# Legislator Tweets About the Green Transition and the Returns of Green versus Brown Stocks

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**Abstract**

To study the impact of green-transition regulation on firm value, we analyze stock returns around legislator tweets about climate change. Green stocks significantly outperform brown stocks in the one-to-ten-minute window around pro-transition tweets. A one standard deviation increase in legislator-tweet sentiment toward the green transition is associated with an average increase of $509,766 in the market value of a green firm relative to an otherwise similar brown firm. For tweets that mention environmental regulations, the spread increases in the weeks preceding a congressional vote and vanishes afterward, with the effect driven by tweets posted ahead of *close* votes. Our findings suggest that the green transition impacts the relative performance of green and brown stocks—at least partly—via a regulatory channel.

*Keywords*: climate change, sustainability, transition regulation, social media, high-frequency identification
*JEL Classification*: D72, G10, G12, G14

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# 1 Introduction

Climate change has prompted legislators to regulate carbon emissions—a process known as the green transition. We study the impact of green-transition regulation on firm value by comparing the returns of green and brown stocks in the minutes around tweets about climate change posted by members of U.S. Congress. We find that green stocks outperform brown stocks in the one-to-ten-minute window around pro-transition tweets, with the return spread statistically significant at the 1% level. The effect is also economically significant: a one standard deviation increase in legislator-tweet sentiment toward the green transition generates an average increase of $509,766 in the market valuation of a green firm relative to an otherwise similar brown firm around a legislator tweet. Moreover, we find that the market correctly anticipates which high-emission firms can decarbonize their operations in response to green-transition shocks. To focus on the regulatory channel, we consider legislator tweets that mention specific environmental regulations, and find that the spread between the returns of green and brown stocks around tweets that support pro-transition regulations increases in the weeks leading to a congressional vote and vanishes afterward, with the effect driven by tweets posted ahead of *close* votes. Our findings suggest that the green transition impacts the relative performance of green and brown stocks, at least in part, via a regulatory channel.

Legislators often use social media platforms such as Twitter (now X) to express their views on the appropriate pace and specific policies required to transition to a green economy. For example, consider the Climate Action Now Act, voted on in the House of Representatives in 2019, which sought to prevent the president from withdrawing the U.S. from the Paris Agreement and require the administration to develop a plan for meeting the agreements emissions reduction goals.[1] As shown in Figure 1, while Democratic Representative Darren Soto tweeted the day before the vote to support the regulation, emphasizing that it would prevent the Trump administration's withdrawal from the Paris Agreement, Republican Representative Doug LaMalfa tweeted to oppose the regulation, urging his colleagues to vote

[1] The bill passed the House of Representatives on May 2, 2019, but was never brought to a vote in the Senate, as the Republican majority, led by then-Senate Majority Leader Mitch McConnell, opposed the measure and declined to advance it, aligning with the Trump administrations decision to exit the Paris Agreement.

**Figure 1:** Legislator tweets about Climate Action Now Act

This figure contains two legislator tweets about the the Climate Action Now Act, voted on in the House of Representatives in 2019, which was intended to prevent the president from withdrawing the United States from the Paris Agreement and require the administration to develop a plan for meeting the agreements emissions reduction goals. While Democratic Representative Darren Soto tweeted the day before the vote to support the regulation, Republican Representative Doug LaMalfa tweeted against it.


against the "partisan attack on American energy production." These statements contain information about the probability that the legislators will support pro-transition regulations in Congress, and thus, may affect firm value.

One would expect transition regulation to have a negative impact on the value of brown firms because of the cost of adapting their production and distribution processes to comply with new regulation, as well as the risk of fines for non-compliance. In contrast, the impact on green firms is likely to be less negative because they are less vulnerable to such regulatory burdens, compared to brown firms. In some cases, green firms can even benefit from climate policies through subsidies or tax incentives. Ultimately, whether and to what extent transition regulation differentially affects green and brown firms is an empirical question. However, measuring the impact of transition regulation on firm value is challenging, among other reasons, because the decision to enact regulation is endogenous and firms may anticipate the introduction of regulation and respond strategically.

To isolate the impact of transition regulation on firm value from that of other potential confounding factors, we leverage the high-frequency identification approach of Bianchi, Gómez-Cram, and Kung (2024) and study the returns of green and brown stocks in the one-to-ten-minute window around legislator tweets about climate change. The rationale for this approach is that legislator tweets contain new information about their views on the green transition, and therefore about the probability that transition regulations will pass future congressional votes. Upon observing the legislator tweets, investors update their expectations about future regulations, and thus their valuations of green and brown firms. Studying stock returns in the minutes around legislator tweets about climate change allows us to isolate the effect of news about green-transition regulation from other confounders. The identification assumption is that no other information is released over such a short window around the tweet that systematically affects the prices of green and brown stocks. To perform the test, we download all tweets posted between January 1, 2014 and March 31, 2023 by the official Twitter accounts of U.S. Congress members. We identify 38,055 legislator tweets about climate change posted during trading hours and use OpenAI's GPT-4.1 to measure their sentiment toward the green transition, defined as the extent to which a tweet is in favor or against the green transition. We validate our GPT sentiment measure by showing in Section IA.1 of the Internet Appendix that it is highly correlated (93.8%) with the average sentiment assigned by five researchers to a random sample of 100 legislator tweets. Each day, we classify the 1,000 largest U.S. stocks as green, gray, or brown based on whether their most recently disclosed greenhouse gas emissions intensity falls in the bottom, middle, or top tercile of the cross section. We then run a panel regression of stock returns around each tweet on tweet sentiment toward the green transition as well as the interaction of tweet sentiment with green and brown dummy variables.

Our main finding is that when legislator-tweet sentiment toward the green transition increases by one standard deviation, the prices of brown firms decrease by 0.077 basis points and those of green firms increase by 0.117 basis points around the legislator tweet, relative to those of gray firms. Thus, legislator support toward the green transition (expressed via twitter) reduces the value of brown firms, which are more exposed to green-transition regulation, and increases the value of green firms, consistent with the notion that such policies benefit firms that use cleaner energy. Overall, a one standard deviation increase in legislator-tweet sentiment toward the green transition generates a spread between the returns of green and brown stocks around a legislator tweet of 0.194 basis points, significant at the 1% level, which translates into an average $509,766 increase in the market valuation of a green firm relative to that of an otherwise similar brown firm around a legislator tweet.

The economic significance of the effect of legislator tweets on stock returns increases as we extend the horizon from 10 minutes after the tweet to one day. For instance, the return spread between the returns of green and brown stocks increases from 0.194 bps to 0.633 bps with each standard deviation increase in tweet sentiment toward the green transition when we extend the event horizon from 10 to 90 minutes. The spread further increases more than tenfold to 2.431 bps one day after the tweet. These findings suggest that it takes at least one day for stock prices to incorporate the information contained in legislator tweets. We further demonstrate that our baseline analysis remains robust to contracting the event horizon around which stock returns are computed, adjusting for market returns, including more granular time fixed effects, using alternative sources of carbon emissions data, and using an alternative carbon intensity measure.

Certain high-emission firms are likely to be more able or willing to adapt their carbon emissions to news about transition regulation than others. If markets can predict which firms will adapt their carbon emissions in response to transition-regulation news, then one would expect that firm returns around pro-transition tweets should be informative about their future carbon emissions. To test this hypothesis, we regress the change in carbon emissions intensity between consecutive firm disclosures on the aggregate stock return around pro-transition legislator tweets during the year leading to the first disclosure. We find that there is no significant relation between the price reaction of *low-emission* firms around legislator tweets and changes in their future carbon emissions intensity, which could be explained by low-emission firms being already carbon efficient. However, high-emission firms with higher returns around pro-transition tweets decarbonize more in the future. This finding reveals that the market correctly identifies and rewards high-emission firms that can better adapt to transition regulation, and thus suggests that the green transition impacts not only firm value, but also real outcomes such as carbon emissions. In addition, our results indicate that brown firms that are not able or willing to decarbonize shoulder a disproportionately large share of the burden imposed by transition regulations.

We then examine the mechanism through which the legislator tweets impact stock prices. First, we show that legislator tweets about climate change contain information that is distinct from that in mainstream media. In particular, we construct a daily ProTransition Sentiment (PTS) index based on legislator tweets. Reassuringly, the PTS index spikes around days on which climate-related regulations are introduced and voted on in Congress. We then study the lead-lag relation between the PTS index and the Media Climate Change Concerns (MCCC) index of Ardia, Bluteau, Boudt, and Inghelbrecht (2023), which proxies for climate-change concerns expressed in mainstream media. To do this, we estimate a vector autoregressive model and find that both indices significantly predict future values of themselves and each other, which demonstrates that legislator tweets do not simply echo or amplify news from mainstream media but contain distinct new information. This suggests the impact of legislator tweets on the relative performance of green and brown stocks occurs via an information channel.

Second, we focus on the regulatory channel by using a dictionary approach to identify a sample of 13,294 legislator tweets that mention specific environmental regulations. Our hypothesis is that these regulatory tweets affect the relative valuation of green and brown firms because they convey information about the likelihood that proposed regulation passes a congressional vote. Consistent with this hypothesis, we find a significant return spread between green and brown firms around regulatory tweets that increases in the weeks leading up to a congressional vote and becomes statistically insignificant afterward. Moreover, because uncertainty about the vote outcome is higher ahead of close votes, we expect tweets posted before such votes to have a larger price impact. Consistent with this hypothesis, we find that the effect of regulatory tweets on the greenbrown return spread is substantially larger in the weeks preceding close votes than in the weeks preceding clear votes. Overall, these findings suggest that the green transition affects the relative performance of green and brown stocks, at least in part, through a regulatory channel.

Our results have implications for policymakers, firms, and investors. Policymakers can alleviate the impact of the green transition on brown firms by adopting a consistent approach to the green transition, thus avoiding abrupt shifts in policy that amplify the negative impact of transition regulation on brown firms. For instance, consider a transition regulation that is approved during a particular presidential or congressional term, but may be repealed or amended during the next term. Firms have to decide whether and how to adapt their operations to the new regulation, knowing that it may be revised or repealed in the future. This reduces firm incentives to adapt and introduces additional costs if Congress eventually revises the regulation in the future. Our work has implications also for high-emission firms—our analysis of the association between stock returns around pro-transition tweets and future carbon emissions suggests that high-emission firms can add value by enhancing their ability to adjust their emissions in response to new regulations. Finally, our manuscript demonstrates that investors should measure asset exposure to transition regulation and manage this exposure in their portfolio—for example, by holding stocks of green firms or brown firms with credible plans to adapt their emissions.

Our work contributes to the climate-finance literature. Pástor, Stambaugh, and Taylor (2021) propose an equilibrium model that incorporates sustainability criteria and generates two predictions. First, "green assets have low expected returns because investors enjoy holding them and because green assets hedge climate risk." Second, "green assets nevertheless outperform" when there are positive shocks to "customers' tastes for green products and investors' tastes for green holdings." A growing literature investigates the first prediction by examining the effect of firm-level carbon emissions on the cross section of stock returns, testing whether investors demand compensation for their exposure to carbon emission risk (Bolton and Kacperczyk, 2021, 2023; Eskildsen et al., 2024). In contrast, we focus on the second prediction of Pástor et al. (2021), similar to Ardia et al. (2023), who construct a daily MCCC index using mainstream media news and show that green firms outperform brown firms when media concerns about climate change increase unexpectedly. However, green stocks should outperform brown stocks not only when climate concerns rise, but also when pro-transition *regulation* becomes more likely, because such regulation burdens noncomplying firms or benefits green firms. Our main contribution is to test this prediction directly by studying stock returns around climate-change tweets posted by legislators.

Moreover, Ardia et al. (2023, p. 7608) acknowledge that endogeneity may be driving the relation between their MCCC index and stock returns: "endogeneity may arise due to a potential feedback loop that an exogenous shock leading to increased concern in climate change affects the pricing of green and brown stocks," and thus they "abstain from any causal interpretation" of their results. Endogeneity may also affect the results in other papers that estimate the correlation between daily or weekly climate-related news indices and stock returns, such as Pástor, Stambaugh, and Taylor (2022), Acharya, Giglio, Pastore, Stroebel, Tan, and Yong (2024), and Arteaga-Garavito, Colacito, Croce, and Yang (2025).[2] Another contribution of our manuscript to the climate-finance literature is to address these endogeneity concerns by leveraging the high-frequency identification approach of Bianchi et al. (2024) to study price movements in the minutes around legislator tweets.

Bianchi et al. (2024) examine legislator tweets that mention specific firms and find that the firm stock returns increase with positive tweet sentiment. Cookson, Fox, Gil-Bazo, Imbet, and Schiller (2026) use a similar identification strategy to analyze the effect of tweets on the distress of U.S. banks during the banking crisis of 2023. In contrast, we shift the focus from firm-specific tweets to *climate-change* tweets, investigating their impact on the prices of a *cross-section* of firms ranked by their carbon emissions intensity.[3]

[2] Pástor et al. (2022) use the climate change concerns index of Ardia et al. (2023) to show that although green assets delivered high returns in recent years, their outperformance reflects unexpectedly strong increases in environmental concerns, not high expected returns, consistent with the predictions of Pástor et al. (2021). Acharya et al. (2024) develop a theoretical model to examine the impact of climate transition risk on the performance of various types of energy firms. To empirically test the model's predictions, they construct three weekly climate transition risk indices based on New York Times news, and analyze the correlation between energy prices, energy firm stock returns, and index innovations. Their empirical results provide strong support for their models predictions. Arteaga-Garavito et al. (2025) construct daily indices based on newspaper-news tweets that measure climate attention across countries and find that a country experiencing more severe climate news shocks tends to see both an inflow of capital and an appreciation of its currency. They also shows that brown stocks experience large and persistent negative returns after a global climate news shock if located in highly exposed countries.

[3] Gómez-Cram and Olbert (2023) study the effect of the global tax reform on firms by examining high-frequency returns around the reform announcements obtained from mainstream media and official sources. In contrast, we study the impact of environmental regulation on firms by using social media posts, which allow a more granular approach. Our focus on the effect of social media posts on the cross section of stock returns also distinguishes our manuscript from the literature that leverages high-frequency identification in macroeconomics (Bernanke and Kuttner, 2005; Nakamura and Steinsson, 2018; Bianchi, Comin, Kung, Kind,

Our work is also related to the emerging literature that uses textual analysis in the context of climate risk. Li, Shan, Tang, and Yao (2024) produce firm-level measures of transition climate risk by applying a dictionary approach to earnings conference calls, and find that transition risk is associated with negative returns for non-proactive firms. Sautner, Van Lent, Vilkov, and Zhang (2023) use machine learning to analyze earnings calls and produce firm-level measures of climate-change exposure, and find that the measures predict asset prices and real outcomes. Kölbel, Leippold, Rillaerts, and Wang (2024) apply BERT, the large language model developed by Google (Devlin et al., 2018), to 10K filings to generate firm-level measures of physical and transition climate risks, and show that disclosure of transition (physical) risk is associated with an increase (decrease) in credit default swap spreads. A distinguishing feature of our work is that we leverage a high-frequency approach to identify the impact of climate-change legislator tweets on the returns of green versus brown stocks.

Empirically, we find that while conventional dictionary-based approaches effectively identify the general tone of social media posts, they often fail to capture sentiment specifically directed toward the green transition. For instance, although the phrase—"carbon tax has decreased"—expresses a negative sentiment toward the green transition, dictionary approaches may classify it as positive because it combines the words *decrease* and *tax*. Instead, we rely on OpenAI's GPT to produce 'context-aware' sentiment that captures this distinction. Thus, our work is related to the emerging literature that uses large language models (LLMs) for economics and finance—Hiew, Huang, Mou, Li, Wu, and Xu (2019) use BERT to obtain social-media post sentiment toward three individual stocks, Chen, Kelly, and Xiu (2022) use GPT and LLaMA embeddings to predict 16 global equity markets based on financial news, Lopez-Lira and Tang (2023) use GPT to predict stock returns based on news headlines, Acharya et al. (2024) use GPT to construct daily transition indexes based on New York Times news articles, Bianchi et al. (2024) study the robustness of their dictionary-based sentiment measure by considering also GPT-generated sentiment in their internet appendix, and Chen, Tang, Zhou, and Zhu (2025) use GPT and DeepSeek to predict the stock market an the macroeconomy based on Wall Street Journal news.

and Matusche, 2019; Gómez-Cram and Grotteria, 2022; Känzig, 2021), which primarily studies aggregate economic quantities such as market returns, inflation, interest rates, and output.

Our work is related to the literature that uses difference-in-differences to examine the impact of carbon regulation on firm emissions. Martin, De Preux, and Wagner (2014) find that the UK carbon tax had a strong negative impact on the electricity use of manufacturing plants, Bartram, Hou, and Kim (2022) show that the California cap-and-trade program led financially constrained firms to shift emissions to other states, Colmer, Martin, Muûls, and Wagner (2025) show that the EU emissions trading system led regulated manufacturing firms to reduce carbon emissions by 15%, and Martinsson, Sajtos, Strömberg, and Thomann (2024) estimate an emission-to-pricing elasticity of two for a Swedish carbon tax. Instead of difference-in-differences, our manuscript relies on a complementary identification strategy based on examining high-frequency stock returns around legislator tweets, which allows us to provide more granular evidence of the impact of environmental regulation on firms and address concerns that firms may anticipate the regulation and act strategically.

Finally, our work is related to the literature that measures the impact of political cycles on how firm value depends on carbon emissions (Santa-Clara and Valkanov, 2003; Pástor and Veronesi, 2020; Addoum and Kumar, 2016). Ramelli, Wagner, Zeckhauser, and Ziegler (2021) show that both carbon-intensive and climate-responsible firms gained following the 2016 election of Donald Trump. They attribute the gains of climate-responsible firms to investors betting on a reversal in climate policy after the 2020 election. Baz, Cathcart, Michaelides, and Zhang (2023) use 10K filings to generate a firm-specific metric of climate-change exposure. They show that the returns of high-exposure firms increased during the twelve months after President Trump's election, a finding they attribute to a subsequent decline in climate-change concern. Mathurin (2024) uses firm press releases to measure firm exposure to environmental policies and green technologies. She shows that the risk premia associated with these two exposures are negatively correlated and their sign and magnitude depend on the political orientation of the government. Our approach based on a real-time stream of legislator tweets provides a more granular view of the effect of politician viewpoints on the value of green versus brown firms.

# 2 Data

This section describes our data. Section 2.1 describes how we obtain legislator tweets, Section 2.2 how we identify climate-change tweets, Section 2.3 how we compile minute-level stock prices, Section 2.4 how we measure legislator-tweet sentiment toward the green transition, and Section 2.5 how we compute carbon emissions intensity.

## 2.1 Compiling legislator tweets

We obtain the official legislative Twitter handles of 489 out of 541 members of the U.S. Congress that served as of March 31, 2023 from *@unitedstatesproject*, as well as information on their house, duration, and party membership. Of the 489 legislators, 244 were Democrats, 242 Republicans, and three independents. For each legislator, we use the Twitter Developer API to collect all tweets posted between January 1, 2014 and March 31, 2023 during each term the legislator served. In total, we obtain 2,830,646 tweets. Of the 2,830,646 tweets, 62.16% were posted by Democrats, 37.12% by Republicans, and only 0.72% by independents.

