Corporate Green Pledges*

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March 12, 2026

Abstract

We build a novel dataset of timestamped corporate decarbonization commitments—green pledges—for U.S. public firms by classifying news articles with large language models and human validation. Firms announcing green pledges tend to be larger and browner than other firms, both within and across industries. Green pledges significantly raise stock prices, consistent with a reduction in the carbon premium, and predict sizable declines in future carbon emissions and emission intensities. These effects tend to be strongest for firms in brown industries. Green pledges thus appear credible, convey relevant new information to investors, and provide meaningful financial incentives to decarbonize.

Keywords: climate finance, decarbonization commitments, text classification, event study, transition risk, carbon premium

JEL Codes: G14, G32, Q54, Q56

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1 Introduction

Firms face significant transision risks as the world moves to a low-carbon economy.[1] By committing to reduce emissions, companies can mitigate their exposure to future carbon regulations and technological change. Indeed, an increasing number of corporations worldwide have announced plans and commitments to lower their carbon emissions.[2] Financial markets may reward such commitments if they lower perceived transition risk and the cost of capital, raising firm value. But firms may also incur substantial adjustment costs and risks, and the sign of the net effect on company values is unclear. We address this question with a new dataset of timestamped decarbonization commitments by public U.S. firms, or "corporate green pledges," constructed from news articles using a large language model and human validation. Our event-study evidence shows that green pledges significantly raise stock market valuations. Investors appear to view these pledges as credible and expect the benefits to outweigh the costs. This market response may provide some financial incentives for decarbonization. We further show that firms significantly reduce their emissions following green pledges, indicating that investors have good reasons to view these announcements as credible.

We define a corporate green pledge as a clear, new, actionable commitment to significantly reduce a firm's future greenhouse gas (GHG) emissions. Using textual analysis, we identify the announcements of such green pledges in Dow Jones News data from 2005 to 2023, which include corporate press releases, earnings announcements, newswires and newspaper articles, and other corporate news. As green pledges are difficult to distinguish from other corporate announcements about GHG emissions, conventional text classification methods would require a large training sample of manually labeled articles and still face substantial challenges on this task. We instead classify the articles with large language models (LLMs), which enable accurate identification of green pledges without the need for training data due to their extensive pre-training, strong contextual understanding, and ability to capture linguistic nuances.[3] We use GPT-4 by OpenAI—verifying robustness to the model choice using several more recent LLMs—to classify 44,605 environmental news articles. The successful use of an LLM requires careful prompt design and validation, for which we follow best practices and

[1] See Bolton and Kacperczyk (2021), Pastor et al. (2021), Ilhan et al. (2020) and Krüger et al. (2020).

[2] A 2024 report by S&P Global finds that "45% of the leading listed US companies have a net-zero commitment" and that on average companies aim to cut Scope 1+2 emissions by 51%. The "Net Zero Stocktake 2024" reports that "nearly 60% of the 1,977 publicly listed companies we track have set net zero targets" and that the "annual revenue covered by net zero targets has increased from $13.8 trillion in December 2020 to $31 trillion in August 2024".

[3] Other studies have found that in empirical economic research LLMs often draw similar conclusions as humans, with the advantage of being able to quickly process large amounts of data (Hansen and Kazinnik, 2023; Cook et al., 2023; Beckmann et al., 2024; Jha et al., 2024).

use human coding. In a random subsample of 1,000 articles, the classification labels from LLMs and human coders show a high level of agreement (91%). From the identified articles, and their associated ISINs and time stamps, we derive a dataset of 7,166 firm-level green pledge events, which allow us to carry out event-study analysis of the stock market effects of decarbonization commitments.

We first document new empirical facts about green pledges of listed U.S. companies. Over our sample period, about 11% of the firms made at least one green pledge, and many of those firms made multiple such announcements. The number of green pledges increases towards the end of our sample, consistent with the substantial increase in climate change concerns (Ardia et al., 2023). We validate our news-based measure by comparing it to standard measures of decarbonization commitments, such as the Carbon Disclosure Project (CDP) data. While there is significant overlap between the two datasets, our methodology identifies significantly more pledges and can track commitments as early as 2005. Green pledges are issued especially by large and brown, high-emission firms, both within and across industries. Because these types of firms are the most relevant for the green transition of the U.S. economy, their commitments to reduce emissions are particularly important.

Using event-study panel regressions, we then estimate the stock market effects of our timestamped corporate green pledges. These announcements have a positive effect on stock market valuations which is both statistically and economically significant, with no evidence of reversal in subsequent trading days. On average, green pledges raise stock prices by 0.14–0.34%, which is a sizable increase relative to the average daily stock return of 0.015%. The estimated effects are robust to the choice of firm-level control variables, fixed effects, event subsets, sample period, and the LLMs used for classification: results based on four newer models from OpenAI, Anthropic, and Google are consistent with our baseline. We rule out the influence of confounding factors such as other corporate news released on event days, industry-specific effects, or the broader impact of environmental news on stock prices. Estimates of dynamic event-study regressions show that green pledges cause immediate and persistent effects on stock market valuations, with little evidence of information leakage before or price reversals after the announcement.

Investors appear to differentiate between credible and weak green pledges. Ambitious pledges and those describing investment plans to reduce the firm's carbon footprint generate a significantly positive stock market reaction. By contrast, less ambitious pledges or those lacking specific information on how emission reductions will be achieved do not lead to significant changes in firm valuation. Furthermore, industries with high emissions—such as utilities, energy, and chemicals—have not only the highest share of pledging firms but also the strongest stock market reactions.

A straightforward explanation of our stock market results is that green pledges lower the carbon premium: As investors learn that a firm will become greener, its stock is perceived to be less exposed to climate transition risk and/or more attractive due to nonpecuniary green investor preferences, lowering its expected return and raising its price. Green pledges could also influence stock prices through changes in expected cash flows, but we find no evidence that they improve analyst earnings forecasts or predict materially higher future profitability or dividend growth. On the whole, green pledges seem more likely to affect discount rates than expected cash flows.

Our evidence on the stock market effects is a novel contribution to the climate finance literature: Positive effects from a lower carbon premium, and potentially from an improved earnings outlook, outweigh the costs and risks in the eyes of investors. While Hartzmark and Shue (2023) conclude that "brown firms face very weak financial incentives to become more green," our results point in the opposite direction: green pledges increase stock valuations, creating positive financial incentives for companies to commit to decarbonization.

Finally, we investigate whether firms "walk the talk" by actually reducing CO_2 emissions following a green pledge, a pressing question given concerns about cheap talk and greenwashing (Bingler et al., 2022). To address it, we estimate difference-in-differences local projections for firm-level CO_2 emissions, using the methodology of Dube et al. (2025). The results show that green pledges are followed by statistically significant reductions in both emission levels and intensities. The reductions are quantitatively meaningful: Emissions of firms that make a green pledge are about 14% lower five years after the announcements, compared to firms that do not make such a commitment. Sectors with the highest carbon emissions exhibit the most substantial reductions. Since these are also the sectors with the strongest stock market reactions, the pattern suggests that pledges in carbon-intensive industries are perceived as credible and have meaningful real effects. Taken together, our findings alleviate concerns about greenwashing and indicate that green pledges tend to provide credible signals about future emissions. We do not interpret these results as evidence that green pledges causally reduce carbon emissions. Rather, pledges reveal credible private information about future emission trajectories—precisely the type of forward-looking signal that investors value and incorporate into prices.

Recent studies have investigated climate commitments using data from the CDP and the Science-Based Target Initiative (SBTi), including Bolton and Kacperczyk (2025), Aldy et al. (2023, 2024), and Jiang (2024). We take an alternative route and develop a news-based identification of green pledges. The resulting new database of timestamped announcements of climate commitments allows us to use event studies to estimate the stock market response and the pricing of transition risks, in contrast to the annually reported announcements in other databases. While our news-based measure shows substantial overlap with CDP and SBTi data, it is more comprehensive as it covers a broader range of firms and a longer sample period.[4] Our results on the prevalence of green pledges differ somewhat from those of Bolton and Kacperczyk (2025), who find in their annual international dataset that once they control for industry effects, green firms appear more likely to make commitments than brown firms. For the U.S., we instead estimate that large and brown firms are more likely to make green pledges, both within and across industries, a result we confirm using both our news-based measure and the CDP commitments. Regarding the future path of emissions, our results are qualitatively consistent with those in Bolton and Kacperczyk (2025), who find that decarbonization commitments in the CDP data tend to be followed by lower emissions.[5]

In related work, Berg et al. (2025) use the CDP data to show that firms often reduce emissions through divestments of pollutive assets, reallocating carbon-intensive operations rather than increasing abatement investment. Our findings provide an interesting contrast, because most green pledges in our sample involve investments in low-carbon technologies, and we estimate that capital expenditures tend to rise after green pledges. This apparent contrast mainly reflects the different perspectives and methodologies: While Berg et al. (2025) analyze realized changes in the emissions reported by firms and asset ownership using CDP disclosures, we focus on forward-looking corporate announcements that reveal firms' stated decarbonization intentions and associated capital reallocation.

Our paper contributes to research on climate transition risk, stock returns, and the carbon premium hypothesis of Pastor et al. (2021). Earlier studies have typically measured transition risk exposure using firm-level emissions and estimated the differential stock returns of green and brown firms, with mixed results. Several influential papers, including Bolton and Kacperczyk (2021, 2023), document higher brown stock returns and thus evidence for a carbon premium. Other studies instead estimate green outperformance (Garvey et al., 2018; In et al., 2019; Pastor et al., 2022; Bauer et al., 2022). Empirical analysis of the carbon premium is typically based on past emissions data as a measure for the exposure to

[4] CDP started recording commitments in 2013, and SBTi started only in 2015. The Net Zero Tracker (www.zerotracker.net) only captures a subset of decarbonization commitments, and does not record the announcement dates.

[5] Various recent studies investigate other aspects of climate commitments and corporate emission targets: Acharya et al. (2024) develop a model of firm-level climate commitments and show evidence using the SBTi data that large firms are more likely to commit to greening. Sastry et al. (2024) study net zero commitments of banks, documenting that such commitments predict decarbonization of bank loan portfolios, but not reductions in credit supply to brown sectors or an increase in financing for renewable projects. Heeb and Kölbel (2024) show that index providers can successfully encourage corporate climate commitments. Ramadorai and Zeni (2024) document that firms' planned and actual emission abatement activities depend on prevailing beliefs about climate regulation and the political situation. Jiang et al. (2025) show that failures of emission targets elicit little attention based on coverage by the media.

transition risks, but this approach has several shortcomings: Emissions data disclosure has largely been voluntary, raising the concern of selection bias; vendor estimates of emissions can be unreliable and are often revised ex post; and emissions data are available to investors only with significant lags (Aswani et al., 2023; Zhang, 2025). While emissions data provide only backward-looking and slow-moving measures of transition risk, green pledges are forward-looking and capture new information about future firm-level greenness and transition risk exposure, which makes them better suited to study the pricing of these characteristics and risks in financial markets. In this way, our event-study results provide clear, novel evidence on the pricing of green and brown stocks.

Another key empirical challenge in climate finance is that average past stock returns tend to be poor measures of expected returns due to the short sample periods, changes in perceptions about climate risk, and mispricing.[6] A possible remedy is to rely on estimates of expected returns for green and brown assets, as in Pastor et al. (2022) and Eskildsen et al. (2024). Alternatively, one can study green and brown stock returns around specific events with news about climate risk or climate policies (e.g., Engle et al., 2020; Ardia et al., 2023; Bauer et al., 2024). We instead focus on firm-level news about future greenness, which allows us to cleanly identify the impact on stock market valuations and draw conclusions about the carbon premium and the pricing of transition risks.

Many studies have used textual analysis to measure climate risks, typically by constructing aggregate indices from newspaper articles. For instance, Engle et al. (2020) use news articles from *The Wall Street Journal* to build a climate news index, Ardia et al. (2023) construct a news-based index of climate change concerns, and Faccini et al. (2023) derive several different climate risk measures from news articles. Only a few studies have used text methods to investigate the pricing of climate risk at the firm level. Sautner et al. (2023a) and Li et al. (2024) use companies' earnings calls to measure firm-level climate change exposure, and Sautner et al. (2023b) document changes in the risk premium associated with such exposure. Dzieliński et al. (2023) investigate the response of stock prices and future GHG emissions to discussions of climate-related topics in earnings calls, and find reductions in future emissions as evidence, consistent with our results, that firms "walk the climate talk." Our measure differs from earlier ones in that it captures news about future firm-level emissions and thus *changes* in greenness and transition risk.

In the climate finance literature, there is an active debate about greenwashing in corporate announcements, and, more specifically, cheap talk in climate commitments (Nemes et al., 2022; Bingler et al., 2022, 2024; Dzieliński et al., 2023; Sastry et al., 2024). Our evidence that

[6] Atilgan et al. (2023) incorporate earnings announcements in their analysis and conclude that the carbon premium in their data sample in fact reflects unexpected returns and mispricing.

green pledges predict reductions in future emissions and emission intensities contributes to this debate. It suggests that corporate green pledges are at least partly credible and should not be discarded wholesale as cheap talk.

Our work is closely related to other studies in climate finance and the ESG literature using event studies to estimate the effects of firm-level news on stock prices and firm prospects. Krüger (2015) studies how stock prices react to positive and negative news regarding a firm's corporate social responsibility (CSR), based on an identification of CSR events from text data. Derrien et al. (2025) document that negative ESG news, measured by RepRisk, tends to lower analyst forecasts for earnings and sales, which is evidence for a cash flow channel in this context. We contribute to this literature by documenting the stock market effects of firm-level news about CO_2 emissions and providing evidence for the importance of a discount rate channel and changes in the carbon premium.

The remainder of the paper proceeds as follows. Section 2 describes our text data and approach to identify decarbonization commitments using a large language model and human coding. Section 3 documents new facts about green pledges, including their variation over time, across industries, and across firms. Section 4 presents our central event-study results of the stock market reaction to green pledges. Section 5 shows estimates of the relationship with future emissions using local projections. Section 6 concludes.

2 Identification of Green Pledges

Our starting point is to define and identify decarbonization commitments of U.S. firms using text data. We use Dow Jones News, a large data set of newswire and newspaper articles from Dow Jones, the Wall Street Journal, Barron's, MarketWatch, and other sources. These news outlets, and especially the newswires, are closely monitored by financial market participants. The data also include press releases, earnings announcements, and other corporate news. Versions of this text dataset have been used in a number of studies in finance and economics.[7] The text data comes with a variety of attributes, including the geographical regions covered by the news, categories of subjects, and the precise timestamps. Additionally, Dow Jones assigns a list of ISINs to each article, which simplifies the process of linking them to firms. Our sample period ranges from January 2005 to December 2023. We refine our selection of articles by including only those related to companies in the United States

[7] Ke et al. (2020) construct a novel sentiment score from this text data, which they use to predict stock returns. Barbaglia et al. (2023) used data from Dow Jones to analyse the gains of using sentiment measures in macroeconomic forecasting. Ravenpack uses Dow Jones Newswires data to construct its popular sentiment scores, which have been used widely in finance and economics (e.g. Kim, 2022; Audrino and Offner, 2024). See Vega et al. (2025) for text analysis using this data in the context of monetary policy communication.

and categorized as environmental news.[8] The resulting sample includes 44,605 news articles and announcements.

To accurately classify green pledges, we first need a workable definition. We define a green pledge as an announcement of a *new, clear, and actionable commitment by a firm to significantly reduce future direct greenhouse gas (GHG) emissions.* This definition aims to identify articles with new information about a firm's expected future emissions, which is relevant for stock market investors. Updates to prior commitments are included only when they introduce more stringent targets or new initiatives. For example, a firm advancing its carbon neutrality target by reallocating capital to renewable energy would qualify as a green pledge. By contrast, statements that merely reaffirm existing goals do not. Green pledges should be about direct emissions, because these are easier to quantify and directly attributable to firm-level decisions, making them the most reliable indicator of a company's decarbonization efforts. We focus on official corporate communications—such as press releases, regulatory filings, and other corporate announcements—and news coverage of a company's climate commitments. Overall, the announcement should contain material new information for financial market participants and the broader public about expected firm-level emissions.

Our goal is to accurately classify the news articles into those that contain corporate green pledges and those that do not. A wide range of text classification methods could, in principle, be used for this classification problem.[9] However, most methods would struggle with this task, because green pledges sound superficially similar to other GHG-related corporate announcements. Achieving adequate accuracy would require a large volume of labeled training data—many thousands of labeled articles—and careful model tuning.

We instead use large language models (LLMs) to classify the news articles. By now, LLMs have been successfully used in a wide range of applications in empirical economic research.[10] Our application requires a suitably chosen prompt with accurate and detailed instructions that are consistent with our definition of a green pledge. In addition, it is necessary to carefully evaluate the results, given the possibility of hallucination, bias, restrictions from content use policies, and other related problems of LLMs. For both our prompt design and for evaluation of the LLM classifications we make extensive use of human coding. Our

[8] Specifically, we use articles tagged with at least one U.S. ISIN, the U.S. indicated as the geographical region, and "environment" as the subject classification, using the metadata provided by Dow Jones.

