Corporate Green Pledges*

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Abstract

We identify corporate commitments for reductions of greenhouse gas emissions—green pledges—from news articles using a large language model. About 8% of U.S. firms have made green pledges, and these companies tend to be larger and browner than those without pledges. Announcements of green pledges significantly and persistently raise stock prices, consistent with reductions in the carbon premium. Firms that make green pledges subsequently reduce their CO_2 emissions. Our evidence suggests that green pledges are credible, have material new information for investors, and can reduce perceived transition risk.

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

As the world transitions towards a low-carbon economy, firms are challenged with the adaption of their business models to succeed in an evolving technological, regulatory and political environment. They face significant transition risks—including liability and reputational risks—as a result of the shift towards a low-carbon economy that will impact their cash flows, profits, and overall long-term prospects.[1] But companies can manage transition risks: By reducing carbon emissions, they can lessen the future impact of carbon pricing regulations and technological breakthroughs that render carbon-intensive businesses costly and ultimately irrelevant. Indeed, more and more corporations all over the world have announced plans and commitments to lower their carbon emissions.[2] Because financial markets are forward-looking, credible commitments to decarbonize in the future could immediately raise company values: As lenders and investors perceive lower transition risks, the required risk premium and cost of capital decline, with a positive impact on the firm's valuation. On the other hand, decarbonization requires potentially large investments and significant changes to existing business models, which lead to substantial costs and risks affecting future cash flows and profits. It is an open question which of these effects is stronger, and whether the overall effect of such commitments on company values is likely to be positive or negative. This paper addresses this question using a new dataset of time-stamped decarbonization commitments for public U.S. firms, or "corporate green pledges," constructed from a large corpus of news articles with the help of human coding and a large language model. Our event-study evidence shows a positive impact of green pledges on stock market valuations that is statistically and economically significant. Investors appear to view the anticipated benefits of green pledges as outweighing the costs, and the market response may provide additional financial incentives for decarbonization. We also document 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 by a company to significantly reduce its future greenhouse gas (GHG) emissions. Using textual analysis, we identify such green pledges in Dow Jones newswire and newspaper articles from 2005 to 2023. This task would be exceedingly challenging for conventional text classification models, because green pledges are difficult to distinguish from other corporate announcements that

[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".

are related to emissions or the green transition but do not contain new commitments. Recognizing these subtle differences and accomplishing satisfactory classifiction accuracy would require a carefully tuned machine-learning model that accounts for semantic information and context, and a very large training sample of labeled articles. We instead classify the articles with a large language model (LLM), which allows us to identify green pledges without a training dataset of manually labeled articles. We use GPT-4 by OpenAI, a model that is well-suited for this complicated classification task because it was trained on vast amounts of textual data, has contextual understanding, and can handle linguistic nuances. Other studies have found that in empirical economic research GPT models often draw similar conclusions as humans, with the advantage of being able to quickly process large amounts of data.[3]

We use GPT-4 to classify 44,605 news texts—including press releases, earnings announcements, articles, and many other pieces of news—that have topics related to the environment. The successful use of an LLM requires a suitably chosen prompt with accurate and detailed instructions, and a careful evaluation of the results, given the possibility of hallucination, bias, restrictions from content use policies, and other common problems with LLMs. For both, the prompt design and the evaluation, we make extensive use of human coding. In a random subsample of 1000 articles, the classifications from GPT and human coders show a high level of agreement (89%). Using the identified articles and the associated ISINs and time stamps, we derive a dataset of 8,320 unique firm-date combinations. These green pledge events are the basis of our subsequent analysis.

The first contribution of our paper is to document new empirical facts about green pledges of listed U.S. companies. Over our sample period, about 8% of the firms made at least one public commitment to reduce future carbon emissions. Many of those firms made multiple announcements, for example, setting increasingly ambitious goals for future reductions. Towards the end of our sample, there is a clear upward trend in the number of green pledges, consistent with the substantial increase in climate change concerns (Ardia et al., 2023). Furthermore, we find that it is especially large and brown firms (i.e., firms with high emissions or emission intensities) who announce green pledges, both within and across industries. Because large and brown firms are the most relevant for the aggregate transition of the U.S. economy to a low-carbon future, their commitments to reduce emissions are particularly important.

We then show that announcements of green pledges have a substantial and persistent positive impact on stock market valuations. Event studies using our timestamped corporate

[3]For example, Hansen and Kazinnik (2023) use GPT models to classify the monetary policy stance based on language in FOMC statements with logical reasoning similar to human coders, and Hansen et al. (2024) show that LLMs come to similar economic predictions as professional forecasters. See Korinek (2023) and Ash and Hansen (2023) for applications of LLMs in economics.

green pledges, daily stock returns, and firm-level accounting and emissions data provide estimates of the announcement effects on stock prices. Green pledges lead to a positive stock return on the day of the announcement, and the effect is both economically and statistically significant. On average, a green pledge raises the stock price by 0.14–0.31%, which is a sizable increase when compared to the average daily stock return of 0.015%. Given that our text-based event indicator contains measurement error, these estimates should be viewed as a lower bound for the true effects of green pledges on stock market values. The estimated effects are robust to the choice of firm-level control variables, fixed effects, subsets of green pledge events, and sample period. For example, we find equally strong effects for the periods before and after the 2015 Paris Agreement. While other firm-level environmental news are also associated with positive stock returns, the effects of green pledges are significantly larger. This placebo test confirms that our text classification method uncovers an important signal about perceived transition risk with consequences for stock market valuations. 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. The estimated impact of green pledges is heterogeneous across firms, as it is significantly positive only for the largest firms and those with the highest emissions.

Finally, we investigate whether firms "walk the talk" and actually lower their future CO_2 emissions following a green pledge. There have been ongoing concerns in the public and academic debate about the greenwashing of firms, that is, attempts by firms to convey a false impression about their environmental footprint (Bingler et al., 2022). To address this issue, we estimate difference-in-differences local projections for firm-level CO_2 emissions, using the methodology of Dube et al. (2023). 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 12% lower 5 years after the announcements compared to firms that do not make such a commitment. These estimates partly alleviate concerns about greenwashing, because they confirm that green pledges indeed predict a shift towards decarbonization.

The paper makes three novel empirical contributions to the climate finance literature. First, we provide evidence that decarbonization tends to increase the value of a firm. Positive effects from lower cost of capital and/or improved earnings outlook appear to outweigh the potential negative effects from increased investment requirements and uncertainties. While Hartzmark and Shue (2023) conclude from their analysis that "brown firms face very weak financial incentives to become more green" our results point in a different direction: The possibility of higher valuations provides positive incentives for companies to commit to decarbonization. Second, our results support the carbon premium hypothesis, that is, higher expected returns for brown firms due to investor preferences for green stocks or the higher transition risk of brown stocks (Pastor et al., 2021). If there is a carbon premium, and investors learn that a firm will become greener, its expected return should decline and its stock price increase, consistent with our findings. Our evidence on this issue is particularly relevant because earlier empirical work has so far not established a consensus on the carbon premium (Bauer et al., 2022; Zhang, 2024). Third, we provide evidence that corporate green pledges are generally not cheap talk, given that they predict future greening in the form of lower emissions. Our paper thereby contributes to the discussions on greenwashing and cheap talk in climate commitments (Nemes et al., 2022; Bingler et al., 2022, 2024; Dzieliński et al., 2023; Sastry et al., 2024).

Several recent papers have also investigated climate commitments using data from the Carbon Disclosure Project (CDP) and the Science-Based Target Initiative (SBTi), including Bolton and Kacperczyk (2023b), Aldy et al. (2023, 2024), and Jiang (2024). Our work contributes a news-based identification of green pledges, and the resulting novel 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.[4] Our results on the prevalence of green pledges differ from the results of Bolton and Kacperczyk (2023b), who find in their annual international dataset that after controlling for industry effects, green firms are more likely to make commitments. They conclude that the aggregate effect of such commitments on global emissions may be rather low, given that large emitters are not yet changing their behavior sufficiently. By contrast, in our sample of U.S. firms, we find that large and brown firms, both within and across industries, are more likely to make commitments. Acharya et al. (2024) develop a model showing that firm-level climate commitments, in particular by large firms, can enhance the credibility of climate policies such as carbon taxes or subsidies for green innovations. Using corporate commitments from the SBTi, they provide evidence for their model predictions and, in line with our results, document 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.

Our paper contributes to the large literature studying the links between climate transition risk and stock returns. Earlier studies have typically measured transition risk exposure using

[4]Our database is also broader and more comprehensive, since SBTi recorded commitments only starting in 2015. The Net Zero Tracker (www.zerotracker.net) only captures a subset of decarbonization commitments, and does not record the announcement dates.

firm-level emissions and estimated the differential stock returns of green and brown firms, with mixed results. Some papers find evidence for a carbon premium, including Bolton and Kacperczyk (2021, 2023c) and Pastor et al. (2022). Other studies do not find evidence for higher returns of brown stocks, or even document green outperformance; see In et al. (2019), Huij et al. (2024), Aswani et al. (2023), Zhang (2024), and Bauer et al. (2022). Empirical analysis of the carbon premium is generally based on past emissions data as a measure for the exposure to transition risks.[5] But this approach has several shortcomings: Emissions data disclosure has largely been voluntary, resulting in potentially severe selection bias. Estimates of emissions from data vendors can also be quite unreliable, as they are highly correlated with measures of firm size and often revised ex post.[6] In general, emissions data provide only backward-looking and slow-moving, noisy measures of transition risk. By contrast, green pledges are forward-looking and capture new information about future transition risk exposure, making them better suited to study the pricing of these risks in financial markets.

A crucial empirical challenge in climate finance is that average past stock returns are not necessarily good measures of expected returns due to the short sample periods and changes in perceptions about climate risk. This problem is illustrated by Atilgan et al. (2023), who incorporate earnings announcements in their analysis and conclude that the carbon premium in their data sample in fact reflects unexpected returns and mispricing. One potential solution to this problem 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, a number of papers have studied brown and green 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 choose a different route by focusing on firm-level news about future greenness, which allows us to cleanly identify the impact on stock market valuations and the pricing of transition risks.

Many studies have used textual analysis for measuring climate risks, usually by constructing broad, aggregate measures of climate risks based on for example 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

[5] Pastor et al. (2022) instead use environmental scores to distinguish green and brown firms. They also find an ex-post green outperformance, although after a model-based adjustment for negative climate news, brown stocks appear to have higher expected returns.

[6] See the critique by Aswani et al. (2023) as well as the reply by Bolton and Kacperczyk (2023a). In fact, Zhang (2024) argues that earlier evidence of a carbon premium appears to be due to forward-looking firm performance information contained in emissions data and vanishes when accounting for publication lags.

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 discusssions 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." Bingler et al. (2022) use the pre-trained ClimateBERT model to construct an index which captures the quality of climate-related annual reports of companies. We instead focus on news about future firm-level emissions and thus *changes* in greenness and transition risk.

Our work is in the long tradition of the empirical asset pricing literature that uses event studies to estimate the stock market effects of firm-level news, going back to seminal contributions by Fama et al. (1969), Ball and Brown (1968), and Sloan (1996); see the surveys of MacKinlay (1997) and Kothari and Warner (2007). Closest to our work is an influential paper by Krüger (2015) who 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. We build on this literature and the event study methodology by investigating the stock market effects of news about CO_2 emissions and corporate plans for a transition to a low-carbon economy.