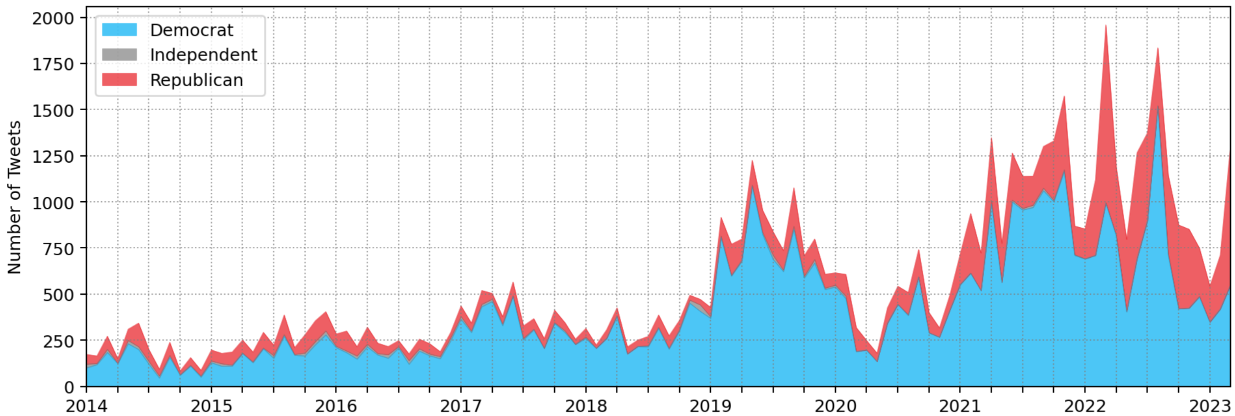
## 2.2 Identifying climate-change tweets

To identify climate-change tweets, we use the ESG4 and ESG9 versions of the large-language model (LLM) FinBERT, which are specifically fine tuned to classify text into ESG categories.[4] The ESG4 model labels text into four categories (Environmental, Social, Governance or None categories) and the ESG9 model into nine categories (Climate Change, Natural Capital, Pollution & Waste, Human Capital, Product Liability, Community Relations, Corporate Governance, Business Ethics & Values, and Non-ESG). The labels produced by the two models are further associated with a confidence score between zero and one.

[4] FinBERT is a domain-specific variant of BERT (Bidirectional Encoder Representations from Transformers) developed by Huang et al. (2020). It is obtained by pre-training BERT on large financial text corpora (e.g., Reuters TRC2, earnings calls, and analyst reports) and subsequently fine-tuned for tasks such as financial sentiment analysis and text classification.

**Figure 2:** Monthly number of climate-change tweets by party

This figure depicts the breakdown of the monthly number of tweets posted by Republicans (red), Democrats (blue), and Independents (gray) between January 2014 and March 2023.




We select 62,067 out of 2,830,646 tweets that are simultaneously labeled as Environmental by the ESG4 model and as Climate Change by the ESG9 model with a confidence score of at least 90%.[5] Figure 2 depicts the time series of the monthly number of climate-change legislator tweets posted by members of each party. Over our sample, 70.7% of climate-change tweets come from Democrats, 27.8% from Republicans, and 1.5% from Independents.

## 2.3 *Compiling high-frequency stock prices*

We select 38,055 out of 62,067 climate-change legislator tweets posted during normal NYSE trading hours. We obtain minute-level stock prices from FirstRate and monthly stock market capitalization from the Center for Research in Security Prices (CRSP). For each calendar year, we sort stocks based on their market capitalization during the last month of the previous calendar year, and select the largest 1,000 stocks, which are liquid stocks whose prices would react quickly to any information in the tweets.

[5] We use both the ESG4 and ESG9 models to ensure that we select tweets that contain climate-change content. One would expect that tweets labeled as Environmental by the ESG4 model would fall into either the Climate Change, Natural Capital, or Pollution & Waste categories of the ESG9 model. However, this is not always the case; tweets classified as Environmental are also sometimes classified into the other six ESG9 categories. This suggests that there is some noise in the classification or that the two models are picking up on slightly different contexts. The latter is plausible because ESG4 FinBERT is trained on 2,000 labeled sentences, while ESG9 FinBERT is separately trained on 14,000 labeled sentences.

## 2.4 Evaluating tweet sentiment toward the green transition

We use OpenAI's GPT-4.1, accessed through the OpenAI API, to measure the sentiment of legislator tweets toward the green transition. Using GPT enables us to obtain contextually relevant responses to specific questions. For each tweet, we use the following prompt:

> *You are a political expert with experience evaluating the stance of public statements toward the green transition. The 'green transition' refers to the comprehensive shift from carbon-intensive energy sources and practices to low-carbon alternatives. Given the following tweet from a member of U.S. Congress, assign a continuous score between –1 and 1, where a value of –1 indicates strong opposition to the green transition, 0 indicates a neutral or ambiguous stance, and 1 indicates strong support for the green transition. If the tweet is unrelated to the green transition, return 99. Return only a single numerical value.*

We set the model temperature to zero to obtain deterministic responses.[6] By providing GPT the option to score tweets 'unrelated' to the green transition as 99, we introduce an additional context-aware robustness check that helps ensure that only genuinely climate-related tweets remain in our sample. Our final sample contains 36,573 unique tweets. Next, we validate the GPT-based tweet sentiment measure by comparing it with the average sentiment generated by five researchers for a random sample of 100 tweets. Section IA.1 of the Internet Appendix shows that the GPT sentiment measure achieves a 93.8% correlation with the average sentiment generated by the researchers.

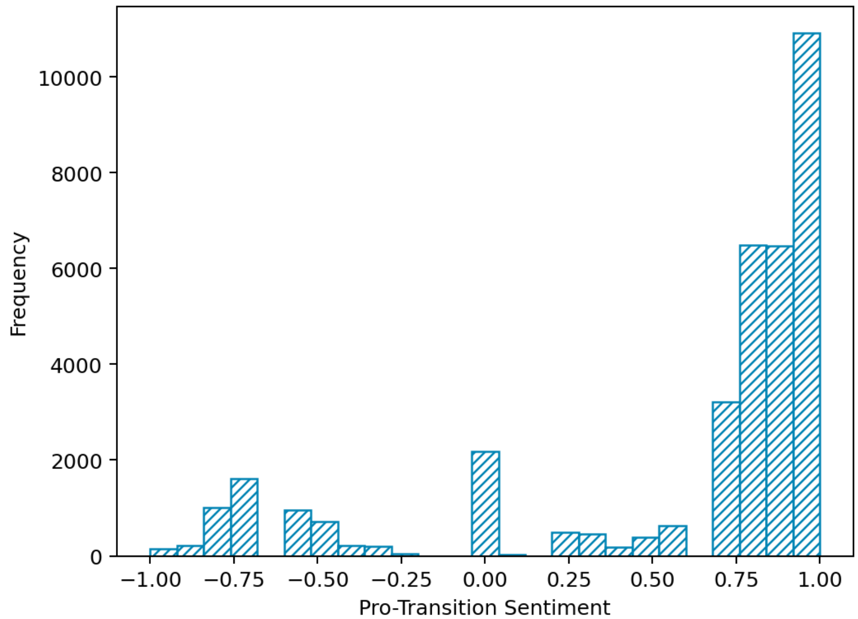
Figure 3 displays the distribution of the numerical sentiment measure. We observe that the distribution is left-skewed and that there are more climate-change legislator tweets in favor of the green transition than against.[7] Figure IA.1 in the Internet Appendix depicts the time series of the average monthly sentiment by party affiliation over the duration of our sample. The figure shows that tweets posted by Democrats are consistently more supportive toward the green transition. The average monthly sentiment of tweets posted by Republicans

[6] Temperature is a GPT hyperparameter ranging between zero and two that controls the creativity, and thus stochasticity, of responses.

[7] We also obtain a categorical measure of sentiment toward the green transition and reassuringly find that the categorical and numerical sentiment measures are similar. For instance, 59.6% of the tweets are strongly supportive toward the green transition, 16.5% weakly supportive, 9.8% neutral, 8.6% weakly opposed, and 5.5% strongly opposed. Thus, the categorical classification is consistent with the distribution of the GPT numerical sentiment in Figure 3.

**Figure 3:** Distribution of GPT sentiment

This histogram depicts the empirical frequency distribution of tweet sentiment toward the green transition obtained from GPT.




is more volatile compated to those by Democrats. The figure shows that the Replublicans are moderately opposed to the green transition during Democratic presidencies and moderately supportive during the Republican presidency.

While conventional dictionary (Loughran and McDonald, 2011) and machine-learning approaches (Kvam, Molnár, Wankel, and Ødegaard, 2022) are likely to adequately measure the overall tone of a tweet, they are unlikely to capture its sentiment toward green transition. In contrast, GPT performs well at measuring tweet sentiment toward the green transition. For instance, Table IA.1 in the Internet Appendix shows the numerical sentiment measure (obtained from GPT) for a randomly selected sample of tweets classified as 'Negative' by the Tone FinBERT model, a version of FinBERT finetuned to measure text sentiment. We find that while the sentiment measure obtained from GPT is not perfect, it correctly identifies several tweets in the table that while containing negative keywords, are overall positive toward the green transition.[8]

[8] Section IA.3.2 of the Internet Appendix shows that our findings are robust to using Open AI's GPT-3.5 to generate sentiment and considering only tweets posted after its training cutoff in September 2021. This shows that our results are not driven by any potential data leakage in our use of Open AI's GPT.

## 2.5 *Obtaining carbon emissions data*

Like Ardia et al. (2023), we use the Refinitiv Eikon API to obtain firms' annual greenhouse gas (GHG) emissions and revenue data. GHG emissions are reported in metric tonnes of carbon dioxide equivalent ($tCO_2e$). Around 97% of the GHG emissions data obtained from Refinitiv is disclosed by firms. We discard the remaining entries that are estimated. We then compute the carbon emissions intensity of a firm in a given fiscal year by dividing the sum of its absolute Scope 1 and Scope 2 GHG emissions by total revenue (expressed in million dollars). Scope 1 emissions are direct GHG emissions that originate from sources owned or controlled by the firm, such as company vehicles and on-site fuel combustion. Scope 2 emissions are indirect GHG emissions that originate from the generation of purchased electricity, steam, heating, and cooling consumed by a firm. Following Ardia et al. (2023), we shift carbon emissions intensity values by one year because emissions are reported with a one-year delay. As a robustness check, we also compute carbon emissions intensity using S&P Trucost data.[9]

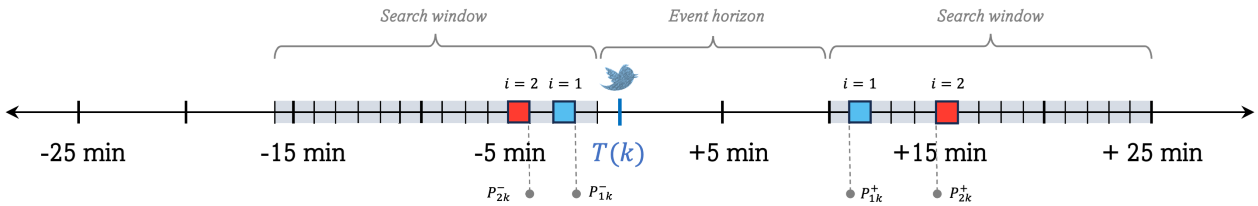
# 3 Empirical analysis

This section examines how legislator-tweet sentiment toward the green transition impacts the relative value of green and brown firms.

[9]Refinitiv also provides data on Scope 3 emissions, which originate from a firm's upstream and downstream activities. We exclude Scope 3 emissions when computing carbon emissions intensity because only 60.7% of the firms that report Scope 1 and Scope 2 emissions report also Scope 3 emissions. Thus, using Scope 3 emissions substantially reduces our sample size. However, as we discuss in Section 3.4, Column (6) of Table 2 shows that our main findings are robust to including Scope 3 emissions when we compute carbon emissions intensity. This is consistent with the findings of Ardia et al. (2023), who note that inclusion of Scope 3 emissions is inconsequential. Table IA.2 in the Internet Appendix ranks the Fama-French 48 industries by their average carbon intensity measures, and reports the average absolute Scope 1, 2, and 3 emissions for each industry.

**Figure 4:** Minute-level stock prices around legislator tweets

This figure illustrates how we query minute-level stock prices around legislator tweets. The symbol $T(k)$ denotes the timestamp of the $k$th tweet. The event horizon is the time interval from one minute before to ten minutes after the tweet. The search windows are the fifteen-minute lookup intervals before and after the event horizon (gray shaded regions). For the search window before the event horizon, we query the closing price for the last minute for which there is price data available. For the search window after the event horizon, we query the opening price for the first minute for which there is price data available. The blue and the red boxes represent minute-level prices of two different stocks.




## 3.1 High-frequency identification

We first describe how we compute high-frequency stock returns around legislator tweets following the approach in Bianchi et al. (2024). Let $T(k)$ be the timestamp of the $k$th tweet. For the $k$th tweet and $i$th stock, we download the following minute-level prices from FirstRate: (i) closing price for the *last* minute in which a trade was recorded within the window $[T(k)-16 \text{ min}, T(k)-1 \text{ min}]$ *before* the tweet, denoted by $P^-_{ik}$, and (ii) opening price for the *first* minute in which a trade was recorded within the window $[T(k)+10 \text{ min}, T(k)+25 \text{ min}]$ *after* the tweet, denoted by $P^+_{ik}$. Figure 4 illustrates this process.

We term the time interval from one minute before to ten minutes after the tweet as the *event horizon* and the fifteen-minute lookup intervals before and after the event horizon as the *search windows*. Because we are working with minute-level prices, querying stock prices one minute before a tweet provides the tightest event horizon achievable.[10] Extending the event horizon to ten minutes after a tweet provides sufficient time for market participants to process and react to the information, while remaining short enough to minimize confounding effects from other events occurring around the time the tweet is posted. We then calculate the log change in the stock price of firm $i$ in the event horizon around the $k$th tweet as:

$$\Delta p_{ik} = \log(P^+_{ik}) - \log(P^-_{ik}).$$

[10]To ensure that $P^-_{ik}$ occurs at least one minute before the tweet is posted, we obtain the closing price associated with the timestamp two minutes before the tweet is posted.

We set $\Delta p_{ik} = 0$ if there are no minute-level prices recorded in FirstRate during either the search window before or after the tweet, and winsorize $\Delta p_{ik}$ at the $0.5^{\text{th}}$ and $99.5^{\text{th}}$ percentiles.[11] Throughout the paper, returns are expressed in basis points.

We now describe our baseline regression. At the beginning of each day, we sort firms by their carbon emissions intensity, and categorize firms in the bottom, middle, and top terciles as *green*, *gray*, and *brown*, respectively.[12] We then estimate the following panel regression:

$$\begin{aligned}\Delta p_{ik} = \quad & \gamma_B \cdot \mathbb{1}_{Brown(i,k)} + \gamma_G \cdot \mathbb{1}_{Green(i,k)} \\ & + \tau \cdot \textit{Sentiment(k)} \\ & + \tau_B \cdot \mathbb{1}_{Brown(i,k)} \times \textit{Sentiment(k)} \\ & + \tau_G \cdot \mathbb{1}_{Green(i,k)} \times \textit{Sentiment(k)} \\ & + \lambda' \cdot X_{ik} + \theta_i + \theta_l + \theta_q + \epsilon_{ik},\end{aligned} \tag{1}$$

where $\mathbb{1}_{Brown(i,k)}$ and $\mathbb{1}_{Green(i,k)}$ are indicator variables equal to one when the $i$th firm is brown or green at the timestamp of the $k$th tweet, *Sentiment(k)* is the $k$th tweet numerical sentiment toward the green transition, obtained as described in Section 2.4 and min-max normalized annually between zero and one, and $X_{ik}$ is a vector containing the firm-specific time-varying controls listed in Table IA.5, which include firm-specific variables and risk-factor returns similar to those considered in the literature (Bolton and Kacperczyk (2021, 2023), Ardia et al. (2023), Bianchi et al. (2024)). The terms $\theta_i$, $\theta_l$, and $\theta_q$ capture firm, legislator, and year-quarter fixed effects, respectively.

The coefficients $\gamma_B$ and $\gamma_G$ measure the average returns of brown and green stocks around legislator tweets with zero normalized sentiment (strongly against the green transition), relative to observations of the same firms when classified as gray, the omitted category. The coefficient $\tau$ measures the marginal effect of legislator-tweet sentiment toward the green transition on the prices of gray firms. The coefficients $\tau_B$ and $\tau_G$ capture the incremental impact of legislator-tweet sentiment on the returns of brown and green stocks, relative to gray stocks. The error term is denoted by $\epsilon_{ik}$. We double-cluster standard errors at the

[11] According to the data provider, missing minute prices imply that no trade occurred during that minute for that stock. Thus, we assume that the tweet did not impact the price of the stock.

[12] At the beginning of each day, we consider the most recent carbon intensity measure available for each stock. If, for a given stock, the available carbon intensity measure is older than one year, then we assume that the information is not available for that stock on that day.

**Table 1:** Impact of legislator tweets on the returns of green versus brown stocks

Columns (1)–(6) of this table report slope coefficients and $t$-statistics in parentheses obtained from estimating the panel regression in Equation (1) for event horizons from one minute before to $s = 10, 15, 30, 60, 90$ minutes and one day after each tweet, respectively. The dependent variable $\Delta p(-01, +s)$ is the log change in stock prices (in basis points) from one minute before to $s$ minutes after each tweet. The sentiment of tweets toward the green transition is obtained using GPT and min-max normalized annually between zero and one. Firms that fall into the top and bottom tercile of carbon emissions intensity are classified as green and brown; the rest are classified as gray, which is the omitted category. The first five rows of the table report the following slope coefficients for the panel regression in Equation (1): $\gamma_B$ (Brown), $\gamma_G$ (Green), $\tau$ (Sentiment), $\tau_B$ (Brown × Sentiment), $\tau_G$ (Green × Sentiment). The sixth row reports the difference between $\tau_G$ and $\tau_B$, (Green − Brown) × Sent. We include firm-specific time-varying controls listed in Table IA.5 of the Internet Appendix. Standard errors are heteroscedasticity robust and double clustered at firm- and tweet-level. We denote $p$-values smaller than 0.10, 0.05, and 0.01 with one (*), two (**), and three (***) stars, respectively.

| | (1) $\Delta p(-01, +10)$ | (2) $\Delta p(-01, +15)$ | (3) $\Delta p(-01, +30)$ | (4) $\Delta p(-01, +60)$ | (5) $\Delta p(-01, +90)$ | (6) $\Delta p(-01, +1\text{d})$ |
|---|---|---|---|---|---|---|
| Brown | 0.133 | 0.0968 | 0.0215 | -0.214 | -0.340 | 3.873* |
| | (1.13) | (0.62) | (0.11) | (-0.72) | (-0.77) | (1.72) |
| Green | -0.364*** | -0.470*** | -0.734*** | -0.958*** | -1.595*** | -6.440** |
| | (-2.86) | (-3.17) | (-3.50) | (-2.76) | (-2.75) | (-2.29) |
| Sentiment | 0.178 | 0.559 | 0.679 | 0.558 | -0.465 | -2.853 |
| | (0.25) | (0.67) | (0.59) | (0.37) | (-0.26) | (-1.18) |
| Brown × Sentiment | -0.272** | -0.268* | -0.335 | -0.129 | -0.312 | -3.221* |
| | (-2.51) | (-1.80) | (-1.55) | (-0.47) | (-0.78) | (-1.90) |
| Green × Sentiment | 0.412*** | 0.515*** | 0.763*** | 1.193*** | 1.915*** | 5.339*** |
| | (3.28) | (3.83) | (4.36) | (3.72) | (3.54) | (2.69) |
| (Green − Brown) × Sent. | 0.683*** | 0.783*** | 1.097*** | 1.322*** | 2.228*** | 8.560*** |
| | (4.16) | (3.38) | (3.84) | (3.84) | (4.05) | (3.00) |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Legislator FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Day FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Adjusted R2 | 0.0384 | 0.0448 | 0.0619 | 0.0952 | 0.1294 | 0.2759 |
| Observations | 10,860,882 | 10,801,579 | 10,491,494 | 9,761,547 | 8,959,290 | 10,776,473 |

firm and tweet levels to account for correlation in errors across tweets for the same firm and across firms for the same tweet.

