.0038)	(0.0034)	(0.0033)	(0.0033)	(0.0043)	(0.0029)	(0.0029)	(0.0036)
Glaciers/Ice Sheets	0.0105	0.0111	0.0110	0.0110	0.0146**	0.0107	0.0107	0.0117**
	(0.0079)	(0.0080)	(0.0076)	(0.0076)	(0.0067)	(0.0067)	(0.0067)	(0.0050)
Global Warming	0.0099	0.0085	0.0080	0.0080	0.0217*	0.0064	0.0064	0.0219**
	(0.0084)	(0.0076)	(0.0069)	(0.0069)	(0.0119)	(0.0058)	(0.0058)	(0.0110)
Government Programs	0.0083*	0.0077*	0.0079*	0.0079*	0.0108*	0.0076**	0.0076**	0.0112**
	(0.0046)	(0.0041)	(0.0041)	(0.0041)	(0.0056)	(0.0037)	(0.0037)	(0.0052)
Hurricanes/Floods	0.0069	0.0062	0.0066	0.0066	0.0122*	0.0063	0.0063	0.0115**
	(0.0050)	(0.0046)	(0.0047)	(0.0047)	(0.0063)	(0.0041)	(0.0041)	(0.0053)
Legal Actions	0.0137**	0.0118**	0.0120**	0.0120**	0.0163	0.0116***	0.0116***	0.0153*
	(0.0063)	(0.0052)	(0.0049)	(0.0049)	(0.0107)	(0.0045)	(0.0045)	(0.0093)
Marine Wildlife	0.0080**	0.0072**	0.0072**	0.0072**	0.0106*	0.0070**	0.0070**	0.0114*
	(0.0040)	(0.0036)	(0.0034)	(0.0034)	(0.0057)	(0.0032)	(0.0032)	(0.0060)
Political Campaign	0.0106*	0.0101*	0.0104*	0.0104*	0.0129**	0.0105*	0.0105*	0.0121**
	(0.0064)	(0.0059)	(0.0058)	(0.0058)	(0.0061)	(0.0054)	(0.0054)	(0.0052)
Renewable Energy	0.0156	0.0139	0.0137	0.0137	0.0168**	0.0142*	0.0142*	0.0173**
	(0.0096)	(0.0088)	(0.0084)	(0.0084)	(0.0077)	(0.0082)	(0.0082)	(0.0072)
Scientific Studies	0.0116	0.0108	0.0109	0.0109	0.0117*	0.0107	0.0107	0.0103**
	(0.0091)	(0.0087)	(0.0087)	(0.0087)	(0.0060)	(0.0078)	(0.0078)	(0.0053)
Social Events	0.0098*	0.0095*	0.0099*	0.0099*	0.0135**	0.0082**	0.0082**	0.0127**
	(0.0057)	(0.0053)	(0.0053)	(0.0053)	(0.0062)	(0.0038)	(0.0038)	(0.0052)
Tourism	0.0092*	0.0083*	0.0084*	0.0084*	0.0103*	0.0076**	0.0076**	0.0094**
	(0.0053)	(0.0049)	(0.0048)	(0.0048)	(0.0054)	(0.0037)	(0.0037)	(0.0045)
UN/IPCC Reports	0.0130	0.0121	0.0122	0.0122	0.0135**	0.0102	0.0102	0.0142**
	(0.0092)	(0.0086)	(0.0085)	(0.0085)	(0.0063)	(0.0068)	(0.0068)	(0.0066)
Water/Drought	0.0119	0.0115	0.0117	0.0117	0.0116*	0.0107	0.0107	0.0110**
	(0.0081)	(0.0078)	(0.0079)	(0.0079)	(0.0060)	(0.0068)	(0.0068)	(0.0051)
Observations	170	170	170	170	169	170	170	169
Mean R-squared	0.014	0.027	0.030	0.030	0.040	0.066	0.066	0.075

