Partisan Corporate Speech

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Abstract

We construct a novel measure of partisan corporate speech using natural language processing techniques and use it to establish three stylized facts. First, the volume of partisan corporate speech has risen sharply between 2012 and 2022. Second, this increase has been disproportionately driven by companies adopting more Democratic-leaning language, a trend that is widespread across industries, geographies, and CEO political affiliations. Third, partisan corporate statements are followed by negative abnormal stock returns, with significant heterogeneity by shareholders' degree of alignment with the statement. Finally, we propose a theoretical framework and provide suggestive empirical evidence that these trends are at least in part driven by a shift in investors' nonpecuniary preferences with respect to partisan corporate speech.

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1 Introduction

Political polarization in the United States is reshaping many institutions, including corporate America (e.g., Fos et al. (2025)). Anecdotal evidence suggests that firms that once remained politically neutral are now taking partisan stances, often aligning with one party's position on issues such as climate change, gun restrictions (Lucas (2019)), racial justice (Hessekiel (2020)), and voting rights (Gelles and Sorkin (2021)). The economic stakes of this shift can be substantial, as illustrated by Disney's 2022 clash with Florida legislators, which led to political retaliation and financial repercussions for the company. Yet, key questions remain open: are these public statements driven by profit-maximization motives? Do they reflect firms' responses to evolving stakeholder preferences, or are they shaped by the political preferences of corporate executives? Empirically addressing these questions has been challenging, in part due to measurement limitations. For example, many existing studies rely on media coverage of partisan corporate statements, potentially introducing selection bias by capturing only those that attract public attention or generate ex-post controversy.

We address this measurement challenge by developing a novel approach to identifying partisan corporate speech and applying it to over a decade of corporate communication on social media. Our core idea is to detect corporate language that closely resembles the language used by Republican or Democratic politicians. Specifically, we first estimate multinomial inverse regressions (MNIR) on tweets from Republican and Democratic members of Congress to identify highly partisan phrases. We then use the resulting estimates to classify all tweets sent by S&P 500 companies with verified Twitter accounts between 2012 and 2022 based on their usage of highly partisan language.

Our approach offers several key advantages. First, it avoids subjective judgment in defining partisan speech. Second, it mitigates selection bias by identifying partisan content ex ante rather than relying on statements that attracted attention ex post. Third, it accounts for time variation in what constitutes partisan speech, adapting to shifts in political discourse. Finally, it captures subtle partisan cues without requiring overt endorsements of politicians or policies. Importantly, our method does not infer corporate intent but rather measures the extent to which corporate statements "sound" partisan.

Using our measure of partisan corporate speech, we establish three stylized facts. Fact 1 is that the frequency of partisan corporate speech has increased sharply over our sample period. Before 2017, partisan corporate statements on Twitter were rare—comprising less than 0.5% of all corporate tweets on average—and roughly evenly split between Democratic- and Republican-sounding speech. The first notable increase occurred in late 2017 when the volume of partisan corporate speech more than doubled.

Fact 2 is that the rise in partisan corporate speech has been driven overwhelmingly by increased Democratic-leaning language. Starting in early 2019, Democratic-sounding speech rose sharply, while Republican-sounding speech remained relatively flat. This divergence is not mirrored in randomly selected tweets or congressional speech patterns, suggesting that the shift is specific to corporate communication rather than a broader trend on Twitter. Moreover, the increase in Democratic-sounding speech is widespread across all sectors—including consumer- and business-oriented industries—as well as across geographies, firm sizes, and firms led by Republican and Democratic CEOs.

Fact 3 is that, on average, partisan corporate tweets are followed by negative abnormal stock returns. The market response varies significantly with the degree of stakeholder alignment, with partisan tweets that align with the political preferences of investors exhibiting a relatively more positive stock price reaction.