[9] For excellent treatments of text analysis methods and their applications in economics and other social sciences, see Grimmer et al. (2022), and Ash and Hansen (2023).

[10] Lopez-Lira and Tang (2024) find that GPT-4 can make accurate stock market predictions based on news headlines. Hansen and Kazinnik (2023) use GPT models to classify the monetary policy stance based on language in FOMC statements, and find logical reasoning similar to human coders. LLMs have been used to evaluate the information in company earnings calls by Cook et al. (2023) and Beckmann et al. (2024), and to evaluate corporate policies by Jha et al. (2024). See Korinek (2023) and Ash and Hansen (2023) for other applications of LLMs in economics.

approach is similar to that of Eloundou et al. (2024) who also use human labeling and LLMs, fine-tuning a prompt to yield good agreement between both. Our main results are based on OpenAI's GPT-4, but we also obtain classifications from several more recent models to verify robustness.

The first step of our text classification was to design a suitable prompt using an iterative process. We started with a simple prompt based on our definition of a green pledge, and then refined the prompt in successive iterations, each time using the model to classify a subset of articles that were also given to human coders and comparing human and model-based classifications. We also asked the LLM for a concise justification for each classification decision, which offers insights into the model's reasoning process and its comprehension of the assignment. Based on these results, we then iteratively modified the prompt, typically making the criteria more stringent to avoid false positives. The result of this process was the following final prompt:

> *Classify the following article as positive or negative depending on whether it contains an announcement that the company will reduce its future emissions of greenhouse gases, such as carbon dioxide. Classify an article as positive only if the company announces a significant reduction of direct emissions, that is, emissions that occur from sources controlled or owned by the company. The announcement should be news and should describe the company's commitments and plans for the future. Do not classify articles as positive that only contain announcements to reduce indirect emissions, that is, emissions that a company causes indirectly from the energy it purchases and uses. Also do not classify articles as positive if they are only about past performance, about a corporate social responsibility (CSR) report describing past emission reductions, about other environmental measures such as waste reduction, use of recycled paper, or planting trees, or announcements by the government. If an article is empty, or does not contain enough information, classify it as negative. Answer 'YES' for positive articles and 'NO' otherwise.*

The second step was to classify our entire corpus of news articles. The specific GPT-4 model we used for our baseline results was `gpt-4-0613`, the latest GPT-4 variant available at the time of our analysis. In order to have a model-based classification that is deterministic, given the text input, we set the temperature, a key parameter of any LLM, to zero.[11] We used OpenAI's Python API to classify the entire dataset of 44,605 news articles.

[11] See Beckmann et al. (2024) for more details on this issue. Note that a zero temperature parameter does not guarantee reproducibility of the results, because the model is not open source and OpenAI could well modify or further fine-tune it.

Table 1: Comparison of classification by GPT-4 and human coders

		Human Coder: Negative	Human Coder: Positive	Total
GPT	Negative	838	19	857
	Positive	67	76	143
	Total	905	95	1000

Confusion matrix for the classifications of 1,000 randomly selected news articles by the model GPT-4 and human coders.

In the following we present three examples of green pledges identified by GPT-4. They demonstrate the successful identification of announcements which contain commitments to reduce GHG emissions:

- *October 14, 2009: Wells Fargo & Company (NYSE: WFC) announced today that it has set a goal to reduce its U.S.–based greenhouse gas emissions by 20 percent below 2008 levels by 2018. The Company is focusing on reducing its carbon footprint as part of its continued environmental commitment to lead by example and to fulfill its pledge as a member of the U.S. Environmental Protection Agency's (EPA's) Climate Leaders program, which Wells Fargo joined last year. [...]*
- *January 16, 2020: Microsoft Corp. on Thursday announced an ambitious goal and a new plan to reduce and ultimately remove its carbon footprint. By 2030 Microsoft will be carbon negative, and by 2050 Microsoft will remove from the environment all the carbon the company has emitted either directly or by electrical consumption since it was founded in 1975. [...]*
- *July 21, 2020: Apple today unveiled its plan to become carbon neutral across its entire business, manufacturing supply chain, and product life cycle by 2030. The company is already carbon neutral today for its global corporate operations, and this new commitment means that by 2030, every Apple device sold will have net zero climate impact. [...]*

The third and final step was to validate the model-based results using human coders. This step is crucial in applied economic research, as it provides an essential benchmark for the accuracy of LLM results (Dell, 2025; Ludwig et al., 2025). We selected a random subset of 1,000 articles and tasked two research associates, who were not otherwise affiliated with this project, each to label half of this validation sample. As instructions to our human coders we simply provided them with the same prompt as we gave to the LLM.

Table 1 shows a confusion matrix comparing the labels of GPT-4 with those of the human coders. We calculate commonly used statistics for binary classifications, treating the human labels as the "truth" for this purpose. The accuracy of the GPT labels, defined as the share of identical classifications between GPT and human coders, is 91%. This high level of agreement partly reflects the large number of negative cases. The precision, defined as the fraction of GPT-positive articles that were also classified as positive by human coders, is 53%, reflecting that human coders applied stricter criteria: they identified 95 news articles as green pledges, while GPT classified 143 as positive. The sensitivity (or recall) is 80%, implying that of the 95 pledges identified by human coders, 76 were also recognized as positives by GPT. Hence, GPT successfully identifies a large fraction of the pledges detected by human coders. Overall, the human validation suggests that GPT-4 classifies most green pledges accurately, with few false negatives. However, its classifications are somewhat less conservative than those of the human coders, implying the presence of some false positives.

The landscape of LLMs is quickly evolving, and OpenAI has released many new models since we initially carried out the classification with GPT-4 and wrote the first version of this paper. To assess whether newer models yield similar results, we have classified the validation sample of 1,000 articles with several recent models from OpenAI, Anthropic, and Google. The results, which are reported in Appendix A.1, show that different newer models tend to classify somewhat fewer articles as green pledges, similar to the tendency of human coders to be more selective, and that there is some notable degree of disagreement across models.[12] A comparison to the human labels shows that newer models tend to have higher precision but lower recall, and that GPT-4 remains overall quite competitive for green pledge classification. Importantly, we will consider labels from different LLMs to assess the robustness of our main stock market event-study results in Section 4.

Our validation exercises confirm that identifying green pledges from news articles is challenging. Standard econometric theory can speak to the likely consequences of imprecise measurement of green pledges for our downstream analysis. The event indicator variable that identifies the time period and firm of a green pledge necessarily contains some measurement error. This variable is a regressor in our event-study regressions for stock returns in Section 4 and in the difference-in-difference estimation in Section 5. Under the assumption that this measurement error is uncorrelated with both the true underlying green pledge indicator and the regression error term, the setting is analogous to a classical errors-in-variables problem.[13] In that case, the resulting bias would attenuate our downstream estimates toward zero,

[12] In additional analysis, we find that disagreement is especially high for longer and more recent articles, as well as for articles on the subject of carbon emissions.

[13] While the mean of the measurement error is positive if we have more false positives than false negatives, this would only bias the intercept of the regressions.

Table 2: Categories and ambition scores of green pledges

		Ambition: Limited	Ambition: Significant	Total
Category	Investment	262	5799	6061
	Divestment	10	90	100
	No specifics	669	32	701
Total		941	5921	6862

Distribution of green pledge articles according to category label and ambition score.

providing a conservative estimate of the true effect of green pledges on stock returns and emissions. More generally, the robustness of our main event-study results across multiple LLMs alleviates concerns about measurement error.

The end result of our classification with GPT is a selection of 6,862 news articles—about 15% of all environmental articles on U.S. public companies—that are deemed by GPT to contain green pledges. Before turning to the analysis of the characteristics and effects of green pledges in the rest of the paper, we can go further with this text data and use LLMs to try to understand the nature and ambition of these commitments.

Firms can reduce their GHG emissions in a number of different ways, but broadly they have the choice of investing in new low-carbon technologies or divesting from carbon-intensive assets. We use an LLM to categorize the articles that were identified as green pledges, according to whether the announcement contains (1) information about new investments to reduce emissions, such as green energy technologies, (2) information about divestments from pollutive assets, such as the sale of high-emission business units, or (3) no specific information on how emission reductions will be achieved.[14] Table 2 shows that the vast majority (88%) of green pledge articles indicate that firms would invest into new technologies to reduce emissions.

Another important question about decarbonization commitments is whether they are actually meaningful and ambitious, or whether they announce only minor reductions in order to avoid missing the targets. We try to address it by having the model score the level of ambition for the emission reduction as either (1) limited or vague commitment with minor expected impact on emissions or (2) significant and specific commitment with substantial impact. As shown in Table 2 most articles were judged to contain announcements of significant and specific plans for emission reductions. Judging from the announced green pledges, the level of ambition would appear to be quite high.

For the following analysis, we identify company-level green pledge *events* from the iden-

[14]The detailed prompt is given in Appendix A.2. We used GPT-4o for this task.

tified *articles*. Each of these articles can tag multiple firms (ISINs), for example, if certain decarbonization initiatives involve several companies. In addition, on a given day there may be multiple identified articles for the same firm, for example, if a press release is followed by coverage in a news article. For our empirical analysis we create unique firm-date events, based on combinations of company ISINs and article date, to represent corporate green pledges. The result is a sample of 7,166 green pledge events.

For many firms, our sample contains more than one green pledge. A simple approach to reduce the noise in our classification is to only consider the first green pledge for each of the 1,528 firms that have made at least one pledge. For the stock market analysis in Section 4, we will consider both types of green-pledge indicators, either using all events for a firm or using only the first identified green pledge for each firm.[15] For estimating the relationship with future emissions in Section 5, we use a difference-in-differences approach with an indicator variable that turns on when a firm makes its first pledge.

3 Green Pledges Over Time and Across Firms

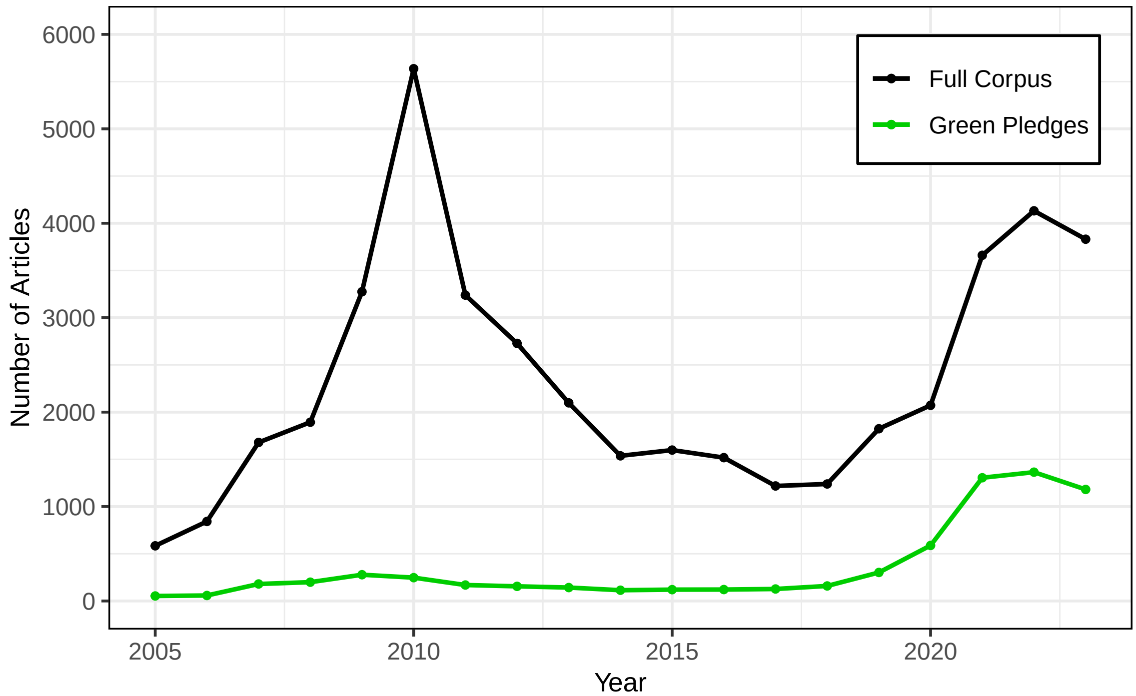
In this section we document patterns of corporate green pledges over time and across firms. In addition, we compare and validate our text-based pledges against other databases, such as the data from the Carbon Disclosure Project.

Figure 1 plots the annual number of (environmental) news articles in our text data, and the number of articles that the LLM identified as containing green pledges. Our data contained a significant number of environmental news articles each year, with a peak in 2010 and a strong increase in recent years. The high number of environmental articles around 2010 can be attributed to the 2009 Copenhagen UN Climate Change Conference and the explosion of Deepwater Horizon in April 2010.[16] Over the early part of our sample period, between 2005 and 2018, the number of green pledge articles was around 150 per

[15] In addition, we also consider two other subsamples of green pledges which impose a more stringent event definition to address two other concerns: First, duplicate or follow-up articles can appear in subsequent days. To address this issue, we require a certain number of days to elapse between two successive events for the same firm. Choosing the required distance as too wide could result in excluding new commitments, while setting it too narrow leads to duplicate events concerning the same green pledge. As a middle ground, we choose a 30-day distance, which we find a reasonable distance to avoid duplicates while not losing new commitments. The second issue arises as articles are sometimes tagging multiple companies. To avoid matching articles to firms that were mentioned in the articles but were not the primary subject of it, we follow Ke et al. (2020) and include only articles tagged with a single company in our analysis. Our "30-day distance" sample contains 5,898 events, and our "single-tag" sample contains 5,237 events.

[16] When computing term-frequency inverse document-frequency (tf-idf) for the year 2010, the most frequent terms are "bp" and "oil". In contrast, the most frequent terms across the entire sample period include "statements", "water", "energy". This disparity underscores the significant impact of the Deepwater Horizon spill on news coverage in 2010.

Figure 1: Number of environmental news and green pledge articles over time



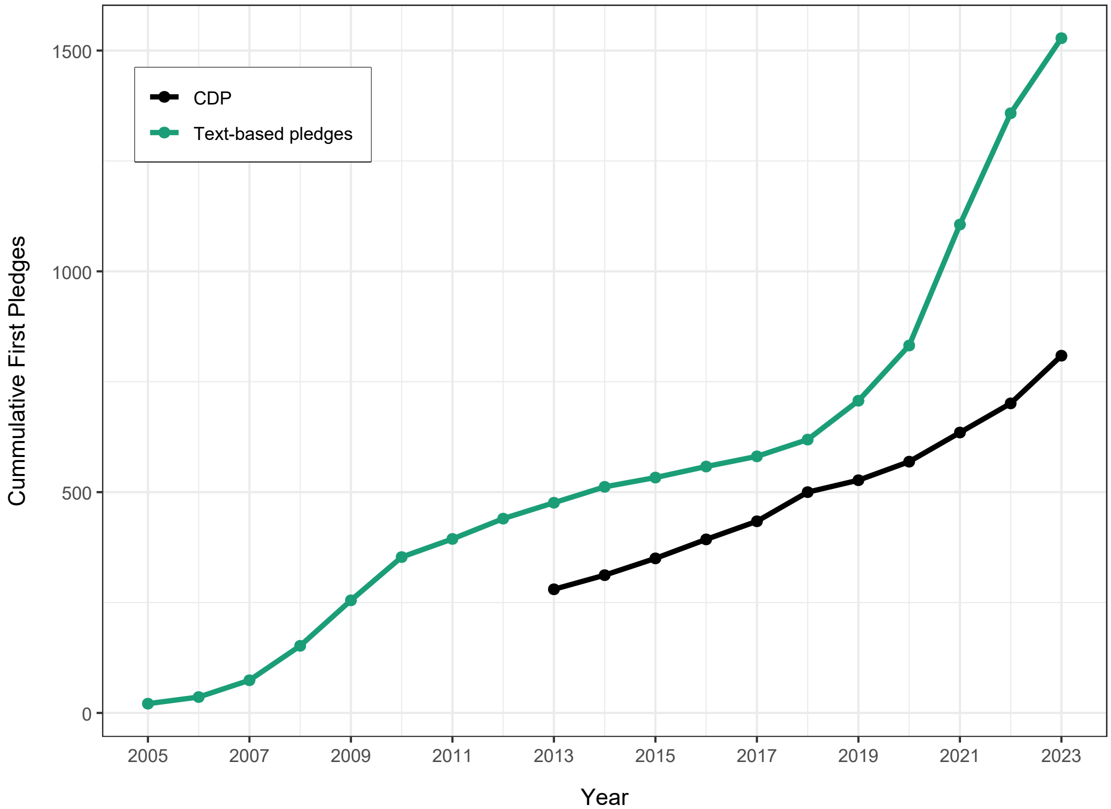
Yearly number of articles in the full text corpus of environmental news articles (black line) and classified as green pledge by GPT (green line). The total number of articles is 44,605 articles, of which 6,862 are classified as green pledges. Sample period: 2005 to 2023.

year. Towards the end of the sample, around 2019, the number of identified articles started increasing substantially, and each year since 2021 there were over 1,000 green pledge articles. This pattern may be due to increased public attention to the risks of climate change—as evidenced for example in the text-based measure of climate change concerns of Ardia et al. (2023)—and increasing climate transition risks that cause more companies to commit to climate mitigation and emission reductions. By contrast, during the years around the Paris Agreement in 2015 there was no appreciable increase in green pledges, suggesting that this international initiative actually had only a modest impact on the corporate sector.