Table 8

News and carbon premium Full+5FL3 model.
Table 8 reports the coefficients for the full + factor L3 model, and the third column shows the robustness of the value. We categorize each theme into our own categories: *Regulatory risk*, *Physical risk*, *Technology risk*, *Awareness*, and *Other*. In the table, *strong* means it appeared significant across all models or most of them (more than 80%), while *weak* means it appeared significant in only one or a few model specifications. The *Notes* column shows whether it has higher significance at lag 2 (as discussed in Section 4.3). Asterisks denote statistical significance (* p<0.05, ** p<0.01, *** p<0.001)

Category	Topic	Coefficient	Robustness	Notes
Regulatory risk	Agreements/Actions	0.0166**	Weak	–
Regulatory risk	Carbon credit market	0.0189*-	Weak	–
Regulatory risk	Carbon tax	0.0152**	Strong	–
Regulatory risk	Climate legislation/regulation	0.0098**	Strong	–
Regulatory risk	Government programs	0.0112**	Strong	–
Regulatory risk	Legal actions	0.0153*	Strong	Lag 2 better
Regulatory risk	Political campaign	0.0121**	Strong	–
Physical risk	Agriculture shifts	0.0161*	Strong	Lag 2 better
Physical risk	Arctic wildlife	0.0084**	Weak	–
Physical risk	Climate summit	0.0062*	Weak	–
Physical risk	Ecosystems	0.0148*	Weak	–
Physical risk	Extreme temperatures	0.0101*	Weak	–
Physical risk	Food shortage/Poverty	0.0083*	Weak	–
Physical risk	Forests	0.0064*	Strong	Lag 2 better
Physical risk	Glaciers/Ice sheet	0.0117**	Weak	–
Physical risk	Global warming	0.0219**	Weak	–
Physical risk	Hurricane/Floods	0.0115**	Weak	–
Physical risk	Marine wildlife	0.0114*	Strong	Lag 2 better
Physical risk	Water drought	0.0110**	Weak	–
Other	Airline industry	0.0130*	Relatively robust	Lag 2 better
Other	Car industry	0.0059*	Strong	–
Other	Cities	0.0098**	Strong	–
Other	Tourism	0.0094**	Strong	–
Other	Corporations/Investments	0.0098**	Strong	–
Awareness	Controversies	0.0092**	Strong	–
Awareness	Scientific studies	0.00103**	Weak	–
Awareness	Social events	0.0127**	Strong	–
Awareness	UN/IPCC reports	0.0142**	Weak	–
Technology	Carbon reduction technologies	0.0148*	Weak	–
Technology	Renewable energy	0.0173**	Relatively strong	–

5. Conclusion

This paper examines whether carbon risk is priced and how its pricing varies with news about climate change. We conduct a cross-sectional analysis of U.S. stock returns using carbon emissions as a firm characteristic. We find robust evidence that firms' carbon intensity significantly and negatively affects stock returns. Our findings show that this effect is driven by carbon intensity, and we do not find a significant and robust result for emissions levels or emissions growth. This study thereby provides supplementary evidence to previous research that correct model specification is achieved when using carbon intensity. We further show that *Scope 2* emissions are the most important scope for investors, and that *Scope 1+2+3* emissions together provide the most robust basis for estimating the carbon return premium. This carbon premium cannot be explained by traditional risk factors in our analysis.

We then examine how climate change news affects the carbon premium. The results show a straightforward link: climate change news has a positive effect on the carbon return premium. We find that, on average, it takes around three months for regulatory risk news to be fully integrated into the market and to affect the carbon premium, while it takes two months for physical risk news. According to our analysis, periods with a salient focus on climate change news increase the perception of risk associated with high-emitting firms, and this increases the carbon premium, reflecting the compensation for risk. We further show that regulatory risk news has a stronger and more robust effect than physical risk news.

The scope of our analysis did not include an investigation of why the carbon premium is negative and is priced in the market, and we left this for future research. However, we suspect and propose that the negative carbon return premium could be due to an unexpected shift in demand toward green assets in recent years (Pástor, Stambaugh, and Taylor, 2022). Several limitations in our industry-level analysis arise from low within-industry variation due to data limitations, which could be improved in future studies by accessing additional data sources. Furthermore, we consider the quality of our emission data and timing issues in the data file as a limitation that could lead to a mismatch in the timing of emissions. Although we attempted to mitigate this effect in our analysis, the study could be improved by having access to more reliable and higher-quality emission data. Another important limitation and area for future research arises from the lack of monthly emissions data. As proven in previous research and due to measurement error, emissions and stock returns should ideally be measured at the same frequency (Crosignani et al., 2025). While we make an assumption to match this frequency, this assumption can create biased results.