To better understand the content of partisan corporate speech, we classify partisan tweets into distinct topics using biterm topic modeling. This analysis reveals that the increase in Democratic-sounding speech is primarily driven by greater discussion of diversity, equity, and inclusion (DEI), climate change, and commemorative events such as Black History Month and Pride Month. Republican-sounding speech, by contrast, tends to focus on the economy, energy, patriotism, and the military. These patterns suggest that firms rarely publicly endorse a political party, but they engage in topics that are polarized across partisan lines. Additionally, only a small fraction of partisan corporate tweets–about 7%–contain explicit actions or commitments, such as corporate donations or measurable targets, which we refer to as "action tweets."

What explains the widespread increase in Democratic-sounding corporate speech? While we may not know for certain why partisan corporate speech surged when it did, the evidence suggests that shifting investor preferences—particularly the rise of nonpecuniary considerations—have played a partial role. First, in the time series, the growth of Democratic-leaning corporate speech is closely correlated with the expansion of assets under management in funds with environmental, social, and governance (ESG) objectives. Second, because institutional investors are broadly diversified across industries and geographies, their influence could help explain why the increase in Democratic-sounding speech is so pervasive. Third, using a difference-in-differences design, we document a notable increase in the use of Democratic language by firms with high BlackRock ownership following Larry Fink's influential 2019 letter to CEOs, which urged corporate leaders to engage on divisive social and political issues.

To explain our empirical findings, we develop a theoretical framework in which firms engage in partisan speech in response to investor preferences. The model features two investor types—Democratic and Republican—who care not only about financial returns but also about their political alignment with the firms in their portfolios. Firms, in turn, seek to maximize their stock price while accounting for potential (dis)utility from taking positions that align (conflict) with investor preferences. The model rationalizes our three stylized facts through an exogenous increase in the extent to which Democratic-leaning investors prioritize political alignment in their investment decisions. As Democratic investors become more sensitive to firms' political stances, companies are increasingly drawn into political disputes where they are forced to take partisan positions. Because Democratic investors now more strongly favor firms that align with their views and more strongly avoid those that do not, partisan corporate speech becomes disproportionately Democratic-leaning. Finally, the model predicts that taking partisan stances reduces firm valuations. The key mechanism behind this result is that firms must secure capital from both aligned and misaligned investors, leading stock prices to be set by the willingness of the least aligned investors to hold the stock.

The rest of this study proceeds as follows. In the next section, we discuss the related literature. Section 3 describes the data and Section 4 develops our main measure of partisan corporate speech. Section 5 presents our three stylized facts. Section 6 explores potential explanations for these empirical facts, and Section 7 provides a theoretical model in which firms engage in partisan speech in response to investor preferences. Section 8 concludes.

2 Related Literature

Our study contributes to several strands of the literature. First, we contribute to a small but rapidly growing literature that studies sociopolitical activism by companies and CEOs. Most of that literature has focused on activism by CEOs. In one of the first attempts to measure the phenomenon, Larcker et al. (2018) use multiple approaches to detect instances of CEO activism, including statements made on Twitter. However, they find that only 11% of all S&P 1500 CEOs have active personal Twitter feeds. In contrast, 84% of S&P 500 companies have an active Twitter account in our sample. Existing studies of investor reactions to corporate and CEO sociopolitical activism have found mixed evidence, with some observing positive stock price reactions at daily frequencies (e.g., Mkrtchyan et al. (2024); Homroy and Gangopadhyay (2025)) and others observing negative reactions (e.g., Bhagwat et al. (2020)). With respect to consumers, Boxell and Conway (2024) and Hou and Poliquin (2023) find that households temporarily adjust their consumption decisions in response to firms' stances on controversial social issues, with mixed findings regarding the overall revenue impact. For employees, Adrjan et al. (2024) document that employer announcements following the

Supreme Court's ruling in Dobbs v. Jackson impact worker sorting. The typical approach in the above studies is to identify instances of sociopolitical activism based on statements that ex-post generated public attention or controversy. Our paper is one of the first to apply natural language processing techniques to data from corporate Twitter accounts to identify partisan corporate speech ex ante. Moreover, to the best of our knowledge, our study is one of the first to provide empirical evidence for a potential link between shifting investor preferences and the growth in partisan corporate speech.