The remainder of this paper is organized as follows. In Section 2 we describe our text data and our approach to identify decarbonization commitments using a large language model. Section 3 documents new facts about green pledges, including their variation over time, across industries, and across firms. In Section 4 we analyze the stock market reaction to green pledges using event-study regressions, and in Section 5 we estimate the response of 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. Our text corpus is a large news data set from Dow Jones consisting of real-time newswire articles, which are monitored closely by financial market participants, and newspaper articles from The Wall Street Journal, Barrons, and MarketWatch. This dataset contains a wide variety of news, including articles written by journalists, press releases, earnings announcements, and many others. 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

[7] Ke et al. (2020) construct a novel sentiment score from this text data, which they use to predict stock returns. Aprigliano et al. (2023) and Barbaglia et al. (2023) have used data from Dow Jones to analyse

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 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 precise definition of a decarbonization commitment or green pledge. We define it as an *announcement of a new, clear, actionable commitment to significantly reduce future direct greenhouse gas (GHG) emissions.* This definition aims to identify articles with new information for investors, so that we can estimate how stock prices respond to expectations of a more environmentally sustainable business model in the future. In short, green pledges should be news. This criterion also applies to updates of existing commitments, which should contain new information or more stringent emission reductions. For example, if a firm announces that it is advancing a carbon neutrality target by reallocating resources towards green energy initiatives, this would be considered a decarbonization commitment. However, news that simply reaffirm or validate prior commitments should not be classified as such. We focus on official news like articles, announcements, and press releases, and exclude informal news like CEO tweets or interviews. Overall, our goal is to ensure that the announcement contains material news for financial market participants and the broader public about the projected future GHG emissions of a company.

With this definition in hand, 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 be used for this task.[9] However, it would be very challenging for most commonly used methods to accurately identify green pledges, because on the surface they sound similar to other types of corporate announcements that are related to GHG emissions but do not contain any clear decarbonization commitments. To pick up on these nuances and achieve good classification accuracy, an algorithm would have to be flexible enough to account for language semantics and context, and be carefully tuned in the training process.

the gains of using sentiment measures in macroeconomic forecasting. Furthermore, Ravenpack, the leading provider of financial news sentiment data, constructs its sentiment scores based on Dow Jones Newswires. Ravenpack sentiment data has been used on different finance applications, such as forecasting of bond yields and stock returns (Kim, 2022; Audrino and Offner, 2024), and event studies of stock market reactions to media news (Cepoi, 2020).

[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 Gentzkow et al. (2019), Grimmer et al. (2022), and Ash and Hansen (2023).

Furthermore, training this text classifier would require a very large amount of pre-labeled text data—certainly many thousand labeled articles—because a complicated classification task with nuanced differences between categories generally requires a large training data set.

We choose a different route in this paper, and instead use a large language model (LLM) to classify the news articles. Specifically, we use GPT-4, one of the most advanced LLMs publicly available at the time of this writing. GPT and similar LLMs have already been successfully used in various application 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 GPT classifications we make extensive use of human coding. Our approach is similar to that of Eloundou et al. (2024) who also use human annotations and GPT-4 classifications, and finetune a prompt to yield good agreement between both.

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 four successive rounds. In each round, we asked the model to classify a subset of articles that were also given to human coders, and compared the human-based and model-based classifications. We also asked 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 modified the prompt in each step, 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*

[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).

are only about past performance, about a corporate social responsability (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 this purpose was `gpt-4-0613`, based on the availability of OpenAI's LLMs at the time of the 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] Using OpenAI's Python API, we were able to have GPT-4 classify the entire dataset of our 44,605 news articles within just a few hours.

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. [...]*

[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 finetune it.

The third and final step was to validate the model-based results using human coders. To this end, we selected a random subset of 1000 articles and asked five research associates, which were not otherwise affiliated with this project, to decide whether or not they contained green pledges. To provide instructions to our human coders, we followed best practices for human classification as laid out in Grimmer et al. (2022) and created a codebook grounded in our definition of decarbonization commitments.[12] We then compared the two classifications, as shown below. It is important to note that while we treat the human labels as the "truth" for the purpose of evaluating the GPT classification, neither label is necessarily correct. Both reviewers might interpret the task differently, hence a high accuracy only reflects an agreement between the two, but does not necessarily imply that they have accurately identified all green pledges.

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

		Human Coder		
		Negative	Positive	Total
GPT	Negative	842	15	857
	Positive	100	43	143
	Total	942	58	1,000

Confusion matrix for the classifications of 1000 randomly selected news articles by the model GPT-4 and human coders.

Table 1 shows a confusion matrix that compares the model-based and human classifications. The accuracy, defined as the fraction of identical classifications, is 89%, suggesting a high level of agreement. However, the high accuracy stems in part from the high number of negatives. The precision, defined as the fraction of GPT-positive articles that were also classified as positive by human coders, is only 30%.[13] The moderate precision reflects the obvious tendency of human coders to be much stricter in the classification: they identified 58 news articles as green pledges, while GPT found 143 positives. The takeaway is that we can be reasonably confident that most corporate announcements of green pledges were picked up by our text algorithm. At the same time, our model-based classification also appears to contain a fair amount of noise in the form of positives that may not truly represent green pledges. This measurement error problem would tend to cause attentuation bias in regressions that include an indicator variable for green pledges, so that our estimates should be viewed as conservative, i.e., as a lower bound for the true effect of green pledges on stock returns and emissions.

[12]The codebook is available in Appendix A.

[13]Using common definitions and considering the human classification as the truth, the sensitivity or recall is 74% and the specificity is 89%. The F2 score is 57%.

To gain further insights into the problem of identifying corporate green pledges, we also compared the classifications for a random subset of 500 articles from two different human coders. A commonly used measure of intercoder reliability is Cohen's κ, a type of correlation statistic which summarizes the agreement of two different classifications (Grimmer et al., 2022). In our case, $\kappa = 0.43$, a value that indicates "moderate agreement" between the two coders. Apparently, even among human coders, it is difficult to clearly identify and agree on announcements of green pledges. The κ comparing the human and GPT classifications is 0.38, in the range of "fair agreement." These numbers suggest that even human coding of all articles would only slightly increase the precision of the identification of green pledges.

The end result of our classification with GPT is a selection of 862 news articles that likely contain green pledges. Each of these articles can tag multiple firms (ISINs), as sometimes competitors are mentioned or certain decarbonization initiatives involve several companies. In addition, on a given day there may be multiple articles identified as green pledges for the same firm, for example, if a press release is followed by coverage in a newswire or Wall Street Journal article. For our empirical analysis we create unique firm-date events—that is, unique combinations of company ISINs and trading days—to represent corporate green pledges. The result is a sample of 5456 green pledge events.

For many firms, our sample contains more than one and sometimes a significant number of green pledges. A simple approach to reduce the noise in our classification is to only consider the first green pledge for each firm. In total, 1049 firms in our sample have made at least one green pledge, so this is also the number of first-pledge-events. 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.[14] For estimating the effects on future emissions in Section 5, we use a difference-in-differences approach that considers a firm as either treated or not, based on an indicator variable that turns on when the firm makes its first pledge.

[14] 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 days distances, 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-days distance" sample contains 4496 events, and our "single-tag" sample contains 4248 events.

3 Green Pledges Over Time and Across Firms

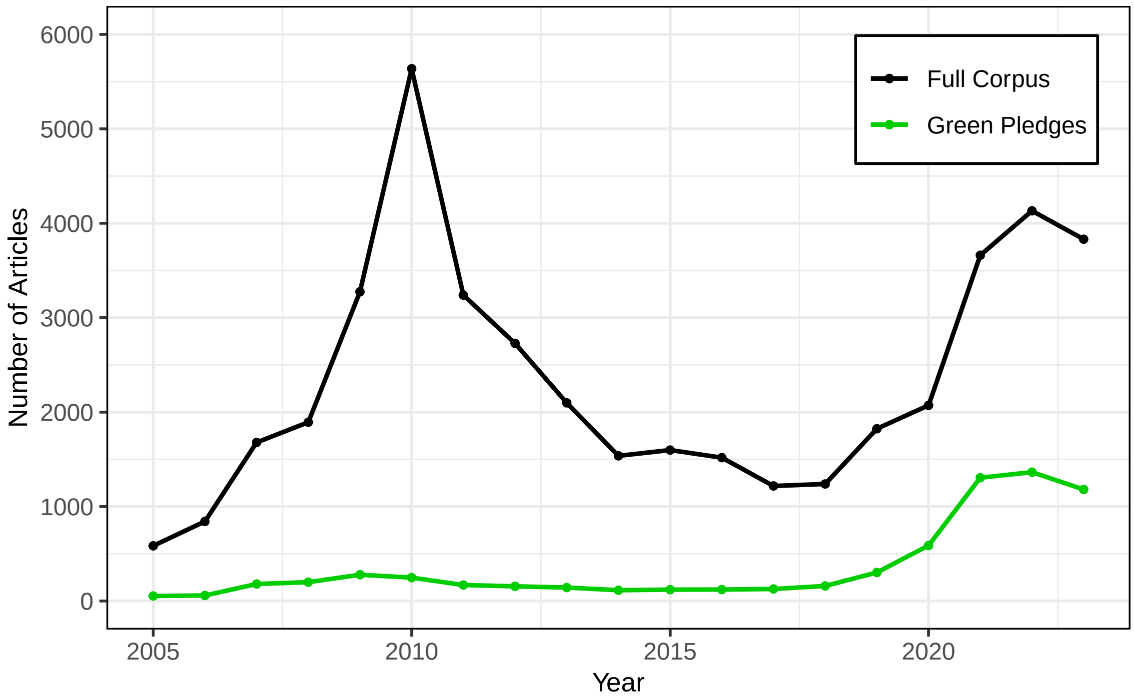
This section shows patterns of corporate green pledges over time and across firms. Figure 1 plots the annual number of total and positive articles, that is, the full sample of environmental articles (black line), and the sample of articles containing green pledges (green line). We observe a significant 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.[15] The number of positive articles—those deemed by GPT to contain a green pledge—started increasing substantially since 2019, and there have been over 1000 green pledge articles each year since 2021. 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), as well as increasing climate transition risks which incentivizes more and more companies to take action and commit to emission reductions. By contrast, the years around the Paris Agreement in 2015 did not see a noticeable increase in corporate green pledges, suggesting that this international initiative had little impact on the corporate sector. Even before the recent increase, there was a significant number of green pledges each year: The number of positive articles between 2005 and 2018 was about 150 per year. It is an important advantage of our methodology that it allows us to identify and analyze corporate green pledges for such a long sample period. Other databases of decarbonization commitments, such as SBTi and the CDP which have been used extensively in related research, only start showing a material number of commitments in the mid 2010s.

In order to investigate the distribution of green pledges across firms and industries, we turn from articles to green pledge events, that is, unique firm-date combinations of green pledges. As noted above, our sample contains 5456 green pledge events, corresponding to 1049 different firms, or 8% of the 12701 firms in our CRSP/Compustat sample. The number of green pledges varies significantly across firms. It is most common for firms to make only one pledge, and this is the case for 419 firms. But the median number of pledges per firm is two, and the distribution has a long right tail.[16] The fact that some firms made several pledges, often in double-digits, is an important reason why we also consider first-pledges in

[15] 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.

[16] Among the firms that made at least one green pledge, the median is 2, the mean is 5.2, the 95% percentile is 21, and the maximum is 83 green pledges per firm. See also Appendix Figure C.1 for the distribution of the number of pledges across firms.