Our proposed solution for future studies is to gather data on monthly emissions of companies using AI and machine learning models together with satellite data, to more confidently estimate monthly emissions of firms, and thereby run more accurate regressions.

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Appendix A

AI Disclosure.
During the writing of this thesis, OpenAI's GPT-5.1 and GitHub Copilot Claude Soonet 4.5 have been used. Their primary purposes were to assist with debugging and to serve as an advanced grammar checker by suggesting improvements in grammar and clarity. These tools were not used to generate full paragraphs or other original content as their role was limited to proposing edits and improving efficiency. We therefore assess that the use of AI has not affected the critical integrity or originality of this thesis.

Appendix B

Carbon premium and Fama–French factors without industry fixed effects.
Appendix B reports time-series regressions of the monthly carbon premium on Fama–French five factors. The sample period is 2010–2024 at a monthly frequency. The dependent variable is the monthly carbon premium estimated for each emissions scope from cross-sectional regressions using log carbon emissions without industry fixed effects. Columns show results for *Scope 1*, *Scope 2*, *Scope 3*, *Scope 1+2*, and *Scope 1+2+3*. For each scope, the carbon premium is regressed on the market excess return (*MKTRF*), size (*SMB*), value (*HML*), profitability (*RMW*), investment (*CMA*), and momentum (*UMD*) factors. Coefficients are reported with Newey–West heteroskedasticity, and autocorrelation-robust standard errors (12 lags) in parentheses. The *Intercept* captures the residual carbon premium after controlling for the risk factors, and the bottom rows report the number of monthly *Observations* and the regression *R-squared*. Asterisks denote statistical significance (* p<0.05, ** p<0.01, *** p<0.001).

Variables	Scope 1	Scope 2	Scope 3	Scope 1+2	Scope 1+2+3
Five-factor regressions without industry FE					
Intercept	-0.0002 (0.0005)	-0.0009* (0.0006)	-0.0013* (0.0007)	-0.0008 (0.0006)	-0.0019* (0.0011)
MKTRF	0.0092 (0.0102)	0.0230 (0.0178)	-0.0094 (0.0231)	0.0251 (0.0189)	0.0212 (0.0396)
SMB	0.0140 (0.0264)	-0.0093 (0.0363)	0.0037 (0.0281)	-0.0144 (0.0358)	-0.0149 (0.0408)
HML	-0.0437 (0.0310)	-0.0446 (0.0323)	0.0881*** (0.0291)	-0.0439 (0.0336)	0.0759 (0.0464)
UMD	-0.0085 (0.0200)	-0.0266 (0.0279)	0.0052 (0.0236)	-0.0231 (0.0289)	-0.0069 (0.0420)
RMW	0.0162 (0.0205)	-0.0003 (0.0333)	0.0027 (0.0305)	-0.0107 (0.0286)	-0.0230 (0.0512)
CMA	0.0186 (0.0282)	-0.0099 (0.0516)	-0.1029** (0.0460)	-0.0011 (0.0475)	-0.0663 (0.0687)
Observations	174	174	171	174	171
R-squared	0.028	0.038	0.056	0.036	0.028

Appendix C

Intercepts from climate-change news regressions.
Appendix C reports time-series regressions of the monthly carbon premium on climate-change news indices over the sample period 2010–2024. The dependent variable is the monthly carbon premium estimated from cross-sectional regressions based on log carbon emissions intensity for *Scope 1+2+3*. Each row corresponds to a different news index from the MCCC and NYT datasets. The *Tag Index* and *Aggregate* series are overall news measures, while the remaining rows report thematic news. The *Simple* column regresses the carbon premium only on the lagged news index. *AR(1)+News* adds the lagged carbon premium to capture persistence. *Full L1* augments *AR(1)+News* with macroeconomic controls (oil price changes, VIX, and policy uncertainty) and a one-month lag of the news index. *Full L2* is identical to *Full L1* but uses a two-month news lag, while *Full L3* uses a three-month lag. *Full+5F L1–L3* extend the corresponding *Full L1–L3* specifications by including the Fama–French five factors. All regressions include year-month and 6-digit industry fixed effects. Coefficients are reported with Newey–West (12-lag) standard errors in parentheses. The last rows report the number of observations and the mean R-squared for each specification. Asterisks denote statistical significance (* p<0.05, ** p<0.01, *** p<0.001).