Second, we contribute to a growing literature on the politicization of corporate America. Studies have documented how political partisanship shapes individuals' views of the economy and their economic decisions, including in high-stakes, professional environments (see Kempf and Tsoutsoura (2024) for a review). Moreover, U.S. executive teams have become more politically homogeneous due to increased partisan sorting, as Fos et al. (2025) show. This paper highlights another dimension of politicization: the increased use of partisan language by U.S. firms on social media. Our measure of partisan corporate speech may be useful for future work studying the role of partisan alignment between various stakeholders and the firm.

Third, we also contribute to the literature that aims at measuring partisanship via speech. Gentzkow et al. (2019) study how the speech used by members of Congress has become more polarized over time. Like Gentzkow et al. (2019), we use MNIR to estimate the probability of using phrases by individuals with different party affiliations.[1] Different than Gentzkow et al. (2019), we use MNIR for a prediction problem. Our aim is to use MNIR to identify when corporations use speech similar to that of Democratic or Republican politicians, as opposed to measuring the extent to which speech is polarized across politicians. Our approach is, therefore, more similar to that of Engelberg et al. (2023), who detect partisanship in the speech of financial regulators by identifying partisan phrases in congressional speech and then observing their usage among regulators, and Cookson et al. (2020), who identify a list of keywords to classify posts on the platform StockTwits as political.[2]

Two contemporaneous papers develop measures of partisan corporate speech similar to ours. One is Barari (2024), who studies how brands use bigrams on Twitter and Instagram, which are commonly used by Republican and Democratic politicians on the same platforms. Our approach has two key differences. First, we can control for speaker demographics among politicians. Democratic politicians may disproportionately use particular bigrams because they are from particular regions or, on average, older or younger than Republican politicians.

[1] Gentzkow et al. (2019), in turn, build on earlier work in the statistics literature on computationally feasible methods for estimating MNIR, notably Taddy (2013) and Taddy (2015).

[2] A rapidly growing literature explores the role of social media as part of the financial information environment of the firm. See Cookson et al. (2024b) for an excellent review.

Second, Gentzkow et al. (2019) describe how using empirical frequencies to measure partisanship can be biased in finite samples due to the infrequent usage of some words. Through simulations, those authors show that our approach is unbiased, even in small samples.

The other contemporaneous paper is Ottonello et al. (2024), who use large language models (LLMs) to study U.S. firms' political speech across multiple mediums, including Twitter. While LLMs offer a very promising direction for measuring partisan speech, our MNIR approach has its own advantages. First, it does not require the researcher to specify a set of political topics or words associated with these political topics. Second, our approach allows for time variation in which bigrams constitute partisan speech, using only information available at a given point in time. In contrast, language models' pretraining data typically includes many years of data and can give rise to look-ahead bias (e.g., Glasserman and Lin (2024); Sarkar and Vafa (2024)).

3 Data and Measure

3.1 Twitter

We measure corporate speech via statements issued by companies on the social media platform Twitter (now called X). While it is well established that user populations differ across different social media platforms (e.g., Cookson et al. (2024a)), we focus on Twitter because it is widely used by large corporations for communication with a broad set of stakeholders, including customers (e.g., Barnes et al. (2020)), investors (e.g., Jung et al. (2018)), and employees (e.g., Meister and Willyerd (2009)). According to Barnes et al. (2020), 96% of Fortune 500 companies were actively using Twitter as of 2019. Importantly, the timing and content of information disseminated on Twitter are fully under the control of the company, whereas press releases have to be picked up by intermediaries to reach a broader set of end users (Jung et al. (2018)).