## 3.2 *Impact of legislator-tweet sentiment on stock prices*

Table 1 reports the results from estimating the panel regression in Equation (1) for various event horizons. Column (1) of Table 1, in particular, reports the results for our base-case event horizon from one minute before to ten minutes after each tweet.

We focus our discussion on the coefficients on the third, fourth, and fifth rows in Table 1, which characterize the impact of legislator-tweet sentiment toward the green transition on the returns of gray, brown, and green firms.[13] The third row reports the slope coefficient for legislator sentiment toward the green transition for gray firms, which is positive (0.178) but statistically insignificant. Therefore, an increase in pro-transition sentiment has no discernible impact on the prices of gray stocks.

The fourth and fifth rows of Table 1 report the slope coefficients for the interactions between the brown and green indicators and pro-transition sentiment. We observe that when legislator-tweet normalized sentiment toward the green transition increases by one standard deviation (0.284), the prices of brown firms decrease by 0.077 basis points ($0.284 \times 0.272$ bps) relative to those of gray firms, significant at the 5% level. In contrast, the prices of green firms increase by 0.117 basis points ($0.284 \times 0.412$ bps) relative to those of gray firms, significant at the 1% level. Thus, legislator support toward the green transition (expressed via twitter) reduces the value of brown firms, which are more exposed to green-transition regulation, and increases the value of green firms, consistent with the notion that such policies benefit firms that use cleaner energy, while leaving gray firms unaffected.

The sixth row shows that a one standard deviation increase in legislator-tweet sentiment toward the green transition generates a spread between the returns of green and brown stocks around a legislator tweet of 0.194 bps ($0.284 \times 0.683$ bps), significant at the 1% level, which translates into an average $509,766 increase in the market valuation of a green firm relative to that of an otherwise similar brown firm around a legislator tweet.[14]

In Section IA.3.1 of the Internet Appendix, we perform a placebo test by estimating the panel regression in Equation (1) using as dependent variable the log change in stock prices from 11 minutes before to one minute before each tweet, which cannot be affected

[13]The first two rows of Table 1 report the slope coefficients on the green and brown firm indicators. Around legislator tweets with zero normalized sentiment (i.e., strongly against the green transition), green firms earn returns that are 0.364 basis points lower than gray firms, significant at the 1% level, while brown firms earn returns that are 0.133 basis points higher, though this difference is not statistically significant. Note that the panel regressions include firm fixed effects, and thus, these return differentials are identified from only within-firm variation in greenness over time.

[14]The average market capitalization in our sample is 26.28 billion dollars. To compute this figure, we first calculate the cross-sectional average market capitalization of the 1,000 largest firms for each year in the sample, and then compute the time-series average of the cross-sectional averages.

directly by any information in the tweet. We find that the impact of legislator sentiment on the return spread between green and brown firms in the minutes before the tweet is insignificant. The result of this placebo test provides reassurance that it is the informational content of legislator tweets that leads to the changes in green versus brown firm value and not events happening before the tweet.

### 3.3 Persistence over time

Does the effect of legislator tweets about climate change on the relative value of green and brown stocks persist or revert over time? To answer this question, we report in Columns (1)–(6) of Table 1 the results from estimating the panel regression in Equation (1) for event horizons from one minute before to $s = 10, 15, 30, 60, 90$ minutes and one day after each tweet, respectively.[15] We must note, however, that a longer event horizon weakens the high-frequency identification because of an increased likelihood of the estimates being contaminated by other events resulting in price movements.

As we extend the event horizon, the sixth row in Table 1 shows that the spread between the returns of green and brown stocks remains significant at the 1% level, and its economic magnitude increases substantially. For instance, when we extend the event horizon from ten to ninety minutes after the tweet, the spread associated with a one standard deviation increase in sentiment toward the green transition more than triples from 0.194 basis points to 0.633 basis points ($0.284 \times 2.228$ bps). When we extend the event horizon to one day after the tweet, the spread between the returns of green versus brown stocks increases more than tenfold to 2.431 bps ($0.284 \times 8.560$ bps) and remains significant at the 1% level.[16] This

[15] We conserve the length of the search windows, while varying the length of the event horizon.

[16] Note that the number of observations decreases as we expand the event horizon from ten to ninety minutes, that is, from 10.86 million in Column (1) to 8.96 million in Column (5). This is because for an event horizon ending at $T(k) + x$ minutes, a tweet must be published at least $x + 15$ minutes before the market closes at 16:00 EST in order for us to query the opening price of the first minute recorded during the fifteen-minute search window after the tweet. Similarly, for event horizons starting at the $T(k) - 1$ minute, tweets must be posted at least sixteen minutes after the market opens at 09:30 EST in order for us to query the closing price of the last minute recorded in a 15-minute search window. Hence, we drop entries with missing price information for which the search windows fall outside trading hours.

finding suggests that it takes at least one day for market prices to incorporate the information contained in the tweets.

### 3.4 Robustness checks

Table 2 shows that the panel regression results reported in Column (1) of Table 1 are robust to using an event horizon starting *five* minutes before the tweet (instead of one minute), using a contracted event horizon that ends *five* minutes after the tweet (instead of ten minutes), using market-adjusted returns as the dependent variable, computed by subtracting the high-frequency one-to-ten-minute returns of the S&P 500 index from those of the stocks, using day-level fixed effects instead of quarter-level fixed effects, categorizing green and brown firms using carbon intensity measures obtained from S&P Trucost (instead of Refinitiv Eikon), categorizing green and brown firms using carbon intensity measures that include Scope 3 emissions (instead of only Scope 1 and 2 emissions).

In the remainder of this section, we provide a detailed discussion of these robustness checks. We focus our discussion on the slopes for the interaction between tweet sentiment and the brown and green indicator variables ($\hat{\tau_B}$ and $\hat{\tau_G}$), which are reported on the fourth and fifth rows of Table 2, as well as on the difference between these two slopes, which is reported on the sixth row. Column (1) of Table 2 reports the results when we compute stock returns using a *five*-to-ten-minute horizon. Although we expect tweet timestamps to be accurate, modifying the event horizon to begin five minutes (instead of one minute) before the tweet buffers against small discrepancies in the recorded timestamps. The coefficient on the interaction between sentiment and the brown indicator remains negative but insignificant. In contrast, the coefficient on the interaction between sentiment and the green indicator continues to be significant at the 1% level and comparable in magnitude to that obtained using one-to-ten-minute returns. The spread between the coefficients on the two interactions reported in the sixth row of Table 2 remains positive and significant at the 1% level. Column (2) reports the estimates for a contracted event horizon that ends five minutes (instead of ten minutes) after the tweet. Because of the tighter event horizon, the spread between green and brown stock returns diminishes in magnitude, from 0.194 (= 0.284 × 0.683) in

**Table 2:** Robustness checks for impact of legislator tweets on stock returns

This table reports slope coefficients and $t$-statistics in parentheses from robustness checks of the results of the panel regression in Equation (1), reported in Column (1) of Table 1. Column (1) reports the results obtained by using an event horizon starting *five* minutes before the tweet (instead of one minute), Column (2) using a contracted event horizon that ends *five* minutes after the tweet (instead of ten minutes), Column (3) using market-adjusted returns as the dependent variable, computed by subtracting the high-frequency one-to-ten-minute returns of the S&P 500 index from those of the stocks, Column (4) using tweet-level fixed effects instead of day-level fixed effects, Column (5) categorizing green and brown firms using carbon intensity measures obtained from S&P Trucost (instead of Refinitiv Eikon), and Column (6) categorizing green and brown firms using carbon intensity measures that include Scope 3 emissions (instead of only Scope 1 and 2 emissions). The first five rows of the table report the following slope coefficients for the panel regression: $\gamma_B$ (Brown), $\gamma_G$ (Green), $\tau$ (Sentiment), $\tau_B$ (Brown $\times$ Sentiment), $\tau_G$ (Green $\times$ Sentiment). The sixth row reports the difference between $\tau_G$ and $\tau_B$, (Green $-$ Brown) $\times$ Sent. We include the firm-specific time-varying controls listed in Table IA.5 of the Internet Appendix. Standard errors are heteroscedasticity robust and double clustered at firm- and tweet-level. We denote $p$-values smaller than 0.10, 0.05, and 0.01 with one (*), two (**), and three (***) stars, respectively.

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | $\Delta p(-05,+10)$ | $\Delta p(-01,+05)$ | MKT Adjusted | Hour FE | S&P Trucost | S3 Emission |
| Brown | 0.0332 | 0.0951 | 0.154 | 0.134 | 0.175 | -0.0427 |
| | (0.26) | (1.17) | (1.25) | (1.12) | (1.41) | (-0.43) |
| Green | -0.370** | -0.163 | -0.362*** | -0.366*** | -0.274** | -0.499*** |
| | (-2.55) | (-1.59) | (-2.85) | (-2.85) | (-1.97) | (-4.08) |
| Sentiment | -0.494 | 0.120 | 0.0256 | -0.408 | 0.250 | -0.0385 |
| | (-0.81) | (0.27) | (0.11) | (-1.00) | (0.37) | (-0.05) |
| Brown $\times$ Sentiment | -0.168 | -0.153 | -0.295** | -0.271** | -0.247** | 0.0213 |
| | (-1.32) | (-1.58) | (-2.43) | (-2.43) | (-2.11) | (0.22) |
| Green $\times$ Sentiment | 0.402*** | 0.182* | 0.420*** | 0.413*** | 0.283*** | 0.609*** |
| | (2.73) | (1.68) | (3.29) | (3.25) | (2.59) | (4.28) |
| (Green $-$ Brown) $\times$ Sent. | 0.570*** | 0.335** | 0.715*** | 0.684*** | 0.530*** | 0.588*** |
| | (2.75) | (2.37) | (4.12) | (4.12) | (3.40) | (3.49) |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Legislator FE | Yes | Yes | Yes | No | Yes | Yes |
| Day FE | Yes | Yes | Yes | No | Yes | Yes |
| Adjusted R2 | 0.0417 | 0.0329 | 0.0083 | 0.1452 | 0.0398 | 0.0385 |
| Observations | 10,826,367 | 10,897,038 | 10,860,551 | 10,860,882 | 10,408,788 | 6,649,816 |

Column (1) of Table 1 to 0.095 ($= 0.284 \times 0.335$) basis points, but remains significant at the 5% level.

Column (3) reports the estimates obtained by using market-adjusted returns as the target variable by subtracting the one-to-ten-minute returns of the S&P 500 index from those of the stocks. The high-frequency returns of the market index are obtained from FirstRate analogously to those of stocks, as described in Section 3.1. The sixth row of Table 2 shows that the spread between the green and brown stock returns around pro-transition tweets increases slightly compared to the baseline results reported in Column (1) of Table 1, from 0.194 to 0.203 (= $0.284 \times 0.715$) basis points. Column (4) shows that the estimated spread in the sixth row remains similar in magnitude and statistically significant when we allow for hour fixed effects. This finding suggests that our results are not driven by unobserved events occurring around the time of the tweet that could simultaneously influence both legislator tweets and stock returns. Column (5) shows that our findings are robust to using the carbon intensity measure from S&P Trucost, instead of that from Refinitive Eikon.

Finally, Column (6) reports estimates obtained by including Scope 3 emissions to construct the carbon emissions intensity used to sort stocks into green and brown portfolios. Our main finding is robust to including Scope 3 emissions: the spread between the interaction terms of the sentiment measure with the green and the brown indicators is positive, only slightly smaller in magnitude than the coefficient reported in Column (1) of Table 1 and significant at the 1%. This is despite the fact that when we include Scope 3 emissions to compute carbon intensity, we lose a disproportionate number of observations for brown firms. For instance, the median carbon intensity measure—computed using Scope 1 and 2 emissions only—of firms that report Scope 3 emissions is 32.04 tCO2e/$M, whereas that for firms that do not report Scope 3 emissions is 55.45 tCO2e/$M (42% higher).

### 3.5 Stock returns and decarbonization

Our results indicate that, relative to green firms, brown firms are penalized by markets following pro-transition legislators tweets. A plausible interpretation is that such tweets signal forthcoming policies that either favor cleaner energy sources or raise the costs of fossil-fuel use. However, high-emission firms are not uniformly constrained; some may be more willing or better positioned to adjust their carbon emissions in anticipation of green-transition regulation. For example, certain firms may operate with more adaptable production technologies, have institutional shareholders supportive of the green transition, or possess technologies that can be modified to reduce emissions at reasonable cost. If markets can predict which firms will adapt their carbon emissions in response to transition regulation, then one would expect that firm returns around pro-transition tweets should be informative about future carbon emissions. To test this hypothesis, we study whether firm stock returns around pro-transition tweets predict the future carbon emissions intensity of low- and high-emission firms.

We compute the change in carbon emissions intensity between subsequent disclosures as:

$$CarbonDelta_{i,t+1} = C_{i,t+1} - C_{it}, \tag{2}$$

where $C_{it}$ is the carbon emissions intensity reported by the $i$th firm at disclosure date $t$. Note that carbon emissions are reported at an annual frequency, but the reporting cycles are heterogeneous across firms, and thus, the disclosure date $t$ for $C_{it}$ is specific to firm $i$. For each disclosure $C_{it}$, we aggregate the one-to-ten-minute returns of firm $i$ around the pro-transition tweets that were posted during the year preceding date $t$:

$$AggReturn_{it} = \sum_{k \in \mathcal{K}_{it}} \Delta p_{ik}(-1, +10), \tag{3}$$

where $\mathcal{K}_{it}$ contains all tweets with timestamp in the year preceding date $t$ that fall into the top quintile of sentiment toward the green transition. In each calendar year, we sort firms by their carbon emissions intensity and categorize firms that fall below and above the median as low- and high-emission firms. We then estimate the following panel regression separately for low- and high-emission firms:

$$CarbonDelta_{i,t+1} = \gamma\, AggReturn_{it} + \theta_i + \theta_y + \varepsilon_{it}, \tag{4}$$

where $\gamma$ is the slope, $\theta_i$ are firm fixed effects, $\theta_y$ are time fixed effects for the calendar year corresponding to the disclosure date $t$, and $\varepsilon_{it}$ is the error term. Because this analysis is conducted at the annual level and the sample covers only eight years, standard errors are clustered at the firm level only.

Panels (a) and (b) of Table 3 report the results from estimating Equation (4) separately for low- and high-emission firms. Column (1) reports results for a specification without fixed effects. Columns (2) and (3) report results obtained when firm and year fixed effects are included, respectively. Column (4) reports results obtained when both firm and year fixed effects are included. We observe that the results for the slope coefficient $\gamma$ are consistent across the four columns.

**Table 3:** Legislator tweets and firm decarbonization

Panels (a) and (b) report the results from estimating Equation (4) separately for low- and high-emission firms. The dependent variable is *CarbonDelta* obtained from Equation (2). The independent variable, *AggReturn*, is obtained from Equation (3). Column (1) reports results for a specification without any fixed effects. Columns (2) and (3) report results obtained when firm and year fixed effects are included, respectively. Column (4) reports results obtained when both firm and year fixed effects are included. Standard errors heteroscedasticity robust and clustered at the firm level. The $t$-statistics are reported in parentheses and $p$-values smaller than 0.10, 0.05, and 0.01 are indicated by one (*), two (**), and three (***) stars, respectively.

| **Panel (a): Low-emission firms** | | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| AggReturn | -0.0000052 | 0.0000117 | -0.0000708 | 0.0000411 |
| | (-0.07) | (0.14) | (-0.80) | (0.40) |
| Constant | -0.618*** | -0.616*** | -0.636*** | -0.623*** |
| | (-6.71) | (-6.53) | (-59.92) | (-50.46) |
| Firm FE | No | No | Yes | Yes |
| Time FE | No | Yes | No | Yes |
| Adjusted R2 | -0.00135 | -0.00768 | 0.0487 | 0.0459 |
| Observations | 743 | 743 | 695 | 695 |

| **Panel (b): High-emission firms** | | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| AggReturn | -0.0500*** | -0.0455*** | -0.0651*** | -0.0608*** |
| | (-5.11) | (-3.94) | (-4.22) | (-3.48) |
| Constant | -57.47*** | -56.90*** | -57.80*** | -57.20*** |
| | (-5.06) | (-5.01) | (-26.72) | (-23.34) |
| Firm FE | No | No | Yes | Yes |
| Time FE | No | Yes | No | Yes |
| Adjusted R2 | 0.0369 | 0.0607 | 0.0608 | 0.0913 |
| Observations | 721 | 721 | 681 | 681 |

For instance, Column (4) of Panel (a) shows that price movements around pro-transition legislator tweets do not predict subsequent changes in the carbon emissions intensity of low-emission firms. The coefficient estimate associated with *AggReturn* is statistically and economically insignificant. This is consistent with low-emission firms not responding to future climate regulation by further reducing their emissions, perhaps because they are already carbon efficient. In contrast, Column (4) of Panel (b) shows that a one standard deviation increase in the *AggReturn* measure (988 bp) is associated with a decrease in subsequent carbon emissions intensity by high-emission firms of 60.07 (988 bp $\times$ 0.0608) tCO2/$M, significant at the 1% level. Thus, high-emission firms that decarbonize more in the future experience higher returns around pro-transition legislator tweets.

This finding reveals that the market correctly identifies and rewards high-emission firms that can better adapt to transition regulation, and thus suggests that the green transition impacts not only firm value, but also real outcomes such as carbon emissions. In addition, our results indicate that brown firms that are not able or willing to decarbonize shoulder a disproportionately large share of the burden imposed by transition regulations.