Figure 1: Number of environmental news and green pledges over time



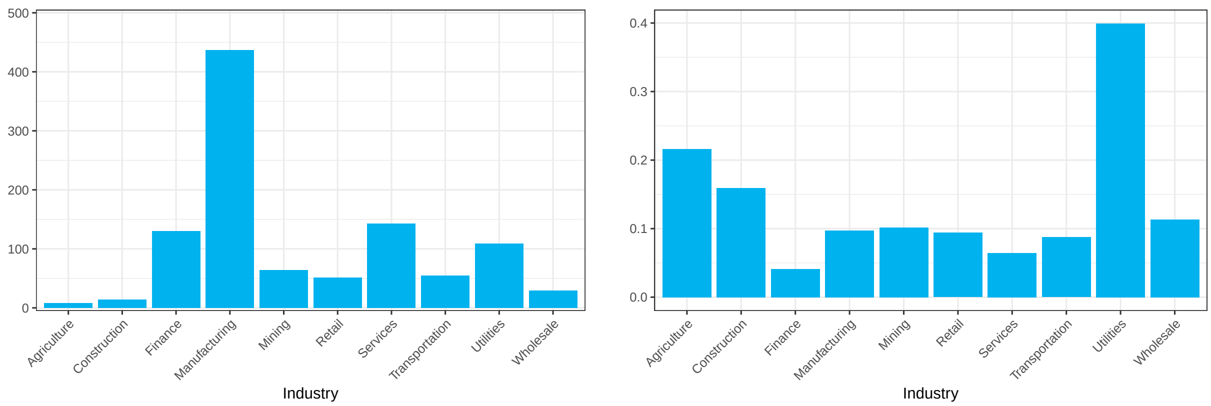
Yearly number of articles in the full text corpus of environmental news articles (black line) and classified as positive by GPT (green line). The total number of articles is 44,605 articles, of which 6,862 are classified as positive, that is, likely containing green pledges. Sample period: 2005 to 2023.

our subsequent analysis as well as a sample which requires a 30-day distance between two pledges by the same firm to get rid of duplicate and follow-up articles, as discussed above.

The main focus of this section is to show evidence of the distribution of green pledges across industries, and of the role of firm characteristics. In essence, we are trying to answer the question what kind of firms are most likely to commit to decarbonize their businesses model. For the transition to a low-carbon economy, it is particularly important that large firms with high carbon emissions 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.

We first study the industry distribution of the firms in our sample. We use SIC codes and apply the industry classification by Bali et al. (2016). Figure 2 shows the distribution of pledging firms across industries. The left panel plots absolute frequencies, that is, the number of firms with a green pledge in each industry. The right panel plots relative frequencies, that is, the number of firms with a pledge divided by the total number of firms in the industry.

Figure 2: Green pledges per industry



(a) Number of firms with a green pledge

(b) Share of firms with a green pledge

Prevalence of U.S. firms with green pledges per industry. Panel (a) plots the total number of firms with a green pledge and panel (b) shows the number of firms with a green pledge divided by the total number of firms in the respective industry. Industry classifications are based on Bali et al. (2016). Sample period: January 2005 to December 2023.

The industry containing by far the most firms with green pledges is the manufacturing sector, with around 440 pledged firms. This is followed by services, financials, and utilities, each with between 100 and 150 firms with pledges. But the prevalence of firms with pledges in the manufacturing sector stems in part from the fact that it contains a very large number of firms. In relative terms, about ten percent of manufacturing firms have made green pledges, very similar to other sectors. The highest share of firms with green pledges is in the utilities sector, where 40% of firms have made a green pledge. This finding is encouraging because the utilities sector is a particularly brown sector, as shown in Appendix Figure C.2. We observe a significant share of firms with green pledges also across other brown sectors, such as manufacturing, agriculture, and mining. Overall, Figure 2 provides some first cross-industry evidence of the stronger tendency of brown firms to decarbonize.

To further explore what kind of firms make decarbonization commitments, we merge the data on green pledges with firm fundamentals and stock market data. Our firm-level analysis uses yearly accounting data from Compustat and emissions from 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

Table 2: Characteristics of firms with and without green pledges

	Green Pledge	No Green Pledge	p-value	t-statistic
Emissions	4.04	0.52	0.0000	8.72
Emission Intensity	0.38	0.13	0.0000	7.50
Size	17.34	1.94	0.0000	45.61
Book-to-market	1.06	1.41	0.0034	-2.94
Leverage	4.22	4.19	0.8038	0.25
Sales growth	0.14	0.21	0.0000	-5.52
Return on equity	0.09	-0.19	0.0000	20.84

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.

provides detailed descriptions and summary statistics for the variables based on accounting financials and emissions.

Table 2 summarizes the characteristics of firms with and without green pledges. The sample includes all firms that have CRSP, Compustat, and emissions data, of which there are 12701 in our sample. Among these, 917 firms made at least one green pledge at some point in our sample, and 11784 firms did not. For both groups of firms, Table 2 reports sample averages of different firm characteristics—first over time for each firm, and then across firms. The last two columns show p-values and t-statistics for the differences in the cross-sectional mean of the time-averaged characteristics between the two groups. All variables are winsorized at the 1%/99% level.

The comparison in Table 2 shows that firms with a green pledge have on average significantly higher emissions, higher emission intensities, and are larger. The differences are both economically and statistically significant. This finding alleviates the concern that commitments to reduce emissions might primarily be 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 (2023b) raise the concern that while unconditionally brown firms are 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 tend to

Table 3: Green pledges and within industry variation of firm characteristics

Model	(1)	(2)	(3)	(4)	(5)	(6)
Log Emissions	0.04***	0.04***			0.03***	0.02***
	(0.004)	(0.004)			(0.002)	(0.003)
Log Size			0.03***	0.02***	0.04***	0.04***
			(0.01)	(0.01)	(0.002)	(0.001)
Book-to-market					−5.37***	−5.14***
					(0.54)	(0.55)
Leverage					3.05***	2.09***
					(0.63)	(0.58)
Return on equity					−29.22***	−20.81***
					(4.43)	(4.57)
Sales growth					−17.92***	−18.95***
					(2.09)	(1.45)
Year FE	Y	Y	Y	Y	Y	Y
Industry FE	N	Y	N	Y	N	Y
Observations	30,653	30,653	111,078	111,078	27,595	27,595
R^2	0.14	0.20	0.12	0.16	0.18	0.23

Panel regressions of green pledge indicators on firm characteristics that are lagged by one year. Pledge indicators are equal to one starting in the year of a firm's first green pledge and remain equal to one thereafter. Controls are book-to-market, leverage, return on equity and sales growth. Columns (2), (4) and (6) include 2-digit SIC industry fixed effects. Standard errors which are clustered by firm and time 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.

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 (2023b). The regressions include lagged firm characteristics and year fixed effects. We consider specifications without and with industry fixed effects based on an SIC 2-digit classification

The results in Table 3 provide robust evidence 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 is positive and statistically significant at the 1% level for all specifications.[17] Our findings

[17] We also estimated regressions using the same set of controls used in Bolton and Kacperczyk (2023b), and found that this leads to the same conclusions as the estimates in Table 3. 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 (2023b).

in Table 3 appear to be at odds with the evidence presented by Bolton and Kacperczyk (2023b), 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 (2023b) 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 narrow down the reasons for the discrepancy between the findings, we revisited their analysis for CDP commitments for a sample of U.S. firms only. In this case, we find similar evidence as reported in Table 3 with brown and large firms being more likely to register a commitment with the CDP, in contrast to the results in Bolton and Kacperczyk (2023b) for the international sample.

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 green pledges spanning most industries, including traditionally high-emission sectors. Our results show that both within and across industries, brown and large firms are more likely to make green pledges.

4 Stock Market Effects

In this section we analyze the stock market reaction to the corporate green pledges. The sign of the effect of green pledges on stock market valuations is *a priori* not clear. On the one hand, valuations may rise because the promised and projected reductions in carbon emissions lower the company's transition risk, including liability, technology and regulatory risks. For example, a firm that unveils plans for a faster decarbonization will be less affected by future carbon taxation or other climate related regulations. In addition to their lower risk, greener stocks can also be more desirable because of inherent green preferences of investors. Pastor et al. (2021) explain both of these channels in a detailed model of the carbon premium. By effectively promising to investors that they will become greener, companies may be able to lower their carbon premium and thus raise their stock price. On the other hand, reductions in carbon emissions will likely require significant up-front investments and potentially far-reaching changes to a company's production processes and business model. Hence, the transition to lower or net-zero emissions may be very costly and risky. The higher costs could weigh significantly on the outlook for earnings and dividends, and the elevated risk could raise the required risk compensation and cost of capital. These forces would tend to push down a company's stock price in response to the announcement of decarbonization plans. The following event-study analysis of stock prices around green pledge announcements will show that the positive effects of corporate green pledges, in the form of lower transition risk exposure and increased investor appeal, appear to be stronger than the negative effects from the costs and risks of decarbonization.

Our analysis uses daily stock market data for a large cross section of U.S. firms from CRSP, including all common equity listed on either NYSE, AMEX or NASDAQ. To analyze the stock price reactions to corporate green pledges, we need to take account of the exact timing of the announcement and assign each green pledge event to a specific trading day. Announcements made after the New York Stock Exchange 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. Appendix B contains a detailed description and summary statistics of the control variables. We also consider emission variables, as described above, in order to investigate the heterogeneity of the effects across green and brown firms.

Using our firm-by-trading-day panel dataset of U.S. firms, 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, δ_t are time fixed effects, and ϵ_{it} is the residual. For industry fixed effects, we use a 2-digit SIC classification. In additional specifications, we use firm fixed effects instead of industry fixed effects to assess the robustness of our results. Throughout the paper, we report standard errors that are clustered by firm and time.

Table 4 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 either with or without 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.

Table 4: Stock market response to green pledges

	All green pledges			First green pledges		
	(1)	(2)	(3)	(4)	(5)	(6)
Green pledge	0.142***	0.156***	0.213***	0.281***	0.285***	0.309***
	(0.04)	(0.04)	(0.04)	(0.11)	(0.11)	(0.11)
Book-to-market	-5.525	-28.971***		-5.509	-28.972***	
	(5.07)	(7.20)		(5.07)	(7.20)	
Leverage	-0.974**	-3.753***		-0.973**	-3.753***	
	(0.39)	(0.63)		(0.39)	(0.63)	
Size	0.004*	-0.110***		0.005*	-0.110***	
	(0.00)	(0.01)		(0.00)	(0.01)	
Sales growth	-13.011***	-0.916		-13.019***	-0.914	
	(4.09)	(3.78)		(4.09)	(3.78)	
Return on equity	54.665***	22.419***		54.658***	22.413***	
	(6.68)	(5.72)		(6.68)	(5.72)	
Number of obs.	14,815,228	14,815,228	17,529,819	14,815,228	14,815,228	17,529,819
R^2	0.18	0.18	0.17	0.18	0.18	0.17
Industry FE	Yes	No	Yes	Yes	No	Yes
Firm FE	No	Yes	No	No	Yes	No
Time FE	Yes	Yes	Yes	Yes	Yes	Yes

Panel regressions of daily stock returns on event dummy for green pledges and firm-specific controls. 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) shows results for a dummy that equals one only on the day of the first green pledge of each firm. Industry fixed effects are based on 2-digit SIC codes. Standard errors, clustered by firm and time, are given in parentheses. ***, **, and * indicate significance at the 1%-, 5%-, and 10%-level, respectively. Sample period: January 2005 to December 2023.

Our green pledge indicators are only a noisy measure of the occurrence of meaningful decarbonization commitments, given the challenges of classifying news articles containing complex and nuanced information about corporate plans for future emissions. As a result, d_{it} likely contains a significant amount of measurement error, as evident from the relatively low precision of the GPT classification compared to human coders in Table 1. With attenuation bias in our estimates of β in regression (1), the actual effect would be larger in magnitude than the estimates we report in Table 4. Our estimates are likely a lower bound for the true stock price impact of corporate green pledges.

The last three columns of Table 4 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 0.28 to 0.31 percentage points, almost twice as large as 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 much smaller effects, possibly because they contain revisions of previous pledges or even delays and revisions of previously set targets. This simple filter of narrowing down our green pledge events appears to be highly effective in identifying the most meaningful and most influential announcements of decarbonization commitments, reducing the measurement error and the attenuation bias in our estimates.