We begin by collecting all tweets sent by companies in the S&P 500 between 2011 and 2022. Manually searching for Twitter usernames or handles similar to the name of the firm, we were able to identify a verified Twitter account for 632 out of 751 companies (84%).[3] In 20 instances, we map more than one Twitter account to the same company. These cases broadly fall into two categories. First, sometimes there is a separate Twitter account for the company and its main brand (e.g., we map both "@CocaColaCo" and "@CocaCola" to the Coca-Cola Company). We do not include brand accounts for brands other than the main

[3]Twitter verifies Twitter accounts for companies and public officials. Once a Twitter account is verified, we can be confident that the Twitter account actually belongs to the entity that it purports to represent.

company brand. Second, some companies have separate Twitter accounts for their U.S. or North American business. In those cases, we include both the worldwide account and the U.S. account (e.g., we map both "@Chubb" and "@ChubbNA" to Chubb Limited). Given that partisan polarization has already been extensively studied in the media context (e.g., Gentzkow and Shapiro (2010)), we exclude firms in newspapers and publishing (SIC code 2711) and television broadcasting (SIC code 4833), as well as Twitter itself. This filter leads to the removal of New York Times, News Corp, Tegna Inc., Fox Corp, and Scripps Network Interactive Inc.

We also obtained Twitter handles for the official Twitter accounts of all members of Congress between 2011 and 2022. Of the 155 politicians who served in the Senate and 781 who served in the House of Representatives during this period of time, we are able to match 150 Senators and 721 Representatives to at least one verified Twitter account. When a Congressperson has more than one Twitter account (e.g., an official and a personal one), we use both accounts. Most politicians whom we are not able to match served early in the sample period before the use of Twitter became ubiquitous among elected officials.

For every Twitter handle we collect, we download the full sample of tweets sent from that Twitter account using the Twitter application programming interface (API). For every tweet, we observe whether the tweet was an original tweet, a retweet, a reply, or a quote tweet. We restrict our sample to tweets that are not replies or @replies.[4] We do not retain replies in our main sample because they are mostly related to issues concerning customer service and thus less relevant to our exercise. After imposing the above restrictions, we obtain ∼4.4 million corporate tweets and ∼8 million politician tweets. In addition to the text of the tweet, the information provided via the API contains the exact date and timestamp of the tweet, as well as a unique tweet ID assigned by Twitter. We restrict our main analysis to the years 2012 onward because tweets by Democratic politicians are relatively sparse in 2011. We frequently observe fewer than 5,000 tweets per month from a relatively small number of unique accounts in that year, with the number of Democratic members of Congress with active Twitter accounts increasing from 146 to 230 between January 2011 and January 2012 (see Internet Appendix Figure IA.1).

Table 1, Panel A provides summary statistics for our sample of corporate tweets after conditioning on firm-years with at least one tweet. The number of unique firms grows over time as more companies establish and actively use their Twitter accounts. The distribution of the number of tweets is strongly right-skewed, with the mean being consistently larger than the median, as a few firms send a very large number of tweets per day. Many of these

[4]An @reply is a tweet that is similar to a direct message and only appears in a follower's feed if the follower follows both the sender and recipient.

companies use their Twitter accounts for customer service (e.g., TripAdvisor).

Before constructing a measure of partisan corporate speech, we pre-process the raw text of each tweet in three steps. First, we tokenize each tweet. Tokenization is the process of breaking up a string that is a complete sentence into individual tokens. This step effectively removes excess spaces and punctuation. We tokenize only alpha-numeric characters, so our measure will not include non-standard characters, such as emojis. We do not remove other Twitter handles referenced in a tweet, called "mentions" or hashtags. Second, we remove "stop words," that is, words that do not substantially contribute to the meaning of the sentence, such as "that" or "the." We construct the set of stop words by combining a list of stop words from the Python NLTK package and a list of the most common words in English from the Python Snowball package. We then add common contractions for words in the union of these two sets (e.g., the word "that's") and the names of states, months, and days of the week to our list of stop words. Finally, we stem the remaining words using the snowball stemmer from the Python package Snowball. Stemming maps all words with the same stem but possibly different suffixes or prefixes to the same word. For example, both "becoming" and "become" are converted to "becom."