Turning now to the firm-level announcements, a crucial question is how our measure of green pledges compares to those recorded in databases of corporate climate commitments. To address it, we carry out a comparison with the CDP data that has been widely used in research in climate finance and climate economics.[17] This database, which begins in 2013, tracks firms' emission reduction targets on an annual basis. Since emission targets are continually updated in the CDP data, we focus on the first recorded CDP commitment

[17]CDP advertises itself as "the world's largest primary corporate environmental dataset." See https://www.cdp.net/en/data for more information. Studies using this data include, among many others, Bolton and Kacperczyk (2021, 2023, 2025) and Ramadorai and Zeni (2024).

Figure 2: Cumulative First Pledges: Text-Based vs. CDP Targets



The figure plots the cumulative number of firms' first green pledges identified with our text-based approach alongside the cumulative number of first emission reduction targets reported in the CDP database. Sample: 2013 to 2023.

for each U.S. firm, which we can compare to the first green pledge identified from our text data. There are 809 U.S. firms in our CDP dataset, of which 547 also have a green pledge in our text data, meaning that we have a substantial overlap of 68%.[18] Our method detects about twice as many firms with green pledges, suggesting that our approach delivers a more comprehensive record of decarbonization commitments than the CDP database. Figure 2 plots annual series of the cumulative number of first decarbonization commitments in both data sets. We identify pledges as far back as 2005, while CDP data starts only in 2013, so we can significantly extend the available sample period. Between 2013 and 2020, both datasets show a broadly similar increase in first green pledges.[19] Since 2020, however, we observe a sharp rise in pledges captured by our text-based approach, likely reflecting heightened

[18]A similar comparison with the SBTi database reveals that among the 400 U.S. firms in that dataset, 305 (76%) were identified as making a green pledge in our text data. That is, the overlap of our green pledges with SBTi commitments is even larger than with CDP commitments.

[19]The similar upward trend shown in Figure 2, also alleviates concerns that the higher number of green pledges in our text-based data is due to false positives.

climate awareness and increased corporate climate action, which the CDP data does not pick up to the same extent. Further analysis of the green pledges that are recorded in both data sources shows that there is a close correspondence of firm-level climate commitments in our text data and in the CDP data, and if anything that our text-based method identifies these commitments in a more timely fashion.[20] Overall, there are similar trends and significant overlap between the two data sources, but our text-based method provides broader coverage and a longer sample period. Of course, another important advantage of our text-based approach is that it includes an exact timestamp for each announcement, which is essential for estimating the stock-market effects of climate commitments.

In the following we analyze the distribution of green pledges across industries and the role of firm characteristics. We focus on the question of what kind of firms are most likely to commit to decarbonizing their business models. For the transition to a low-carbon economy, it is particularly important that large, high-emission firms commit to reduce their carbon footprint. If instead green pledges are announced predominantly by firms that use green technology already, or by firms that have low emissions in the first place and hence a low exposure to transition risks, the aggregate impact on emissions would be small. In this case, green pledges would be less useful for the transition of the U.S. economy to a low-carbon future.

As the following analysis requires firm characteristics, we merge the data on green pledges with data from financial reports and emissions (both of which are annual). Our accounting data comes from Compustat and our emissions data are from S&P/Trucost. We use two emission variables: level of emissions, defined as the sum of scope 1 (direct) and scope 2 (indirect) emissions (in million tons of CO_2 equivalents), and emission intensity defined as the sum of scope 1 and scope 2 emissions divided by revenue (in million USD). Following earlier work in climate finance, we exclude scope 3 emissions because these indirect emissions from upstream and downstream activities of the reporting firm are very large in magnitude and particularly difficult to estimate (Bauer et al., 2022; Huij et al., 2024). Appendix B provides detailed descriptions and summary statistics for the variables based on accounting financials and emissions.

After the data merge, our sample contains 5,603 green pledge events, corresponding to 995 different firms. This number of firms with climate commitments corresponds to 11% of the 8,882 public U.S. firms in our Compustat sample.[21] The number of green pledges

[20] Appendix Figure C.2 shows that these green pledges are most likely to occur either at a similar time in both data sets, or earlier in the text data than in the CDP data.

[21] We ensure that the set of firms is identical to the one used in Section 4, where we also merge with CRSP stock market data. From the original 1,528 firms with green pledges, we retained 995 in our final sample. This reduction arises for two reasons: first, CRSP does not cover all securities, such as OTC stocks; second,

Table 3: Pledges and emissions across industries

Industry	Firms	Pledges/firm	Share pledged	Emissions	Intensity
Utilities	145	8.03	0.66	20.63	2.38
Energy	337	1.27	0.22	8.01	0.61
Chemicals	167	1.92	0.29	2.87	0.48
Other	1,156	0.81	0.12	2.43	0.23
Manufacturing	631	1.05	0.21	1.49	0.22
Nondurables	342	0.85	0.20	0.83	0.10
Retail	693	0.55	0.12	0.81	0.07
Telecommunication	230	0.34	0.05	0.68	0.02
Durables	190	1.67	0.14	0.59	0.04
Business Equipment	1,733	0.37	0.11	0.37	0.04
Health Care	1,635	0.06	0.03	0.14	0.04
Finance	1,611	0.17	0.05	0.06	0.01

Summary statistics for firms, pledges and emissions across 12 Fama-French industries. For each industry, the table shows the total number of firms, the number of pledges per firm, the share of firms with pledges, the average level of carbon emissions (scope 1+2, measured in million tons of CO_2), and the average emission intensity (in kilotons of CO_2 per USD million of revenue). Sample period: January 2005 to December 2023.

varies significantly across firms. It is most common for firms to make only one pledge, and this is the case for 392 firms. But the median number of pledges per firm is two, and the distribution has a long right tail.[22] The fact that some firms made several pledges, sometimes in double-digits, is an important reason why we also consider restricted subsamples of green pledge events in our subsequent analysis in order to avoid duplicates and follow-up articles, such as the sample of first pledges.

To study the cross-industry distribution of firms and green pledges we use the 12 Fama-French industries, which are based on a mapping of Standard Industrial Classification (SIC) codes into distinct economic sectors and widely used in financial market research.[23] Table 3 presents industry-level summary statistics with industries ordered by the emissions from brown to green. We report the number of firms and green pledges per industry, the number of pledges per firm and share of firms with pledges, as well as average firm-level emissions

we filter out securities that are not ordinary or Class A common shares, as well as those not traded on the NYSE, AMEX, or NASDAQ.

[22]Among the firms that made at least one green pledge, the median is 2, the mean is 5.6, and the 95th percentile is 22 green pledges per firm. See also Appendix Figure C.1 for the distribution of the number of pledges across firms.

[23]For the purpose of controlling for industry effects in our empirical analysis—using fixed effects, for example—we will rely on the more granular 48-industry Fama-French classification. The two classifications are consistent with each other in a hierarchical sense: the 12-industry classification aggregates the 48 industries into broader economic sectors.

Table 4: Characteristics of firms with and without green pledges

	Pledge	No Pledge	p-value	t-statistic
Emissions	3.85	0.16	0.00	7.16
Emission Intensity	0.43	0.08	0.00	7.44
Size	22.94	1.49	0.00	10.51
Book-to-market	0.50	0.69	0.00	−10.85
Leverage	5.69	6.46	0.27	−1.11
Sales growth	0.49	1.87	0.05	−1.95
Return on equity	0.17	-0.66	0.00	3.77

Summary statistics for firms with and without green pledges. For both groups, sample averages of the different firm characteristics are reported as well as p-Values and t-statistics for the differences in means between the two groups. Firm characteristics are winsorized at the 1%/99% level.

and average emission intensities.

The utilities sector stands out as being both the brownest sector—with the highest firm-level emissions and emission intensities—and having by far the highest number of green pledges, averaging 8.03 pledges per firm. Other carbon-intensive industries, such as energy, chemicals, and manufacturing, also record relatively high levels of pledging activity, with 1.27, 1.92, and 1.05 pledges per firm, respectively. In contrast, firms in low-emission industries such as finance, health care, and business equipment show far fewer pledges, averaging only 0.17, 0.06, and 0.37 pledges per firm, respectively. This tendency for brown industries to have more frequent pledges is also evident in the share of firms that have made any green pledges in our sample. For instance, in the utilities sector, 66% of firms have announced a green pledge, compared to 5% in the finance sector. Overall, these results indicate that firms in high-emission, high-intensity sectors are significantly more likely to announce decarbonization commitments than those in greener industries.

To study the firm-level characteristics associated with green pledge announcements, Table 4 compares the attributes of firms with and without such pledges. Specifically, the table reports for both groups the average firm characteristics, first averaged over time for each firm and then across firms within each group. The final two columns display the p-values and t-statistics testing for differences in the cross-sectional means of these characteristics. All variables are winsorized at the 1%/99% level to reduce the influence of outliers.

In line with the industry level analysis, Table 4 shows that firms with a green pledge have on average significantly higher emissions and higher emission intensities. In addition, these firms tend to be larger. The differences are both economically and statistically significant. This finding alleviates the concern that decarbonization commitments are primarily made by green firms, with a resulting smaller impact on aggregate emissions. We also find significant differences for book-to-market value, sales growth, and return on equity: Firms with green pledges tend to have higher valuations, lower sales growth, and higher profitability.

Bolton and Kacperczyk (2025) raise the concern that while unconditionally brown firms appear more likely to make decarbonization commitments, *within industries* greener firms appear to be more likely to make such commitments, according to their analysis. The authors conclude that it is the greener firms, who likely have already adapted their business models to reduce emissions, who make green pledges, and that consequently such pledges may have only modest effects on aggregate emissions and a small role for the green transition.

To address this issue, and to get a more nuanced picture of the type of firm that tends to make green pledges, we estimate panel regressions that control for industry effects and firm characteristics, using a firm-by-year panel dataset. The dependent variable is a binary indicator that takes the value of one in the year a firm makes its first green pledge and remains one in the subsequent years, following the definition of Bolton and Kacperczyk (2025). The regressions include lagged firm characteristics (from the previous year) and year fixed effects. We consider specifications without and with industry fixed effects based on the Fama-French 48-industry classifications.

The results in Table 5 clearly demonstrate that brown firms and large firms are more likely to make green pledges, even after controlling for industry fixed effects and various firm-level characteristics. The effects of log emissions and size on the issuance of a green pledge are positive and statistically significant at the 1% level for all specifications. These results are robust to the use of only reported emissions data, excluding vendor estimates of firm-level emissions; in fact, the findings become even stronger when considering disclosed emissions only.[24]

Our findings in Table 5 appear to be at odds with the evidence presented by Bolton and Kacperczyk (2025), who find that in panel regressions with industry fixed effects green firms are more likely to make decarbonization commitments. There are two fundamental differences between the dataset used in Bolton and Kacperczyk (2025) and this paper. First, they identify green pledges by using firms who sign up to carbon initiatives such as the CDP and the SBTi, while we use green pledges identified from newspaper articles. Second, Bolton and Kacperczyk use an international sample of firms while we focus on the US stock market. To better understand the source of the discrepancy, we revisited the analysis of Bolton and

[24]Separate results using only disclosed emissions or only Trucost's estimates of firm-level emissions are reported in Appendix Table C.2. Furthermore, we estimated regressions using the same set of controls used in Bolton and Kacperczyk (2025), and found that this leads to the same conclusions as the estimates in Table 5. As some of these controls are not available for all firms, we only use the set of controls reported in the table for our main analysis. Our findings also remain essentially unchanged when using GICS 6-digit industry classification for the industry fixed effects as in Bolton and Kacperczyk (2025).

Table 5: Green pledges and within industry variation of firm characteristics

Model	(1)	(2)	(3)	(4)	(5)	(6)
Log Emissions	0.06***	0.06***			0.04***	0.03***
	(0.004)	(0.003)			(0.002)	(0.002)
Size			0.04***	0.03***	0.06***	0.07***
			(0.01)	(0.01)	(0.001)	(0.002)
Book-to-market					4.03**	4.82*
					(2.05)	(2.54)
Leverage					0.15***	0.12***
					(0.04)	(0.04)
Return on equity					−0.01***	−0.01***
					(0.001)	(0.001)
Sales growth					0.003	0.01
					(0.01)	(0.01)
Year FE	Y	Y	Y	Y	Y	Y
Industry FE	N	Y	N	Y	N	Y
Observations	20,917	20,917	66,454	66,454	18,932	18,932
R^2	0.21	0.26	0.16	0.21	0.26	0.30

Panel regressions for a yearly green pledge indicator variable, which is equal to one starting in the year of a firm's first green pledge and thereafter. Independent variables are firm characteristics lagged by one year. Controls are book-to-market, leverage, return on equity and sales growth. Columns (2), (4) and (6) include 48-industry Fama-French fixed effects. Standard errors which are clustered by firm and year in each model are given in parentheses. ***, **, and * indicate significance at the 1%-, 5%-, and 10%-level, respectively. Values are winsorized at the 1%/99% level. Sample period: January 2005 to December 2023.

Kacperczyk (2025) using CDP commitments for a sample restricted to U.S. firms. These estimates using CDP pledges of U.S. firms closely mirror our findings for text-based green pledges in Table 5.[25] Thus, the differences between our results and those in Bolton and Kacperczyk (2025) may be due to their use of a global sample of stocks.

This section has provided new evidence on the distribution of green pledges over time, across industries, and across firm characteristics. Green pledges have occurred in significant numbers since the beginning of our sample in 2005, they have increased over time, and become particularly widespread since around 2020. We observe significantly more green pledges in high-emission sectors. Both within and across industries, brown and large firms are more likely to make green pledges.

[25] See Appendix Table C.1 for these estimates.

4 Stock Market Effects

The key question of our paper is how stock market valuations react to corporate green pledges. This is an empirical question because the sign of this reaction is *a priori* not clear. Positive effects on valuations can result from a lower trajectory of projected emissions that reduce the carbon premium, due to lower transition risk exposure or stronger appeal to green investors (Pastor et al., 2021). However, the existence and size of the carbon premium has not been firmly established (Bauer et al., 2022; Zhang, 2025). The effects of decarbonization on future profits and dividends could go either way: If green pledges signal that firms managed to get access to profitable green investment projects, this could cause positive effects. But decarbonization projects may require significant up-front investments and potentially far-reaching changes to a company's production processes and business model. The transition to lower or net-zero emissions could be costly, weighing on the outlook for earnings and dividends. In addition, the risks involved in this transition could actually raise the required risk compensation and cost of capital. There is no clear theoretical prediction for the net effects of green pledges on either expected dividends or discount rates.

We use event studies to identify the effects of the announcements of corporate green pledges on stock prices. The identification assumption is that the corporate announcement is predetermined with regard to the company's stock return on the day of the announcement. By making this assumption, we follow a long tradition in empirical asset pricing of using event studies to identify the stock market effects of corporate news.[26] The announcements of green pledges provide new information to investors about a company's trajectory and strategy for GHG emissions, and we estimate the stock price response to this new information.

Our analysis uses daily stock market data for U.S. firms from CRSP, including all common equity listed on either NYSE, AMEX or NASDAQ. To accurately assign a corporate green pledge to a trading day, we take into account the timestamp of the news article; announcements made after NYSE closes (at 4pm Eastern time) are assigned to the subsequent trading day. We use several standard control variables in our event study, including size, book-to-market ratio, leverage, sales growth, and return on equity. For those control variables that require annual accounting data, we use a publishing lag of four months, following common practice in empirical asset pricing, to ensure that the information was available to investors at the time of the green pledge.[27] Appendix B contains a detailed description and summary statistics of the control variables.

[26] For surveys of this event-study literature within empirical asset pricing, see MacKinlay (1997) and Kothari and Warner (2007).

[27] For example, the accounting data for 2022 is used for stock returns from May 2023 onwards.

Table 6: Stock market response to green pledges

	All green pledges			First green pledges		
	(1)	(2)	(3)	(4)	(5)	(6)
Green pledge	0.135***	0.150***	0.205***	0.326***	0.335***	0.338***
	(0.037)	(0.038)	(0.040)	(0.104)	(0.104)	(0.100)
Size	0.007***	−0.099***		0.007***	−0.099***	
	(0.002)	(0.008)		(0.002)	(0.008)	
Book-to-market	−7.968*	−23.177***		−7.957*	−23.179***	
	(4.273)	(5.307)		(4.273)	(5.307)	
Leverage	−0.198	−0.520		−0.197	−0.520	
	(0.184)	(0.376)		(0.184)	(0.376)	
Sales growth	−8.190***	0.652		−8.194***	0.653	
	(3.063)	(2.879)		(3.064)	(2.879)	
Return on equity	44.760***	15.262***		44.751***	15.258***	
	(6.471)	(4.826)		(6.470)	(4.826)	
Number of pledges	5,012	5,012	5,603	842	842	990
Observations	14,788,589	14,788,589	17,511,046	14,788,589	14,788,589	17,511,046
R^2	0.189	0.190	0.176	0.189	0.190	0.176
Industry FE	Y	N	Y	Y	N	Y
Firm FE	N	Y	N	N	Y	N
Day FE	Y	Y	Y	Y	Y	Y

Panel regressions for daily stock returns. Columns (1)–(3) show results for an event dummy that equals one on all days that a firm announces a green pledge, and columns (4)–(6) show results for a dummy that equals one only on the day of the first green pledge of each firm. Alternative specifications use fixed effects (FE) for industry, based on 48-industry Fama-French classification, firm, and trading day. Standard errors, clustered by firm and trading day, are given in parentheses. ***, **, and * indicate significance at the 1%-, 5%-, and 10%-level, respectively. Sample period: January 2005 to December 2023.