We establish the robustness of these findings in several ways. First, we consider two other subsets 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. As Appendix Table C.1 shows, the results are very similar to those for the sample of all green pledges, indicating that neither duplicate and follow-up articles nor firms that are tagged within green pledges of other firms have a significant effect on our findings.

Another important check for our results is the following placebo test: We 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 a negatively-classified news article. The key question is whether the coefficient on the green pledge dummy is significantly larger than the coefficient on this additional "other environmental news" event dummy.

Table 5 shows the results for regressions using all green pledges in columns (1) and (2), and using only first green pledges in columns (3) and (4). The coefficient on the dummy for other environmental news is significantly positive in all four regressions. Apparently, any environmental news are "good news" on average and tend 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 at the 5%-level when including all green pledges, and at the 0.1%-level when including only first pledges. These estimates confirm that we are truly picking up the effect of green pledges, which is substantially higher 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.

A related question about "other news" is whether our estimates might be confounded by earnings announcements, which have long been known to drive stock prices (Beaver, 1968). As a robustness check, we dropped all observations from our sample where green pledges coincided with earnings announcements on the same days. The estimation results, which we omit for the sake of brevity, were essentially identical to those reported in Table 4, indicating

Table 5: Green pledges vs. other environmental news

	All green pledges		First green pledges	
	(1)	(2)	(3)	(4)
Green pledge	0.137***	0.205***	0.278**	0.305***
	(0.04)	(0.04)	(0.11)	(0.11)
Other env. news	0.057***	0.094***	0.066***	0.110***
	(0.02)	(0.02)	(0.02)	(0.02)
Book-to-market	-5.556		-5.552	
	(5.07)		(5.07)	
Sales growth	-13.001***		-13.004***	
	(4.09)		(4.09)	
Leverage	-0.976**		-0.976**	
	(0.39)		(0.39)	
Size	0.004*		0.004*	
	(0.00)		(0.00)	
Return on equity	54.689***		54.688***	
	(6.68)		(6.68)	
Number of Obs.	14,815,228	17,529,819	14,815,228	17,529,819
R^2	0.180	0.168	0.180	0.168
p-value	0.047	0.013	0.000	0.000

Panel regressions of daily stock returns on the green pledges event dummy and a dummy capturing all other environmental news which are not classified as a green pledge. The total number of environmental news not classified as green pledge is 26,821. Column (1) shows results for the sample of all green pledges with industry fixed effects and column (2) shows results without controls. Columns (3)-(4) show the corresponding results for the sample of first green pledges. All regressions include industry fixed effects, based on 2-digit SIC codes, and time fixed effects. Standard errors, clustered by firm and time, are given in parentheses. ***, **, and * indicate significance at the 1%-, 5%-, and 10%-level, respectively. 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. Sample period: January 2005 to December 2023.

that the presence of earnings announcements is not important for our findings.

We also consider the robustness of our results with regard to a sample split for the periods before and after the Paris agreement in December 2015. Increased climate concerns since the Paris agreement might lead to a stronger stock market reaction following a green pledge. The estimates in Appendix Table C.2 suggest that green pledges had positive effects on stock prices in both sample periods. Overall, we find that our results tend to be robust to different sample splits.

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 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.

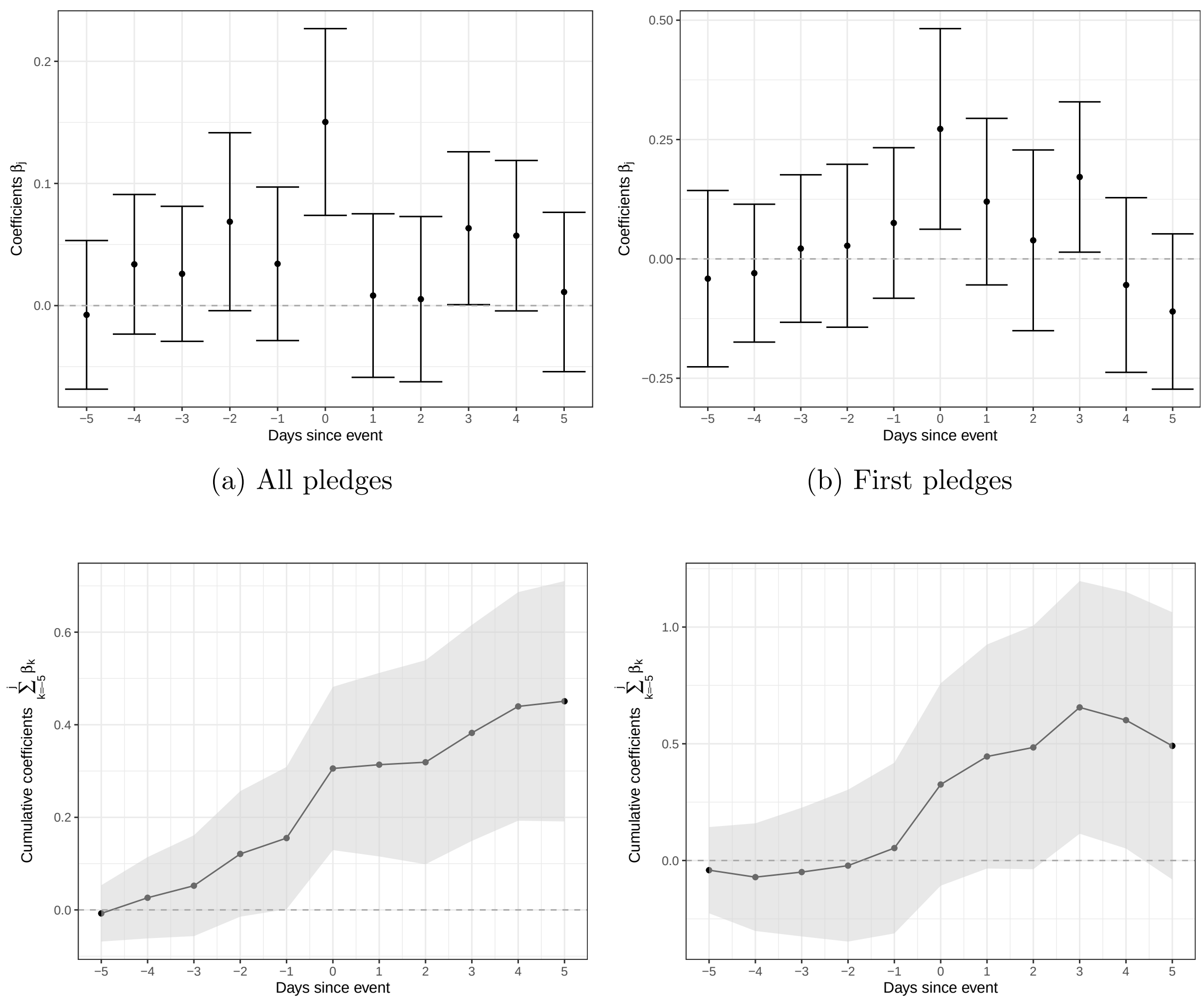
Figure 3 shows estimates of the coefficients β_j in the top two panels, and the cumulative effects in the bottom two panels, together with 95%-confidence intervals based on clustered standard errors. The left two panels correspond to the regression using all green pledges, and the right two panels correspond to the regression using only first green pledges. Our estimates do not show any 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.[18]

We now turn to the question of heterogeneity. Do the stock market effects of climate commitments depend on the industry, the firm's size, or its greennes? Firm heterogeneity and the 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 lower exposure to transition risks, we would expect to see an especially strong market reaction for brown firms with high emissions, due to the fact that they have larger transition risk exposures to begin with. If, however, mainly green firms see reductions in the carbon carbon premium and hence, their cost of capital, green investing could be ineffective or even counterproductive as brown firms might response to relatively higher cost of capital by increasing emissions to realize short term profits (Hartzmark and Shue, 2023).

To investigate industry-level heterogeneity, we estimate equation (1) separately for each

[18]Figures C.3 and C.4 in Appendix C show the corresponding results the 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 that requires a 30 day distance between two consecutive pledges. The results are very similar to those shown in Figure 3.

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. 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 time and are shown around the point estimate. Sample period: December 2005 to January 2023.

industry. As in Section 3, we use the industry classifications by Bali et al. (2016). For each industry, we estimate the panel regression first using all green pledges, and then using only the first green pledges. In both cases the regression includes the usual firm-level controls and time fixed effects. To assess the effects in brown and green industries, we also calculte industry-level emissions and emission intensities.[19] The results are reported in Table 6. The estimates

[19]We use emissions defined as the sum of scope 1 and scope 2 emissions (in million tons of CO_2), and

Table 6: Stock market reaction to green pledges across industries

Industry	Green pledges	First pledges	Number of obs.	Carbon emissions	Emission intensity
Utilities	0.118**	0.148	502,645	21.442	2.658
	(0.05)	(0.26)			
Mining	0.070	0.163	577,368	3.429	0.621
	(0.19)	(0.33)			
Transportation	0.008	0.374	617,985	3.419	0.301
	(0.10)	(0.57)			
Manufacturing	0.171***	0.570***	5,866,646	2.018	0.158
	(0.07)	(0.19)			
Retail	0.470*	0.258	852,831	1.097	0.063
	(0.26)	(0.29)			
Wholesale	0.002	-0.558	430,460	0.627	0.061
	(0.29)	(0.46)			
Agriculture	1.005	1.401	35,756	0.564	0.941
	(1.09)	(1.65)			
Construction	-0.007	0.167	187,999	0.354	0.077
	(0.17)	(0.29)			
Services	0.180*	0.050	2,456,987	0.216	0.045
	(0.11)	(0.24)			
Finance	-0.034	-0.117	3,228,772	0.085	0.010
	(0.10)	(0.19)			

Event-study regression (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 time fixed effects. Standard errors clustered by firm and time in each model are given in parentheses. ***, **, and * indicate significance at the 1%-, 5%-, and 10%-level, respectively. The table also reports the average firm level carbon emissions (scope 1+2, measured in million tons of CO_2), and the average emission intensity, per industry (in kilotons of CO_2 per USD million of revenue). Sample period: January 2005 to December 2023.

for all pledges show that in brown industries with high emission levels and intensities, such as the utilities sector and manufacturing, green pledges significantly increase firm values. For other, less carbon intense industries, the effect appears to be less pronounced. For the sample of first pledges, we obtain higher standard errors due to significantly less pledges per industry, and only the manufacturing sector shows a significantly positive coefficient.

Next, we test directly whether the stock market reaction to green pledges is stronger for brown firms compared to green firms. Our goal is to assess whether brown firms, which have

emission intensity as the ratio of emissions and revenue (in kilotons of CO_2 per USD million of revenue). We first average emission levels or intensities across all firms in an industry on each date, and then calculate the industry-level statistic as the average across time.

the potential to contribute most to the transition to a low-carbon economy, can increase their valuations by committing to become greener. We measure greenness of a firm by using either the level of carbon emissions or by using emission intensities. Emission levels have been proposed as a direct proxy for firm's exposures to transition risks by Bolton and Kacperczyk (2021) and Bolton and Kacperczyk (2023c). Emission intensities have been used for example by Aswani et al. (2023) and Zhang (2024). In addition to emissions, we examine firm size, which has long been known to be an important determinant of expected return and a firm's risk premium (Banz, 1981; Fama and French, 1995), and also plays a role in firms' differential responses to monetary policy (Ehrmann and Fratzscher, 2004), and fiscal policy (Eskandari and Zamanian, 2023).