# 4 Mechanism

We now investigate the mechanisms through which legislator tweets impact the prices of green versus brown stocks. In Section 4.1, we examine the information channel by showing that a daily pro-transition sentiment index based on legislator tweets contains information that is distinct from that communicated by climate-related news in mainstream media. In Section 4.2, we study the regulatory channel showing that, for tweets that mention specific environmental regulations, the spread between the return of green and brown stocks increases in the weeks leading to a congressional vote and disappears afterward. Moreover, this spread is significant in the run-up to close votes but insignificant before votes with clear outcomes.

## *4.1 The information channel*

In this section, we examine whether the information contained in legislator tweets about climate change is distinct from that in mainstream media news. To do this, we first construct a daily ProTransition Sentiment (PTS) index based on the legislator tweets, and then study whether there is a lead-lag relation between the Media Climate Change Concerns (MCCC) index of Ardia et al. (2023) and the PTS index.

We construct a daily PTS index as the product of (i) the fraction of tweets posted by members of the U.S. Congress on a given day that concern climate change and (ii) the average sentiment toward the green transition across those tweets. Figure 5 depicts day-specific PTS values (light gray markers) and the 20-day moving average of the PTS index (solid black line), shifted forward by 10 days so that the time series is aligned with calendar events. The figure also annotates the 20 environmental regulations introduced to Congress during our sample period that received most legislator tweets. For each regulation, the vertical dashed red lines—from left to right—demarcate the dates on which the regulation was (i) introduced, (ii) voted on in the sponsoring chamber, and (iii) voted on in the other chamber. For example, the 'Infrastructure Investment and Jobs Act' was introduced and voted on in the House of Representatives on June 4, 2021 and July 1, 2021, respectively, and subsequently voted on in the Senate on August 10, 2021.[17] The absence of a second and third vertical line implies that the regulation was not put to a vote in the sponsoring chamber and the other chamber, respectively. For example, the 'Climate Action Now Act' was introduced and voted on in the House of Representatives on March 27, 2019 and May 2, 2019, respectively. However, it was never put to a vote in the Senate.

Figure 5 reveals consistent spikes in the PTS index around the days on which the regulations are introduced or voted on. For instance, there are three spikes in the PTS index around the introduction and the two votes for the 'Inflation Reduction Act', and there is a large spike around the introduction of the 'Paris Climate Act'. This evidence suggests that the PTS index provides a quantitative measure of daily legislator sentiment toward the green transition, as evidenced by the interplay between the index and key regulatory milestones.

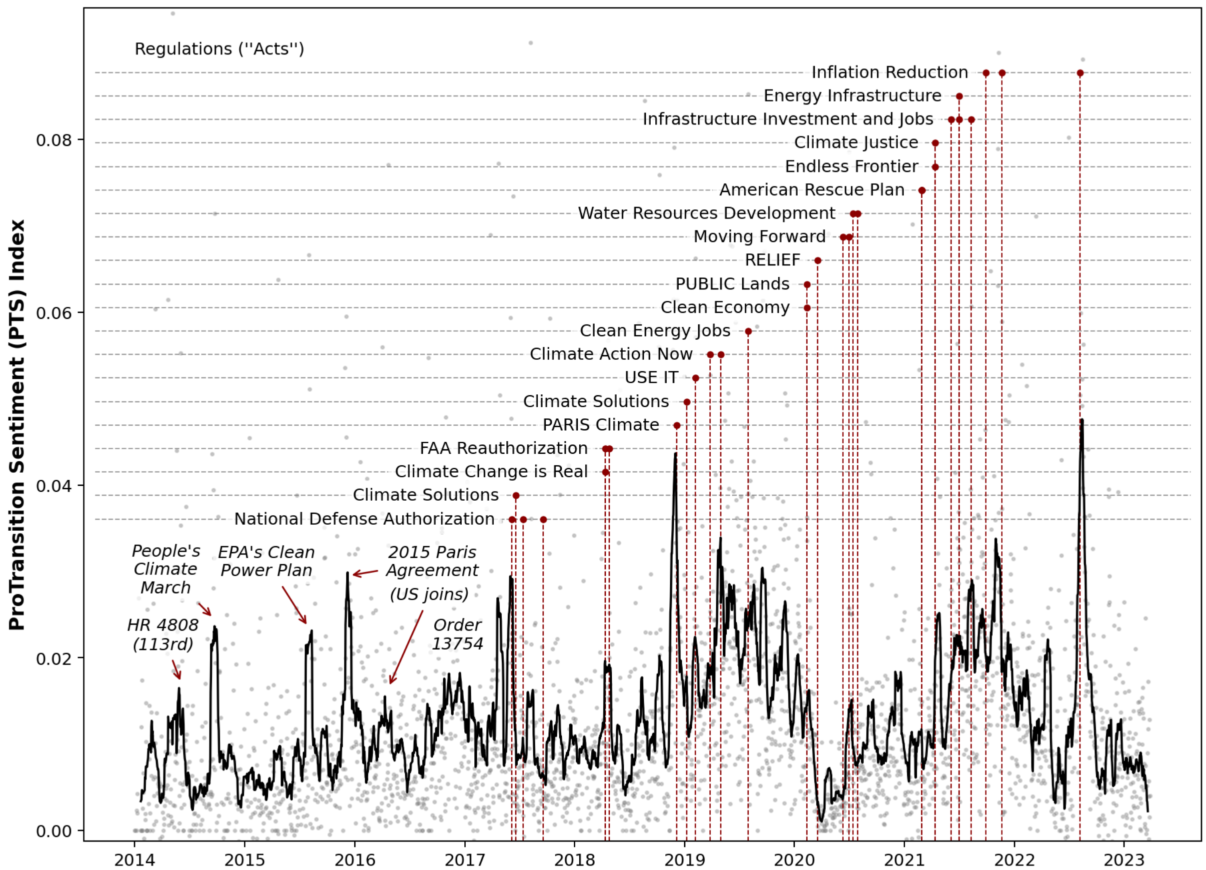
If legislator tweets convey information that is both distinct from that in mainstream media news and relevant, then we would expect current values of the PTS index to be able to forecast future values of the Media Climate Change Concerns (MCCC) index of Ardia et al. (2023).[18] Conversely, if legislator tweets simply mirror news already in the media, then they should have no predictive power with respect to future news. Instead, tweets

[17]Sometimes, regulations are introduced or voted on within days of each other. For example, the 'Energy Infrastructure Act' was introduced within days of the first vote for the 'Infrastructure Investment and Jobs Act'. In such instances, we overlap the vertical dashed red lines to improve visual clarity.

[18]Ardia et al. (2023) construct the Media Climate Change Concerns (MCCC) index by using risk and sentiment lexicon to calculate the level of concern expressed in climate-related articles from twelve major U.S. news outlets. The article-specific measures are then carefully aggregated to produce a daily climate-change concerns index. The resultant index measures and combines the degree of risk and negativity expressed in mainstream media with respect to climate change.

**Figure 5:** ProTransition Sentiment (PTS) index

This figure shows the daily ProTransition Sentiment (PTS) index, constructed as the product of (i) the fraction of tweets posted by members of the U.S. Congress on a given day that concern climate change and (ii) the average sentiment toward the green transition across those tweets. The figure depicts day-specific PTS values (light gray markers) and the 20-day moving average of the PTS index (solid black line), shifted forward by 10 days so that the time series is aligned with calendar events. The figure also annotates the 20 environmental regulations introduced to Congress during our sample period that received most legislator tweets. For each regulation, the vertical dashed red lines—from left to right—demarcate the dates on which the regulation was (i) introduced, (ii) voted on in the sponsoring chamber, and (iii) voted on in the other chamber. Missing vertical lines imply that a congressional vote did not take place.




themselves should be largely predictable from past news. To test this hypothesis, we study whether there is a lead-lag relation between the MCCC index of Ardia et al. (2023) and the PTS index. We standardize the PTS and MCCC indices so that their time series have zero mean and unit standard deviation.[19] To determine whether there is a lead-lag relation

[19]We verify that the time series are stationary using the augmented Dickey-Fuller test (ADF) implemented using `statsmodels.tsa.stattools.adfuller` package in Python with default settings. The null hypothesis is that there is a unit root, with the alternative that there is no unit root. The ADF statistic for PTS (MCCC) is $-11.05$ ($-5.25$), which rejects the null hypothesis. We further validate that each series is stationary by estimating the following equation: $\Delta y_t = \alpha + \beta t + \theta y_{t-1} + \delta_1 \Delta y_{t-1} + \delta_2 \Delta y_{t-2} + \epsilon_t$, where $y_t$ represents the value of the series at time $t$, $\Delta y_t := y_t - y_{t-1}$, $\alpha$ captures drift, $\beta$ is the parameter associated with time

between the two indices, that is, whether past values of one index can predict the other index, we follow DeMiguel, Nogales, and Uppal (2014, p. 1036) and estimate the following vector autoregressions:

$$\mathrm{MCCC}_t = \alpha_1 + \beta_{11}\mathrm{MCCC}_{t-1} + \beta_{12}\mathrm{PTS}_{t-1} + \varepsilon_{1t}, \tag{5a}$$

$$\mathrm{PTS}_t = \alpha_2 + \beta_{21}\mathrm{MCCC}_{t-1} + \beta_{22}\mathrm{PTS}_{t-1} + \varepsilon_{2t}, \tag{5b}$$

where $\mathrm{MCCC}_t$ and $\mathrm{PTS}_t$ are the indices on day $t$, $\alpha_1$ and $\alpha_2$ are the intercepts, $\beta_{ij}$ for $i, j \in \{1, 2\}$ are the slopes for the lagged indices, and $\varepsilon_1$ and $\varepsilon_2$ are the error terms. If $\beta_{12}$ is significant, we infer that the PTS index leads the MCCC index and, if $\beta_{21}$ is significant, then the MCCC index leads the PTS index.

Columns (2) and (4) of Table 4 report the results obtained from estimating the vector autoregressions in Equations (5a) and (5b). We find that both $\hat{\beta}_{12}$ and $\hat{\beta}_{21}$ are significant, that is, both the MCCC and PTS indices lead each other. This demonstrates that neither index fully subsumes the information in the other and each index captures unique aspects of the green transition.

To further gauge the importance of each index in predicting the other, we also estimate autoregressions for each of the two indices separately, that is:

$$\mathrm{MCCC}_t = \alpha_1 + \beta_1\mathrm{MCCC}_{t-1} + \varepsilon_{1t}, \tag{6a}$$

$$\mathrm{PTS}_t = \alpha_2 + \beta_2\mathrm{PTS}_{t-1} + \varepsilon_{2t}. \tag{6b}$$

Columns (1) and (3) of Table 4 report the results obtained from estimating the separate autoregressions in Equations (6a) and (6b). Comparing Columns (1) and (2) in Table 4, we observe that, when we predict the MCCC index, introducing the lagged PTS index increases the adjusted R-squared by 2.6%. Similarly, comparing Columns (3) and (4) in Table 4, we find that, when we predict the PTS index, introducing the lagged MCCC index increases the adjusted R-squared by 0.9%. Thus, each index helps to predict the other even controlling for lagged values of the target index.

index $t$ to capture trends, and $\epsilon_t$ is the error term. We observe that $\hat{\theta}$ is negative and statistically significant, indicating that the time series is stationary.

**Table 4:** Lead-lag relation between PTS and MCCC indices

This table reports the results from estimating vector autoregressive models for our ProTransition Sentiment (PTS) index and the Media Climate Change Concerns (MCCC) index of Ardia et al. (2023). Columns (2) and (4) report the results obtained from estimating the vector autoregressive model for the two indices formulated in Equations (5a) and (5b). Columns (1) and (3) report the results obtained from estimating the separate autoregressive models for the PTS and MCCC indices formulated in Equations (6a) and (6b). We construct a daily ProTransition Sentiment (PTS) index as the product of (i) the fraction of tweets posted by members of the U.S. Congress on a given day that concern climate change and (ii) the average sentiment toward the green transition across those tweets. We standardize the PTS and MCCC indices so that their time series have zero mean and unit standard deviation. Standard errors are heteroscedasticity robust. The t-statistics are reported in parentheses and $p$-values smaller than 0.10, 0.05, and 0.01 are denoted by one (*), two (**), and three (***) stars, respectively.

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | MCCC(t) | MCCC(t) | PTS(t) | PTS(t) |
| MCCC(t-1) | 0.474*** | 0.432*** | | 0.0991*** |
| | (26.41) | (23.55) | | (5.31) |
| PTS(t-1) | | 0.165*** | 0.341*** | 0.317*** |
| | | (8.75) | (10.21) | (9.35) |
| Constant | 0.0254 | 0.0222 | 0.00524 | 0.00174 |
| | (1.54) | (1.36) | (0.30) | (0.10) |
| Adjusted R2 | 0.225 | 0.251 | 0.121 | 0.130 |
| Observations | 2799 | 2799 | 2799 | 2799 |

Our results suggest that both indices contain distinct information. While it is natural for legislators to discuss the green transition following heightened media concerns about climate change, the latter can also follow the former for several reasons. For instance, the news might echo the support expressed by legislators toward environmental regulation. Legislators would also be better positioned to anticipate future events such as environmental summits or international partnerships aimed toward mitigating climate change. Moreover, legislator tweets could highlight material information that the mainstream media has missed. Overall, we find that the legislator tweets contain distinct information and do not simply track that contained in mainstream news. Section IA.3.3 of the Internet Appendix provides additional support for the notion that legislator tweets do not simply amplify news from mainstream media by showing that our baseline results about the impact of legislator-tweet sentiment on the returns and green and brown stocks are robust to controlling for interactions between innovations to the MCCC index and the green and brown indicator variables.[20]

[20]Section IA.4.1 of the Internet Appendix shows that the sentiment of less popular tweets (with below median likes or retweets) has a higher and more significant impact on the spread between the returns of

## 4.2 *The regulatory channel*

In this section, we focus on the regulatory channel by looking at the high-frequency returns of green versus brown stocks around legislator tweets that mention specific regulations introduced to Congress during our sample period.

### 4.2.1 Identifying regulatory tweets and measuring their sentiment

We start by scraping all 1,620 climate-related regulations on GovTrack that were introduced to the U.S. Congress during our sample period.[21] We then construct a dictionary that contains a bag-of-words specific to each regulation. Section IA.2.1 of the Internet Appendix provides a detailed description of the approach we use to create the dictionary. We parse all 2,830,646 legislator tweets against this dictionary and identify 13,294 tweets posted during NYSE trading hours that mention one of the 20 climate-change regulations listed in Table 5, which are the regulations most frequently mentioned in legislator tweets among those introduced to Congress during our sample.

For these regulation-specific tweets, we use GPT-4.1 to measure the legislator support (LSupport) toward the regulation mentioned in the tweet using the following prompt:

*You are a political expert with experience evaluating statements about U.S. Congress regulations. The following tweet was posted by a member of the U.S. Congress on {post date} and mentions the following regulation: {bill number} ({congress}) — {regulation name}. Assign a continuous score between -1 and 1, where a value of -1 indicates strong opposition to the regulation mentioned, 0 indicates a neutral or ambiguous stance, and 1 indicates strong support to the regulation mentioned. If the tweet is unrelated to the regulation mentioned, return 99. Return only a single numerical value.*

green and brown stocks compared to more popular tweets. This suggest that the type of tweet content that impacts the relative value of green and brown firms is different from the one that generates Twitter likes and retweets. In addition, Section IA.4.2 of the Internet Appendix shows that the magnitude of the impact of tweets posted by members of the House and Senate on the spread between the returns of green and brown stocks is similar, although it is more statistically significant for tweets by members of the House, possibly because there are many more tweets by members of the House.

[21] We scrape all regulations introduced in the 113th through 117th U.S. Congresses that fall under 'Environmental Protection' or 'Climate Change and Greenhouse Gases'.

**Table 5:** Regulations discussed in environmental tweets

This table enumerates the 20 regulations introduced to Congress during our sample with the highest number of mentions in our sample of legislator tweets about climate change. Regulations are listed in descending order of number of mentions. The first column titled 'Regulation' reports the name of the regulation. The second column titled 'Code' reports the corresponding bill number. Bill numbers starting with "H.R." are initiated (introduced) by members of the the House of Representatives (lower chamber). Bill numbers started with "S." are initiated by the members of the Senate (upper chamber). The third column titled 'Congress' reports the sequential number of the two-year term of the legislative body. The fourth column titled 'Introduction' reports the date on which the regulation was introduced in the sponsoring house. The fifth and sixth columns titled 'House' and 'Senate' report the dates on which the regulation was deliberated and voted on in the lower and upper chamber, respectively. Missing dates imply that the bill has either not been deliberated or voted upon in a given chamber, or that it failed to pass the preceding vote in the other chamber. Regulations ratified by both chambers are sent to the President, who signs it into law. The dates on which the regulations are signed into law are reported by the last column titled 'President'.

| **Regulation** | **Code** | **Congress** | **Introduction** | **House** | **Senate** | **President** |
|---|---|---|---|---|---|---|
| American Rescue Plan Act | H.R. 1319 | 117th | February 24, 2021 | February 27, 2021 | March 06, 2021 | March 11, 2021 |
| Inflation Reduction Act | H.R. 5376 | 117th | September 27, 2021 | November 19, 2021 | August 07, 2022 | August 16, 2022 |
| PUBLIC Lands Act | S. 3288 | 116th | February 12, 2020 | | | |
| Infrastructure Investment and Jobs Act | H.R. 3684 | 117th | June 04, 2021 | July 01, 2021 | August 10, 2021 | November 15, 2021 |
| Climate Action Now Act | H.R. 9 | 116th | March 27, 2019 | May 02, 2019 | | |
| Moving Forward Act | H.R. 2 | 116th | June 11, 2020 | July 01, 2020 | | |
| RELIEF Act | H.R. 6290 | 116th | March 19, 2020 | | | |
| Energy Infrastructure Act | S. 2377 | 117th | July 19, 2021 | | | |
| Endless Frontier Act | H.R. 2731 | 117th | April 21, 2021 | | | |
| FAA Reauthorization Act | H.R. 4 | 115th | April 13, 2018 | April 27, 2018 | | |
| Climate Justice Act | H.R. 2394 | 117th | April 13, 2021 | | | |
| Climate Change is Real Act | H.R. 5552 | 115th | April 18, 2018 | | | |
| National Defense Authorization Act | H.R. 2810 | 115th | June 07, 2017 | July 14, 2017 | September 18, 2017 | December 12, 2017 |
| Climate Solutions Act | H.R. 330 | 116th | January 08, 2019 | | | |
| PARIS Climate Act | H.R. 7220 | 115th | December 06, 2018 | | | |
| Water Resources Development Act | H.R. 7575 | 116th | July 13, 2020 | July 29, 2020 | | |
| Clean Economy Act | S. 3269 | 116th | February 11, 2020 | | | |
| Clean Energy Jobs Act | S. 2393 | 116th | July 31, 2019 | | | |
| USE IT Act | S. 383 | 116th | February 07, 2019 | | | |
| Climate Solutions Act | H.R. 2958 | 115th | June 20, 2017 | | | |

The variable *post date* refers to the date on which the tweet was posted, *bill number* refers to the code assigned to the regulation (e.g., H.R. 9), *congress* refers to the congressional term during which the regulation was introduced (e.g., 116th), and *regulation name* refers to the name of the regulation being mentioned in the tweet (e.g., Climate Action Now Act).