We estimate the panel regression

$$R_{it} = \beta d_{it} + \gamma X_{it} + \alpha_s + \delta_t + \epsilon_{it} \tag{1}$$

where R_{it} is the stock return of company i on day t, d_{it} is an event dummy that equals one if the firm announced a green pledge on this day, X_{it} includes the firm-specific control variables, α_s are industry fixed effects based on the 48 Fama-French industries, δ_t are day fixed effects, and ϵ_{it} is the residual. In alternative specifications, we use firm fixed effects instead of industry fixed effects to assess the robustness of our results. Standard errors are clustered by firm and day in all our panel regressions.

Table 6 shows the estimation results. The first three columns report the estimates for regressions using the full set of green pledge events, using different fixed effects and firm-level controls. Across all three specifications, the estimated effect is positive and statistically significant at the 1%-level. The size of the estimated coefficient indicates that the daily stock return increases by between 0.14 and 0.21 percentage points when a firm announces a green pledge. The average daily return in our sample is about 0.015% (see Table B.1), meaning that on event days returns are about ten times larger than on non-event days. In other words, the estimated effect is both statistically and economically highly significant. Furthermore, if there is attenuation bias in estimates of β as a result of the measurement error in d_{it} discussed in Section 2, the true stock price impact of corporate green pledges may be even larger than these estimates.

The last three columns of Table 6 report the estimates for regressions using only the first green pledge for each firm. In these regressions the estimate for β is in the range of 0.33 to 0.34 percentage points, substantially larger than for the regressions using all pledges. Clearly, the estimated positive effect is particularly strong for the first green pledge issued by a firm, and consecutive pledges by the same firm appear to have smaller effects. One possible reason for the larger effects is that the first pledge tends to be more informative or more ambitious than subsequent pledges. Another possibility is that our identified first pledges are less likely to contain measurement error, and therefore the estimates would be less affected by attenuation bias. Either way, this simple filter appears quite effective in identifying the most meaningful announcements.

While our results are based on green pledges identified with OpenAI's model GPT-4, many newer models have been developed since we wrote the first version of this paper. To assess the robustness of our main event-study results, we use four more recent models by OpenAI, Anthropic and Google to identify green pledges from our news articles, and also use a majority-vote label using all five models. Appendix Table C.5 shows that across all models, the stock market effects of green pledges are significantly positive and of roughly similar magnitude.

An important question is whether the observed stock market reactions to green pledges truly reflect the pledges themselves, or whether they are instead driven by generally positive reactions to any environmental news. To answer it, we carry out a type of placebo test, and estimate the impact of corporate environmental news that were *not* classified as green pledges by adding to regression (1) a separate event dummy that captures whether firm i on trading day t was covered by another, non-pledge environmental news article. The key question is whether the coefficient on the green pledge dummy is larger than the coefficient on this additional "other environmental news" event dummy. Panel A of Table 7 shows the results for regressions with all green pledges in the first two columns, and with only first green pledges in the last two columns. The coefficient on the dummy for other environmental news is significantly positive in all four regressions. Apparently, any environmental news is "good news" on average and tends to increase a company's stock return, potentially due to an attention effect (Chan, 2003). But the coefficient on the green-pledge event dummy is two to four times larger than the coefficient on the other-news indicator. Tests for the equality of the coefficients on the two indicator variables reject the null hypothesis with p-values between 0.01 and 0.07. These estimates confirm that the stock market effect of green pledges is significantly stronger than the "placebo effect" of environmental news coverage. The particularly pronounced differences for the case of first green pledges again support the notion that these event indicators contain the most positive information for investors because they are better measures of substantial decarbonization announcements.

Because green pledges can coincide with other significant firm- or industry-specific announcements, or days with strong industry performance, it is possible that our estimates pick up these confounding factors and pledges are not actually the primary driver of the stock market response. To address the issue of confounding firm-level news, we construct "clean" green pledge events by excluding all green pledges that coincide with any other news announcements (environmental or other) on the same day.[28] Panel B of Table 7 reports the stock market regression results for this reduced sample of green pledges. Across specifications, the coefficients on the green pledge dummy remain positive and of broadly similar magnitude to that in Table 6, although they become slightly smaller and the standard errors larger due to the substantially reduced number of pledges relative to our full set of events.[29] Second, we examine whether industry-specific events or periods of strong industry performance affect our results. One specific concern is that firms might strategically time their pledges during such periods of positive industry news. To check whether the estimated stock market response is confounded by industry news, we control for industry returns in two different ways, using the 48 Fama-French industries either to include industry-by-day fixed effects or own-industry returns as an additional regressor. Panel C of Table 7 shows that neither specification materially affects the coefficient on the green pledge dummy, alleviating the concern about industry-level confounding factors.

Appendix C reports the results of several other robustness tests. For two other subsets

[28] That is, we consider all news articles in the Dow Jones dataset, not just environmental news. Using this broadest set of news coverage, we aim to minimize the risk that other non-environmental announcements, including earnings announcements, could bias our results.

[29] We also checked whether our estimates might be affected by earnings announcements, which have long been known to drive stock prices (Beaver, 1968). When we dropped all observations from our sample where green pledges coincided with earnings announcements on the same days, the estimates were essentially identical to our baseline results in Table 6. Thus, earnings announcements do not appear to be relevant for our findings.

Table 7: Green pledges vs. other news

	All green pledges		First green pledges	
(A) Other environmental news				
Green pledge	0.13***	0.20***	0.32***	0.33***
	(0.04)	(0.04)	(0.10)	(0.10)
Other env. news	0.06***	0.10***	0.06***	0.11***
	(0.02)	(0.02)	(0.02)	(0.02)
Number of obs.	14,788,589	17,511,046	14,788,589	17,511,046
Number of pledges	5,012	5,603	842	990
p-value	0.069	0.018	0.013	0.027
Firm controls	Y	N	Y	N
Day FE	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y
(B) Clean event window				
Green pledge	0.10**	0.18***	0.22*	0.27**
	(0.05)	(0.05)	(0.12)	(0.12)
Number of obs.	14,788,589	17,511,046	14,788,589	17,511,046
Number of pledges	2,011	2,281	407	499
Firm controls	Y	N	Y	N
Day FE	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y
(C) Industry effects				
Green pledge	0.13***	0.13***	0.29***	0.30***
	(0.03)	(0.04)	(0.10)	(0.10)
Industry return		0.45***		0.45***
		(0.01)		(0.01)
Number of obs.	14,788,589	14,788,589	14,788,589	14,788,589
Number of pledges	5,012	5,012	842	842
Firm controls	Y	Y	Y	Y
Day FE	N	Y	N	Y
Industry-by-day FE	Y	N	Y	N

Panel regressions for daily stock returns, controlling for potentially confounding news. Panel A includes the green pledges event dummy and a dummy for other environmental news which are not classified as a green pledge (26,821 events). The last row reports p-values for testing the hypothesis that the two dummy coefficients, for green pledge events and other environmental news, are equal. Panel B uses the green pledges event dummy but excludes events that had other news on the same day. Panel C uses the green pledges event dummy and additionally controls for industry-level returns or industry-by-day fixed effects. Standard errors, clustered by firm and day, are given in parentheses. ***, **, and * indicate significance at the 1%-, 5%-, and 10%-level, respectively. Sample period: January 2005 to December 2023.

of our green pledge events—either using pledges in news articles that tag only a single firm (ISIN), or requiring at least a 30-day distance between two consecutive pledges by a firm—the estimated effects are very similar to those for the sample of all green pledges, as shown in Appendix Table C.3. We also investigate whether our estimates change if we split the sample with the Paris agreement in December 2015, since increased climate concerns since the Paris agreement might have altered the sensitivity of the carbon premium and stock prices to green pledges. The estimates in Appendix Table C.4 suggest that green pledges had positive effects on stock prices in both sample periods. While more granular sample splits cause problems with statistical power, overall our results seem to be quite robust across different sample periods.

Our analysis so far has focused on the contemporaneous effects of green pledges. We now turn to estimates of the dynamic effects before and after the events, in order to understand (a) whether there might be leakage of news prior to the green pledge announcements, and (b) whether there are lagged effects, and potentially a partial reversal, after the announcements. We add five leads and lags of the event dummy and estimate the new panel regression

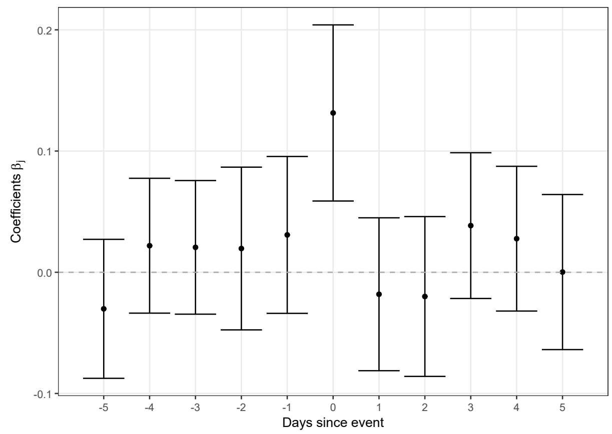
$$R_{it} = \sum_{j=-5}^{5} \beta_j d_{i,t-j} + \gamma X_{it} + \alpha_s + \delta_t + \epsilon_{it}, \tag{2}$$

where $d_{i,t-j} = 1$ implies that there was a green pledge event j days before the return observation on day t.

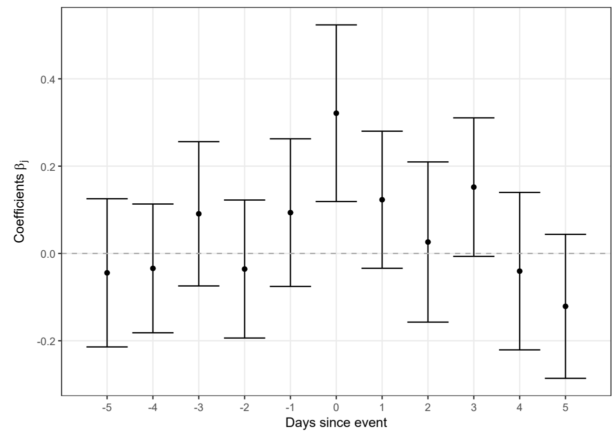
Figure 3 shows estimates of the coefficients β_j in the top two panels, and the cumulative effects in the bottom two panels, together with 95%-confidence intervals based on clustered standard errors. The left two panels correspond to the regression using all green pledges, and the right two panels correspond to the regression using only first green pledges. Our estimates show little evidence for information leakage prior to green pledge events. For the sample with all green pledges, there is a moderate upward drift in the cumulative effects leading up to the event, but none of the coefficients β_j for $j < 0$ is statistically significant at the 5%-level. For the sample with first green pledges, there is no noticeable pre-event drift at all. The positive effect on the announcement days is not reversed in the subsequent days. Instead, the positive valuation effects continue to slightly increase over the days after the announcement; some of the coefficients for the effects several days later are positive and marginally statistically significant. Overall, the estimates in Figure 3 suggest that green pledges lead to a persistent increase in the stock market valuation, consistent with a reduction in the carbon premium and the firm's cost of capital.[30]

[30] Figures C.3 and C.4 in Appendix C show the corresponding results for the specifications with either firm fixed effects, no controls, the sample of pledges that only tag a single firm as well as the sample of pledges

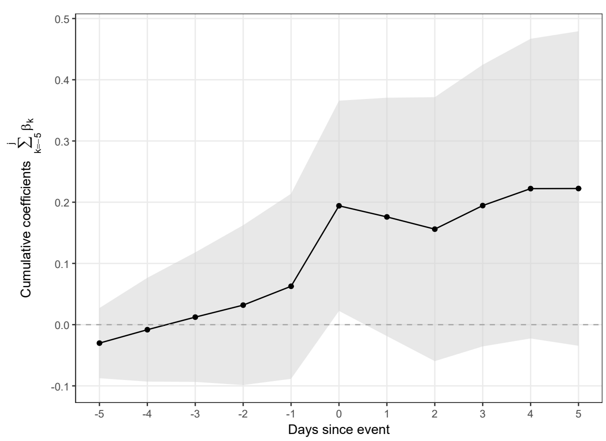
Figure 3: Stock return response around green pledges



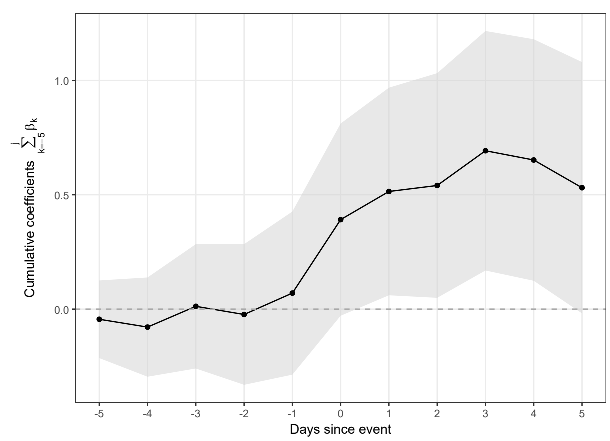
(a) All pledges



(b) First pledges



(c) All pledges – cumulative



(d) First pledges – cumulative

Dynamic event study estimates of the effects of green pledges on daily stock returns. The dependent variable is the daily stock return, and the independent variable is the green pledges event dummy. The top two panels plot the coefficients β_j of regression (2) for leads and lags of the event dummy. Panel (a) shows results for the sample with all green pledges and panel (b) for only first green pledges. Controls are book-to-market, sales growth, leverage, size, and return on equity. The bottom two panels show the cumulative effects, $\sum_{k=-5}^{j} \beta_k$. All plots show 95% confidence intervals based on standard errors clustered by firm and day and are shown around the point estimate. Sample period: December 2005 to January 2023.

We now examine how the specificity and ambition of the announced emission reduction plans influence the financial market response to green pledges, using the categories of pledges documented in Table 2. We estimate event-study regressions with three separate indicator variables that capture investment pledges, divestment pledges, and pledges without specific

that requires a 30 day distance between two consecutive pledges. The results are very similar to those shown in Figure 3.

information on how emission reductions will be achieved. The results, reported in Table 8, show that investment pledges are followed by a significantly positive stock market reaction, suggesting that investors view such strategies as credible means of reducing emissions. Divestment pledges yield positive but imprecisely estimated and therefore statistically insignificant coefficients, due to the small sample size of only 72 divestment pledges and the resulting lack of statistical power. Notably, other, unspecific pledges are not associated with positive stock market reactions, indicating that investors recognize the limited credibility of such commitments and may view them as attempts at greenwashing. We further analyze pledges by ambition level. Pledges with high ambition scores elicit a significant and strong positive stock market reaction, while low-ambition pledges, which are likely to have only marginal effects on emissions, show no significant impact on firm valuations. Taken together, these findings provide further evidence that markets reward credible and ambitious commitments to reduce future emissions, whereas vague or low-impact pledges are discounted by investors as largely symbolic.

Finally, we turn to the issue of heterogeneity and investigate whether the stock market effects of climate commitments depend on the industry of the firm. Differential effects of climate-conscious investing play a central role for the transition to a low carbon economy. For example, if green pledges really imply a reduced exposure to transition risks, we would expect to see an especially strong market reaction for firms in brown industries, due to the fact that they have larger transition risk exposures to begin with. If, however, mainly firms in green industries see reductions in the carbon premium and hence their cost of capital, green investing could be ineffective or even counterproductive as brown firms might respond to relatively higher cost of capital by increasing emissions to realize short-term profits (Hartzmark and Shue, 2023).

To examine industry-level heterogeneity, we estimate equation (1) separately for each of the 12 Fama-French industries described in Table 3. We use two specifications, one with all green pledges and one with first pledges only, including standard firm controls and day fixed effects. The results are shown in Table 9, where industries are again ordered by emissions. The positive stock price response tends to be particularly pronounced in the most carbon-intensive sectors. While the statistical significance varies, in part due to substantial differences in the number of firms and pledges across industries, the estimated effect is especially strong in the utilities, energy, and chemicals sectors, the most emission-intensive industries. By contrast, in low-emission industries such as finance and health care, the coefficients are negative and statistically insignificant. The evidence aligns with the interpretation that green pledges in carbon-intensive sectors have the greatest value for investors.