To investigate heterogeneous effects of green pledges depending on firm characteristics, we sort firms into five equal-sized groups based on either emission levels, emission intensities, or size. For emission-based measures, we sort firms annually, while for firm size, which is measured using market value, the sorts are formed anew every trading day. This grouping approach has two advantages over a regression with interaction effects for size or greenness: First, it reduces the impact of measurement errors in the variable measuring heterogeneity. Second, it allows for possible non-linear effects. For each of the quintile groups, we run our main panel regression as specified in equation (1) with firm-level controls as well as industry and time fixed effects.

Table 7 shows that the stock market response to green pledges is particularly strong for firms with high emission levels. In particular, for emission levels, only stocks within the top quintile (firms with high emissions) exhibit a significant increase in the stock price following a green pledge, with an increase of 9 basis points on average. We find similar effects for large firms with only the stocks in the top quintile showing a significant response to green pledges. As size and log emissions are highly correlated, heavy emitters for which investors require a high carbon premium also tend to be large firms. For emission intensities, we only find a weakly significant stock market reaction for the second highest quintile. This might indicate that level of emissions are a better proxy for the exposure towards transitional risks as suggested by Bolton and Kacperczyk (2023c). Table C.3 in Appendix C shows the corresponding results for the sample of first pledges which shows similar results.[20] One caveat of this analysis is the loss of power for the groups with green or small firms, due to the small number of green pledges in these groups. But the estimates in Table 7 quite clearly shows that the stocks of large and high-carbon firms exhibit strong responses to green pledges.

To summarize, we find evidence that corporate green pledges have a significantly positive

[20]Note that the power of our tests is rather low in this case as each group only contains a small number of green pledges.

Table 7: Cross-sectional response of stock returns to green pledges

	Quintile				
	5	4	3	2	1
(A): Emissions					
Coefficient	0.094**	0.068	0.433	0.145	0.530
	(0.05)	(0.08)	(0.32)	(0.27)	(0.45)
R^2	0.34	0.35	0.33	0.30	0.30
Nr. of obs.	757,179	835,481	889,130	842,668	944,896
Nr. of events	1,929	463	237	90	30
(B): Emission intensity					
Coefficient	0.117	0.217*	0.089	0.089	0.000
	(0.08)	(0.11)	(0.08)	(0.13)	(0.12)
R^2	0.33	0.30	0.27	0.31	0.46
Nr. of obs.	741,486	776,389	953,928	880,731	916,820
Nr. of events	1,435	338	467	285	224
(C): Size					
Coefficient	0.077**	0.027	0.495	1.072	0.788
	(0.03)	(0.13)	(0.31)	(0.88)	(1.13)
R^2	0.37	0.36	0.32	0.17	0.05
Nr. of obs.	2,538,665	2,513,622	2,575,396	2,609,900	2,612,323
Nr. of events	2,442	423	161	108	33

Regressions of daily stock returns on the green pledge event dummies for quintile groups based on log carbon emission, emission intensity, and size. Quintile 5 corresponds to the largest and brownest firms. Controls are book-to-market, sales growth, leverage, size, and return on equity. All regressions include industry and time fixed effects. Standard errors which are clustered by firm and time 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.

impact on firms' stock valuations, suggesting that they reduce the carbon premium. By announcing plans to reduce emissions, companies effectively promise to become greener, with the consequence that their stock price rises. The value that investors attribute to decarbonization—either due to lower transition risks or higher desirability in the presence of green preferences—outweighs the implied costs and risks from the reduction in emissions. The evidence also suggests that the stock market reaction is particularly strong for brown firms with high emission levels. A simple explanation for this pattern is that brown firms can achieve a larger reduction of transition risk exposure and the carbon premium via green pledges, while green firms can at best marginally improve their carbon footprint and change their transition risk.

In principle, the positive impact of green pledges on firm valuations could also be due to changes in dividend expectations. However, there is no theoretical reason to expect green firms to have higher dividends than brown firms, and the climate finance literature has focused on the carbon premium hypothesis to explain differences between green and brown stock returns. Both theoretically and empirically, it appears more plausible that green pledges affect discount rates than dividend expectations.[21]

By announcing green pledges, firms can lower their carbon premium and cost of capital. This effect could provide a market-based incentive for decarbonization commitments. The lower cost of capital could also help firms finance their decarbonization strategies and green investments. Our results suggest an overall positive effect of climate-related investing for the transition to a low-carbon economy.

5 Future Emissions

Our stock market results suggest that investors tend to view corporate green pledges as credible. But are the announced commitments really followed by reductions in firm-level emissions, or are such announcements empty promises that reflect the desire of firms to polish their environmental image? In the words of Bingler et al. (2022), do firm "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 carry out difference-in-differences estimation of changes in firm-level emissions after corporate green pledges. The basic idea is to compare 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.

Two aspects of our empirical setting complicate the estimation of the "treatment effects" of green pledges on emissions. Treatments are of course staggered, as different firms announce them 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

[21] Using a Campbell-Shiller decomposition of stock price effects, Ardia et al. (2023) find that the discount rate channel is the primary channel through which climate transitions risks are priced. In additional results from difference-in-differences estimation, we did not find any evidence for effects of green pledges on future earnings, cash flows, or dividends.

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. 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 are 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., 2023).

We use the local projections difference-in-differences (LP-DiD) approach by Dube et al. (2023) for our baseline estimates of the dynamic response of emissions to green pledges. This 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 addition to its simplicity and reliability, a further advantage of LP-DiD is that it allows the common trend assumption to hold conditionally, given that the likelihood of making a green pledge might depend on pre-treatment firm characteristics.[22] In a firm-by-year panel, we estimate the LP-DiD specification

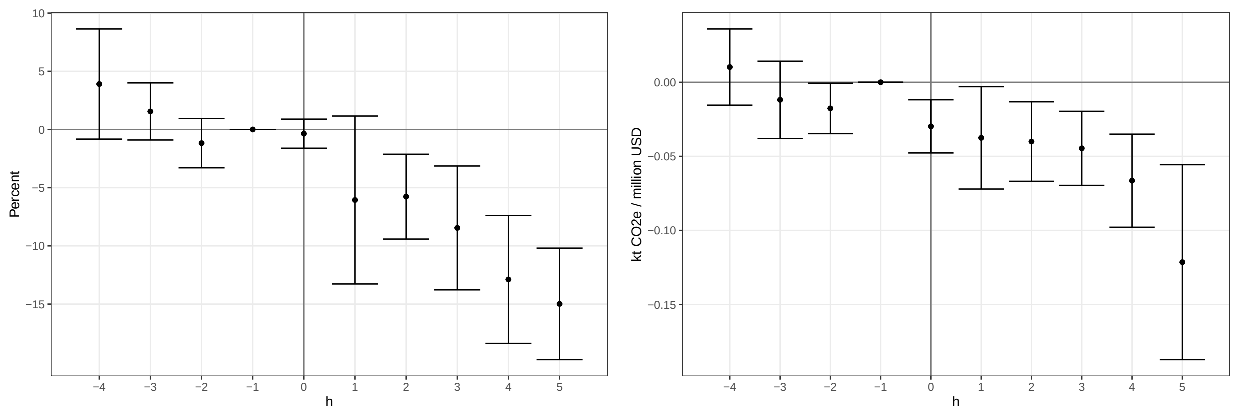
$$y_{i,t+h} - y_{i,t-1} = \beta^h \Delta D_{it} + \sum_{p=1}^{P} \gamma_p^h \Delta y_{i,t-p} + \sum_{m=1}^{M} \sum_{p=0}^{P} \gamma_{mp} \Delta x_{m,i,t-p} + \delta_t^h + \epsilon_{it}^h, \tag{3}$$

where the indicator D_{it} captures the treatment, i.e., whether firm i has issued a green pledge in year t or before.[23] 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 estimates the effects of green pledges on log emissions or emission intensity h years after the pledge. Our LP-DiD regression (3) also includes time 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

[22] Given the heterogeneity of treatment effects, an important question is how these effects are aggregated. Dube et al. (2023) show that under the assumption that the covariates have linear and homogeneous effects, the LP-DiD baseline specification implies a variance-weighted average treatment effect.

[23] In other words, for firm i the indicator D_{it} equals one in the year of its first pledge and all subsequent years. Note that 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.

Figure 4: Impact of green pledges on carbon emissions



(a) Log emissions

(b) Emission intensity

LP-DiD estimates of the effects of green pledges on the log-level of emissions (left panel) or the emission intensity (right panel), using regression (3). 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. The number of observations corresponds to the one-year horizon.

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 six percent lower emissions after one year and 15 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 that issue 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 0.05 (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 intensities are not significantly different between firms with and without a pledge.

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

Table 8: 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	-6.06^{*}	-10.63^{***}	-5.24	-6.26	-5.90^{**}	-7.99^{***}
	(3.68)	(0.89)	(3.20)	(4.67)	(2.11)	(2.98)
5 years	-14.98^{***}	-20.00^{***}	-5.02	-12.66^{**}	-4.45^{*}	-12.00^{**}
	(2.44)	(1.95)	(3.53)	(5.81)	(2.71)	(5.71)
Observations	11,198	20,424	17,305	30,640	17,305	30,640
(B) Emission intensity						
1 year	-0.038^{**}	-0.045^{*}	-0.036	-0.065^{**}	-0.048^{**}	-0.056^{**}
	(0.017)	(0.023)	(0.031)	(0.035)	(0.018)	(0.024)
5 years	-0.123^{***}	-0.125^{***}	-0.079^{*}	-0.102^{*}	-0.098^{*}	-0.096^{**}
	(0.035)	(0.033)	(0.047)	(0.057)	(0.054)	(0.049)
Observations	11,197	20,400	17,302	30,608	17,302	30,608
Controls	Y	N	Y	N	Y	N
Time FE	Y	Y	Y	Y	Y	Y
Firm FE	N	N	Y	Y	Y	Y

Alternative estimates of the average treatment effect on firm level emissions one and five years after a firm's first green pledge. Columns 1 and 2 show LP-DiD estimates following Dube et al. (2023), 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. Sample period: January 2005 to December 2023.

difference between a firm's emissions after making a green pledge and the emissions it would have produced had it not committed to the pledge. This common objective allows for a meaningful comparison of the estimated effects across different methods. Table 8 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 8 also shows that controlling for pre-treatment firm characteristics only slightly reduces the estimated magnitudes. Overall, the estimates in Table 8 demonstrate the robustness of our main results across different estimation methods and specifications.

Two points should be kept in mind when interpreting the results in this section. First, these estimates do not capture causal effects, since green pledges are of course neither random nor exogenous and thus not "treatments" in the traditional sense. A firm may well have had long-standing plans for decarbonization, and the public release of these plans is merely the last step before their implementation. Our estimates capture a predictive relationship, akin to Granger causality, but this predictive relationship is key to understanding the actual information content of corporate green pledges. Second, our evidence shows reductions in emissions, but does not directly speak to the question *how* firms decrease their emissions. There are two broadly different strategies, among others: Companies could invest in green technologies and in this way lower emissions in their production processes. Alternatively they might simply divest from certain high-emission business lines, potentially selling these to other companies. Berg et al. (2024) note that divestment is often the main reason for emission reduction of large emitters.

Although corporate green pledges neither cause lower emissions nor tell investors how emissions will be reduced, they contain new information that lowers the expected trajectory for future firm-level emissions. And because emissions are a meaningful proxy measure for a firm's exposure to climate transition risk, green pledges can lower the perceived transition risk exposure and required carbon premium. Alternatively, lower emissions can increase the appeal of a stock for investors that have non-pecuniary green preferences. Through these two channels, our finding that emissions decrease after a green pledge rationalizes the strong and positive stock market response documented in Section 4. The estimated decline in emissions gives investors good reasons to view corporate green pledges as credible, and reduces concerns about greenwashing and cheap talk in climate commitments.