Next, we ascertain the stance of the 20 regulations toward the green transition by asking GPT to classify each regulation as either 'strongly opposed', 'weakly opposed', 'neutral', 'weakly supportive', or 'strongly supportive'. Section IA.2.2 of the Internet Appendix describes the prompt used to classify the regulations. We find that 10 out of the 20 regulations are strongly supportive toward the green transition, two regulations are weakly supportive, and the remaining eight are ambiguous. We validate this GPT assessment by manually inspecting the summaries of the 19 bills.

We map the categories 'strongly opposed', 'weakly opposed', 'neutral', 'weakly supportive', and 'strongly supportive' to numerical values (RStance) of $-1$, $-0.5$, 0, 0.5, and 1, respectively. Finally, for each tweet, we compute a pro-transition support (PTLSupport) measure by multiplying the tweet legislator support (LSupport) toward the regulation and the pro-transition stance of the regulation (RStance) mentioned in the tweet. Figure IA.2 in the Internet Appendix shows the distribution of PTLSupport.

#### 4.2.2 Analyzing the impact of regulatory tweets on stock prices

Armed with a sample of regulatory legislator tweets and a measure of their pro-transition legislative support (PTLSupport), we are ready to study the impact of regulatory-tweet sentiment on stock returns. Our hypothesis is that regulatory tweets affect stock prices because they convey information about the probability that a given regulation will pass a congressional vote. Consistent with this mechanism, we would expect their impact to be stronger when legislators post tweets immediately before the vote. To examine this prediction, Columns (1)(4) of Table 6 report the results from estimating the panel regression for tweets posted within the four, three, two, and one weeks leading up to a congressional vote on the regulation mentioned in the tweets and posted by members of the house in which the vote took place. The regression specification is identical to that in Equation (1),

**Table 6:** Impact of legislator support toward pro-transition regulation

This table reports slope coefficients and t-statistics in parentheses obtained from estimating the panel regression in Equation (1) on the sample of legislator tweets that mention the 20 environmental regulations listed in Table 5. The dependent variable is the log change in stock prices (in basis points) from one minute before to ten minutes after each tweet, $\Delta p(-01,+10)$. The sentiment measure in the original specification is replaced by pro-transition legislative support (PTLSupport). PTLSupport measures the stance of a tweet toward pro-transition regulation between zero (strong opposition) and one (strong support) and is min-max normalized quarter on quarter. Stocks that fall into the top and bottom tercile of carbon emissions intensity are classified as green and brown, with the rest classified as gray. Columns (1)–(3) report the results from estimating the panel regression for tweets mentioning the specific regulation being voted on during the four, two, and one week(s) leading up to a congressional vote by members of the chamber in which the vote took place, respectively. Columns (4) and (5) report the results from estimating the panel regression for tweets posted during one and two weeks following the congressional vote(s). The first five rows of the table report the following slope coefficients: $\gamma_B$ (Brown), $\gamma_G$ (Green), $\tau$ (PTLSupport), $\tau_B$ (Brown $\times$ PTLSupport), $\tau_G$ (Green $\times$ PTLSupport). The sixth row reports the difference between $\tau_G$ and $\tau_B$, (Green $-$ Brown) $\times$ PTLS. We include the time-varying controls listed in Table IA.5 of the Internet Appendix. Standard errors are heteroscedasticity robust and double clustered at firm- and tweet-level. We denote $p$-values smaller than 0.10, 0.05, and 0.01 with one (*), two (**), and three (***) stars, respectively.

| | (1)<br>Leading 4wk | (2)<br>Leading 2wk | (3)<br>Leading 1wk | (4)<br>Lagging 1wk | (5)<br>Lagging 2wk |
|---|---|---|---|---|---|
| Brown | -0.838 | -0.710 | -0.689 | 1.495 | 0.124 |
| | (-0.94) | (-0.74) | (-0.65) | (0.69) | (0.09) |
| Green | -0.317 | -0.591 | -1.948 | 5.265*** | 1.356 |
| | (-0.18) | (-0.33) | (-0.93) | (5.79) | (1.81) |
| PTLSupport | 13.89* | 13.78* | 27.31** | 11.86 | 30.80*** |
| | (2.15) | (2.11) | (2.61) | (1.91) | (6.15) |
| Brown × PTLSupport | -0.632 | -0.672 | -0.457 | -1.499 | -0.654 |
| | (-1.02) | (-1.00) | (-0.66) | (-0.95) | (-0.89) |
| Green × PTLSupport | 2.831* | 3.095* | 4.117* | -3.637*** | -0.770 |
| | (1.87) | (1.97) | (2.19) | (-4.46) | (-1.06) |
| (Green − Brown) × PTLS | 3.463** | 3.767** | 4.574* | -2.138 | -0.116 |
| | (2.28) | (2.41) | (2.01) | (-0.99) | (-0.08) |
| Controls | Yes | Yes | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes | Yes | Yes |
| Legislator FE | Yes | Yes | Yes | Yes | Yes |
| Day FE | Yes | Yes | Yes | Yes | Yes |
| Adjusted R2 | 0.1628 | 0.1642 | 0.1885 | 0.1626 | 0.1460 |
| Observations | 113,686 | 105,782 | 84,898 | 37,648 | 69,915 |

after replacing Sentiment with PTLSupport (min-max normalized quarter on quarter). As a placebo test, in Columns (5) and (6), we report estimation results one and two weeks after the vote. Under our hypothesis, we would expect little to no response from the market to regulation-specific tweets posted after the regulation has been voted.

Consistent with the hypothesis that regulatory tweets contain information about the probability that a regulation will pass a congressional vote, the sixth row of Column (1) shows that a one standard deviation increase in legislator support toward pro-transition regulation (0.307) in tweets posted four weeks before the vote leads to an increase in the spread between the return of green and brown firms of 1.063 bps ($= 0.307 \times 3.463$), significant at the 5% level. The results in Columns (2) to (3) provide support to the stronger prediction that regulatory tweets have a larger impact as the date of the vote approaches: the spread between the returns of green and brown firms increases when they are published two weeks and one week before the vote relative to tweets posted four weeks before. In Column (3), which reports results for regulatory tweets posted in the week preceding the vote, the impact of tweets on the spread between green and brown stock returns increases from 1.063 bps, as reported in Column (1), to 1.404 bps ($= 0.307 \times 4.574$), significant at the 10% level. Columns (4) and (5) of Table 6 show that, one and two weeks after the congressional vote, the increase in the spread between the returns of green and brown firms around pro-transition regulatory tweets becomes insignificant, consistent with those tweets containing little valuable information for investors.

If regulatory tweets contain information about the probability that regulation passes a congressional vote, then we would also expect tweets posted before the vote to have a larger impact on stock prices when the uncertainty about the vote outcome is higher. To test this hypothesis, we split our sample into votes that eventually passed by a *close* margin and those that passed by a *clear* margin. More specifically, we compute the voting margin by dividing the difference between the *Yay* (for) and *Nay* (against) votes by the total number of votes cast for a given regulation. A congressional vote is considered close when the voting margin is less than 3%, and clear otherwise.[22]

Columns (1) to (3) of Table 7 report the results from estimating the panel regression for tweets posted in the weeks preceding a close vote, and Columns (4) to (6) in the weeks preceding a clear vote. Consistent with the hypothesis that regulatory tweets are more infor-

[22] We classify votes into close or clear based on a 3% threshold because it results in a reasonable number of observations in the subsample associated with "close" votes. However, Table IA.6 in the Internet Appendix shows that our findings are robust to using a 5% threshold to categorize close votes. Also, we do not decrease the threshold beyond 3% because it would result in all votes in the upper chamber being classified as "clear".

**Table 7:** Voting margin and legislator support toward pro-transition regulation

This table reports the results from estimating the panel regression (1), after replacing Sentiment with PTLSupport, separately for tweets posted in the weeks preceding close or clear congressional votes, within the sample of legislator tweets that mention the 20 environmental regulations listed in Table 5. PTLSupport is min-max normalized quarter on quarter. We compute the voting margin by dividing the difference between the *Yay* (for) and *Nay* (against) votes by the total number of votes cast for a given regulation. A congressional vote is considered "close" when the voting margin is less than 5%, and "clear" otherwise. Columns (1) through (3) reproduce Columns (1) through (3) of Table 6 for tweets posted in the weeks preceding *close* congressional votes, and Columns (4) through (6) for tweets posted in the weeks preceding *clear* congressional votes. The dependent variable is the log change in stock prices (in basis points) from one minute before to ten minutes after each tweet, $\Delta p(-01, +10)$. PTLSupport measures the stance of a tweet toward pro-transition regulation between zero (strong opposition) and one (strong support). Stocks that fall into the top and bottom tercile of carbon emissions intensity are classified as green and brown, with the rest classified as gray. The first five rows of the table report the following slope coefficients: $\gamma_B$ (Brown), $\gamma_G$ (Green), $\tau$ (PTLSupport), $\tau_B$ (Brown $\times$ PTLSupport), $\tau_G$ (Green $\times$ PTLSupport). The sixth row reports the difference between $\tau_G$ and $\tau_B$, (Green $-$ Brown) $\times$ PTLS. We include the time-varying controls listed in Table IA.5 of the Internet Appendix. Standard errors are heteroscedasticity and double clustered at firm- and tweet-level. We denote $p$-values smaller than 0.10, 0.05, and 0.01 with one (*), two (**), and three (***) stars, respectively.

| | (1) CLOSE Leading 4wk | (2) CLOSE Leading 2wk | (3) CLOSE Leading 1wk | (4) CLEAR Leading 4wk | (5) CLEAR Leading 2wk | (6) CLEAR Leading 1wk |
|---|---|---|---|---|---|---|
| Brown | -2.552 | -1.627 | 1.318 | -0.521 | -0.822 | -1.415 |
| | (-1.36) | (-0.85) | (0.34) | (-0.72) | (-0.91) | (-1.43) |
| Green | -2.624 | -3.245 | -3.383 | 2.180 | 2.095 | 1.760 |
| | (-1.48) | (-1.58) | (-0.99) | (0.85) | (0.73) | (0.55) |
| PTLSupport | 16.12 | 16.11 | 25.36 | 12.28* | 12.02* | 29.45 |
| | (1.26) | (1.22) | (1.17) | (2.43) | (2.38) | (2.79) |
| Brown × PTLSupport | -1.449 | -1.438 | -1.169 | 0.451 | 0.728 | 1.113 |
| | (-1.52) | (-1.38) | (-1.20) | (0.69) | (1.04) | (2.34) |
| Green × PTLSupport | 3.402 | 3.425 | 5.959** | 0.762 | 1.040 | 0.743 |
| | (1.43) | (1.38) | (5.13) | (0.42) | (0.47) | (0.29) |
| (Green − Brown) × PTLS | 4.851** | 4.863* | 7.129*** | 0.311 | 0.312 | -0.370 |
| | (3.16) | (2.99) | (5.98) | (0.23) | (0.19) | (-0.15) |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Legislator FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Day FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Adjusted R2 | 0.0953 | 0.0955 | 0.1266 | 0.2142 | 0.2202 | 0.2427 |
| Observations | 34,768 | 34,367 | 27,261 | 78,918 | 71,414 | 57,636 |

mative about the probability that a regulation passes a congressional vote when uncertainty about the outcome of the vote is higher, Table 7 shows that the impact of regulatory tweets on the spread between green and brown stock returns is substantially larger in weeks leading to a close vote, compared to weeks leading to a clear vote. For instance, the sixth row of

Column (3) shows that a one standard deviation increase in legislator support toward pro-transition regulation leads to a 2.189 bps (= $0.307 \times 7.129$) increase in the spread between the returns of green and brown firms around regulatory tweets posted one week before a *close* vote, significant at the 1% level. In contrast, the sixth row of Column (6) shows no significant impact of regulatory tweets on the spread for clear votes one week before the vote.

By narrowing the focus to regulation-specific tweets, in this section we provide evidence that the impact of legislator tweets on stock returns is more pronounced when tweets are more informative about the probability that regulation passes congressional votes. This evidence supports the hypothesis that investors learn in real time from legislators' regulatory tweets about the likelihood of future climate regulation. Taken together, the results in this section suggest that the green transition impacts the relative value of green and brown stocks, at least partly, via a regulatory channel.

# 5 Conclusion

We study the impact of green-transition regulation on firm value by comparing the returns of green and brown stocks in the minutes around tweets about climate change posted by members of U.S. Congress. We find that green stocks outperform brown stocks in the one-to-ten-minute window around pro-transition tweets, with the return spread statistically significant at the 1% level. The effect is also economically significant: a one standard deviation increase in legislator-tweet sentiment toward the green transition generates an average increase of $509,766 in the market valuation of a green firm relative to an otherwise similar brown firm around a legislator tweet. We further link stock returns around legislator posts to the future carbon emissions of firms and find that investors correctly identify and reward high-emission firms that can decarbonize in response to transition-regulation news.

We construct a daily pro-transition sentiment index, which spikes around key legislative events, and show that it contains information distinct from that communicated in mainstream media concerns related to climate change. To focus on the regulatory channel, we consider legislator tweets that mention environmental regulations, and find that the spread between the returns of green and brown stocks around tweets that support pro-transition regulations increases in the weeks leading to a congressional vote and vanishes afterward, with the effect driven by tweets posted ahead of *close* votes. Our findings suggest that the green transition impacts the relative performance of green and brown stocks, at least partly, via a regulatory channel.

Our results have important implications for policymakers, firms, and investors. Policymakers can alleviate the impact of the green transition on brown firms by adopting a consistent approach to the green transition, thus avoiding abrupt shifts in policy that amplify the impact of green-transition regulation on brown firms. High-emission firms can add value by enhancing their ability to adjust their emissions in response to new transition regulation. Finally, investors can manage their exposure to green-transition regulation by holding stocks of green firms or brown firms with the ability to adapt their emissions.

# References


V. V. Acharya, S. Giglio, S. Pastore, J. Stroebel, Z. Tan, and T. Yong. Climate transition risks and the energy sector. *Available at SSRN 5130945*, 2024.

J. M. Addoum and A. Kumar. Political sentiment and predictable returns. *The Review of Financial Studies*, 29(12):3471–3518, 2016.

D. Ardia, K. Bluteau, K. Boudt, and K. Inghelbrecht. Climate change concerns and the performance of green vs. brown stocks. *Management Science*, 69(12):7607–7632, 2023.

M. J. Arteaga-Garavito, R. Colacito, M. M. M. Croce, and B. Yang. International climate news. *Available at SSRN 4713016*, 2025.

S. M. Bartram, K. Hou, and S. Kim. Real effects of climate policy: Financial constraints and spillovers. *Journal of Financial Economics*, 143(2):668–696, 2022.

S. Baz, L. Cathcart, A. Michaelides, and Y. Zhang. Firm-level climate regulatory exposure. *Available at SSRN 3873886*, 2023.

B. S. Bernanke and K. N. Kuttner. What explains the stock market's reaction to federal reserve policy? *The Journal of Finance*, 60(3):1221–1257, 2005.

F. Bianchi, D. Comin, H. Kung, T. Kind, and A. Matusche. Slow recoveries through fiscal austerity: New insights in the effects of fiscal austerity. Technical report, ZEW Policy Brief, 2019.

F. Bianchi, R. Gómez-Cram, and H. Kung. Using social media to identify the effects of congressional viewpoints on asset prices. *The Review of Financial Studies*, 37(7):2244–2272, 2024.

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

P. Bolton and M. Kacperczyk. Global pricing of carbon-transition risk. *The Journal of Finance*, 78(6):3677–3754, 2023.

J. Chen, G. Tang, G. Zhou, and W. Zhu. ChatGPT and Deepseek: Can they predict the stock market and macroeconomy? *arXiv preprint arXiv:2502.10008*, 2025.

Y. Chen, B. T. Kelly, and D. Xiu. Expected returns and large language models. *Available at SSRN 4416687*, 2022.

J. Colmer, R. Martin, M. Muûls, and U. J. Wagner. Does pricing carbon mitigate climate change? firm-level evidence from the european union emissions trading system. *Review of Economic Studies*, 92(3):1625–1660, 2025.

J. A. Cookson, C. Fox, J. Gil-Bazo, J. F. Imbet, and C. Schiller. Social media as a bank run catalyst. *Journal of Financial Economics*, 176:104218, 2026.

V. DeMiguel, F. J. Nogales, and R. Uppal. Stock return serial dependence and out-of-sample portfolio performance. *The Review of Financial Studies*, 27(4):1031–1073, 2014.

J. Devlin, M.-W. Chang, K. Lee, and K. Toutanova. BERT: Pre-training of deep bidirectional transformers for language understanding. *arXiv preprint arxiv:1810.04805*, 2018.

M. Eskildsen, M. Ibert, T. I. Jensen, and L. H. Pedersen. In search of the true greenium. *Available at SSRN 4744608*, 2024.

R. Gómez-Cram and M. Grotteria. Real-time price discovery via verbal communication: Method and application to Fedspeak. *Journal of Financial Economics*, 143(3):993–1025, 2022.

R. Gómez-Cram and M. Olbert. Measuring the expected effects of the global tax reform. *The Review of Financial Studies*, 36(12):4965–5011, 2023.

J. Z. G. Hiew, X. Huang, H. Mou, D. Li, Q. Wu, and Y. Xu. BERT-based financial sentiment index and LSTM-based stock return predictability. *arXiv preprint arXiv:1906.09024*, 2019.

A. Huang, H. Wang, and Y. Yang. FinBERT – A large language model approach to extracting information from financial text. *Available at SSRN 3910214*, 2020.

D. R. Känzig. The macroeconomic effects of oil supply news: Evidence from OPEC announcements. *American Economic Review*, 111(4):1092–1125, 2021.

J. F. Kölbel, M. Leippold, J. Rillaerts, and Q. Wang. Ask BERT: How regulatory disclosure of transition and physical climate risks affects the CDS term structure. *Journal of Financial Econometrics*, 22(1):30–69, 2024.

E. Kvam, P. Molnár, I. Wankel, and B. A. Ødegaard. Do sustainable company stock prices increase with ESG scrutiny? Evidence using social media. *Available at SSRN 4057988*, 2022.

Q. Li, H. Shan, Y. Tang, and V. Yao. Corporate climate risk: Measurements and responses. *The Review of Financial Studies*, 37(6):1778–1830, 2024.

A. Lopez-Lira and Y. Tang. Can ChatGPT forecast stock price movements? Return predictability and large language models. *arXiv preprint arXiv:2304.07619*, 2023.

T. Loughran and B. McDonald. When is a liability not a liability? Textual analysis, dictionaries, and 10-Ks. *The Journal of Finance*, 66(1):35–65, 2011.

R. Martin, L. B. De Preux, and U. J. Wagner. The impact of a carbon tax on manufacturing: Evidence from microdata. *Journal of Public Economics*, 117:1–14, 2014.