Table 8: Stock market reaction to green pledges based on different categories and ambitions

	(1)	(2)	(3)	(4)	(5)	(6)
Investment	0.15***	0.16***	0.22***			
	(0.04)	(0.04)	(0.04)			
Divestment	0.10	0.12	0.07			
	(0.24)	(0.24)	(0.24)			
Other	0.04	0.05	0.09			
	(0.10)	(0.10)	(0.10)			
Ambition low				0.04	0.05	0.08
				(0.08)	(0.08)	(0.08)
Ambition high				0.15***	0.17***	0.23***
				(0.04)	(0.04)	(0.04)
Number of pledges	5,012	5,012	5,603	5,012	5,012	5,603
R^2	0.19	0.19	0.18	0.19	0.19	0.18
Industry FE	Y	N	Y	Y	N	Y
Firm FE	N	Y	N	N	Y	N
Firm controls	Y	Y	N	Y	Y	N

Panel regression for daily stock returns, with green pledges event dummies for different categories and ambition scores as regressors. Three categories of green pledges: investments in new technologies (4,943 green pledges), divestments of pollutive assets (74 green pledges), and other pledges with no specific information on how emission reductions are achieved (587 green pledges). Two levels of ambition: low (788 green pledges) and high (4,816 green pledges). Firm controls are book-to-market, sales growth, leverage, size, and return on equity. Industry fixed effects are based on Fama-French 48-industries. All regressions include day fixed effects. Standard errors, clustered by firm and day, are given in parentheses. ***, **, and * indicate significance at the 1%-, 5%-, and 10%-level, respectively. Sample period: January 2005 to December 2023.

The positive estimated effects of green pledges on stock prices show that investors attribute a value to decarbonization that outweighs the perceived costs and risks, and that they view the news of green pledges as a net-positive. This leads to the question whether green pledges raise valuations by lowering risk premia and thus discount rates, or by raising expected future dividends.

The most straightforward explanation for the positive stock market effects is a discount rate channel based on changes in the carbon premium, the expected excess return on brown stocks relative to green stocks (Pastor et al., 2021). Indeed, the climate finance literature has generally focused on the carbon premium hypothesis to explain differences between green and brown stock returns.[31] By announcing decarbonization commitments, firms can lower the expected path for future emissions, and reduce their carbon premium via two different

[31] See Bolton and Kacperczyk (2021, 2023) among many others. Relatedly, Ardia et al. (2023) use a Campbell-Shiller decomposition of stock price effects and find that the discount rate channel is the primary channel through which climate transition risks are priced.

Table 9: Stock market reaction to green pledges across industries

	Green Pledge		First Pledge	
Industry	Coefficient	Standard Error	Coefficient	Standard Error
Utilities	0.087**	0.036	0.271	0.218
Energy	0.164	0.131	0.571*	0.337
Chemicals	0.472**	0.208	1.268**	0.640
Other	0.026	0.068	0.035	0.292
Manufacturing	0.027	0.123	0.640*	0.344
Nondurables	0.141	0.102	0.221	0.318
Retail	0.399**	0.195	0.126	0.252
Telecommunication	0.071	0.164	−0.549	0.680
Durables	−0.003	0.184	0.639	0.703
Business Equipment	0.285***	0.105	0.280	0.197
Health Care	−0.032	0.231	−0.030	0.466
Finance	−0.069	0.104	−0.109	0.184

Event-study regressions for daily stock returns (1) estimated separately for each industry. Results are shown for the sample of all pledges as well as for only first pledges. Controls are book-to-market, sales growth, leverage, size, and return on equity. All regressions include day fixed effects. Standard errors clustered by firm and day in each model are given in parentheses. ***, **, and * indicate significance at the 1%-, 5%-, and 10%-level, respectively. Sample period: January 2005 to December 2023.

effects. First, emissions are a proxy measure for a firm's exposure to climate transition risk, and green pledges would reduce this exposure and the required carbon risk premium. Second, a lower path of emissions can increase the appeal of a stock for investors that have non-pecuniary green preferences, and lower the "carbon aversion premium" (Bauer et al., 2025). By lowering its transition risk and increasing its green investor appeal, a green pledge can make the stock more attractive to investors, lowering its discount rate and raising its price.

An alternative explanation is a cash flow channel: Green pledges could raise stock valuations because they cause investors to revise upward their expectations for future earnings and dividends. Derrien et al. (2025) show that ESG news seem to affect firm value primarily by shifting analyst earnings forecasts, as opposed to discount rate effects. We address this issue using the same empirical methodology and IBES earnings expectations data, and find no evidence that green pledges affect analyst earnings forecasts. Across all horizons, the estimated effects of green pledges on EPS forecasts are statistically insignificant. We confirm this result in several robustness checks, including restricting the sample to first pledges, treating green pledges as absorbing, using log changes, and employing mean instead of median forecasts.[32] In additional analysis, we show that green pledges also do not seem to materially improve future profitability or dividend growth.[33] Overall, while we cannot rule out that factors beyond the carbon premium contribute to the observed stock market response—and the monthly frequency of the IBES data may limit the power to detect small effects on earnings expectations—our evidence suggests that green pledges are more likely to affect discount rates than expected cash flows.

Our stock market evidence speaks to the credibility of green pledges. The significant price effects suggest that investors do not completely discount these announcements as cheap talk and view them at least partly as credible. We have documented that the effects on stock prices are particularly strong for first green pledges, for green pledges with specific investment plans, for pledges with high levels of ambition, and for firms in brown industries. One likely reason for the stronger price effects of these types of pledges is that they cause larger reductions in expected emissions, due to their stronger credibility and/or higher ambition.[34] On the whole, investors appear to distinguish between more and less credible green pledges, with the result that the strength of the price impact depends on the degree of credibility.

A related question is what enforcement mechanisms or incentives could prevent firms from making decarbonization commitments that are never followed by any actions and emission reductions. In other words, what incentives prevent cheap talk and make green pledges credible? Research in corporate finance going back to Diamond (1989) has documented the importance of reputation and disclosure quality for financing conditions and market value (Healy and Palepu, 2001). In the context of climate-related and ESG disclosures, Lyon and Maxwell (2011) explain theoretically how reputation and possible monitoring can discipline cheap talk in climate commitments, and Krüger (2015) shows that negative CSR events, including failure to live up to stated goals, are punished by financial markets. On the other hand, recent work by Jiang et al. (2025) suggests limited accountability and low awareness, with failures to meet climate targets hardly covered by the media. More evidence on the financial consequences of walking back decarbonization commitments is surely needed to better understand the related incentives and consequences. Nevertheless, there are well-documented mechanisms and empirical findings indicating significant incentives for firms to follow through on their green pledges. Our finding that ambitious pledges with specific investment plans generate the strongest market reactions (Table 8) is consistent with the view

[32] For detailed results on earnings forecasts, see Appendix Table C.6.

[33] We estimate the effects of green pledges on future return on assets, return on equity, and dividend growth, using the difference-in-differences methodology described in Section 5. These estimates, reported in Appendix Table C.7, reveal no significant effects on ROE or dividend growth, and only small positive effects on ROA—an increase of 1.6 percentage points after five years.

[34] In addition, stocks in brown industries may see larger price effects because they are generally more exposed to transition risk and include a larger carbon premium.

that markets can distinguish credible commitments from cheap talk, providing incentives for credible corporate green pledges.

In sum, our findings show that green pledges lead to higher stock market valuations, likely because they reduce firms' carbon premia and cost of capital. This market response creates an incentive for firms to commit to decarbonization and may further facilitate the financing of green investments. This evidence points to a positive role of climate-related investing in supporting firm-level decarbonization and the transition to a low-carbon economy.

5 Future Emissions

The significantly positive stock market effects of corporate green pledges suggest that investors tend to view these pledges as partly credible signals of future emission reductions. But are the announced commitments really followed by reductions in firm-level emissions? In the words of Bingler et al. (2022), do firms "walk the climate talk" and follow up their climate commitments with measurable actions? This question is particularly pressing given increasing concerns about greenwashing and cheap talk in climate-related announcements and disclosures (Nemes et al., 2022; Bingler et al., 2022, 2024; Dzieliński et al., 2023). Companies may falsely represent themselves as environmentally friendly by manipulating environmental metrics or re-branding products and marketing strategies touting their clean energy or pollution reduction efforts. And their green pledges might just be cheap talk, without meaningful subsequent reductions in emissions.

To address this question, we estimate the response of future firm-level emissions to announcements of corporate green pledges. We use difference-in-differences (DiD) estimation, which compares changes in emissions before and after the issuance of a green pledge to the changes in emissions for firms that have not made such pledges. Since firms decide strategically whether and when to announce a green pledge, instead of pledges being an exogenous treatment, this estimation naturally does not identify the causal effects of the announcements themselves. Instead, the estimates capture the extent to which green pledges predict changes in future emissions, which is precisely the type of new information that stock market investors would find relevant. Put differently, while pledges do not cause emission reductions, they reveal credible private information about future emission trajectories that investors value and incorporate into prices.[35]

[35] It is hard to imagine a setting in which a corporate *announcement* could be exogenous, as it is always the endogenous result of strategic planning and, in most cases, shareholder value maximization. For example, a firm may well have had long-standing plans for decarbonization with the goal to increase the firm's value, and the public release of these plans is merely the last step before their implementation. Through the lens of DiD estimation, the parallel trends assumption is naturally violated in our setting, since firms with green

Two aspects of our empirical setting complicate the accurate estimation of the "treatment effects"—or more accurately, of the information content—of green pledges for future emissions. Sticking with the common terminology in the DiD literature, the "treatments" are of course staggered, as different firms announce their green pledges at different times. While variation in treatment timing is by itself not necessarily problematic, the combination with heterogeneous treatment effects can render standard event-study estimates unreliable. Since decarbonization commitments may differ widely in terms of their ambition, specificity, and timelines, but are all captured by a simple binary indicator, treatment effects should indeed be expected to be heterogeneous in our context. With staggered treatments and heterogeneous treatment effects, standard two-way fixed effects (TWFE) estimates may yield inconsistent estimates of the average treatment effect (Baker et al., 2022; Roth et al., 2023). The problem is the "forbidden" comparisons between newly treated units and previously treated units, as the latter may still be experiencing delayed treatment effects. Various approaches have been proposed to estimate average treatment effects in a way that addresses the limitations of TWFE (Callaway and Sant'Anna, 2021; Sun and Abraham, 2021; Dube et al., 2025).

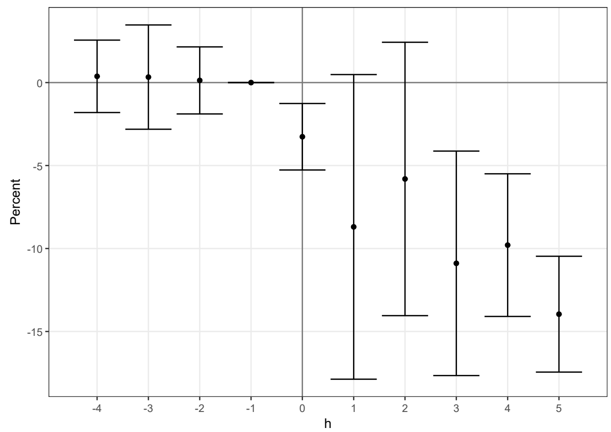
We use the local projections difference-in-differences (LP-DiD) approach by Dube et al. (2025) for our baseline estimates of the dynamic response of emissions to green pledges. This simple and reliable method accounts for heterogeneous treatment effects by including only "clean controls," that is, firms that have not yet been treated themselves at the time of each treatment under consideration. In a firm-by-year panel, we estimate the LP-DiD specification

$$y_{i,t+h} - y_{i,t-1} = \beta^h \Delta D_{it} + \sum_{p=1}^{P} \gamma_p^h \Delta y_{i,t-p} + \sum_{m=1}^{M} \sum_{p=0}^{P} \gamma_{mp} \Delta x_{m,i,t-p} + \delta_t^h + \epsilon_{it}^h, \tag{3}$$

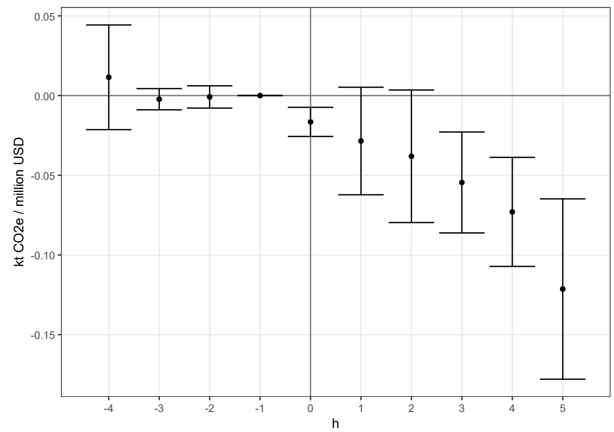
where the indicator D_{it} captures whether firm i has issued a green pledge in year t or before. Since the indicator D_{it} equals one in the year of its first pledge and all subsequent years, the treatment is "absorbing"—the most common assumption in difference-in-differences estimation—and we estimate the effects of each company's first green pledge. The sample is restricted to the observations that are either newly treated ($\Delta D_{it} = 1$) or clean controls ($D_{i,t+h} = 0$). The variable y_{it} denotes either log carbon emissions or emission intensity, in both cases based on the sum of scope 1 and scope 2 emissions. The regression

pledges are likely on a different emission trajectory than other firms. We are estimating the differences in emission trends between the two types of firms, which is not a causal effect of the announcement but nevertheless the relevant object of interest for predicting emissions. Examples of other financial research using DiD for prediction and other purposes besides causal inference are surveyed by Gow et al. (2016).

Figure 4: Impact of green pledges on carbon emissions



(a) Log emissions



(b) Emission intensity

Local projection difference-in-differences regression estimates with the log-level of emissions (left panel) or emission intensity (right panel) as the dependent variable and green pledges as the independent variable. Controls include lagged values of size, book-to-market, leverage, profitability, revenue growth, and log PP&E, as well as lagged emissions (log-levels or intensities). Error bars correspond to 95% confidence intervals based on Driscoll and Kraay (1998) standard errors.

estimates the effects of green pledges on log emissions or emission intensity h years after the pledge. Our LP-DiD regression (3) also includes year fixed effects, δ_t^h, lagged emissions, and current and lagged values of M different controls. Lagged values of $y_{i,t}$ are included to account for the pattern documented above that brown firms are more likely to commit to decarbonization. We control for firm characteristics that could be correlated with the treatment, including size, book-to-market ratio, leverage, profitability, revenue growth, and log PP&E. By the nature of the LP-DiD estimation, the controls are included as first differences, and we set $P = 2$ for the number of lags.

Figure 4 plots the estimated effects on log emissions (left panel) and emission intensities (right panel) from four years before the pledge to five years after. Firms who make a decarbonization commitment significantly reduce their carbon emissions after the pledge, compared to firms without such commitments. Green pledges predict nine percent lower emissions after one year and 14 percent lower emissions after five years, compared to firms without a pledge. Prior to the announcement there is no significant difference in emissions, which alleviates concerns that firms issuing a green pledge are simply confirming an existing downward trajectory for emissions. For changes in emission intensity, we find broadly similar results, as shown in the right panel of Figure 4. Following a green pledge, emission intensity falls significantly, with a decrease of 0.03 (kilotons of CO_2 equivalents per million US dollars revenue) in the first year and 0.12 after five years. Prior to the pledges, changes in emission

Table 10: Average treatment effect of green pledges on carbon emissions

	LP-DiD		TWFE		S&A	
	(1)	(2)	(3)	(4)	(5)	(6)
(A) Log emissions						
1 year	-8.70^{***}	-10.22^{***}	-3.35	-6.86	-3.56^{*}	-8.68^{***}
	(3.32)	(3.68)	(3.30)	(5.50)	(2.02)	(2.46)
5 years	-13.96^{**}	-9.84	-5.13	-6.07	-6.29^{**}	-7.50
	(6.52)	(6.57)	(4.06)	(6.27)	(2.78)	(5.62)
Observations	7,989	14,167	12,793	21,792	12,793	21,792
(B) Emission intensity						
1 year	-0.027^{*}	-0.030	-0.011	-0.054^{*}	-0.016	-0.042^{**}
	(0.014)	(0.034)	(0.028)	(0.029)	(0.018)	(0.021)
5 year	-0.121^{***}	-0.104^{***}	-0.054	-0.100^{**}	-0.081	-0.091^{**}
	(0.032)	(0.033)	(0.042)	(0.050)	(0.050)	(0.043)
Observations	7,988	14,162	12,791	21,783	12,791	21,783
Controls	Y	N	Y	N	Y	N
Year FE	Y	Y	Y	Y	Y	Y
Firm FE	N	N	Y	Y	Y	Y

Alternative estimates of the average "treatment effect" of green pledges on one- and five-year-ahead log level of emissions (Panel A) or emission intensity (Panel B). Columns 1 and 2 show LP-DiD estimates following Dube et al. (2025), and the first column corresponds to the estimates in Figure 4 for $h = 1$ and $h = 5$. Columns 3 and 4 report standard two-way fixed effects (TWFE) estimates. Columns 5 and 6 show estimates using the Sun and Abraham (2021) approach. Estimates for log emissions are in the top panel, and estimates for emission intensities are in the bottom panel. Standard errors are Driscoll-Kraay for LP-DiD, and clustered (by year and firm) for TWFE and S&A. ***, **, and * indicate significance at the 1%-, 5%-, and 10%-level, respectively. The number of observations corresponds to the one-year horizon. Sample period: January 2005 to December 2023.

intensities are not significantly different between firms with and without a pledge.