Next, we convert the set of words in each tweet into n-grams. N-grams are N-length sequences of adjacent words. We use both unigrams and bigrams for different steps of the analysis. Unigrams contain only one word, whereas bigrams include two words, an example of which is "big data."

3.2 Information on Elected Officials' Demographics

We collect additional demographic and biographical information on the elected officials in our sample by scraping the biographical directory of the United States Congress at `https://bioguide.congress.gov`. Specifically, we collect information on the official's home state, the highest educational degree attained, and age. To construct a proxy for a Congressperson's ethnicity, we use the Python package "ethnicolr," which infers the ethnicity of individuals from their place of birth, state of residence, age, and name.

3.3 Firm-Level Information

For our analysis of firm heterogeneity, we obtain data from several additional sources. We use the CRSP/Compustat Merged database to obtain fiscal year-end information on the size of total book assets, market capitalization, industry codes, and headquarter location. To measure the composition of the firm's investor base, we collect quarterly data on total institutional ownership from the Thomson Reuters 13F database, as well as quarterly stock holdings of funds with a sustainability mandate from Morningstar. To obtain a proxy for the political leaning of the firm's workforce, we use two alternative measures. The first measure uses the geographical distribution of employee reviews from Glassdoor by computing the share of reviews originating from red versus blue states, using the election outcomes of the 2016 presidential election downloaded from the website of the Federal Election Commission. To qualify as a red or a blue state, we require a vote share advantage of at least five percentage points. The second measure computes the percentage of the firm's workforce affiliated with the Democratic versus the Republican party by linking proprietary resume data provided by Revelio Labs to commercial voter registration data provided by L2, Inc. Finally, we obtain data on the political party affiliations of CEOs from Fos et al. (2025), who link U.S. executives covered by ExecuComp to voter registration data.

3.4 Stock Returns

To measure changes in stock market valuations around corporate tweets, we download daily stock returns from CRSP accessed through the WRDS daily event study interface. To estimate abnormal returns, we use the Fama and French (1993) and Carhart (1997) four-factor model estimated over days $t = -300$ to $t = -50$ and winsorize abnormal returns at the 1% and 99% level.

4 A New Measure of Partisan Corporate Speech

We construct our measure of partisan corporate speech to capture the extent to which corporations use language that resembles that of Democratic or Republican politicians. Intuitively, if a corporate tweet uses language that is highly predictive of being used by a Democrat (Republican), we classify it as Democratic- (Republican-) sounding. To implement this idea, we apply multinomial inverse regression (MNIR)—a natural language processing method previously used to detect partisan speech in Congressional discourse (Gentzkow et al. (2019)). We first estimate MNIR using tweets from Republican and Democratic politicians to identify bigrams that are strongly associated with either party. We then apply these estimates to classify corporate tweets as partisan. In addition, we use topic modeling to group partisan corporate tweets by their subject matter. We describe both methodologies in more detail below.

4.1 Multinomial Inverse Regression

Following the approach in Taddy (2015), we assume that bigram counts (c_{it}) sent by tweeter i at time t are drawn from a multinomial distribution:

$$\boldsymbol{c}_{it} \sim \mathrm{MN}\left(m_{it}, \boldsymbol{q}_t^{P(i)}\left(\boldsymbol{x}_{it}\right)\right). \tag{4.1}$$

There are J total bigrams that the speaker could use. c_{it} is a vector of length J. The j^{th} entry is the number of times the tweeter uses the j^{th} bigram. There are two arguments to the multinomial distribution $\mathrm{MN}(\cdot)$. m_{it} is the total number of bigrams spoken at time t, referred to as the "verbosity." $\boldsymbol{q}_t^{P(i)}$ is the vector of choice probabilities, also of length J. This vector depends on the covariates of the tweeter at a given point in time, denoted by vector $\boldsymbol{x}_{it}$, as well as on the party affiliation of the tweeter, $P(i) \in \{R, D\}$. We let R and D denote the set of all politician-year pairs for Democratic and Republican politicians, respectively.