Variables	Simple	AR(1)+News	Full L1	Full L2	Full L3	Full+5F L1	Full+5F L2	Full+5F L3
				Intercepts from news regressions with 6-digit industry FE				
Tag Index	-0.0211**	-0.0194**	-0.0159**	-0.0159**	-0.0168**	-0.0230**	-0.0230**	-0.0248**
	(0.0099)	(0.0088)	(0.0077)	(0.0077)	(0.0078)	(0.0114)	(0.0114)	(0.0122)
Aggregate	-0.0283*	-0.0259*	-0.0227**	-0.0227**	-0.0288**	-0.0296**	-0.0296**	-0.0356**
	(0.0147)	(0.0133)	(0.0112)	(0.0112)	(0.0126)	(0.0151)	(0.0151)	(0.0167)
cluster_Business Impact	-0.0252**	-0.0217**	-0.0185**	-0.0185**	-0.0305**	-0.0278**	-0.0278**	-0.0409**
	(0.0128)	(0.0108)	(0.0091)	(0.0091)	(0.0139)	(0.0141)	(0.0141)	(0.0197)
cluster_Environmental Impact	-0.0292*	-0.0271*	-0.0232**	-0.0232**	-0.0275**	-0.0302*	-0.0302*	-0.0339**
	(0.0157)	(0.0146)	(0.0118)	(0.0118)	(0.0124)	(0.0158)	(0.0158)	(0.0164)
cluster_Societal Debate	-0.0263**	-0.0242**	-0.0221**	-0.0221**	-0.0246**	-0.0287**	-0.0287**	-0.0313**
	(0.0129)	(0.0117)	(0.0103)	(0.0103)	(0.0103)	(0.0139)	(0.0139)	(0.0142)
cluster_Research	-0.0222	-0.0204	-0.0185	-0.0185	-0.0233**	-0.0257	-0.0257	-0.0309*
	(0.0146)	(0.0133)	(0.0118)	(0.0118)	(0.0118)	(0.0157)	(0.0157)	(0.0163)
Agreements/Actions	-0.0206*	-0.0187*	-0.0161*	-0.0161*	-0.0254**	-0.0234*	-0.0234*	-0.0329**
	(0.0117)	(0.0103)	(0.0095)	(0.0095)	(0.0118)	(0.0133)	(0.0133)	(0.0162)
Agriculture Shifts	-0.0226**	-0.0202***	-0.0163**	-0.0163**	-0.0218*	-0.0234**	-0.0234**	-0.0305*
	(0.0089)	(0.0073)	(0.0071)	(0.0071)	(0.0114)	(0.0100)	(0.0100)	(0.0166)
Airline Industry	-0.0215**	-0.0200**	-0.0162**	-0.0162**	-0.0204*	-0.0241**	-0.0241**	-0.0284*
	(0.0103)	(0.0092)	(0.0081)	(0.0081)	(0.0105)	(0.0117)	(0.0117)	(0.0151)
Arctic Wildlife	-0.0160***	-0.0153***	-0.0125*	-0.0125*	-0.0138**	-0.0194**	-0.0194**	-0.0218**
	(0.0062)	(0.0058)	(0.0074)	(0.0074)	(0.0066)	(0.0094)	(0.0094)	(0.0101)
Car Industry	-0.0196**	-0.0182**	-0.0158*	-0.0158*	-0.0148*	-0.0242*	-0.0242*	-0.0234*
	(0.0097)	(0.0087)	(0.0084)	(0.0084)	(0.0076)	(0.0128)	(0.0128)	(0.0122)
Carbon Credits Market	-0.0229*	-0.0195*	-0.0160*	-0.0160*	-0.0243*	-0.0250*	-0.0250*	-0.0305*
	(0.0127)	(0.0112)	(0.0093)	(0.0093)	(0.0128)	(0.0143)	(0.0143)	(0.0164)
Carbon Reduction Technologies	-0.0161*	-0.0123*	-0.0093	-0.0093	-0.0215*	-0.0189*	-0.0189*	-0.0319*