A concern about firm-level emissions data is that many firms do not report emissions, and vendor estimates can be noisy and unreliable (e.g., Aswani et al., 2023). To address this concern, we estimate local projections using only firms with reported emissions, excluding observations with Trucost estimates. The estimates, shown in Appendix Figure C.5, show that the results remain qualitatively unchanged, and in fact become slightly stronger in this subsample, alleviating concerns about an undue influence of estimated emissions.

In Appendix C, we also use LP-DiD estimation for other dependent variables, to try to understand the predictive power of green pledges for future investment and profitability (see Appendix Table C.7). As discussed in Section 4, these results are helpful for interpreting the stock market results and are consistent with the explanation that green pledges affect stock prices primarily via changes in the carbon premium.

The LP-DiD approach is one of several methods designed to estimate the average treatment effect (ATE) in the presence of staggered treatment and heterogeneous treatment effects. Sun and Abraham (2021) modify TWFE estimation by including only clean controls and incorporating a cohort-specific dummy variable to capture heterogeneous treatment effects across cohorts, and then estimate the ATE using the appropriate weighted average of cohort-specific effects. These and alternative approaches proposed in the literature ultimately aim to estimate the same object of interest, the ATE, which in our setting is the difference between a firm's emissions after making a green pledge and the emissions it would be expected to produce without the pledge. This common objective allows for a meaningful comparison of the estimated effects across different methods. Table 10 shows such a comparison, including results for LP-DiD, conventional TWFE estimation, and the Sun and Abraham (2021) (S&A) method. The top panel reports the estimated effects on log emissions, and the bottom panel shows the effects on emission intensities. We obtain estimates for two different time horizons—one year and five years after the pledge—and both for regressions with and without controls. All the different estimation results consistently show a decrease in emissions and intensities following a green pledge. While point estimates differ somewhat across methods, the estimated reduction is generally substantive and in the majority of the cases statistically significant. Table 10 also shows that controlling for pre-treatment firm characteristics only slightly reduces the estimated magnitudes. Overall, these estimates demonstrate the robustness of our main results across different estimation methods and specifications.

A related question is which firms actually reduce their emissions, and whether these are the same firms that experience the strongest stock market reactions. To address it, we estimate the LP-DiD regressions separately for each industry. Table 11 shows the estimated coefficients for 5-year changes in emission levels (in percent) and emission intensity across the 12 Fama-French industries considered above. Firms in the two sectors with the highest carbon emissions—utilities and energy—exhibit the most substantial reductions in both emission levels and emission intensities following the green pledges, consistent with the positive stock market effects documented in Table 9. Besides these two particularly brown industries, the pattern is less clear and there is a fair amount of heterogeneity in the industry-level estimates that is not evidently related to industry brownness.[36] Neverthe-

[36]The retail sector is somewhat puzzling, as it shows both a significantly positive stock market reaction to green pledges and a significant increase in emission intensity. This pattern likely reflects sector-specific factors: Retail firms have relatively low direct emissions, making emission intensity measures sensitive to small changes in emissions or revenues. In addition, many retail pledges focus on supply chains and logistics (Scope 3 emissions), while our analysis relies on Scope 1 and 2 emissions. Finally, transition investments in logistics or store infrastructure may temporarily increase energy use before reductions materialize.

Table 11: Emission changes across industries

	Carbon Emission		Emission Intensity	
Industry	Coefficient	Standard Error	Coefficient	Standard Error
Utilities	-43.676^{***}	10.057	-0.031^{***}	0.007
Energy	-51.754^{***}	6.833	-0.010	0.017
Chemicals	12.557	12.077	0.002^{***}	0.001
Other	14.811	13.518	0.004^{*}	0.002
Manufacturing	2.794	3.412	-0.010^{***}	0.003
Nondurables	-2.244	5.716	0.008	0.012
Retail	5.171	6.382	0.229^{**}	0.105
Telecommunication	-38.065	45.098	-0.871^{***}	0.271
Durables	-41.165^{***}	14.774	0.002	0.002
Business Equipment	-29.006^{***}	4.954	-0.119^{***}	0.023
Health Care	-14.851^{*}	8.060	-0.010^{***}	0.003
Finance	3.062	4.806	-0.015	0.070

Local projection difference-in-differences regressions for five-year forward log level of emissions or emission intensity, estimated separately for each of the 12 Fama–French industries. Controls include lagged values of size, book-to-market, leverage, profitability, revenue growth, and log PP&E, as well as lagged emissions (log-levels or intensities). All regressions include year fixed effects. Standard errors are based on Driscoll and Kraay (1998). ***, **, and * indicate significance at the 1%-, 5%-, and 10%-level, respectively. Sample period: January 2005 to December 2023.

less, there is some evidence that in the brownest industries, which are also those with the strongest stock market reactions as documented in Section 4, green pledges are particularly useful and credible signals for future emission reductions.

There are various ways for firms to reduce their emissions. As discussed above in Section 2, there are two fundamentally different strategic directions: Companies can *invest* in green technologies and in this way lower emissions in their production processes. Alternatively, they might *divest* from certain high-emission business lines, potentially selling these to other companies. In Section 2 we showed that in the vast majority of green pledges, the text of the announcement indicates plans for additional investment. Consistent with this pattern, additional LP-DiD estimates show that after announcing green pledges, firms tend to significantly increase their investment.[37]

Overall, corporate green pledges appear to contain relevant new information and they lower the expected trajectory for future firm-level emissions. This finding helps rationalize the significant positive stock market response to green pledges documented in Section 4. The estimated decline in emissions suggests that investors have good reasons to view corporate

[37] Appendix Table C.7 shows LP-DiD estimates of the effects of green pledges on capital expenditure at 1- and 5-year horizons, which are significantly positive.

green pledges as credible, thereby mitigating concerns about greenwashing and cheap talk in climate commitments.

6 Conclusion

The transition to a net-zero economy poses a major challenge for corporations, including regulations that make CO_2 emissions costly and could render high-carbon business models obsolete. By making commitments to reduce carbon emissions, companies can lower their exposure to such transition risks and make their stocks more attractive to investors. However, decarbonization strategies can be costly and the outcomes are risky. Furthermore, announcements of planned decarbonization may be regarded as cheap talk instead of credible signals about future emissions. Whether such announcements have any effects on stock prices, and whether they are in fact followed by changes in emissions, are important empirical questions in climate finance.

Using a new database of corporate climate commitments derived from news articles, this paper studied the stock market effects of these commitments. Our event-study results showed that decarbonization commitments lead to a significant increase in stock prices, indicating that the positive effects on company valuations outweigh the costs and risks from decarbonization. Our evidence is consistent with the carbon premium hypothesis of Pastor et al. (2021) and suggests that companies are able to reduce their transition risk exposure, appeal to green investors, and ultimately lower their carbon premium by issuing green pledges.

Corporate green pledges do not appear to be cheap talk, but are instead followed by significant reductions in firm-level emissions and emission intensities. This result rationalizes the positive stock market reaction, because investors have good reasons to view green pledges as credible. It also suggests that the financial incentive for climate commitments, in the form of higher stock valuations and lower cost of capital, appears to be justified as the corporate announcements are followed by corporate climate actions. Given that these voluntary commitments are also more prevalent for large and brown firms, they have the potential to meaningfully contribute to the green transition of the U.S. economy.

Our work opens up several avenues for future research. First and foremost, our method for using an LLM to identify and classify green pledges could be improved and refined, using more sophisticated prompting strategies, new types of models (including those with reasoning abilities), fine-tuned and/or local models, and additional criteria for evaluating the ambition, urgency, specificity, and credibility of the announced commitments. Given the global scale of the issue, another natural extension of our work is to incorporate data from other countries, in particular those of the European Union given their ambitious climate goals and the availability of high-quality data on firm emissions. A central open question is whether and how firms are held accountable for their green pledges and climate targets. More direct evidence on market reactions and the financial consequences of failing to meet emission targets is needed to better understand the incentives for firms to follow through on their climate commitments. More broadly, future research should address the question of whether on aggregate, corporate climate commitments are sufficient to decarbonize the economy, or quantify the shortfall between corporate commitments and national net-zero goals. Recent results for the U.S. corporate sector from Pastor et al. (2024) suggest that there is a significant shortfall relative to the goals set forth in the Paris Agreement.

Appendix

A Details on article classification

A.1 Comparison with newer LLMs

We used four additional, newer LLMs by OpenAI, Anthropic and Google to classify articles: GPT-5.1 and GPT-5.2 by OpenAI; Claude Sonnet 4.6 by Anthropic; and Gemini 2.5 Flash by Google. These models are considered the frontier for LLMs at the time of this writing (March 2026). We use the exact same prompt for all models, and choose parameters in our API calls to minimize reasoning and randomness, for example by setting the "temperature" parameter equal to zero.

Table A.1: Green pledges in validation sample

		Comparison GPT-4		Comparison human labels			
Model	Pos.	Agreement	κ	Agreement	Precision	Recall	MCC
GPT-4	143	1.00	1.00	0.91	0.53	0.80	0.61
GPT-5.1	79	0.92	0.58	0.93	0.68	0.57	0.59
Majority vote	69	0.92	0.59	0.93	0.71	0.52	0.57
Claude Sonnet 4.6	56	0.91	0.50	0.94	0.77	0.45	0.56
Gemini 2.5 Flash	81	0.91	0.55	0.93	0.63	0.54	0.54
GPT-5.2	40	0.90	0.40	0.93	0.78	0.33	0.47

Comparison of classifications in validation sample with a random subset of 1,000 articles. First column is number positive labels, i.e., green pledges. Second and third column show agreement of other models with GPT-4: share of agreement (based on number of identical labels) and Cohen's kappa measure of agreement that adjusts for chance. Last four columns show agreement of LLM labels with human labels: share of agreement, precision (share of model-classified pledges confirmed by human coders), recall (share of human-identified pledges classified positive by the model), and Matthews Correlation Coefficient (MCC, summarizes overall classification accuracy accounting for class imbalance). Models are sorted by MCC.

We first use the validation sample of 1,000 randomly chosen articles to compare the classifications for the five LLMs. We also include a majority-vote classification that identifies green pledges if an article is classified as positive by at least three of the models. Table A.1 reports a comparison of the new alternative classifications with the one from the GPT-4 model. For reference, the first row reports statistics for GPT-4 itself, which classifies 143 articles in the validation sample as positive, i.e., green pledge. All other models classify fewer articles as positive. The models GPT 5.1 and Gemini 2.5 Flash yield around 80 positives, while the other models are even more selective in their identification of green pledges, yielding less than 60 positives. The share of agreement with GPT-4 labels is generally high, around

90%, in part due to the large number of negatives. Cohen's κ, a measure of agreement that takes into account chance agreement in unbalanced samples, is in the range of 0.4–0.6, a level generally viewed as indicating a "moderate" degree of agreement.

Even more revealing is the comparison of the LLM classifications to the human labels, reported in the last four columns of Table A.1. The other models achieve broadly similar accuracy as GPT-4. The main difference across models is the precision-recall tradeoff: Newer models tend to classify fewer articles as pledges, yielding higher precision but lower recall relative to GPT-4. The higher recall of GPT-4 comes at the cost of more false positives, i.e., lower precision. Interestingly, despite being the oldest model in the comparison, GPT-4 achieves the highest agreement with human labels according to Matthews Correlation Coefficient (MCC), a measure that summarizes overall classification accuracy accounting for class imbalance. This suggests that the newer models, while more capable on general benchmarks, are not necessarily better calibrated to the specific task of identifying green pledges as defined by our codebook—likely because they are more conservative in classifying ambiguous cases as pledges.

Table A.2: Disagreement on full article corpus across LLMs

Votes	Articles	Percentage
0	37,033	83.0%
1	3,598	8.1%
2	1,150	2.6%
3	756	1.7%
4	717	1.6%
5	1,350	3.0%

Summary of disagreement for classification with five LLMs. The five models are GPT-4, GPT-5.1, GPT-5.2, Claude Sonnet 4.6, Gemini 2.5 Flash. Agreement (0 or 5 votes for green pledges) for 86.0% of articles, disagreement (1 to 4 votes) for 14.0% of articles.

We then use all models to classify the entire corpus of news articles. This allows us to better understand disagreement across models, which we discuss next. These labels will also be used for a robustness analysis of our stock market results below in Appendix C.

Table A.2 shows the distribution of votes for green pledges among the five models. For 83% of the articles, all five models agreed that they do not contain a green pledge. Overall, the models agreed on 86% of the articles, a high level of agreement mainly driven by the large number of unanimous non-pledge articles. Among the articles with at least one model voting for green pledge, three-quarters show disagreement, and about one-quarter are unanimously green pledges. Most of the articles with disagreement (8.1% of articles) involve only a single dissenting model. As an overall measure of agreement, we can calculate Fleiss's κ, which equals 0.56, corresponding to a "moderate" degree of agreement, consistent with our analysis of the validation sample above.

In additional analysis we have investigated which article characteristics tend to lead to more disagreement. We found that disagreement is especially high for longer and more recent articles. Disagreement is also higher among articles tagged (by the data provider) with the topic "CO2," likely because the absence of any mention of carbon emissions makes it straightforward to classify an article as negative.

Importantly, the event-study results for stock returns are robust to using classifications from any of these models, as shown below in Appendix C. This suggests that our core findings do not depend on the specific choice of language model.

A.2 Prompt for categories and ambition score

We used the following prompt to categorize and score the identified green pledge announcements:

> You are given a news article or press release with an announcement of a decarbonisation commitment by a firm, that is, plans of a company to reduce its future greenhouse gas (GHG) emissions, such as carbon dioxide (CO_2). Your task is to categorize and score the announcement.
> Categorize it according to how the company primarily plans to reduce carbon emissions:
>
> > 1 = Investment in New Technologies: The announcement contains information about new investments with the primary purpose to reduce carbon emissions, for example, investments into low-carbon production processes, green energy technologies, efficiency improvements, or carbon capture.
> >
> > 2 = Divestment of Pollutive Assets: The announcement contains information about divestments or sale of pollutive assets to reduce emissions, for example, selling coal plants, divesting from high-carbon business units, or discontinuing operations in high-emission sectors.
> >
> > 3 = No Specific Information: The announcement provides little or no specific information on how the emission reductions will be achieved, that is, it only states the goal or target without mentioning concrete steps like investment or divestment.
>
> Score the level of ambition of the planned emission reduction:

1 = Limited or vague commitment with minor expected impact on firm's emissions

2 = Significant and specific commitment with substantial expected impact on firm's emissions

Instructions:

– Carefully read the article.

– Assign one of the three categories and one of the two ambition scores.

– Briefly explain in 1–2 sentences why you chose the category and ambition score.

Output Format: JSON object with the following keys:

"label": Category (1-3) as an integer.

"label_name": Name of the category as a string.

"ambition_score": Ambition score (1-2) as an integer.

"reasoning": Brief explanation of label and score as a string.

B Summary Statistics

Table B.1 provides summary statistics of the firm-level variables employed in our empirical analysis. Returns are from CRSP, using only common equity from NYSE, AMEX or NASDAQ, and the other variables are from Trucost and/or Compustat. The accounting and emission variables are reported annually. Stock returns and firm size (market cap) are measured daily. All variables are winsorized at the 1%/99% level. The average daily return is 0.01%, with a standard deviation of 3.18%. Firms emit on average 2.06 million tons of CO_2 annually and 0.23 kilotons of CO_2 for every million dollars earned. We use similar firm-level control variables in our event study as Bolton and Kacperczyk (2021). These variables include: previous day size measured by log of market capitalization, book-to-market as book equity divided by market capitalization at the end of the year, leverage as total assets divided by book equity, sales growth as the 1-year growth of revenue, and return on equity as income divided by book equity of the previous fiscal year. For the controls that include accounting data, we require a publishing lag of four months when matching them with stock-level returns.

Table B.1: Summary statistics

	Mean	SD	q1	q25	Median	q75	q99	No. Obs
Return (%)	0.01	3.18	−39.24	−1.37	0.00	1.32	45.28	17,511,046
Emissions	2.06	10.06	0.00	0.01	0.07	0.38	304.01	21,794
Log Emission	10.98	2.93	1.53	9.16	11.13	12.85	18.19	21,794
Size	13.20	2.13	7.13	11.63	13.15	14.68	18.60	17,508,145
Emission intensity	0.23	0.78	0.00	0.01	0.04	0.08	10.27	21,785
Book-to-market	0.66	0.73	0.00	0.27	0.50	0.82	49.23	71,655
Leverage	4.30	8.86	1.01	1.50	2.23	4.36	1,779.87	71,909
Sales growth	0.15	0.68	−1.29	−0.03	0.07	0.19	66.65	65,229
Return on equity	−0.06	0.70	−27.42	−0.07	0.08	0.16	28.96	64,115

Summary statistics for daily returns, annual environmental measures, and accounting variables for U.S. firms. Returns are shown in percent. Emissions are measured as the sum of scope 1 and scope 2 emissions (million tons of CO_2), emission intensity is defined as the sum of scope 1 and scope 2 emissions divided by revenue, size as market capitalization, book-to-market as book equity at the previous fiscal year end divided by market capitalization at the end of the year, leverage as total assets divided by book equity, sales growth as the 1-year growth of revenue, return on equity as income divided by book equity of the previous fiscal year. Values are winsorized at the 1%/99% level. Sample period: January 2005 to December 2023.