G. Martinsson, L. Sajtos, P. Strömberg, and C. Thomann. The effect of carbon pricing on firm emissions: Evidence from the swedish co2 tax. *The Review of Financial Studies*, 37(6):1848–1886, 2024.

H. Mathurin. Pricing of green regulatory and technological risks. *Available at SSRN 5065450*, 2024.

E. Nakamura and J. Steinsson. High-frequency identification of monetary non-neutrality: The information effect. *The Quarterly Journal of Economics*, 133(3):1283–1330, 2018.

L. Pástor and P. Veronesi. Political cycles and stock returns. *Journal of Political Economy*, 128 (11):4011–4045, 2020.

L. Pástor, R. F. Stambaugh, and L. A. Taylor. Sustainable investing in equilibrium. *Journal of Financial Economics*, 142(2):550–571, 2021.

L. Pástor, R. F. Stambaugh, and L. A. Taylor. Dissecting green returns. *Journal of Financial Economics*, 146(2):403–424, 2022.

S. Ramelli, A. F. Wagner, R. J. Zeckhauser, and A. Ziegler. Investor rewards to climate responsibility: Stock-price responses to the opposite shocks of the 2016 and 2020 US elections. *The Review of Corporate Finance Studies*, 10(4):748–787, 2021.

P. Santa-Clara and R. Valkanov. The presidential puzzle: Political cycles and the stock market. *The Journal of Finance*, 58(5):1841–1872, 2003.

Z. Sautner, L. Van Lent, G. Vilkov, and R. Zhang. Firm-level climate change exposure. *The Journal of Finance*, 78(3):1449–1498, 2023.

# Internet Appendix to

# Legislator Tweets about the Green Transition and the Returns of Green versus Brown Stocks

This Internet Appendix describes details of some of the analysis carried out in the main body of the manuscript as well as the results of additional analyses. Section IA.1 discusses our validation of the GPT-generated measures of sentiment. Section IA.2 gives details of our approach to identify tweets that mention specific regulations and evaluate legislator support toward those regulations. Section IA.3 reports the results of additional tests to examine the relation between the informational content of tweets and stock returns, and Section IA.4 to study the heterogeneity in the impact of legislator sentiment on stock returns based on tweet popularity and chamber affiliation.

## IA.1 Validating the GPT-generated sentiment

In Section 2.4 of the main body of the manuscript, we obtain the legislator sentiment toward green transition using GPT-4.1. In this section, we validate the sentiment measure by comparing it to that produced manually by five researchers for a random sample of 100 tweets.

We ask five researchers to independently assign each tweet a rating between $-10$ (strong *opposition* to the green transition) and 10 (strong *support* to the green transition); a value of 0 implies that the tweet is neutral, ambiguous, or unrelated to climate change. Panels (a) through (e) of Figure IA.3 depict the distribution of the sentiment measure assigned by the five researchers. Panel (f) of Figure IA.3 depicts the numerical sentiment measure (between $-1$ to 1) obtained from GPT-4.1 in Section 2.4. The values of researcher generated sentiment are divided by 10 to facilitate comparison with the GPT generated measure. We observe that the sentiment scores assigned by researchers I, III, and IV are more polarized than those assigned by researchers II and V. Thus, there is variation in how the support of a legislator tweet toward green transition is perceived.

Table IA.3 shows the matrix of correlations between the sentiment scores generated by the five researchers and GPT. Our main observation is that the sentiment scores generated by the five researchers are highly correlated with those generated by GPT, with the correlation between every manually generated measure and the GPT measure above 65%. Next, we compute the *average* sentiment produced by the five researchers for each tweet and compare it with the sentiment produced by GPT. The first row of Table IA.4 shows that the correlation between the average sentiment produced by the five researchers and that by GPT is 93.8%. Next, we compute the average sentiment produced by the research team after dropping one researcher at a time and report its correlation with the sentiment produced by GPT. These correlation values are reported in the subsequent rows of Table IA.4 and range between 82% and 88.8%.

# IA.2 Details of regulatory-channel analysis

This section gives a detailed description of the methodology we use to identify legislator tweets that mention environmental regulation and how we measure the support of a particular legislation toward the green transition.

## IA.2.1 *Identifying regulatory tweets*

We now describe how we identify legislator tweets that mention specific climate regulations. We start by scraping all regulations on GovTrack introduced during the 113th through the 117th U.S. Congress that are categorised as '*Environmental Protection*' and '*Climate Change and Greenhouse Gases*'. We obtain 1,620 climate-regulations over the duration of our sample.

Next, we programmatically construct a bag-of-words for each regulation, which contains three categories of keywords. The first category of keywords is the bill number, as regulators often tweet about a regulation using its bill number directly. For example, consider the tweet by Republican representative Doug LaMalfa on January 05, 2019 that mentions the Climate Action Now Act: *H.R.9 would seek to prevent the President from withdrawing from the misguided Paris Climate Agreement. This is a bad idea. Watch my speech on the House floor urging my colleagues to vote against this partisan attack on American energy production.* We parse tweets against four permutations of the bill number with and without spaces and dots. Hence, to check whether the tweet mentions the Climate Action Now Act, it is parsed against '`H.R.9`', '`H.R. 9`', '`HR9`', and '`HR 9`'.

The second category of keywords is the name of the regulation. Before parsing the tweets, we truncate the name of the regulation by removing the year tag and the keyword 'Act'. For instance, to inspect whether a tweet mentions the Clean Energy Jobs Act of 2019, we check whether it contains '`clean energy jobs`'. Sometimes, the name of the regulation with the keyword 'Act' becomes too short and becomes conflated with instances of text that are not related to the regulation. For instance, using the phrase '`use it`' to search for the USE IT Act returns many false positives, as this phrase can commonly occur in many other contexts. Thus, if the truncated version of the regulation contains two or fewer words, then we search for it by adding back the keyword 'Act'. For example, we use the phrase '`use it act`' to search for the USE IT Act, whereas '`american rescue plan`' to search for the American Rescue Plan Act of 2021. The dictionary search for regulation names is not case-sensitive.

The third category of keywords is hashtags associated with the regulation. Hashtags are widely used in social media communications. We parse tweets against three types of hashtags. The first set of hashtags is obtained by adding a hash (`#`) in front of the truncated names of the regulation with and without the keyword 'Act'. For example, the GREEN Act of 2021 will be associated with hashtags `#GREEN` and `#GREENAct`. These hashtags are case sensitive. The second type of hashtag is obtained by adding a hash (`#`) before and the congress number after the truncated regulation name without the keyword 'Act'. Thus, the above regulation would be associated with the hashtag `#GREEN117`. This hashtag is not case-sensitive. When searching for these keywords, we assert that they are standalone (or independent) words and not part of another longer phrase (for example, `#green-energy`).

For each regulation, we search for the three categories of keywords in a given tweet if it is posted during the congressional term corresponding to the regulation. We parse all 1,648,005 legislator tweets posted during the NYSE trading hours to obtain 19,084 tweets that mention 437 unique regulations. Of these, we retain 13,294 tweets that mention one of the 20 climate-change regulations listed in Table 5, which are the regulations most frequently mentioned in legislator tweets among those introduced to Congress during our sample period.

### *IA.2.2 Obtaining regulation-stance toward the green transition*

We now ascertain the stance of the 20 regulations in Table 5 toward the green by querying GPT in the following manner for each regulation:

> You are a political expert with experience evaluating the stance of U.S. Congress regulations toward the green transition. The 'green transition' refers to the comprehensive shift from carbon-intensive energy sources and practices to low-carbon alternatives.
>
> Determine whether the {regulation name} with code {bill number} by the {congress number}th U.S. Congress is 'strongly opposed', 'weakly opposed', 'neutral', 'weakly supportive', or 'strongly supportive' toward the green transition. If the regulation is unrelated to the green transition, return 'ambiguous'.
>
> First, return only a single option from the above list, indicating the stance.
>
> Then, provide a bulleted list of specific reasons that support your selected stance. Response format:

Stance: <one of: strongly opposed, weakly opposed, neutral, weakly supportive, strongly supportive, ambiguous>

Justification extracts:

* “<exact phrase or sentence from bill summary 1>”
* “<exact phrase or sentence from bill summary 2>”

If no extracts are relevant, output only the stance and a single bullet:

* “No relevant extracts found.”

Return nothing else.

In the prompt above, {regulation name} is the name of the regulation (for example, Clean Economy Act of 2019), {bill number} is the bill number (for example, S. 3269), and {congress number} is the congessional term during which the regulation for introduced (for example, 116).

We map the labels ‘strongly opposed’, ‘weakly opposed’, ‘neutral’, ‘weakly supportive’, or ‘strongly supportive’ to numerical values (RStance) of $-1$, $-0.5$, 0, 0.5, and 1, respectively. These values are used to compute the pro-transition legislator support (PTLSupport) in the main body of the manuscript (see Section 4.2.1).

## IA.3 Tests for legislator tweets driving stock prices

In the main body of the manuscript, we show that there is a significant association between legislator-tweet sentiment toward the green transition and the spread in the returns of green and brown firms. In this section, we perform three additional tests to examine the relation between the informational content of legislator tweets and firm value. First, a placebo test that shows the impact of legislator sentiment on the spread between the returns of green and brown stocks is insignificant in the ten-minute window *before* the tweets. Second, an out-of-sample test that shows the impact of legislator sentiment obtained from GPT-3.5 on the spread between the returns of green and brown stocks is significant for tweets posted after the GPT-3.5 training cutoff of September 2021. Third, a test that shows that the impact of legislator sentiment on the green versus brown stock return spread continues to be significant after controlling for innovations to media climate change concerns index.

The results of these tests reinforce the interpretation that legislators sentiment toward the green transition has a genuine and economically meaningful impact on the relative valuation of green versus brown firms.

### *IA.3.1 Placebo test*

In this section, we conduct a *placebo* test to reinforce the link between the informational content in legislator tweets and firm value. If the movement in stock prices is due to the informational content of the tweets, then the impact of the legislator tweets on prices in the ten-minute window *before* the tweets should be *insignificant*. To test this hypothesis, we compute the log change in stock prices (in basis points) from 11 minutes before to one minute before each tweet: $\Delta p(-11, -01)$. We then estimate Equation (1) with $\Delta p(-11, -01)$ as the dependent variable and report the results in Table IA.7.

The sixth row of Table IA.7 shows that the impact of legislator sentiment on the spread between the returns of green and brown stocks in the ten-minute window before the tweet is insignificant with a $t$-statistic of 0.98. This suggests that it is indeed the informational content of legislator tweets that moves stock prices during the ten-minute window following the tweets.

### *IA.3.2 Out-of-sample test*

In the main body of the manuscript, we use GPT-4.1 to estimate the tweet sentiment toward the green transition. In this section, we perform an *out-of-sample* test by using the sentiment obtained from GPT-3.5 for tweets posted *after* the GPT-3.5 model training cutoff in September 2021.[23] This guarantees that the model has not been exposed to, or trained using, the informational content of the tweets. The results are reported in Table IA.8.

The sixth row of Column (1) shows that a one standard deviation increase in legislator-tweet sentiment toward the green transition generates a spread between the returns of green and brown stocks around a legislator tweet of 0.268 bps ($0.236 \times 1.134$ bps), significant at the 5% level, which translates into an average \$704,304 increase in the market valuation of a green firm relative to that of an otherwise similar brown firm around a legislator tweet.[24]

[23] The sentiment obtained from GPT-3.5 achieves a 70% correlation with the average sentiment produced by human researchers as opposed to 93.8% by GPT-4.1.

[24] The standard deviation of the sentiment obtained from GPT-3.5 is 0.268 bps.

This out-of-sample test shows that the economic magnitude and statistical significance of the effect are very similar to those obtained in the baseline specification, confirming that our results are not driven by data leakage or overfitting to the language model's training sample.

### *IA.3.3 Controlling for innovations to media climate change concerns*

In Section 4.1, we show that the information contained in legislator tweets on climate change is different from that contained in Media Climate Change Concerns (MCCC) index of Ardia et al. (2023). The MCCC index proxies climate-change concerns expressed in mainstream media. Ardia et al. (2023) show that innovations to this index are associated with a spread in returns between green and brown stocks. In this section, we introduce the innovations to the MCCC index (UMC) as a control in the panel regression in Equation (1) to examine whether these innovations confound the impact of the legislator-tweet sentiment toward the green transition.[25] Following Ardia et al. (2023), we obtain UMC as the residuals obtained from estimating an ARX(1) model on MCCC with the five Fama-French and the momentum factors as controls.[26]

The sixth and seventh rows of Table IA.9 report the slope coefficient associated with the interaction between the UMC index and the green and brown portfolio indicators. We only report the slope coefficients associated with the interaction terms because the UMC index is at a daily frequency; thus, its partial effect is absorbed by the day fixed effects. The eighth row reports the difference between $\tau_G$ and $\tau_B$, (Green $-$ Brown) $\times$ Sentiment. Lastly, the ninth row reports an equivalent measure for the UMC index, (Green $-$ Brown) $\times$ UMC. The table shows that although an increase in the UMC index is associated with higher prices of green stocks at the 10% significance level, the interaction between UMC and the spread between the returns of green and brown stocks is insignificant. Importantly, our main finding is robust to controlling for MCCC innovations: the difference between the interactions between the green and brown indicator variables and the legislator-tweet sentiment continues to be significant at the 1% confidence level.[27]

[25] Table IA.10 shows that using MCCC instead of UMC does not alter our conclusions.

[26] Using the five Fama-French and the momentum factors as controls in the ARX(1) model corresponds to the CTRL-6 set of controls used in Ardia et al. (2023).

[27] We have repeated the analysis in Tables IA.9 and IA.10 using versions of the UMC and MCCC indices that are min-max normalized annually between zero and one and the slope for the interactions between the green and brown indicator variables and the legislator-tweet sentiment continues to be significant at the 1% level.

These results provide reassurance that it is the news contained in the tweets, and not that reported in mainstream media, that drives stock prices in the 10-minute window following legislator tweets.

## IA.4 Heterogeneity in legislator sentiment impact

We now examine heterogeneity in the impact of legislator sentiment on the spread between the returns of green and brown stocks depending on (i) the popularity of the legislator tweets proxied through the ex-post number of likes and retweets received on Twitter and (ii) the congressional chamber of the legislator who posted the tweet.

### *IA.4.1 Ex-post tweet popularity*

In this section, we study the heterogeneity in the impact of legislator tweets on the spread between the returns of green and brown stocks based on social media popularity on Twitter. We measure popularity using the number of 'likes' and 'retweets' received by a given tweet. Columns (1) and (2) of Table IA.11 report the results obtained from estimating the panel regression in Equation (1) for tweets that received below and above the median likes during a given calendar year. The sixth row shows that the estimate of the slope associated with the impact of legislator sentiment on the difference in the returns of green and brown stocks is positive (0.790) and significant at the 1% level for tweets that received below median likes. However, the magnitude of this slope becomes smaller (0.575) for tweets that received above median likes and is less significant (at the 10% level). Columns (3) and (4) reproduce Columns (1) and (2) for retweets. The results are consistent with those for likes. The slopes associated with tweets that received below (1.061) and above the median (0.312) retweets remain positive. However, the slope corresponding to tweets with below median retweets is economically larger in magnitude and significant at 1% level, whereas that associated with above median retweets is insignificant.

Thus, we find that the sentiment of less popular tweets (with below median likes or retweets) has a higher and more significant impact on the spread between the returns of green and brown stocks compared to more popular tweets. This suggest that the type of tweet content that impacts the relative value of green and brown firms is different from the one that generates Twitter likes and retweets. This is also consistent with the view that market participants who trade on the information contained in the tweets are unlikely to popularise those tweets by liking or retweeting them on social media. In addition, institutional investors are highly unlikely to review tweets one-by-one directly on Twitter. They may use an API to download the tweets in order to systematically analyse the textual information, or use third-party tools such as the `TWTR <GO>` functionality on Bloomberg to identify relevant tweets. In such instances, there is very little reason for investors to incur the additional cost burden to popularise the tweets either programmatically or non-programmatically.

### *IA.4.2 Congressional chamber*

We now examine the heterogeneity in the impact of legislator sentiment on the spread between the returns of green and brown stocks based on the congressional chamber of which the author is a member. Columns (1) and (2) of Table IA.12 report results for tweets posted by the members of the House of Representatives and the Senate. The sixth row of Columns (1) and (2) shows that a one standard deviation increase in legislator-tweet sentiment toward the green transition generates an economically similar spread between the returns of green and brown stocks around a legislator tweet. However, the estimate of the slope corresponding to members of the House of Representatives is significant at the 1% level while that of the Senate is significant at the 10% level. Taken together, these results indicate that legislator sentiment operates similarly across chambers, with differences in precision driven by statistical power rather than chamber-specific effects.

**Figures and Tables for Internet Appendix**

**Figure IA.1:** Average monthly numerical sentiment toward the green transition by party

This figure plots the average monthly numerical sentiment toward the green transition of tweets posted by Republicans (red) and Democrats (blue) between January 2014 and March 2023. The vertical dashed lines demarcate changes in U.S. presidency.

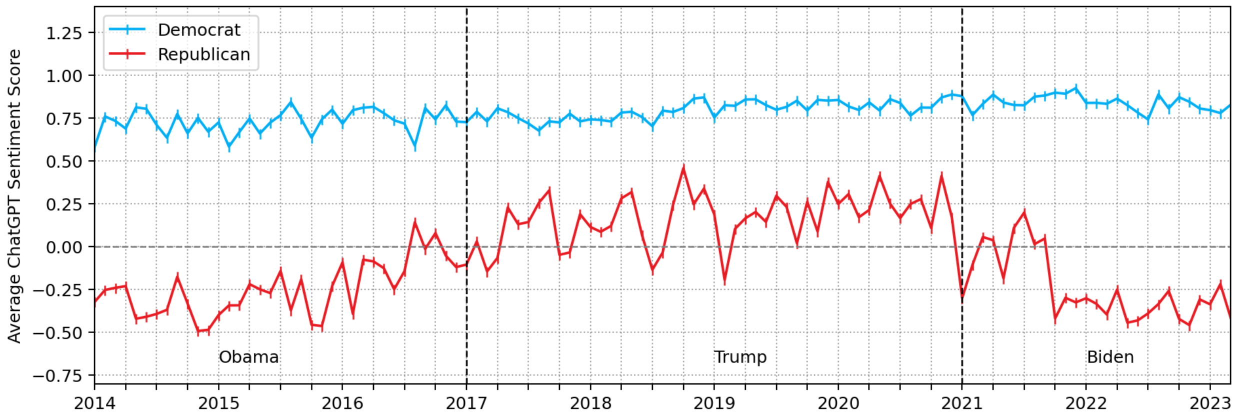


**Figure IA.2:** Distribution of pro-transition legislative support

This histogram depicts the empirical distribution of pro-transition legislative support (PTLSupport) obtained as described in Section 4.2.1, which measures the stance of a tweet toward pro-transition regulation between zero (strong opposition) and one (strong support).