6 Conclusion

The transition to a net-zero economy poses a major challenge for corporations. Regulations to reduce emissions will impose future costs on firms and might make their business models obsolete. By committing to reduce emissions, companies can lower their exposure towards such transition risks and make their stock more attractive to investors. However, strategies to reduce emissions can be costly and have negative effects on profitability. The outcomes from decarbonization strategies are also uncertain and involve risks. Hence, whether commitments to reduce emissions have positive or negative effects on firm valuations is ambiguous.

Using a new database of corporate climate commitments derived from news articles with a large language model, we study the stock market effects of these commitments. Event-study results clearly show that firms who commit to decarbonize experience a significant increase in their stock price. Our results suggest that a decarbonization commitment reduces the carbon premium, as stocks become greener and thus more desirable due to lower transition risk and/or green preferences, and that investors perceived these positive effects on company valuations to outweigh the costs and risks from decarbonization. This evidence supports the view that investors require significant compensation for transition risks, consistent with the carbon premium hypothesis of Pastor et al. (2021), and that companies are able to reduce their transition risk exposure and 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 emission levels and emission intensities. This result rationalizes the positive stock market reaction, because investors have good reasons to view green pledges as credible. Furthermore, this result suggests that the financial incentive for climate commitments, in the form of higher stock valuations and lower cost of capital, appear 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 binary classification method using GPT-4 can be extended in several directions. Using an open-source, local language model would ensure reproducibility and allow for fine-tuning of the model (Cook et al., 2023). To go beyond our binary classification, LLMs can be used to differentiate between different types of commitments according to their stringency and ambition, the amount and time horizon of the planned reductions of emissions (e.g., net-zero versus other commitments), specificity and concreteness of the goals, existence of actionable plans, and other criteria. For promising new work in this direction, see for example Colesanti Senni et al. (2024); their approach could be extended to score the ambition, credibility, and feasibility of decarbonization commitments using common indicators. Announcements that score higher on these dimensions may well lead to an even more positive stock market reaction. 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. On the methodological side, while our analysis indicates that the carbon premium declines in response to green pledges, it does not speak to the relative importance of transition risk premia in brown stocks vs. investor preferences for green stocks, the two key channels proposed in the literature to explain a carbon premium (Pastor et al., 2021, 2022). Combining our event-study methodology with data on green investor fund flows, as in Patozi (2024), could potentially help researchers make progress on this important issue. Finally, future research should address the question whether on aggregate, corporate climate commitments are sufficient to decarbonize the economy, or quantify the shortfall between corporate commitments and national net-zero goals. New 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 Codebook

In the following we present the codebook provided to the human coders in order to identify green pledges in the newswire articles. In particular, we assigned them the following task:

> In a new research project, we are investigating the financial and environmental effects of corporate announcements of decarbonization commitments. To identify these announcements from corporate news articles, we need your help!
> A *decarbonization commitment* is defined as follows: *A firm makes a clear, actionable commitment to significantly reduce future greenhouse gas emissions.* Greenhouse gases include carbon dioxide (CO_2) and methane.
> In the attached Excel list, you will find a random selection of news articles from Dow Jones (DJ newswires and Wall Street Journal articles). We are asking you to please identify decarbonization commitments in these articles.
>
> *Please read carefully through each article, decide whether it constitutes a decarbonization commitment.* Then label it accordingly with "yes" (positive: the announcement contains a decarbonization commitment) or "no" (negative—no decarbonization commitment).
>
> Please 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.

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 0.02%, with a standard deviation of 3.02. Firms emit on average 2.26 million tons of CO_2 annually and 0.24 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

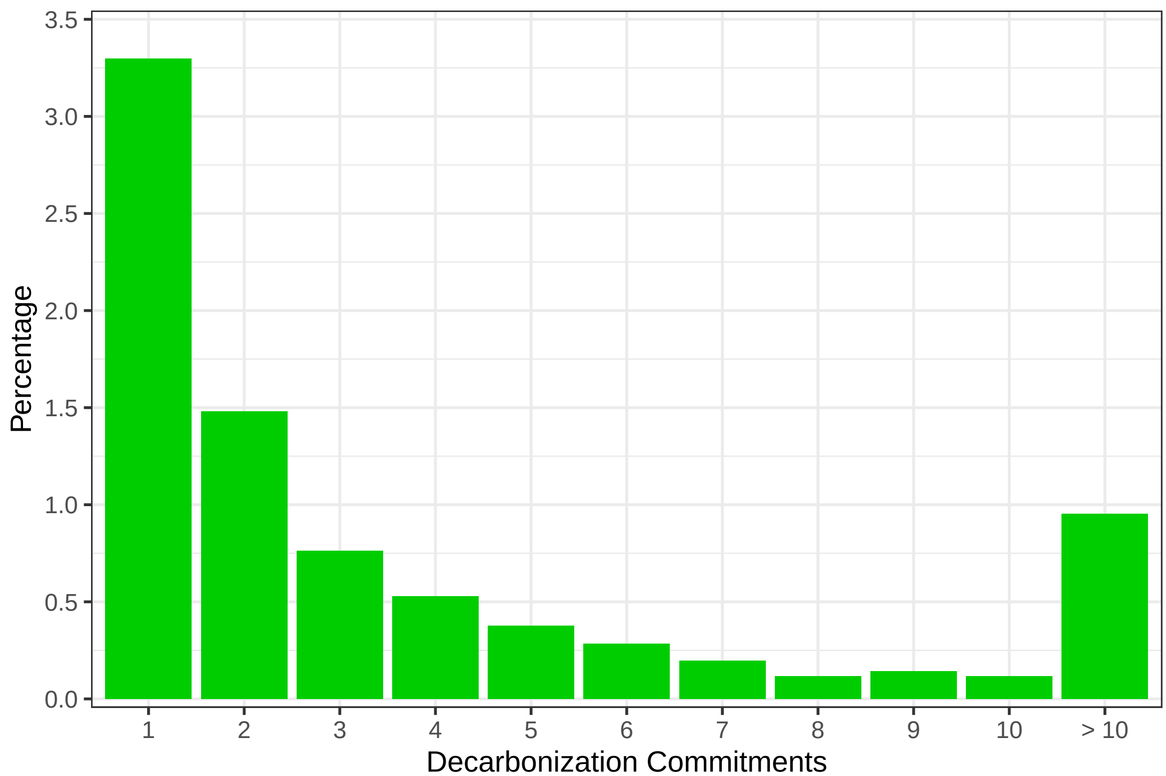
	Mean	SD	q1	q25	Median	q75	q99	No. Obs
Return (%)	0.02	3.02	-10.26	-1.11	0.00	1.07	11.57	44,277,215
Emissions	2.26	8.59	0.00	0.01	0.08	0.50	63.27	30,436
Log Emissions	11.25	2.92	4.17	9.42	11.32	13.12	17.96	30,436
Emission intensity	0.24	0.70	0.00	0.01	0.04	0.09	4.78	30,412
Size	12.62	2.17	7.80	11.11	12.56	14.08	17.90	44,271,554
Book-to-market	1.35	3.94	0.03	0.30	0.55	0.94	32.57	93,675
Leverage	4.13	5.13	1.04	1.50	2.22	4.08	34.38	94,234
Sales growth	0.15	0.50	-0.84	-0.03	0.07	0.20	3.44	84,244
Return on equity	-0.04	0.55	-3.24	-0.06	0.08	0.16	1.45	83,261

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 3.3% of the firms have made one commitment over the full sample period. Roughly 1.5% of the firms have made two commitments over time and 0.75% have made three commitments. About 1% of the companies have made more than ten green pledges over time. Notably, 11,653 of U.S. firms (91.75%) have not made any green pledge at all.

Figure C.1: Distribution of green pledges across firms

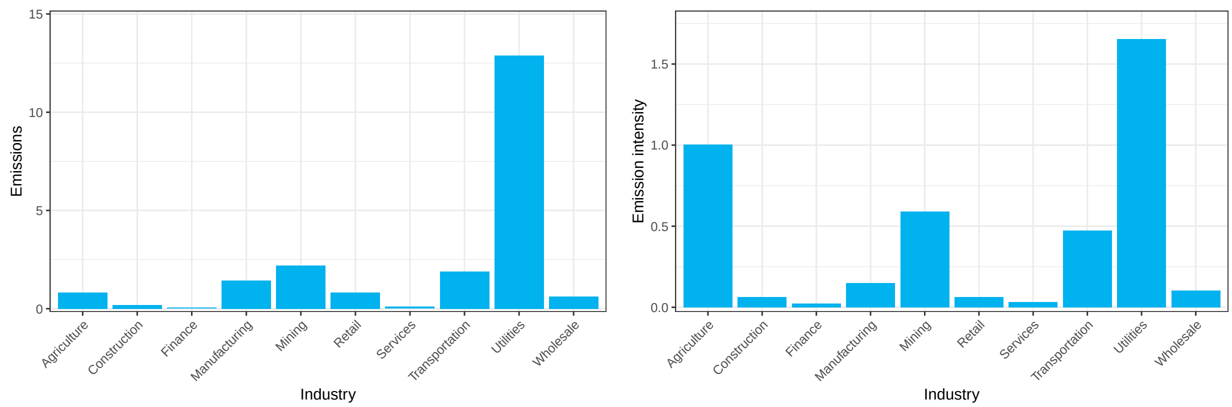


The figure shows the percentage of firms with a given number of decarbonization commitments over our sample. Sample period: January 2005 to December 2023.

Figure C.2, panel (a) reports the average firm level emissions for each industry. For this, we first compute average firm-level emissions over time and then calculate the average across firms within the respective industry. Firms in the utilities sector have the highest emissions (12.9 million tons CO_2 on average), followed by traditional brown industries such as mining, manufacturing and transportation. Panel (b) shows emission intensities by industry, presenting a similar pattern as emission levels. Utilities has the highest emission intensity, with firms emitting on average 1.66 kilotons of CO_2 per million US dollars of revenue, followed by agriculture, mining and transportation.

Table C.1 shows results for the stock market response to green pledges estimated using

Figure C.2: Average emissions and emission intensities per industry



(a) Emisson levels

(b) Emission intensity

Emissions per industry. Panel (a) plots the average emissions and panel (b) the emission intensities for each industry, using the industry classifications of Bali et al. (2016). Emissions are measured in million tons of CO_2, emission intensity is measured in kilotons of CO_2 per million US dollars. Values are winsorized at the 1%/99% level. Sample period: January 2005 to December 2023.

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 4 with daily stock returns being on average about 0.12% higher on the announcement day of a green pledge compared to non-announcement days and the effect is significant at the 1% level for both specifications.

Table C.2 reports results for the stock market to green pledges for the sub-periods 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 towards 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 emission in order to keep the global surface temperature to below 2°C above pre-industrial levels. Bolton and Kacperczyk (2021) and Bolton and Kacperczyk (2023c) 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

Table C.1: Stock market response to green pledges - robustness

	(1)	(2)
Green pledges	0.124***	0.130***
	(0.04)	(0.04)
Book-to-market	-5.518	-5.519
	(5.07)	(5.07)
Leverage	-0.973**	-0.973**
	(0.39)	(0.39)
Size	0.005*	0.004*
	(0.00)	(0.00)
Sales growth	-13.014***	-13.014***
	(4.09)	(4.09)
Return on equity	54.660***	54.661***
	(6.68)	(6.68)
Number of Obs.	14,815,228	14,815,228
R^2	0.18	0.18
Fixed effects		
Sector	Yes	Yes
Time	Yes	Yes
Firm	No	No

Panel regressions of daily stock returns on the green pledges event dummy. 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 fixed effects are based on 2-digit SIC codes. Standard errors, clustered by firm and time, are given in parentheses. ***, **, and * indicate significance at the 1%-, 5%-, and 10%-level, respectively. Sample period: January 2005 to December 2023.