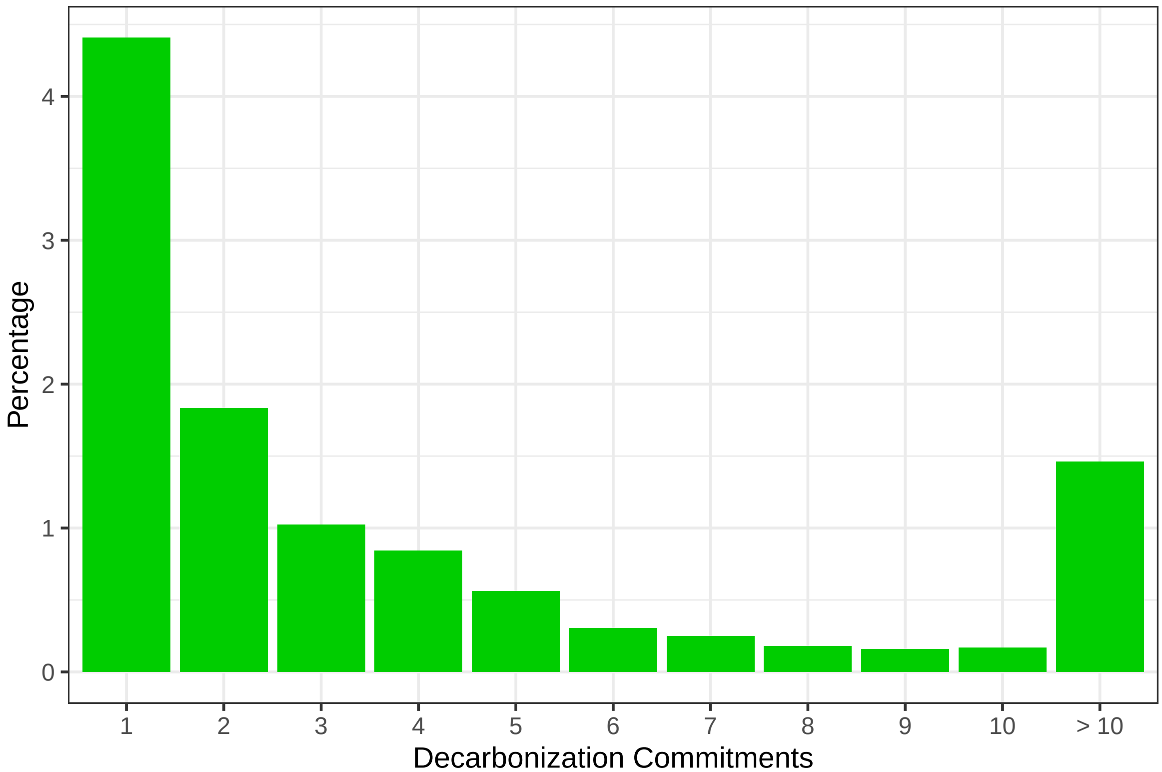
C Additional Tables and Figures

Figure C.1 shows the percentage of firms in our sample with a given number of green pledges. About 4.4% of firms have announced exactly one decarbonization commitment over our sample period. Roughly 1.8% of firms have made two commitments and 1.0% have made three commitments. About 1.5% of the companies have made more than ten green pledges over time. The bars add up to the share of firms that have made at least one green pledge, which is 11.2%. The remaining 7,887 of U.S. firms (88.8%) have not made any green pledge at all.

Figure C.2 provides a comparison of green pledges in our text data and in the CDP database, which is discussed in Section 3. For firms that have green pledges in both data sources, the figure shows the distribution of the number of years between a firm's first pledge in our dataset and its first emissions target in the CDP database. Most CDP targets are recorded in the same year or in the year after the green pledge occurs in our text data. This suggests a close correspondence of firm-level climate commitments in our text data and in the CDP data, and if anything that our text-based method identifies these commitments in a more timely fashion.

Table C.1 provides evidence that also in the CDP sample, large and brown firms are more likely to announce a decarbonization commitment. Log emissions and size are significant at the 1% level which holds even after including industry fixed effects.

Figure C.1: Distribution of green pledges across firms

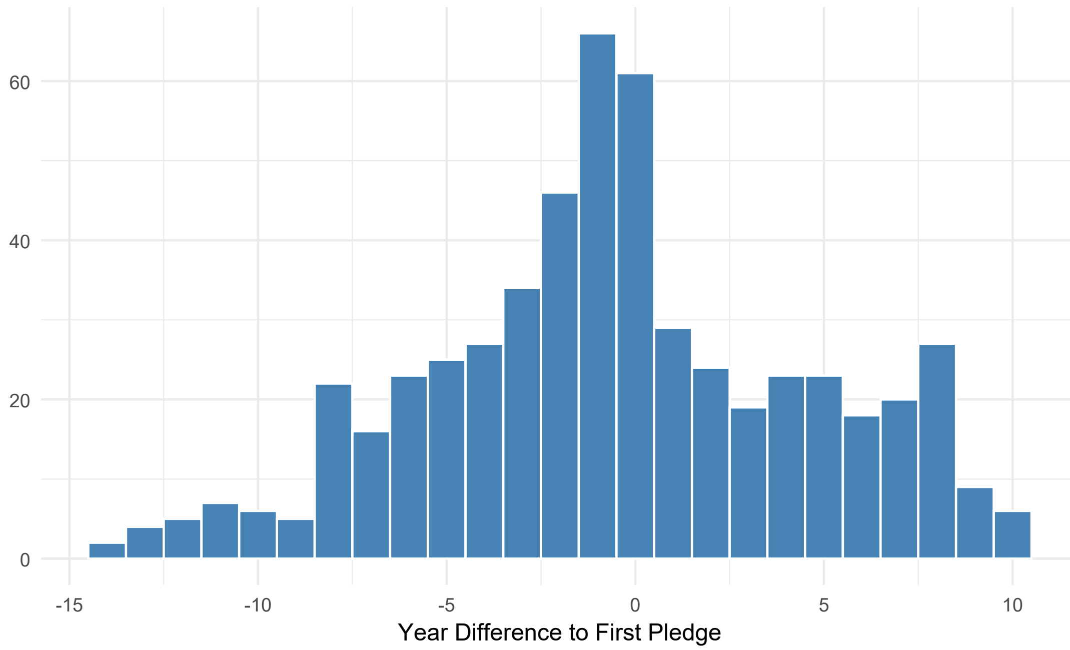


The figure shows the percentage of firms with a given number of decarbonization commitments over our sample, excluding firms that made no green pledges at all. Sample period: January 2005 to December 2023.

Table C.2 shows results for panel regressions with emissions explaining the tendency for green pledges, as in Table 5, but with separate estimates for reported emissions (Panel A) and estimated emissions (Panel B). Just like in Table 5, the dependent variable is a binary indicator that takes the value of one in the year a firm makes its first green pledge and remains one in the subsequent years, following the definition of Bolton and Kacperczyk (2025). We consider specifications without and with industry fixed effects based on the Fama-French 48-industry classifications. The table confirms that brown firms and large firms are more likely to make green pledges also when using only reported or only estimated emissions.

Table C.3 shows results for the stock market response to green pledges estimated using equation (1) for the following two definitions of green pledges: Column (1) shows result for the sample of green pledges that only uses articles that tag a single firm. Column (2) shows results for the sample of green pledges that require at least a 30 day distance between two consecutive announcements by the same firm. The results are highly similar compared to the sample of all green pledges considered in Table 6 with daily stock returns being on average about 0.12% higher on the announcement day of a green pledge compared to

Figure C.2: Distribution of first pledges gap between CDP and text-based sample



The figure plots the distribution of the number of years between a firm's first green pledge in our text-based sample and the first year it registered an emissions target in the CDP database. Sample: 2013 to 2023.

non-announcement days and the effect is significant at the 1% level for both specifications.

Table C.4 reports results for the stock market response to green pledges for the subperiods before and after the Paris agreement. Our findings from Section 4 suggest that investors require a significant premium for holding stocks that are exposed to transitional risks. The magnitude of this premium depends on two factors: the likelihood investors assign to new climate regulations as well as investors' awareness of such risks. Both factors have likely increased since the Paris Agreement in 2015 in which most governments around the world have signed an agreement to significantly curb aggregate emissions in order to keep the global surface temperature to below 2°C above pre-industrial levels. Bolton and Kacperczyk (2021) and Bolton and Kacperczyk (2023) provide evidence that the carbon premium has increased since the Paris Agreement. Hence, if the carbon premium hypothesis holds, we should observe a particularly strong stock market reaction to green pledges after the agreement. We test this hypothesis by running our main regression (1) for the subsamples before and after the Paris Agreement. We find that for the sample of all green pledges, both before and after the agreement, green pledges lead to a significantly positive stock market reaction providing evidence for a significant carbon premium even in the early sample before the agreement. The coefficient on the green pledge dummy is slightly higher in the post-Paris period with lower standard errors. Hence, we find a slightly stronger stock market reaction

Table C.1: CDP firm commitments and within industry variation of firm characteristics

Model	(1)	(2)	(3)	(4)	(5)	(6)
Log Emission	0.02***	0.03***			0.01***	0.01***
	(0.003)	(0.004)			(0.002)	(0.002)
Log Size			0.02***	0.02***	0.03***	0.02***
			(0.01)	(0.004)	(0.004)	(0.003)
Book-to-market					3.63*	3.48*
					(2.11)	(2.09)
Leverage					0.09**	0.07**
					(0.04)	(0.03)
Return on equity					−0.004***	−0.004***
					(0.001)	(0.001)
Sales growth					0.05**	−0.001
					(0.02)	(0.03)
Year FE	Y	Y	Y	Y	Y	Y
Industry FE	N	Y	N	Y	N	Y
Observations	14,786	14,786	28,698	28,698	13,481	13,481
R^2	0.10	0.14	0.09	0.12	0.13	0.16

Panel regressions with the CDP emission target indicator as the dependent variable and firm characteristics lagged by one year as independent variables. The CDP target indicator is equal to one if the firm answered yes to the question whether it has an emission target for the specific year. Controls are book-to-market, leverage, return on equity and sales growth. Columns (2), (4) and (6) include 48 Fama-French industry fixed effects. Standard errors which are clustered by firm and year in each model are given in parentheses. ***, **, and * indicate significance at the 1%-, 5%-, and 10%-level, respectively. Firm characteristics are winsorized at the 1%/99% level. Sample period: 2013 to 2023.

after the Paris agreement. Note that for the sample of first pledges we find an insignificant post-Paris stock market reaction which can be explained by the majority of first pledges taking place in the pre-Paris sample.

Figures C.3 and C.4 show the stock return response and cumulative stock return response for ±5 days around the green pledges respectively. Panel (a) shows results using the sample of all green pledges without controls and panel (b) using firm instead of industry fixed effects. Panel (c) shows results for the sample of green pledges that only tag a single firm and panel (d) for the sample that requires at least a 30 day distance between two consecutive pledges by a firm.

Table C.5 reports the event study regressions of daily stock returns on green pledges, where pledges are classified using different LLM models. In addition to our baseline model, GPT-4, we include classifications generated by GPT-5.1, GPT-5.2, Sonnet 4.6, and Gemini 2.5 Flash. We further construct a cross-model consensus measure based on majority voting,

Table C.2: Green pledges and within industry variation of firm characteristics for estimated and reported emissions

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A - Reported emissions						
Log Emissions	0.08***	0.08***			0.06***	0.03***
	(0.003)	(0.003)			(0.002)	(0.004)
Size			0.05***	0.04***	0.07***	0.09***
			(0.01)	(0.01)	(0.001)	(0.004)
Observations	7,383	7,383	51,003	51,003	6,850	6,850
R^2	0.20	0.26	0.24	0.27	0.25	0.30
Panel B - Estimated emissions						
Log Emissions	0.02***	0.02***			0.02***	0.01***
	(0.002)	(0.003)			(0.002)	(0.003)
Size			0.02***	0.02***	0.01***	0.02***
			(0.003)	(0.003)	(0.003)	(0.003)
Observations	13,538	13,538	15,561	15,561	12,083	12,083
R^2	0.07	0.13	0.03	0.12	0.08	0.15
Year FE	Y	Y	Y	Y	Y	Y
Industry FE	N	Y	N	Y	N	Y
Controls	N	N	N	N	Y	Y

Panel regressions with the green pledge indicator as the dependent variable and firm characteristics lagged by one year as independent variables. The pledge indicator is equal to one starting in the year of a firm's first green pledge and remains equal to one thereafter. Panel A restricts the sample to firms that reported emissions, and Panel B restricts it to firms whose emissions were estimated. Controls are book-to-market, leverage, return on equity and sales growth. Columns (2), (4) and (6) include 48-industry Fama-French fixed effects. Standard errors which are clustered by firm and year in each model are given in parentheses. ***, **, and * indicate significance at the 1%-, 5%-, and 10%-level, respectively. Values are winsorized at the 1%/99% level. Sample period: January 2005 to December 2023.

which identifies a green pledge if an article is classified as positive by at least three out of the five models. We find consistent results across all five models and the majority-vote classification: The estimated stock market effects are of broadly similar magnitude, and statistically and economically significant. This holds true for both the specifications with all green pledges (panel A) and first pledges (panel B). These results demonstrate the robustness of our event-study estimates to the use of different LLMs for green pledge classification.

Figure C.5 plots the estimated effects of green pledges on log emissions (left panel) and emission intensities (right panel) from four years before the pledge to five years after, using only reported emissions data. The results are very similar to those obtained using the full

Table C.3: Stock market response to green pledges - robustness

	(1)	(2)
Green pledges	0.109***	0.122***
	(0.038)	(0.041)
Size	0.007***	0.007***
	(0.002)	(0.002)
Book-to-market	−7.962*	−7.964*
	(4.273)	(4.273)
Leverage	−0.198	−0.198
	(0.184)	(0.184)
Sales growth	−8.192***	−8.192***
	(3.063)	(3.063)
Return on equity	44.755***	44.756***
	(6.471)	(6.471)
Observations	14,788,589	14,788,589
Number of pledges	3,942	4,103
R^2	0.19	0.19

Panel regressions with daily stock returns as the dependent variable and the green pledges event dummy as the main independent variable. Column (1) shows results for the sample of green pledges that only considers articles that tag a single firm, and column (2) shows results for the sample of green pledges that require at least a 30 day distance between two consecutive announcements by the same firm. Controls are book-to-market, leverage, size, sales growth, and return on equity. Industry and day fixed effects are included. Industry fixed effects are based on 48-industry Fama-French classification. Standard errors, clustered by firm and day, are given in parentheses. ***, **, and * indicate significance at the 1%-, 5%-, and 10%-level, respectively. Sample period: January 2005 to December 2023.

emissions dataset—including vendor-estimated emissions—in Figure 4, and if anything show a slightly stronger negative response of emissions. These estimates alleviate concerns that the observed reductions might be driven by Trucost's proprietary estimation model for emissions.

Table C.6 reports results on the response of analyst earnings forecasts to green pledges using monthly data from the Institutional Brokers Estimate System (IBES). The dataset includes, among other variables, monthly mean and median earnings per share (EPS) forecasts for different horizons at the firm level. We merge these forecasts with our dataset of firm-level green pledges and financial variables.