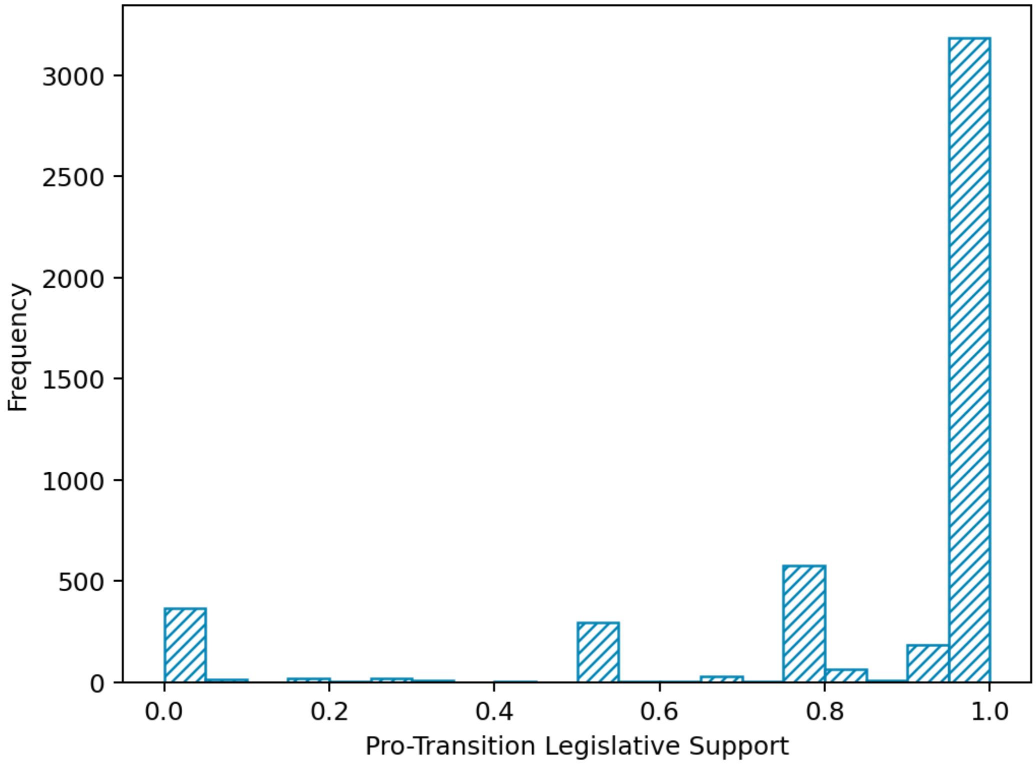


**Figure IA.3:** Distribution of manually assigned sentiment measures

Panels (a) through (e) depict the distribution of sentiment toward green transition assigned manually and independently by five researchers (between −10 to 10). Panel (f) depicts the sentiment measure (between −1 to 1) obtained from GPT-4.1 in Section 2.4. The values for researcher generated sentiment in panels (a) through (e) are scaled by 10 to facilitate comparison with the GPT generated sentiment.

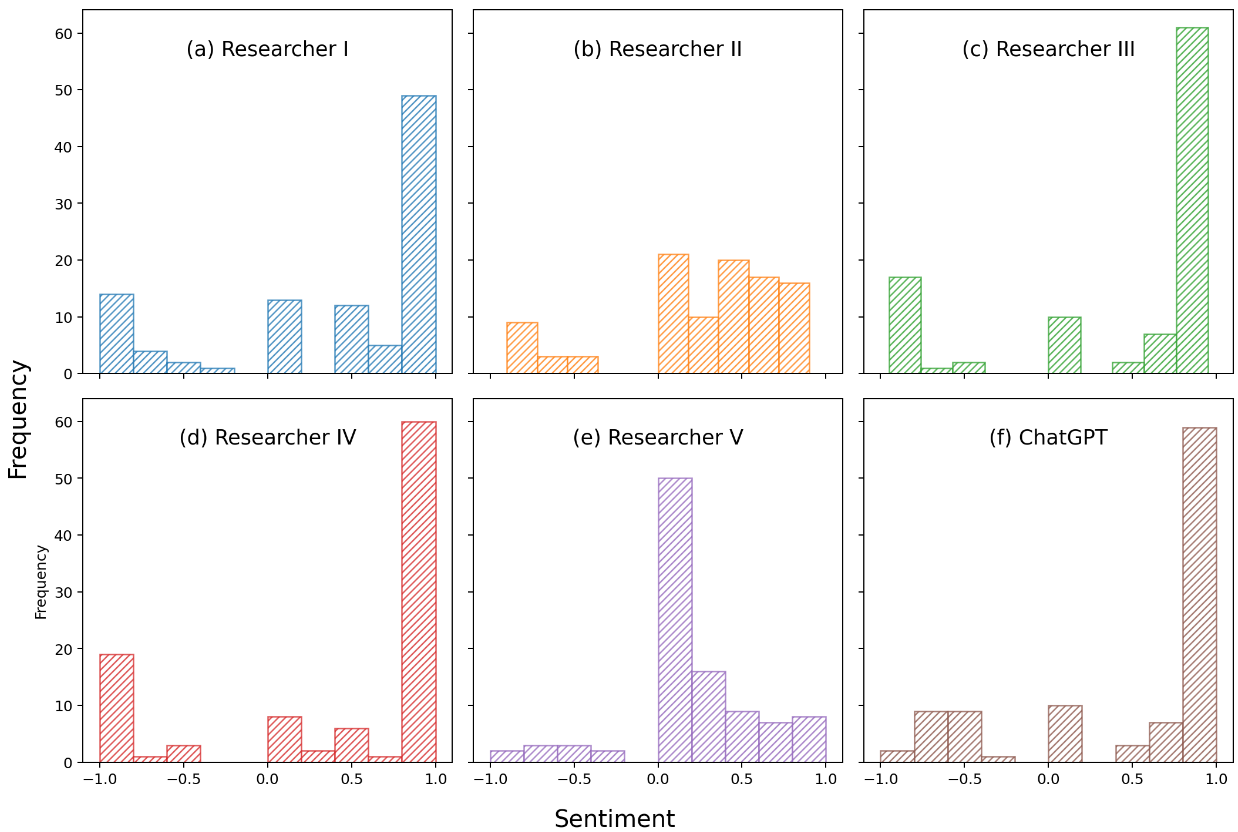


**Table IA.1:** GPT sentiment for tweets classified "Negative" by FinBERT

This table reports the sentiment toward the green transition obtained from GPT-4.1 for a random sample of tweets classified as Negative by the Tone FinBERT model.

| | Tweets classified at "Negative" by FinBERT | GPT Score |
|---|---|---|
| 1 | The Russian war on Ukraine makes clear that we cannot depend on foreign oil forever. To keep energy prices affordable and create a livable future for our children, we had to invest in #AmericanMade clean energy. The Inflation Reduction Act does just that. | 1.00 |
| 2 | Hurricane Ida devastated communities up and down the East Coast while wildfires persist on the West Coast. Extreme flooding, lethal storms, dangerous wildfires. This is our future if we dont take serious steps to address the climate crisis now. | 1.00 |
| 3 | RT @RepDonBeyer: Climate change is one of the gravest dangers our society has faced in our lifetimes. The bill we are about to pass is mos... | 1.00 |
| 4 | To reach our ambitious climate goals, we must unleash the full power of American clean energy and that includes offshore wind energy development. The former administrations arbitrary offshore wind leasing moratorium would stifle the growth of our clean energy economy in NC. | 1.00 |
| 5 | Along with our thoughts & prayers to Pakistan, the U.S. must send tangible aid for flood victims. What were witnessing are the deadly effects of climate change extending beyond the borders of top CO2 emission-producing nations. Together, we must do more to save our planet. | 0.90 |
| 6 | There is no single barrier to the transition to electric vehicles, but rather an entire ecosystem of challenges to address. We must do more to accelerate our transition to an electric vehicle future. My op-ed in @thehill | 0.90 |
| 7 | New Jersey is a top #solar state & we must make sure we support our clean-energy workforce. This #solartariff move is bad for our state & I oppose it –> ”President Trump Slaps Tariffs on Solar Panels in Major Blow to Renewable Energy" via @TIME: | 0.80 |
| 8 | RT @CCLCharlotteNC: We appreciate your concern for the #climate and action towards #cleanenergy @RepAdams @RepRichHudson! | 0.80 |
| 9 | Banning Russian oil imports is a necessary step to continue to put economic pressure on Putin and support our Ukrainian allies. This situation underscores why we must invest in clean energy long-term to reduce our dependence on foreign oil. | 0.80 |
| 10 | Solar tariffs could cost us 100,000 jobs in the solar industry and hurt our transition to a cleaner energy future. I've joined my colleagues, including @RepScottPeters, in calling on the Biden admin to protect domestic solar energy capacity & halt consideration of solar tariffs. | 0.80 |
| 11 | We advanced investments in resilient infrastructure against the dire effects of climate change. North Carolina knows the detrimental effects of extreme weather too well. From highways to roads to farms, hurricanes cost our state billions of dollars. | 0.70 |
| 12 | Republicans are delivering on their Commitment to America. The Lower Energy Costs Act is just one example. We know Americans are suffering in President Bidens America, but we are hard at work to end the multitude of crises created by this administrations failed policies! | 0.00 |
| 13 | Europe was dependent on Russia for its energy. Now, Russia has cut off its gas supply to Europe, creating a catastrophic energy crisis. This is why Republicans want America to be energy independent, not reliant on adversaries for critical energy needs. | -0.40 |
| 14 | WATCH: By closing the Keystone XL Pipeline, President Biden has killed American jobs and limited our ability to produce clean energy here at home. I introduced a resolution in @HouseCommerce to condemn this terrible move. | -0.70 |
| 15 | FACT CHECK: FALSE. Gas in California cost $3.36 per gallon on average in January 2021, when President Biden took office. The sky-high price of gas is unmistakably a result of President Biden and Democrats disastrous energy policies. | -0.80 |
| 16 | Democrats rush to green energy agenda has created an energy crisis in California. I was proud to join @boblatta, @RepGusBilirakis, and @RepJohnJoyce's letter to President Biden sounding the alarm on the states decision to ban gas-powered cars by 2035. | -0.80 |
| 17 | Rush-to-green energy policies created a widespread energy crisis in Europe as we head into winter. This should serve as a warning that enacting rushed Green New Deal energy policies in the U.S. would be nothing short of a catastrophe. | -0.90 |
| 18 | Californias rush-to-green energy policies have sent energy prices soaring, including at the gas pump. House Democrats Green New Deal climate mandates would force the rest of our nation to face the same disastrous fate as California. | -0.90 |
| 19 | Democrat-run Californias failed, far-left climate policies have created an energy crisis for Californians. This should be a warning to everyone that Democrats rush-to-green energy policies would be a disaster for our nation. | -1.00 |
| 20 | Democrats green energy only policies are a total failure! Democrat-run California is declaring a grid emergency. They cant even keep the lights on, yet they want everyone to drive electric vehicles that will further strain the power grid. | -1.00 |

## **Table IA.2:** Carbon emissions for Fama-French 48 industries

This table reports the (absolute) Scope 1, 2, and 3 carbon emissions and carbon emissions intensity averaged across firms in each of the Fama-French 48 industries, obtained from Refinitiv. Absolute carbon emissions are reported in metric tonnes of carbon-dioxide equivalent (tCO2e). The carbon emissions intensity of a firm in a given fiscal year is obtained by dividing the sum of its absolute Scope 1 and Scope 2 GHG emissions by total revenue (expressed in million dollars). Industries are sorted in an ascending order by their carbon emissions intensity. To categorize firms into industries, we link tickers in emissions data to CUSIPs obtained from CRSP. We then link CUSIPs to SIC codes obtained from Compustat. We then map these SIC codes to the corresponding Fama-French industry classifications using the definitions on Ken French's website.

| | Industry | Scope 1 | Scope 2 | Scope 3 | Intensity |
|---|---|---|---|---|---|
| 1 | Insurance | 11,119 | 58,541 | 256,153 | 4.96 |
| 2 | Banking | 85,407 | 507,727 | 497,034 | 9.29 |
| 3 | Recreation | 9,312 | 52,725 | 725,761 | 11.99 |
| 4 | Business Services | 30,963 | 247,228 | 845,818 | 14.14 |
| 5 | Apparel | 29,288 | 91,703 | 2,860,287 | 15.46 |
| 6 | Real Estate | 17,943 | 17,974 | 4,521,554 | 17.14 |
| 7 | Printing and Publishing | 19,277 | 134,941 | 1,160,446 | 19.66 |
| 8 | Wholesale | 148,763 | 97,171 | 12,788,785 | 19.67 |
| 9 | Tobacco Products | 274,127 | 265,522 | 3,138,091 | 20.16 |
| 10 | Computers | 38,481 | 277,267 | 6,321,508 | 20.94 |
| 11 | Measuring and Control Equipment | 36,750 | 94,473 | 1,005,097 | 21.42 |
| 12 | Defense | 284,372 | 797,762 | 26,699,347 | 21.57 |
| 13 | Construction | 90,099 | 30,169 | 1,505,612 | 21.69 |
| 14 | Medical Equipment | 105,007 | 161,297 | 2,909,812 | 22.46 |
| 15 | Healthcare | 135,113 | 494,937 | 1,841,901 | 26.81 |
| 16 | Retail | 666,578 | 1,385,147 | 8,573,759 | 34.48 |
| 17 | Communication | 547,863 | 3,164,319 | 4,228,587 | 37.41 |
| 18 | Machinery | 118,630 | 221,445 | 131,741,114 | 41.75 |
| 19 | Consumer Goods | 396,655 | 460,887 | 23,587,101 | 43.26 |
| 20 | Aircraft | 330,942 | 522,363 | 6,638,688 | 43.28 |
| 21 | Trading | 21,883 | 197,339 | 190,512 | 45.04 |
| 22 | Shipbuilding, Railroad Equipment | 54,801 | 69,798 | 31,861 | 51.96 |
| 23 | Automobiles and Trucks | 454,429 | 1,015,292 | 119,519,381 | 58.47 |
| 24 | Pharmaceutical Products | 250,149 | 299,499 | 2,534,873 | 71.37 |
| 25 | Rubber and Plastic Products | 55,292 | 172,968 | 1,390,118 | 75.89 |
| 26 | Beer & Liquor | 3,800,645 | 1,896,167 | 27,105,002 | 86.74 |
| 27 | Entertainment | 169,944 | 475,641 | 645,072 | 91.76 |
| 28 | Electronic Equipment | 316,274 | 475,287 | 3,826,229 | 95.32 |
| 29 | Candy & Soda | 1,367,703 | 2,732,258 | 26,672,261 | 101.09 |
| 30 | Fabricated Products | 55,659 | 41,508 | – | 102.34 |
| 31 | Food Products | 1,157,164 | 663,036 | 7,423,648 | 102.96 |
| 32 | Electrical Equipment | 98,717 | 111,212 | 5,816,558 | 131.86 |
| 33 | Restaurants, Hotels, Motels | 263,139 | 1,076,852 | 9,382,590 | 164.91 |
| 34 | Personal Services | 1,538,768 | 84,728 | 3,886,528 | 206.50 |
| 35 | Construction Materials | 685,089 | 469,601 | 1,487,454 | 220.13 |
| 36 | Textiles | 995,130 | 817,932 | 546,690 | 231.74 |
| 37 | Business Supplies | 2,253,913 | 1,503,909 | 6,184,353 | 278.99 |
| 38 | Shipping Containers | 1,834,866 | 1,033,090 | 4,615,030 | 333.35 |
| 39 | Precious Metals | 1,591,431 | 770,847 | 3,036,569 | 412.14 |
| 40 | Non-Metallic and Industrial Metal Mining | 2,046,440 | 1,284,317 | 846,727 | 428.44 |
| 41 | Agriculture | 54,960 | 538 | – | 511.20 |
| 42 | Transportation | 11,989,562 | 280,562 | 4,045,709 | 576.07 |
| 43 | Petroleum and Natural Gas | 16,475,804 | 1,738,141 | 125,520,137 | 691.89 |
| 44 | Chemicals | 3,785,647 | 1,426,095 | 18,617,774 | 758.60 |
| 45 | Steel Works Etc | 8,255,203 | 2,131,831 | 13,103,009 | 1,119.81 |
| 46 | Almost Nothing | 19,845,106 | 241,514 | 5,251,020 | 1,756.65 |
| 47 | Coal | 6,976,498 | 666,579 | – | 1,914.86 |
| 48 | Utilities | 15,334,635 | 1,158,413 | 22,524,289 | 2,018.30 |

**Table IA.3:** Correlation between manually generated and GPT sentiment

This table shows the correlations between the sentiment generated by the five researchers and GPT.

| | Researcher I | Researcher II | Researcher III | Researcher IV | Researcher V | GPT-4.1 |
|---|---|---|---|---|---|---|
| Researcher I | 1.000 | 0.823 | 0.856 | 0.881 | 0.611 | 0.892 |
| Researcher II | | 1.000 | 0.834 | 0.803 | 0.639 | 0.829 |
| Researcher III | | | 1.000 | 0.907 | 0.671 | 0.919 |
| Researcher IV | | | | 1.000 | 0.624 | 0.887 |
| Researcher V | | | | | 1.000 | 0.670 |
| GPT-4.1 | | | | | | 1.000 |

**Table IA.4:** Correlation between average researcher and GPT sentiment

The first row reports the correlation between the average sentiment produced by the research team and that by GPT. The subsequent rows report correlations with the sentiment produced by GPT after dropping one researcher at a time.

| | Correlation with GPT |
|---|---|
| Overall Average | 0.938 |
| Dropped Researcher I | 0.820 |
| Dropped Researcher II | 0.888 |
| Dropped Researcher III | 0.856 |
| Dropped Researcher IV | 0.871 |
| Dropped Researcher V | 0.879 |

## **Table IA.5:** Time-varying controls

This table lists the time-varying controls included in the panel regression in Equation (1) in Section 3.1 of the manuscript.

| **Control** | **Definition** |
|---|---|
| *Daily firm-specific variables* | |
| Lagged Return | Close-to-close excess return ($\texttt{retx}_{t-1}$) obtained from the Center for Research in Security Prices (CRSP). |
| Cumulative Month Return | Compounded excess return over the past 21 trading days: $\prod_{k=1}^{22}(1+\texttt{retx}_{t-k})-1$, obtained from CRSP. |
| Cumulative Week Return | Compounded excess return over the past five trading days: $\prod_{k=1}^{6}(1+\texttt{retx}_{t-k})-1$, obtained from CRSP. |
| Realized Volatility | Standard deviation of daily excess returns over the past 21 trading days: $\left(\sum_{k=1}^{21}(\texttt{retx}_{t-k}-\bar{r})^2/20\right)^{1/2}$, where $\bar{r}=\sum_{k=1}^{21}\texttt{retx}_{t-k}/21$ is the average return over the window, obtained from CRSP. |
| Size | Logarithm of contemporaneous daily market capitalization: $\log(\texttt{prc}_t \times \texttt{shrout}_t)$, where $\texttt{prc}$ is the absolute price and $\texttt{shrout}$ is shares outstanding, obtained from CRSP. |
| *Quarterly firm-specific variables* | |
| Book to Market | Ratio of book value of equity to market value of equity ($\texttt{bm}$) corresponding to the most recent quarter obtained from the WRDS Financial Ratios Suite. |
| ROE | Return on equity ($\texttt{roe}$) corresponding to the most recent quarter obtained from the WRDS Financial Ratios Suite. |
| Leverage | Debt-to-equity ratio ($\texttt{de-ratio}$) corresponding to the most recent quarter obtained from the WRDS Financial Ratios Suite. |
| Capital Intensity | Logarithm of property, plant, and equipment corresponding to the most recent quarter, $\texttt{logppe}$, obtained from Compustat. |
| Investment | Ratio of capital expenditure ($\texttt{capexy}$) to total assets ($\texttt{atq}$) corresponding to the most recent quarter obtained from Compustat |