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 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 (c) for the sample that requires at least a 30 day distance between two consecutive pledges

Table C.2: Stock market response to first green pledges before and after the Paris agreement

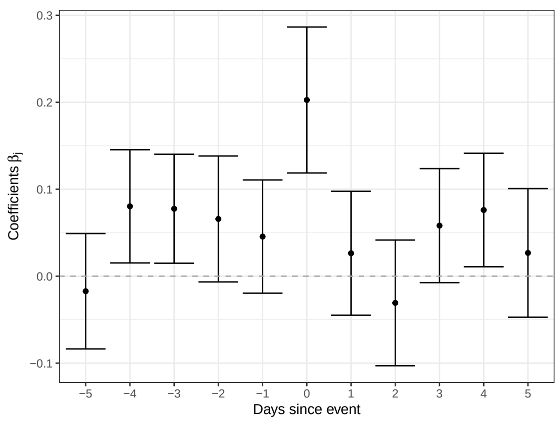
	All green pledges		First green pledges	
Model:	Pre-Paris	Post-Paris	Pre-Paris	Post-Paris
Green pledges	0.1282**	0.1413***	0.3702**	0.2263
	(0.0616)	(0.0481)	(0.1734)	(0.1380)
Book-to-market	-3.052	-11.85	-3.050	-11.81
	(6.224)	(7.578)	(6.224)	(7.579)
Sales growth	-18.40***	-8.909	-18.40***	-8.919
	(4.442)	(5.595)	(4.442)	(5.595)
Leverage	-1.151**	-0.6660	-1.151**	-0.6642
	(0.5354)	(0.5090)	(0.5354)	(0.5089)
log size	0.0015	0.0084***	0.0015	0.0084***
	(0.0035)	(0.0030)	(0.0035)	(0.0030)
Return on equity	59.20***	48.88***	59.20***	48.86***
	(7.060)	(8.576)	(7.060)	(8.575)
Fixed effects				
Industry	Yes	Yes	Yes	Yes
Time	Yes	Yes	Yes	Yes
Number of Obs.	9,278,188	5,537,040	9,278,188	5,537,040
R^2	0.17	0.20	0.17	0.20

Panel regressions of daily stock returns on the green pledges event dummy. 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. Industry fixed effects are based on 2-digit SIC codes. Standard errors, clustered by firm and time, are given in parentheses. ***, **, and * indicate significance at the 1%-, 5%-, and 10%-level, respectively.

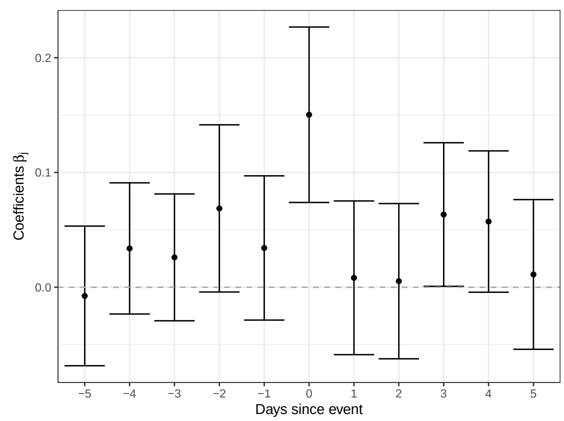
by a firm.

Table C.3 shows the stock market reaction to first green pledges for different sorting groups. Stocks are assigned to each quintile group based on either emissions levels, emission intensities or size. We find that the positive stock market reaction to first green pledges is primarily driven by firms with high emission levels and intensities.

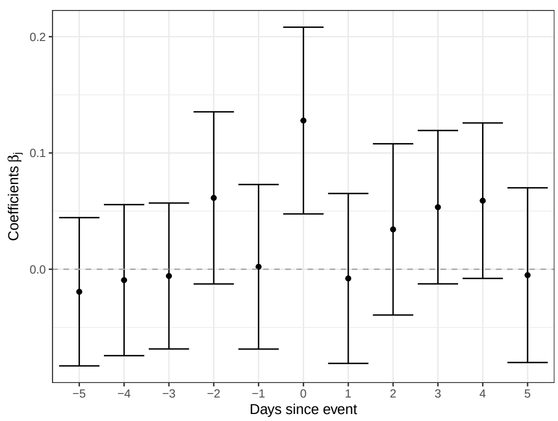
Figure C.3: Stock return response around green pledges - robustness



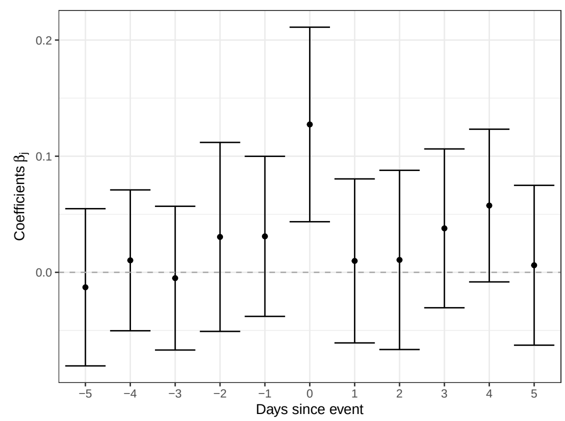
(a) No controls



(b) Firm-time fixed effects



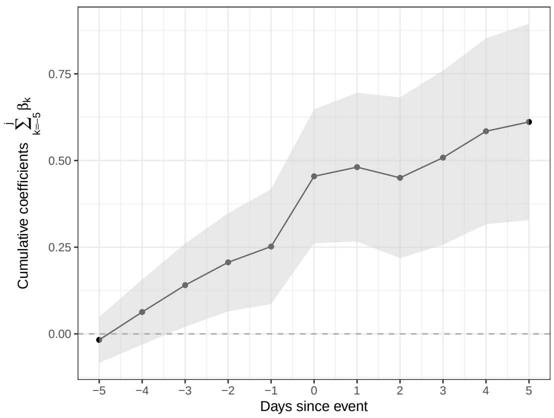
(c) Only pledges that tag a single firm



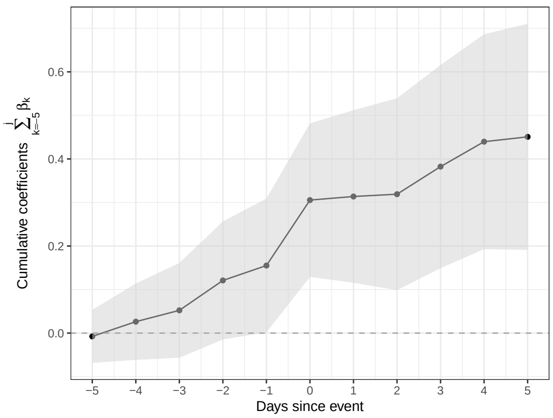
(d) 30 day distance between pledges

The figure plots the coefficients β_j of the equation (2) which regresses stock returns on event dummies, 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 (c) 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 time and are shown around the point estimate. Sample period: December 2005 to January 2023.

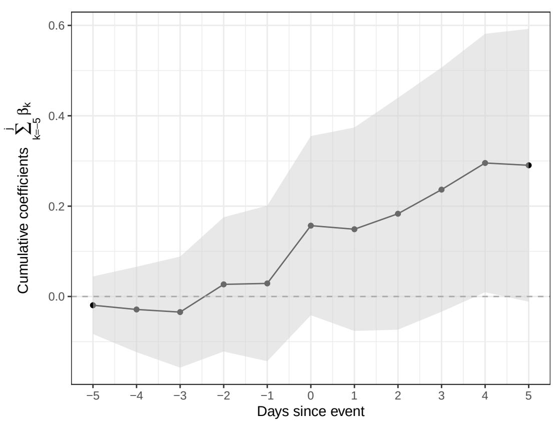
Figure C.4: Cumulative stock return response around green pledges - robustness



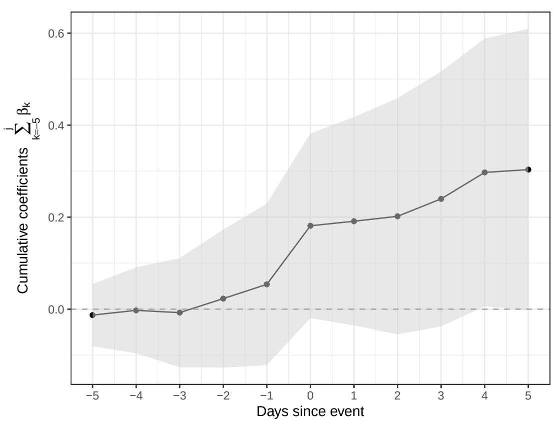
(a) No controls



(b) Firm-time fixed effects



(c) At maximum one mentioned ISIN per article



(d) At least 30 days between firm announcements

The figure plots the cumulative coefficients β_j of the equation (2) which regresses stock returns on event dummies, 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 (c) 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 time and are shown around the point estimate. Sample period: December 2005 to January 2023.

Table C.3: Cross-sectional response of stock returns to first green pledges

	Quintile				
	5	4	3	2	1
(A): Emissions					
Coefficient	0.337*	0.158	0.007	0.358	-0.342
Std. err.	(0.20)	(0.20)	(0.28)	(0.42)	(0.52)
R^2	0.34	0.35	0.33	0.30	0.30
Nr. of obs.	757,179	835,481	889,130	842,668	944,896
Nr. of events	162	134	82	42	13
(B): Emission intensity					
Coefficient	0.311	0.271	-0.131	0.228	0.027
Std. err.	(0.24)	(0.29)	(0.25)	(0.25)	(0.20)
R^2	0.33	0.30	0.27	0.31	0.46
Nr. of obs.	741,486	776,389	953,928	880,731	916,820
Nr. of events	139	74	73	88	59
(C): Size					
Coefficient	0.094	0.174	0.882*	0.368	1.156
Std. err.	(0.10)	(0.24)	(0.47)	(1.31)	(1.60)
R^2	0.37	0.36	0.32	0.17	0.05
Nr. of obs.	2,538,665	2,513,622	2,575,396	2,609,900	2,612,323
Nr. of events	335	132	79	20	18

This table reports the results from regressions of daily stock returns on the first green pledge event dummies for quintile group based on log carbon emission, emission intensity, and size. Controls are book-to-market, sales growth, leverage, size, and return on equity. All regressions include industry and time fixed effects. Standard errors which are clustered by firm and time 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.

References

Acharya, Viral V., Robert F. Engle, and Olivier Wang (2024) "Strategic Commitments to Decarbonize: The Role of Large Firms, Common Ownership, and Governments," Working Paper.

Aldy, Joseph E., Patrick Bolton, Zachery M. Halem, Marcin T. Kacperczyk, and Peter R. Orszag (2024) "Show and Tell: An Analysis of Corporate Climate Messaging and its Financial Impacts," SSRN Working Paper.

Aldy, Joseph E., Patrick Bolton, Marcin Kacperczyk, and Zachery M. Halem (2023) "Behind schedule: The corporate effort to fulfill climate obligations," *Journal of Applied Corporate Finance*, 35 (2), 26–34.

Aprigliano, Valentina, Simone Emiliozzi, Gabriele Guaitoli, Andrea Luciani, and Libero Marcucci, Juri and Monteforte (2023) "The power of text-based indicators in forecasting Italian economic activity," *International Journal of Forecasting*, 39 (2), 791–808.

Ardia, David, Keven Bluteau, Kris Boudt, and Koen Inghelbrecht (2023) "Climate Change Concerns and the Performance of Green vs. Brown Stocks," *Management Science*, 69 (12).