	(0.0092)	(0.0074)	(0.0079)	(0.0079)	(0.0111)	(0.0110)	(0.0110)	(0.0164)
Carbon Tax	-0.0281**	-0.0260**	-0.0224**	-0.0224**	-0.0234**	-0.0284**	-0.0284**	-0.0318**
	(0.0138)	(0.0124)	(0.0108)	(0.0108)	(0.0108)	(0.0140)	(0.0140)	(0.0156)
Cities	-0.0239**	-0.0219**	-0.0176**	-0.0176**	-0.0194**	-0.0244*	-0.0244*	-0.0271**
	(0.0121)	(0.0109)	(0.0089)	(0.0089)	(0.0089)	(0.0126)	(0.0126)	(0.0131)
Climate Legislation/Regulations	-0.0209**	-0.0189**	-0.0162**	-0.0162**	-0.0146**	-0.0227**	-0.0227**	-0.0218**
	(0.0090)	(0.0077)	(0.0076)	(0.0076)	(0.0067)	(0.0107)	(0.0107)	(0.0097)
Climate Summits	-0.0123**	-0.0110**	-0.0085	-0.0085	-0.0143*	-0.0177*	-0.0177*	-0.0218*
	(0.0055)	(0.0048)	(0.0063)	(0.0063)	(0.0074)	(0.0095)	(0.0095)	(0.0113)
Controversies	-0.0244**	-0.0222**	-0.0208**	-0.0208**	-0.0185***	-0.0294**	-0.0294**	-0.0253**
	(0.0124)	(0.0109)	(0.0100)	(0.0100)	(0.0072)	(0.0147)	(0.0147)	(0.0105)
Corporations/Investments	-0.0253**	-0.0233**	-0.0192**	-0.0192**	-0.0202**	-0.0266**	-0.0266**	-0.0282**
	(0.0111)	(0.0099)	(0.0089)	(0.0089)	(0.0086)	(0.0128)	(0.0128)	(0.0132)
Ecosystems	-0.0264*	-0.0247*	-0.0201*	-0.0201*	-0.0215**	-0.0273*	-0.0273*	-0.0286*
	(0.0149)	(0.0141)	(0.0109)	(0.0109)	(0.0104)	(0.0153)	(0.0153)	(0.0149)
Extreme Temperatures	-0.0235	-0.0222	-0.0192*	-0.0192*	-0.0226**	-0.0234*	-0.0234*	-0.0290*
	(0.0147)	(0.0138)	(0.0112)	(0.0112)	(0.0109)	(0.0136)	(0.0136)	(0.0149)
Food Shortage/Poverty	-0.0214*	-0.0197*	-0.0154*	-0.0154*	-0.0161**	-0.0229*	-0.0229*	-0.0233*
	(0.0115)	(0.0103)	(0.0082)	(0.0082)	(0.0080)	(0.0123)	(0.0123)	(0.0122)
Forests	-0.0189**	-0.0172**	-0.0135*	-0.0135*	-0.0135*	-0.0209*	-0.0209*	-0.0210*
	(0.0088)	(0.0078)	(0.0073)	(0.0073)	(0.0076)	(0.0109)	(0.0109)	(0.0113)
Glaciers/Ice Sheets	-0.0213*	-0.0211*	-0.0195*	-0.0195*	-0.0221**	-0.0276*	-0.0276*	-0.0272**
	(0.0122)	(0.0119)	(0.0105)	(0.0105)	(0.0096)	(0.0147)	(0.0147)	(0.0126)
Global Warming	-0.0211	-0.0187	-0.0162	-0.0162	-0.0306**	-0.0228*	-0.0228*	-0.0394**
	(0.0131)	(0.0118)	(0.0107)	(0.0107)	(0.0146)	(0.0138)	(0.0138)	(0.0199)
Government Programs	-0.0235**	-0.0217**	-0.0172**	-0.0172**	-0.0203**	-0.0249*	-0.0249*	-0.0292**
	(0.0114)	(0.0101)	(0.0087)	(0.0087)	(0.0096)	(0.0127)	(0.0127)	(0.0145)
Hurricanes/Floods	-0.0212*	-0.0193*	-0.0158*	-0.0158*	-0.0233**	-0.0233*	-0.0233*	-0.0299**