MNIR is a bag-of-words model. It disregards the word order or punctuation that human readers use to parse the meaning of sentences. We follow Taddy (2015) in using bigrams as opposed to unigrams to capture some degree of lexical dependence inherent in sentence structure. Using bigrams enables MNIR to distinguish between tweets that use word sequences like "defund police" and tweets that use these two words in completely different parts of the text.

The method described in Taddy (2015) gives a computationally tractable method to estimate the parameters in this multinomial distribution using Poisson regression. The output of this procedure yields the vector of choice probabilities: $\boldsymbol{q}_t^{P(i)}\left(\boldsymbol{x}_{it}\right)$.

We estimate the above model over bigrams used in tweets by members of Congress with a verified Twitter account between 2012 and 2022. Following Gentzkow et al. (2019), we analyze speech at the level of politician–time, with t corresponding to a calendar year. Also similar to the approach in Gentzkow et al. (2019), we include the control variables home state, indicators for the highest educational degree attained, age, gender, and ethnicity, to account for demographic variables correlated with speech and party affiliation.[5]

We estimate MNIR year-by-year over the set of bigrams used at least forty times by at least twenty distinct speakers in that year. This restriction is imposed because bigrams are sometimes used by chance by only a single party, which can result in a disproportionate number of non-partisan bigrams being spuriously classified as partisan (see Gentzkow et al.

[5] We code independents in the Senate as belonging to the party with which they caucus. For the House of Representatives, we code Paul Mitchell and Justin Amash as Republicans, reflecting that for the substantial majority of their time in office they were both Republican lawmakers.

(2019)). We judge that truly partisan phrases should be used relatively frequently and by a large set of speakers.

Next, we compute the posterior probability a listener with a neutral prior would have over an arbitrary politician's party with unknown demographics after hearing a particular bigram. We begin by computing the probability that a Republican politician would use the j^{th} bigram by taking the average across all Republican politicians in that year:

$$q_{jt}^{R} = \frac{1}{|R|} \sum_{i \in R} \boldsymbol{q}_t^{P(i)}(\boldsymbol{x}_{it})' \cdot e_j, \tag{4.2}$$

where e_j is a vector of zeros with a single entry of one at element j. q_{jt}^{D} is defined analogously. We then compute the posterior probability that a politician is a Republican after the listener hears the j^{th} bigram, denoted p_{jt}^{R}, using Bayes' rule:

$$p_{jt}^{R} = \frac{q_{jt}^{R}}{q_{jt}^{R} + q_{jt}^{D}}. \tag{4.3}$$

For bigrams that are not used at least forty times by at least twenty different Twitter accounts in year t, we set $q_{jt}^{R} = \frac{1}{2}$. Additionally, we set $q_{j}^{R} = \frac{1}{2}$ for four bigrams: "top stori," "today via," "stori today," and "join us." A few Republican Congresspeople use these phrases very frequently, resulting in MNIR classifying these bigrams as partisan despite the unambiguously non-partisan nature of these bigrams.

We display the ten bigrams most associated with Republican and Democratic politicians' speech each year in Table 2 after computing the average change in the posterior probability p_{jt}^{R} for a given congressional speaker if a given bigram was removed from the dataset. The list of bigrams is intuitive. Among the most Democratic bigrams are those referring to voting rights, gun violence, and climate change. Among the most Republican bigrams are references to law enforcement, tax reform, and small businesses. The ability of our method to detect partisan speech appears to improve over time: the early years of our sample period (2012 to 2015) yield some less intuitive bigrams, such as "listen live" and "pls rt," which could be due to Twitter usage among Congresspeople increasing over time. Importantly, in our robustness tests discussed in Section 5.1.1 below, we show that our stylized facts are not sensitive to the precise time period in which our MNIR is estimated.