To test whether green pledges affect earnings forecasts, we closely follow Derrien et al. (2025), who analyzed the effect of ESG news on EPS forecasts. Our dependent variable is the first difference in EPS forecasts, scaled by the absolute value of the previous period's forecast. Since long-term growth forecasts are already expressed in percentage terms, we use their first difference. The main independent variable is a dummy that equals one if the firm

Table C.4: Stock market response to first green pledges before and after the Paris agreement

	All green pledges		First green pledges	
	Pre-Paris	Post-Paris	Pre-Paris	Post-Paris
Green pledges	0.13**	0.13***	0.37**	0.30**
	(0.06)	(0.05)	(0.17)	(0.13)
Size	0.003	0.01***	0.003	0.01***
	(0.003)	(0.003)	(0.003)	(0.003)
Book-to-market	−6.55	−12.44*	−6.54	−12.41*
	(5.11)	(6.72)	(5.11)	(6.72)
Leverage	−0.67	−0.06	−0.67	−0.06
	(0.44)	(0.11)	(0.44)	(0.11)
Sales growth	−10.24***	−5.07	−10.24***	−5.08
	(3.92)	(4.72)	(3.92)	(4.72)
Return on equity	51.33***	37.91***	51.33***	37.89***
	(7.24)	(8.13)	(7.24)	(8.13)
Observations	9,256,490	5,532,099	9,256,490	5,532,099
Number of pledges	1,472	3,540	343	499
R^2	0.18	0.21	0.18	0.21

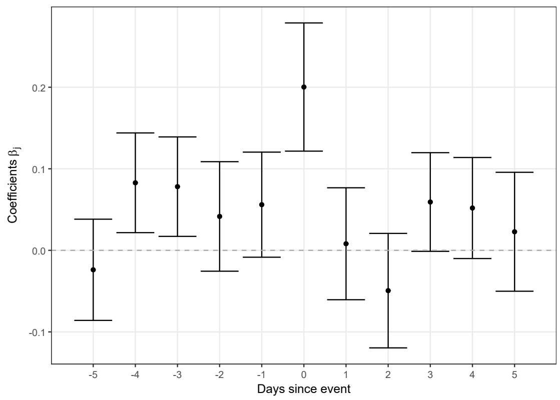
Panel regressions with daily stock returns as the dependent variable and the green pledges event dummy as the main independent variable. Column (1) shows results for all green pledges for the sample period before the Paris agreement from January 1, 2005 to December 11, 2015. Column (2) shows results for all green pledges the sample period after the agreement from December 12, 2015 to December 31, 2023. Columns (3) and (4) show the corresponding results for the sample of first green pledges. Controls are book-to-market, sales growth, leverage, size, and return on equity. Day and industry fixed effects are included. Industry fixed effects are based on 48-industry Fama-French classification. Standard errors, clustered by firm and day, are given in parentheses. ***, **, and * indicate significance at the 1%-, 5%-, and 10%-level, respectively.

made at least one green pledge within the past six months, and zero otherwise. As control variables, we include the growth in capital expenditures divided by total assets, ROA, and net debt divided by total assets. All specifications include industry-by-month and firm fixed effects.

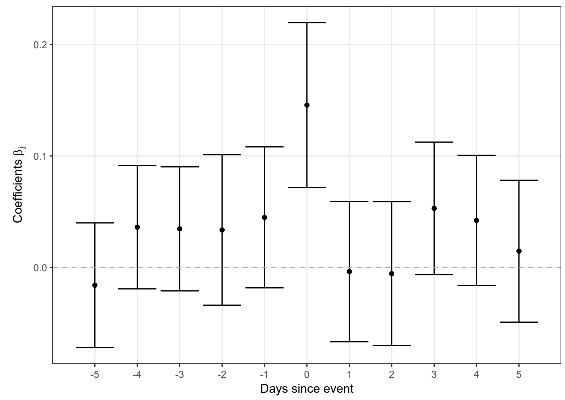
Table C.6 presents the results. The columns report changes in median EPS forecasts for horizons ranging from one to four quarters, one to three years, and long-term growth forecasts. Across all forecast horizons, the estimated effect of green pledges on median EPS forecasts is statistically insignificant. We carried out several robustness checks to validate this result.[38] Specifically, we re-estimated the model using our baseline specification from Table 6, replacing stock returns with changes in EPS forecasts. We also tested alternative specifications by restricting the sample to first pledges, treating the green pledges as ab-

[38] The results are omitted for the sake of brevity.

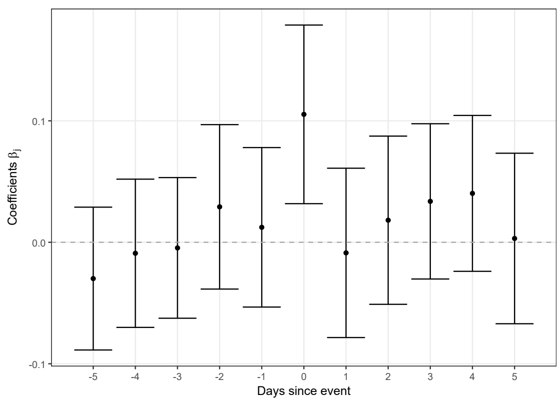
Figure C.3: Stock return response around green pledges - robustness



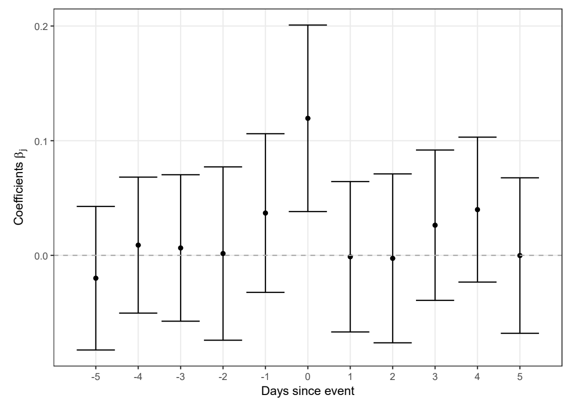
(a) No controls



(b) Firm-day fixed effects



(c) Only pledges that tag a single firm



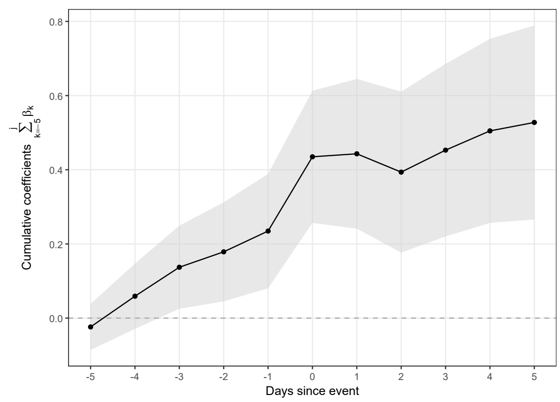
(d) 30 day distance between pledges

Dynamic event study estimates of the effects of green pledges on daily stock returns. The dependent variable is the daily stock return, and the independent variables are the green pledges event dummy, and five lags and leads. Panel (a) shows results using the sample of all green pledges without controls and panel (b) using firm instead of industry fixed effects. Panel (c) shows results for the sample of green pledges that only tag a single firm and panel (d) for the sample that requires at least a 30 day distance between two consecutive pledges by a firm. Controls are book-to-market, sales growth, leverage, size, and return on equity. 95% confidence intervals are estimated using standard errors clustered by firm and day and are shown around the point estimate. Sample period: December 2005 to January 2023.

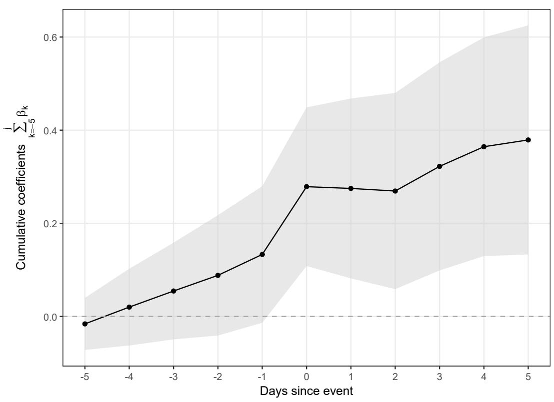
sorbing, using log changes, and using mean forecasts instead of medians. In every case, the impact of green pledges on earnings forecasts remains insignificant.

Table C.7 reports how various accounting variables respond to green pledges using the local projection difference-in-differences introduced in Section 5. Column 1 presents estimates for log of capital expenditures, Column 2 for R&D expenses scaled by total assets, Column 3 for return on assets (ROA), Column 4 for return on equity (ROE), and Column 5 for dividend growth. For each variable, we report the estimated effects at horizons of one and five years. We find that capital expenditures increase by about 5 percent both one and five

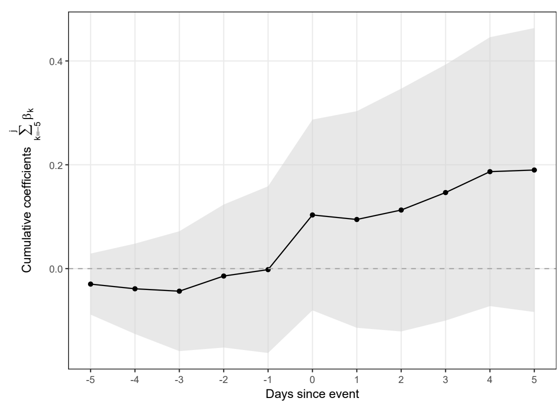
Figure C.4: Cumulative stock return response around green pledges - robustness



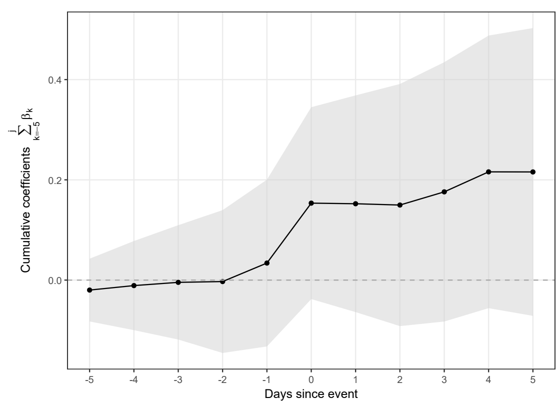
(a) No controls



(b) Firm-day fixed effects



(c) At maximum one mentioned ISIN per article



(d) At least 30 days between firm announcements

Dynamic event study estimates of the effects of green pledges on daily stock returns. The dependent variable is the daily stock return, and the independent variable is the green pledges event dummy. Panel (a) shows results using the sample of all green pledges without controls and panel (b) using firm instead of industry fixed effects. Panel (c) shows results for the sample of green pledges that only tag a single firm and panel (d) for the sample that requires at least a 30 day distance between two consecutive pledges by a firm. Controls are book-to-market, sales growth, leverage, size, and return on equity. 95% confidence intervals are estimated using standard errors clustered by firm and day and are shown around the point estimate. Sample period: December 2005 to January 2023.

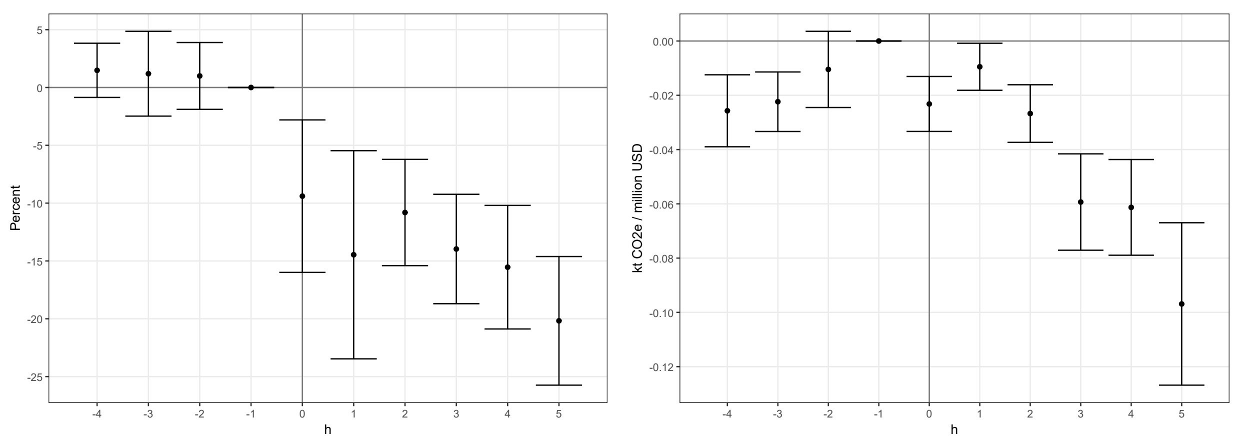
years after a green pledge. In addition, ROA shows a modest but statistically meaningful rise, increasing by 0.46 percentage points after one year and by 1.7 percentage points after five years.

Table C.5: Stock return response to green pledges classified by different LLM models

	GPT-4	GPT-5.1	GPT-5.2	Sonnet 4.6	Gemini 2.5 Flash	Majority vote
(A) Green pledges						
Coef.	0.150***	0.079*	0.126**	0.113**	0.149***	0.097**
	(0.038)	(0.041)	(0.050)	(0.051)	(0.046)	(0.045)
Observations	14,788,589	14,788,589	14,788,589	14,788,589	14,788,589	14,788,589
Nr of pledges	5,603	2,870	1,568	1,810	2,887	2,345
R^2	0.19	0.19	0.19	0.19	0.19	0.19
(B) First pledges						
Coef.	0.335***	0.212**	0.163*	0.251***	0.313***	0.207**
	(0.104)	(0.096)	(0.085)	(0.092)	(0.118)	(0.094)
Observations	14,788,589	14,788,589	14,788,589	14,788,589	14,788,589	14,788,589
Nr of pledges	990	703	513	566	688	638
R^2	0.19	0.19	0.19	0.19	0.19	0.19

Panel regressions with daily stock returns as the dependent variable and the green pledges event dummy as the main independent variable. Each column shows estimation results based on green pledges classified by different LLM models. The Consensus classification is based on majority voting, i.e., it takes a value of 1 if at least 3 out of 5 models classify the article as a green pledge. Panel A presents results for all green pledges and Panel B reports results for first pledges. Controls are book-to-market, sales growth, leverage, size, and return on equity. Day and firm fixed effects are included. Standard errors, clustered by firm and day, are given in parentheses. ***, **, and * indicate significance at the 1%-, 5%-, and 10%-level, respectively.

Figure C.5: Impact of green pledges on reported carbon emissions



(a) Log emissions

(b) Emission intensity

Local projection difference-in-differences with log-level of reported emissions (left panel) or reported emission intensity (right panel) as the dependent variable and the green pledges event dummy as the independent variable. Controls include lagged values of size, book-to-market, leverage, profitability, revenue growth, and log PP&E, as well as lagged emissions (log-levels or intensities). Error bars correspond to 95% confidence intervals based on Driscoll and Kraay (1998) standard errors.

Table C.6: IBES earnings forecast

	(1) Q1	(2) Q2	(3) Q3	(4) Q4	(5) One Year	(6) Two Years	(7) Three Years	(8) LTG
Green pledges[t-6,t]	−0.08	−0.01	−0.18	−0.13	−0.05	−0.18	−0.13	−0.87
	(0.30)	(0.24)	(0.22)	(0.19)	(0.14)	(0.12)	(0.10)	(1.72)
CAPX/Assets	0.38	0.36	0.03	0.03	0.03	−0.02	−0.33	0.06
	(0.61)	(0.45)	(0.42)	(0.58)	(0.34)	(0.30)	(0.40)	(4.56)
ROA	2.71***	4.17***	2.18***	1.39***	2.17***	1.08***	0.39	−6.91*
	(0.78)	(0.63)	(0.57)	(0.47)	(0.45)	(0.37)	(0.37)	(3.72)
Net debt/Assets	2.49***	2.46***	2.78***	2.76***	1.79***	1.57***	1.47***	−4.69
	(0.90)	(0.63)	(0.71)	(0.64)	(0.53)	(0.45)	(0.41)	(4.50)
Number of pledges	4,273	4,258	4,236	4,195	4,291	4,289	4,110	3,203
Observations	499,231	490,942	479,864	465,047	507,251	500,820	362,765	299,496
R^2	0.11	0.10	0.11	0.12	0.10	0.12	0.11	0.07

Monthly panel regressions of the growth in median EPS forecasts on a green pledge event dummy and control variables. Columns (1)–(8) use as the dependent variable the first difference in EPS forecasts for horizons of one to four quarters, one to three years, and long-term growth. For all horizons except long-term growth, the dependent variable is scaled by the absolute value of the lagged forecast. All forecast values are expressed in percentages. The main independent variable equals one if the firm made at least one green pledge within the six months preceding the forecast, and zero otherwise. All specifications include month × industry and firm fixed effects. Standard errors, clustered by firm and month, are given in parentheses. ***, **, and * indicate significance at the 1%-, 5%-, and 10%-level, respectively.

Table C.7: Response of firm characteristics to green pledges

	Log CAPX	R&D	ROA	ROE	Dividend growth
1-year	5.03***	0.00	−0.20	7.01	3.83
	(1.27)	(0.06)	(0.16)	(6.1)	(14.98)
5-year	4.69**	−0.39	1.57***	64.96	5.35
	(2.08)	(0.25)	(0.34)	(43.52)	(8.95)
Observations	31,189	18,185	28,077	27,826	10,055
Number of pledges	447	237	426	419	264
R^2	0.31	0.10	0.28	0.29	0.47

Local projection difference-in-differences with log of capital expenditure, research and development expenses divided by total assets, ROA (net income divided by beginning of year total assets), ROE (net income divided by beginning of year book equity), and dividend growth as dependent variables. The independent variable is the green pledges event dummy. All variables are in percent. Controls include lagged values of size, book-to-market, leverage, profitability, revenue growth, and log PP&E, as well as lagged values of the dependent variable. Driscoll and Kraay (1998) standard errors are given in parentheses. ***, **, and * indicate significance at the 1%-, 5%-, and 10%-level, respectively. The number of observations, number of pledges, and R^2 correspond to the one-year horizon. Sample period: January 2005 to December 2023.

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