Ash, Elliott and Stephen Hansen (2023) "Text algorithms in economics," *Annual Review of Economics*, 15, 659–688.

Aswani, Jitendra, Aneesh Raghunandan, and Shiva Rajgopal (2023) "Are Carbon Emissions Associated with Stock Returns?" *Review of Finance*, 28 (1), 75–106.

Atilgan, Yigit, K. Ozgur Demirtas, Alex Edmans, and A. Doruk Gunaydin (2023) "Does the Carbon Premium Reflect Risk or Mispricing?" working paper, European Corporate Governance Institute.

Audrino, Francesco and Eric A. Offner (2024) "The impact of macroeconomic news sentiment on interest rates," *International Review of Financial Analysis*, 94, 103293.

Baker, Andrew C, David F Larcker, and Charles CY Wang (2022) "How much should we trust staggered difference-in-differences estimates?" *Journal of Financial Economics*, 144 (2), 370–395.

Bali, Turan G., Robert F. Engle, and Scott Murray (2016) *Empirical asset pricing: The cross section of stock returns*: John Wiley & Sons.

Ball, Ray and Philip Brown (1968) "An Empirical Evaluation of Accounting Income Numbers," *Journal of Accounting Research*, 6 (2), 159–178.

Banz, Rolf W. (1981) "The relationship between return and market value of common stocks," *Journal of Financial Economics*, 9 (1), 3–18.

Barbaglia, Luca, Sergio Consoli, and Sebastiano Manzan (2023) "Forecasting with economic news," *Journal of Business & Economic Statistics*, 41 (3), 708–719.

Bauer, Michael D., Daniel Huber, Glenn D. Rudebusch, and Ole Wilms (2022) "Where is the carbon premium? Global performance of green and brown stocks," *Journal of Climate Finance*, 1, 100006.

Bauer, Michael D., Eric A. Offner, and Glenn D. Rudebusch (2024) "The Effect of U.S. Climate Policy on Financial Markets: An Event Study of the Inflation Reduction Act," forthcoming *Advances in Econometrics*.

Beaver, William H. (1968) "The Information Content of Annual Earnings Announcements," *Journal of Accounting Research*, 6, 67–92.

Beckmann, Lars, Heiner Beckmeyer, Ilias Filippou, Stefan Menze, and Guofu Zhou (2024) "Unusual Financial Communication - Evidence from ChatGPT, Earnings Calls, and the Stock Market," SSRN Working Paper.

Berg, Tobias, Lin Ma, and Daniel Streitz (2024) "Out of sight, out of mind: Divestments and the Global Reallocation of Pollutive Assets," SSRN Working Paper.

Bingler, Julia, Mathias Kraus, Markus Leippold, and Nicolas Webersinke (2022) "Cheap talk and cherry-picking: What ClimateBert has to say on corporate climate risk disclosures," *Finance Research Letters*, 47, 102776.

——— (2024) "How cheap talk in climate disclosures relates to climate initiatives, corporate emissions, and reputation risk," *Journal of Banking & Finance*, 164, 107191.

Bolton, Patrick and Marcin Kacperczyk (2021) "Do investors care about carbon risk?" *Journal of Financial Economics*, 142 (2), 517–549.

——— (2023a) "Are carbon emissions associated with stock returns? Comment," *Review of Finance*, 28 (1), 107–109.

——— (2023b) "Firm Commitments," Finance Working Paper 990/2024, Columbia Business School, European Corporate Governance Institute.

——— (2023c) "Global Pricing of Carbon-Transition Risk," *Journal of Finance*, 78 (6), 3677–3754.

Callaway, Brantly and Pedro HC Sant'Anna (2021) "Difference-in-differences with multiple time periods," *Journal of Econometrics*, 225 (2), 200–230.

Cepoi, Cosmin-Octavian (2020) "Asymmetric dependence between stock market returns and news during COVID-19 financial turmoil," *Finance Research Letters*, 36, 101658.

Chan, Wesley S. (2003) "Stock price reaction to news and no-news: drift and reversal after headlines," *Journal of Financial Economics*, 70 (2), 223–260.

Colesanti Senni, Chiara, Tobias Schimanski, Julia Bingler, Jingwei Ni, and Markus Leippold (2024) "Combining AI and Domain Expertise to Assess Corporate Climate Transition Disclosures," SSRN Working Paper.

Cook, Thomas R., Sophia Kazinnik, Anne Lundgaard Hansen, and Peter McAdam (2023) "Evaluating Local Language Models: An Application to Financial Earnings Calls," Research Working Paper 23-12, Federal Reserve Bank of Kansas City.

Driscoll, John C. and Aart C. Kraay (1998) "Consistent covariance matrix estimation with spatially dependent panel data," *Review of Economics and Statistics*, 80 (4), 549–560.

Dube, Arindrajit, Daniele Girardi, Oscar Jorda, and Alan M Taylor (2023) "A local projections approach to difference-in-differences event studies," Working Paper 31184, National Bureau of Economic Research.

Dzieliński, Michał, Florian Eugster, Emma Sjöström, and Alexander F. Wagner (2023) "Do firms walk the climate talk?" Research Paper 22-14, Swiss Finance Institute.

Ehrmann, Michael and Marcel Fratzscher (2004) "Taking stock: Monetary policy transmission to equity markets," *Journal of Money, Credit and Banking*, 719–737.

Eloundou, Tyna, Sam Manning, Pamela Mishkin, and Daniel Rock (2024) "GPTs are GPTs: Labor market impact potential of LLMs," *Science*, 384 (6702), 1306–1308.

Engle, Robert F., Stefano Giglio, Bryan T. Kelly, Heebum Lee, and Johannes Stroebel (2020) "Hedging Climate Change News," *Review of Financial Studies*, 33 (3), 1184–1216.

Eskandari, Ruhollah and Morteza Zamanian (2023) "Heterogeneous responses to corporate marginal tax rates: Evidence from small and large firms," *Journal of Applied Econometrics*, 38 (7), 1018–1047.

Eskildsen, Marc, Markus Ibert, Theis Ingerslev Jensen, and Lasse Heje Pedersen (2024) "In search of the true greenium," SSRN Working Paper.

Faccini, Renato, Rastin Matin, and George Skiadopoulos (2023) "Dissecting climate risks: Are they reflected in stock prices?" *Journal of Banking & Finance*, 155, 106948.

Fama, Eugene F., Lawrence Fisher, Michael C. Jensen, and Richard Roll (1969) "The Adjustment of Stock Prices to New Information," *International Economic Review*, 10 (1), 1–21.

Fama, Eugene F. and Kenneth R. French (1995) "Size and book-to-market factors in earnings and returns," *Journal of Finance*, 50 (1), 131–155.

Gentzkow, Matthew, Bryan T. Kelly, and Matt Taddy (2019) "Text as data," *Journal of Economic Literature*, 57 (3), 535–574.

Grimmer, Justin, Margaret E. Roberts, and Brandon M. Stewart (2022) *Text as data: A new framework for machine learning and the social sciences*: Princeton University Press.

Hansen, Anne Lundgaard, John J. Horton, Sophia Kazinnik, Daniela Puzzello, and Ali Zarifhonarvar (2024) "Simulating the Survey of Professional Forecasters," Working Paper.

Hansen, Anne Lundgaard and Sophia Kazinnik (2023) "Can ChatGPT Decipher Fedspeak?," SSRN Working Paper.

Hartzmark, Samuel M. and Kelly Shue (2023) "Counterproductive sustainable investing: The impact elasticity of brown and green firms," SSRN Working Paper.

Huij, Joop, Dries Laurs, Philip A. Stork, and Remco C. J. Zwinkels (2024) "Carbon Beta: A Market-Based Measure of Climate Risk Transition Exposure," Working Paper.

Ilhan, Emirhan, Zacharias Sautner, and Grigory Vilkov (2020) "Carbon Tail Risk," *The Review of Financial Studies*, 34 (3), 1540–1571.

In, Soh Young, Ki Young Park, and Ashby Monk (2019) "Is 'Being Green' Rewarded in the Market? An Empirical Investigation of Decarbonization and Stock Returns," working paper, Stanford Global Project Center.

Jha, Manish, Jialin Qian, Michael Weber, and Baozhong Yang (2024) "ChatGPT and corporate policies," Working Paper 32161, National Bureau of Economic Research.

Jiang, Shifu (2024) "Corporate decarbonisation targets, stock performance, and investment," Working Paper.

Ke, Zheng Tracy, Bryan T. Kelly, and Dacheng Xiu (2020) "Predicting returns with text data," Working Paper 26186, National Bureau of Economic Research.

Kim, Jae Hyoung (2022) "Labor Market Information and Predictable Returns," Swedish House of Finance Research Paper.

Korinek, Anton (2023) "Generative AI for economic research: Use cases and implications for economists," *Journal of Economic Literature*, 61 (4), 1281–1317.

Kothari, Sagar P. and Jerold B. Warner (2007) "Econometrics of event studies," in *Handbook of Empirical Corporate Finance*, 3–36: Elsevier.

Krüger, Philipp (2015) "Corporate Goodness and Shareholder Wealth," *Journal of Financial Economics*, 115 (2), 304–329.

Krüger, Philipp, Zacharias Sautner, and Laura T. Starks (2020) "The Importance of Climate Risks for Institutional Investors," *The Review of Financial Studies*, 33 (3), 1067–1111.

Li, Qing, Hongyu Shan, Yuehua Tang, and Vincent Yao (2024) "Corporate Climate Risk: Measurements and Responses," *The Review of Financial Studies*, 37 (6), 1778–1830.

Lopez-Lira, Alejandro and Yuehua Tang (2024) "Can ChatGPT Forecast Stock Price Movements? Return Predictability and Large Language Models," arXiv preprint arXiv:2304.07619.

MacKinlay, A. Craig (1997) "Event studies in economics and finance," *Journal of Economic Literature*, 35 (1), 13–39.

Nemes, Noémi, Stephen J. Scanlan, Pete Smith et al. (2022) "An integrated framework to assess greenwashing," *Sustainability*, 14 (8), 4431.

Pastor, Lubos, Robert F. Stambaugh, and Lucian A. Taylor (2021) "Sustainable Investing in Equilibrium," *Journal of Financial Economics*, 142 (2), 550–571.

——— (2022) "Dissecting green returns," *Journal of Financial Economics*, 146 (2), 403–424.

——— (2024) "Carbon Burden," Working Paper 33110, National Bureau of Economic Research.

Patozi, Alba (2024) "Green transmission: Monetary policy in the age of ESG," SSRN Working Paper.

Roth, Jonathan, Pedro HC Sant'Anna, Alyssa Bilinski, and John Poe (2023) "What's trending in difference-in-differences? A synthesis of the recent econometrics literature," *Journal of Econometrics*, 235 (2), 2218–2244.

Sastry, Parinitha R., Emil Verner, and David Marques Ibanez (2024) "Business as Usual: Bank Net Zero Commitments, Lending, and Engagement," Working Paper 32402, National Bureau of Economic Research.

Sautner, Zacharias, Laurence van Lent, Grigory Vilkov, and Ruishen Zhang (2023a) "Firm-level climate change exposure," *Journal of Finance*, 78 (3), 1449–1498.

——— (2023b) "Pricing Climate Change Exposure," *Management Science*, 69 (12), 7540–7561.

Sloan, Richard G. (1996) "Do Stock Prices Fully Reflect Information in Accruals and Cash Flows about Future Earnings?" *The Accounting Review*, 71 (3), 289–315.

Sun, Liyang and Sarah Abraham (2021) "Estimating dynamic treatment effects in event studies with heterogeneous treatment effects," *Journal of Econometrics*, 225 (2), 175–199.

Zhang, Shaojun (2024) "Carbon Returns Across the Globe," *Journal of Finance*, forthcoming.