**Table IA.6:** Voting margin and legislator support toward pro-transition regulation

This table reports slope coefficients and t-statistics in parentheses obtained from estimating the panel regression in Equation (1) on the sample of legislator tweets that mention environmental regulations in the weeks preceding congressional votes based on the tightness of the voting margin. We compute the voting margin by dividing the difference between the *Yay* (for) and *Nay* (against) votes by the total number of votes cast for a given regulation. A congressional vote is considered "close" when the voting margin is less than 3%, and "clear" otherwise. Columns (1) through (3) reproduce Columns (1) through (3) of Table 6 for tweets posted in the weeks preceding congressional votes that were close. Columns (4) through (6) reproduce Columns (1) through (3) of Table 6 for tweets posted in the weeks preceding congressional votes that were clear. The dependent variable is the log change in stock prices (in basis points) from one minute before to ten minutes after each tweet, $\Delta p(-01, +10)$. PTLSupport measures the stance of a tweet toward pro-transition regulation between zero (strong opposition) and one (strong support). Stocks that fall into the top and bottom tercile of carbon emissions intensity are classified as green and brown, with the rest classified as gray. The first five rows of the table report the following slope coefficients for the panel regression in Equation (1): $\gamma_B$ (Brown), $\gamma_G$ (Green), $\tau$ (PTLSupport), $\tau_B$ (Brown $\times$ PTLSupport), $\tau_G$ (Green $\times$ PTLSupport). The sixth row reports the difference between $\tau_G$ and $\tau_B$, (Green $-$ Brown) $\times$ PTLS. We include the time-varying controls listed in Table IA.5 of the Internet Appendix. Standard errors are heteroscedasticity and double clustered at firm- and tweet-level. We denote $p$-values smaller than 0.10, 0.05, and 0.01 with one (*), two (**), and three (***) stars, respectively.

| | (1) CLOSE Leading 4wk | (2) CLOSE Leading 2wk | (3) CLOSE Leading 1wk | (4) CLEAR Leading 4wk | (5) CLEAR Leading 2wk | (6) CLEAR Leading 1wk |
|---|---|---|---|---|---|---|
| Brown | -3.670 | -2.506 | -4.820 | -0.138 | -0.368 | -0.928 |
| | (-1.30) | (-0.98) | (-1.81) | (-0.19) | (-0.45) | (-0.99) |
| Green | -0.554 | -0.741 | 4.657 | 1.893 | 1.801 | 1.624 |
| | (-0.22) | (-0.30) | (0.95) | (0.77) | (0.66) | (0.56) |
| PTLSupport | 16.13 | 16.11 | 25.38 | 12.37* | 12.14* | 29.56* |
| | (1.22) | (1.15) | (1.10) | (2.48) | (2.46) | (2.98) |
| Brown × PTLSupport | -1.518 | -1.482 | -1.209 | 0.315 | 0.539 | 0.914 |
| | (-1.59) | (-1.32) | (-1.03) | (0.50) | (0.78) | (1.94) |
| Green × PTLSupport | 3.455 | 3.457 | 5.953* | 0.640 | 0.880 | 0.605 |
| | (1.37) | (1.29) | (4.08) | (0.38) | (0.43) | (0.26) |
| (Green − Brown) × PTLS | 4.973* | 4.939 | 7.162** | 0.325 | 0.341 | -0.308 |
| | (2.97) | (2.61) | (4.64) | (0.27) | (0.23) | (-0.14) |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Legislator FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Day FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Adjusted R2 | 0.0946 | 0.0953 | 0.1282 | 0.2140 | 0.2199 | 0.2416 |
| Observations | 33,585 | 33,148 | 26,436 | 80,101 | 72,597 | 58,425 |

## **Table IA.7:** Impact of legislator tweets on returns: Placebo test

This table reports slope coefficients and $t$-statistics in parentheses obtained from estimating the panel regression in Equation (1) for an event horizon corresponding to the ten minutes before tweets to perform a *placebo test*. The dependent variable $\Delta p(-11, -01)$ is the log change in stock prices (in basis points) from 11 minutes before to one minute before each tweet. The sentiment of tweets toward the green transition is obtained using GPT and min-max normalized annually between zero and one. Firms that fall into the top and bottom tercile of carbon emissions intensity are classified as green and brown; the rest are classified as gray, which is the omitted category. The first five rows of the table report the following slope coefficients for the panel regression in Equation (1): $\gamma_B$ (Brown), $\gamma_G$ (Green), $\tau$ (Sentiment), $\tau_B$ (Brown $\times$ Sentiment), $\tau_G$ (Green $\times$ Sentiment). The sixth row reports the difference between $\tau_G$ and $\tau_B$, (Green $-$ Brown) $\times$ Sent. We include firm-specific time-varying controls listed in Table IA.5 of the Internet Appendix. Standard errors are heteroscedasticity robust and double clustered at firm- and tweet-level. We denote $p$-values smaller than 0.10, 0.05, and 0.01 with one (*), two (**), and three (***) stars, respectively.

| | (1)<br>$\Delta p(-11, -01)$ |
|---|---|
| Brown | -0.166 |
| | (-0.80) |
| Green | -0.187 |
| | (-0.76) |
| Sentiment | 0.233 |
| | (0.28) |
| Brown $\times$ Sentiment | -0.175 |
| | (-0.82) |
| Green $\times$ Sentiment | 0.202 |
| | (0.68) |
| (Green $-$ Brown) $\times$ Sent. | 0.376 |
| | (0.98) |
| Controls | Yes |
| Firm FE | Yes |
| Legislator FE | Yes |
| Day FE | Yes |
| Adjusted R2 | 0.0541 |
| Observations | 10,718,725 |

**Table IA.8:** Impact of legislator tweets on returns: Out of sample test

This table reports slope coefficients and $t$-statistics in parentheses obtained from estimating the panel regression in Equation (1) using sentiment obtained from GPT-3.5 for tweets posted in the period *after* the model training cutoff in September 2021. The dependent variable $\Delta p(-01, +10)$ is the log change in stock prices (in basis points) from one minute before to ten minutes after each tweet. The sentiment of tweets toward the green transition is min-max normalized annually between zero and one. Firms that fall into the top and bottom tercile of carbon emissions intensity are classified as green and brown; the rest are classified as gray, which is the omitted category. The first five rows of the table report the following slope coefficients for the panel regression in Equation (1): $\gamma_B$ (Brown), $\gamma_G$ (Green), $\tau$ (Sentiment), $\tau_B$ (Brown $\times$ Sentiment), $\tau_G$ (Green $\times$ Sentiment). The sixth row reports the difference between $\tau_G$ and $\tau_B$, (Green $-$ Brown) $\times$ Sent. We include firm-specific time-varying controls listed in Table IA.5 of the Internet Appendix. Standard errors are heteroscedasticity robust and double clustered at firm- and tweet-level. We denote $p$-values smaller than 0.10, 0.05, and 0.01 with one (*), two (**), and three (***) stars, respectively.

| | (1)<br>$\Delta p(-01, +10)$ |
|---|---|
| Brown | 0.0687 |
| | (0.24) |
| Green | -0.498** |
| | (-2.27) |
| Sentiment | -0.867 |
| | (-0.45) |
| Brown $\times$ Sentiment | -0.563* |
| | (-2.04) |
| Green $\times$ Sentiment | 0.570** |
| | (2.57) |
| (Green $-$ Brown) $\times$ Sent. | 1.134** |
| | (2.66) |
| Controls | Yes |
| Firm FE | Yes |
| Legislator FE | Yes |
| Day FE | Yes |
| Adjusted R2 | 0.0471 |
| Observations | 4,807,129 |

**Table IA.9:** Impact of legislator tweets on returns: Controlling for MCCC innovations

This table reports slope coefficients and $t$-statistics in parentheses obtained from estimating the panel regression in Equation (1) with an added interaction term between the innovations (UMC) to the daily Media Climate Change Concerns (MCCC) index of Ardia et al. (2023) and the green and brown portfolio indicators. The MCCC index proxies climate-change concerns expressed in mainstream media. UMC are the residuals obtained from estimating an ARX(1) model on MCCC with the five Fama-French and the momentum factors as controls (which corresponds to the CTRL-6 set of controls used in Ardia et al. (2023)). The dependent variable $\Delta p(-01, +10)$ is the log change in stock prices (in basis points) from one minute before to ten minutes after each tweet. The sentiment of tweets toward the green transition is min-max normalized annually between zero and one. Firms that fall into the top and bottom tercile of carbon emissions intensity are classified as green and brown; the rest are classified as gray, which is the omitted category. The first five rows of the table report the following slope coefficients for the panel regression in Equation (1): $\gamma_B$ (Brown), $\gamma_G$ (Green), $\tau$ (Sentiment), $\tau_B$ (Brown × Sentiment), $\tau_G$ (Green × Sentiment). The sixth and seventh rows report the slope coefficient associated with the interaction between the UMC index and the green and brown portfolio indicators (Green × UMC and Brown × UMC). We only report the slope coefficients associated with the interaction terms because the UMC index is at a daily frequency; thus, its partial effect is absorbed by the day fixed effects. The eighth row reports the difference between $\tau_G$ and $\tau_B$, (Green − Brown) × Sent. The ninth row reports an equivalent measure for the UMC index, (Green − Brown) × UMC. We include firm-specific time-varying controls listed in Table IA.5 of the Internet Appendix. Standard errors are heteroscedasticity robust and double clustered at firm- and tweet-level. We denote $p$-values smaller than 0.10, 0.05, and 0.01 with one (*), two (**), and three (***) stars, respectively.

| | (1)<br>$\Delta p(-01, +10)$ |
|---|---|
| Brown | 0.108 |
| | (0.93) |
| Green | -0.402*** |
| | (-3.06) |
| Sentiment | 0.179 |
| | (0.25) |
| Brown × Sentiment | -0.270** |
| | (-2.50) |
| Green × Sentiment | 0.413*** |
| | (3.30) |
| Brown × UMC | 0.108 |
| | (0.99) |
| Green × UMC | 0.191* |
| | (1.79) |
| (Green − Brown) × Sent. | 0.683*** |
| | (4.16) |
| (Green − Brown) × UMC | 0.084 |
| | (0.60) |
| Controls | Yes |
| Firm FE | Yes |
| Legislator FE | Yes |
| Day FE | Yes |
| Adjusted R2 | 0.0384 |
| Observations | 10,873,346 |

**Table IA.10:** Impact of legislator tweets on returns: Controlling for MCCC index

This table reports slope coefficients and $t$-statistics in parentheses obtained from estimating the panel regression in Equation (1) with an added interaction term between the daily Media Climate Change Concerns (MCCC) index of Ardia et al. (2023), which proxies climate-change concerns expressed in mainstream media, and the green and brown portfolio indicators. The dependent variable $\Delta p(-01, +10)$ is the log change in stock prices (in basis points) from one minute before to ten minutes after each tweet. The sentiment of tweets toward the green transition and the MCCC index is min-max normalized annually between zero and one. Firms that fall into the top and bottom tercile of carbon emissions intensity are classified as green and brown; the rest are classified as gray, which is the omitted category. The first five rows of the table report the following slope coefficients for the panel regression in Equation (1): $\gamma_B$ (Brown), $\gamma_G$ (Green), $\tau$ (Sentiment), $\tau_B$ (Brown $\times$ Sentiment), $\tau_G$ (Green $\times$ Sentiment). The sixth and seventh rows report the slope coefficient associated with the interaction between the MCCC index and the green and brown portfolio indicators (Green $\times$ MCCC and Brown $\times$ MCCC). We only report the slope coefficients associated with the interaction terms because the MCCC index is at a daily frequency; thus, its partial effect is absorbed by the day fixed effects. The eighth row reports the difference between $\tau_G$ and $\tau_B$, (Green $-$ Brown) $\times$ Sent. The ninth row reports an equivalent measure for the MCCC index, (Green $-$ Brown) $\times$ MCCC. We include firm-specific time-varying controls listed in Table IA.5 of the Internet Appendix. Standard errors are heteroscedasticity robust and double clustered at firm- and tweet-level. We denote $p$-values smaller than 0.10, 0.05, and 0.01 with one (*), two (**), and three (***) stars, respectively.

| | (1)<br>$\Delta p(-01, +10)$ |
|---|---|
| Brown | 0.00839 |
| | (0.06) |
| Green | -0.518*** |
| | (-3.22) |
| Sentiment | 0.180 |
| | (0.25) |
| Brown $\times$ Sentiment | -0.274** |
| | (-2.52) |
| Green $\times$ Sentiment | 0.408*** |
| | (3.28) |
| Brown $\times$ MCCC | 0.291 |
| | (1.08) |
| Green $\times$ MCCC | 0.363 |
| | (1.53) |
| (Green $-$ Brown) $\times$ Sent. | 0.683*** |
| | (4.16) |
| (Green $-$ Brown) $\times$ MCCC | 0.072 |
| | (0.20) |
| Controls | Yes |
| Firm FE | Yes |
| Legislator FE | Yes |
| Day FE | Yes |
| Adjusted R2 | 0.0384 |
| Observations | 10,860,882 |

## **Table IA.11:** Impact of legislator tweets on returns: Ex-post tweet popularity

This table reports slope coefficients and $t$-statistics in parentheses obtained from estimating the panel regression in Equation (1) for subsamples of tweets based on their ex-post popularity on Twitter. Columns (1) and (2) report results for tweets that are associated with below and above the median likes associated with a tweet in a given calendar year. Columns (3) and (4) reproduce the results for retweets. The dependent variable $\Delta p(-01, +10)$ is the log change in stock prices (in basis points) from one minute before to ten minutes after each tweet. The sentiment of tweets toward the green transition is obtained using GPT and min-max normalized annually between zero and one. Firms that fall into the top and bottom tercile of carbon emissions intensity are classified as green and brown; the rest are classified as gray, which is the omitted category. The first five rows of the table report the following slope coefficients for the panel regression in Equation (1): $\gamma_B$ (Brown), $\gamma_G$ (Green), $\tau$ (Sentiment), $\tau_B$ (Brown $\times$ Sentiment), $\tau_G$ (Green $\times$ Sentiment). The sixth row reports the difference between $\tau_G$ and $\tau_B$, (Green $-$ Brown) $\times$ Sent. We include firm-specific time-varying controls listed in Table IA.5 of the Internet Appendix. Standard errors are heteroscedasticity robust and double clustered at firm- and tweet-level. We denote $p$-values smaller than 0.10, 0.05, and 0.01 with one (*), two (**), and three (***) stars, respectively.

| | (1) LIKES Below Median | (2) LIKES Above Median | (3) RETWEETS Below Median | (4) RETWEETS Above Median |
|---|---|---|---|---|
| Brown | 0.166 | 0.0960 | 0.270 | 0.00390 |
| | (1.02) | (0.48) | (1.60) | (0.02) |
| Green | -0.418** | -0.295 | -0.519*** | -0.187 |
| | (-2.43) | (-1.44) | (-2.65) | (-1.02) |
| Sentiment | -0.0628 | 0.258 | -0.365 | 1.492 |
| | (-0.07) | (0.25) | (-0.34) | (1.02) |
| Brown $\times$ Sentiment | -0.302* | -0.264 | -0.475** | -0.105 |
| | (-1.77) | (-1.38) | (-2.52) | (-0.53) |
| Green $\times$ Sentiment | 0.488*** | 0.310 | 0.586** | 0.207 |
| | (2.86) | (1.37) | (2.59) | (1.03) |
| (Green $-$ Brown) $\times$ Sent. | 0.790*** | 0.575* | 1.061*** | 0.312 |
| | (3.03) | (1.88) | (3.15) | (0.88) |
| Controls | Yes | Yes | Yes | Yes |
| Firm FE | Yes | Yes | Yes | Yes |
| Legislator FE | Yes | Yes | Yes | Yes |
| Day FE | Yes | Yes | Yes | Yes |
| Adjusted R2 | 0.0583 | 0.0584 | 0.0562 | 0.0614 |
| Observations | 5,117,449 | 4,932,822 | 5,338,732 | 4,711,541 |

**Table IA.12:** Impact of legislator tweets on returns: Tweet impact by chamber

This table reports slope coefficients and $t$-statistics in parentheses obtained from estimating the panel regression in Equation (1) for subsamples of tweets based on the Congressional chamber. Columns (1) and (2) report results for tweets that are posted by the members of the House of Representatives and the Senate. The dependent variable $\Delta p(-01, +10)$ is the log change in stock prices (in basis points) from one minute before to ten minutes after each tweet. The sentiment of tweets toward the green transition is obtained using GPT and min-max normalized annually between zero and one. Firms that fall into the top and bottom tercile of carbon emissions intensity are classified as green and brown; the rest are classified as gray, which is the omitted category. The first five rows of the table report the following slope coefficients for the panel regression in Equation (1): $\gamma_B$ (Brown), $\gamma_G$ (Green), $\tau$ (Sentiment), $\tau_B$ (Brown $\times$ Sentiment), $\tau_G$ (Green $\times$ Sentiment). The sixth row reports the difference between $\tau_G$ and $\tau_B$, (Green $-$ Brown) $\times$ Sent. We include firm-specific time-varying controls listed in Table IA.5 of the Internet Appendix. Standard errors are heteroscedasticity robust and double clustered at firm- and tweet-level. We denote $p$-values smaller than 0.10, 0.05, and 0.01 with one (*), two (**), and three (***) stars, respectively.

| | (1)<br>House | (2)<br>Senate |
|---|---|---|
| Brown | 0.155 | 0.00328 |
| | (1.20) | (0.01) |
| Green | -0.313** | -0.583** |
| | (-2.19) | (-2.26) |
| Sentiment | 0.103 | 1.125 |
| | (0.11) | (0.70) |
| Brown × Sentiment | -0.277** | -0.206 |
| | (-2.19) | (-0.89) |
| Green × Sentiment | 0.399*** | 0.481* |
| | (2.88) | (1.65) |
| (Green − Brown) × Sent. | 0.675*** | 0.687* |
| | (3.44) | (1.66) |
| Controls | Yes | Yes |
| Firm FE | Yes | Yes |
| Legislator FE | Yes | Yes |
| Day FE | Yes | Yes |
| Adjusted R2 | 0.0427 | 0.1001 |
| Observations | 8,758,150 | 2,102,728 |