	(0.0119)	(0.0108)	(0.0089)	(0.0089)	(0.0106)	(0.0128)	(0.0128)	(0.0146)
Legal Actions	-0.0288**	-0.0255**	-0.0240**	-0.0240**	-0.0301*	-0.0321**	-0.0321**	-0.0370*
	(0.0123)	(0.0105)	(0.0096)	(0.0096)	(0.0155)	(0.0141)	(0.0141)	(0.0196)
Marine Wildlife	-0.0192**	-0.0175**	-0.0155**	-0.0155**	-0.0196**	-0.0236**	-0.0236**	-0.0297**
	(0.0085)	(0.0075)	(0.0076)	(0.0076)	(0.0090)	(0.0113)	(0.0113)	(0.0148)
Political Campaign	-0.0257*	-0.0242**	-0.0211**	-0.0211**	-0.0243**	-0.0297**	-0.0297**	-0.0311**
	(0.0132)	(0.0120)	(0.0101)	(0.0101)	(0.0106)	(0.0150)	(0.0150)	(0.0147)
Renewable Energy	-0.0333*	-0.0301*	-0.0261*	-0.0261*	-0.0297**	-0.0361*	-0.0361*	-0.0387**
	(0.0179)	(0.0163)	(0.0133)	(0.0133)	(0.0126)	(0.0194)	(0.0194)	(0.0174)
Scientific Studies	-0.0255	-0.0237	-0.0213*	-0.0213*	-0.0210**	-0.0289*	-0.0289*	-0.0273**
	(0.0159)	(0.0148)	(0.0125)	(0.0125)	(0.0098)	(0.0168)	(0.0168)	(0.0132)
Social Events	-0.0245**	-0.0233**	-0.0194**	-0.0194**	-0.0230**	-0.0253**	-0.0253**	-0.0298**
	(0.0122)	(0.0111)	(0.0093)	(0.0093)	(0.0099)	(0.0123)	(0.0123)	(0.0139)
Tourism	-0.0212**	-0.0194**	-0.0159**	-0.0159**	-0.0171**	-0.0228*	-0.0228*	-0.0241**
	(0.0103)	(0.0093)	(0.0080)	(0.0080)	(0.0082)	(0.0117)	(0.0117)	(0.0120)
UN/IPCC Reports	-0.0244*	-0.0227*	-0.0196*	-0.0196*	-0.0203**	-0.0258*	-0.0258*	-0.0298**
	(0.0141)	(0.0129)	(0.0109)	(0.0109)	(0.0093)	(0.0146)	(0.0146)	(0.0149)
Water/Drought	-0.0268*	-0.0254*	-0.0212*	-0.0212*	-0.0196**	-0.0275*	-0.0275*	-0.0270**
	(0.0151)	(0.0142)	(0.0115)	(0.0115)	(0.0094)	(0.0154)	(0.0154)	(0.0135)
Observations	170	170	170	170	169	170	170	169
Mean R-squared	0.014	0.027	0.030	0.030	0.040	0.066	0.066	0.075

Appendix D

Distribution of Carbon Intensity Measures.
Appendix D presents frequency histograms of *Carbon Intensity (tCO₂e/Revenue)* for *Scope 1*, *Scope 2*, *Scope 3*, and their combinations, and the corresponding *Log Carbon Intensity*. The raw variables are highly right-skewed, whereas the log-transformed intensities exhibit much more regular, approximately symmetric distributions. *Mean*, *Median*, and *Skewness* are reported in each panel. Interpretation guide:
|Skewness| < 0.5: Fairly symmetric
0.5 < |Skewness| < 1: Moderately skewed
|Skewness| > 1: Highly skewed