Finally, in order to obtain a measure of the partisanship of a corporate tweet, we apply the estimates from the MNIR obtained using the tweets of Congresspeople to tweets sent by corporations. In this step, the unit of observation is an individual tweet. We calculate the posterior that the corporate sender of tweet k in year t is Republican or Democrat from the expression

$$p_k^R = \frac{\prod_{j \in J^\star} q_{jt}^R}{\prod_{j \in J^\star} q_{jt}^R + \prod_{j \in J^\star} q_{jt}^D}, \tag{4.4}$$

where $J^\star$ denotes the set of bigrams used in the corporate tweet. We refer to variable p_k^R as the "partisan speech index" (PSI) and define a tweet as partisan speech if p_k^R or $p_k^D = 1 - p_k^R$ is sufficiently close to one. Intuitively, the posterior will be close to zero if a tweet comprises phrases such as the ones in the "Democratic" columns in Table 2 and close to one if the tweet uses phrases from the "Republican" columns in Table 2.

For most of our analysis, we use a cutoff of $p_k^R \leq 0.03$ and $p_k^R \geq 0.97$ to identify highly Democratic and Republican corporate tweets, respectively. We would also like to distinguish between tweets that are directly related to the business of the sender versus tweets that are not directly related. For example, our model frequently codes discussion of the climate transition as partisan. However, there is a substantive difference between a discussion of the climate transition by a utility company versus a telecommunications company. In the first case, the company is much more likely to be taking a stance on an issue directly relating to the firm's business operations. We are more interested in the second case, where firms make partisan statements on issues that are not directly related to their business. To classify tweets as business-related, we combine a measure of the subject matter of the tweet with information about the tweeting firm's industry. We describe this procedure in greater detail in Section 4.2 below.

Panels B and C of Table 1 provide summary statistics for the sample of Democratic and Republican tweets, using a threshold of $p_k^R \leq 0.03$ and $p_k^R \geq 0.97$. Partisan tweets make up a relatively small share of all corporate tweets. The distribution of partisan tweets is also highly right-skewed, with a significantly larger mean than the median.

Table 3 lists the most important partisan bigrams by U.S. companies within the set of partisan corporate tweets. We measure bigram importance by first examining the set of corporate tweets coded as partisan, meaning that the tweet-level PSI is ≤ 0.03 or ≥ 0.97. We then rank the bigrams our model labels as partisan, meaning they have a bigram-level $q_{jr}^R \leq 0.03$ or ≥ 0.97, by their frequency within the set of partisan tweets. Those that appear most frequently are listed in Table 3.

The list of the most important Republican and Democratic bigrams in corporate Twitter speech is largely very sensible. For example, in 2019, Democratic bigrams most commonly used by corporations include "lgbtq equal," "pay gap," "authent(ic) selv(es)," as well as references to climate action ("bring clean"). In the same year, the Republican bigrams most commonly used by corporations include "tune foxbusi(ness)," "american energi," and "gas line." That said, the list in Table 3 also reveals, as expected, that our approach is not free of measurement error, as the list also includes a few less obvious bigrams, such as “wall system,” “warp speed,” or “watch whole.” Despite some noise in our measurement, we show below that our measure of partisan corporate speech picks up meaningful and plausible variation across firms and around major events.

4.2 Topic Model

To better understand the content of the tweets that our above method characterizes as partisan, we decompose the subject matter of these tweets into distinct topics using a biterm topic model. Topic models model documents as draws from abstract topics, with topics being probability distributions over words. An example topic could feature a high probability of using the words “trade,” “tariff,” and “embargo.” A reasonable label for such a topic would be “trade.” An important characteristic of a good topic model is that it is easy to interpret.

After estimating the MNIR, we take two resulting sets of tweets: those with $p_k^R \leq 0.1$ and those with $p_k^D \geq 0.9$. We choose less stringent cut-offs for the purpose of our topic model in order to have a sufficiently large set of partisan tweets to analyze. We then train a single topic model on the union of the two sets of partisan tweets. Moreover, for the sake of computational tractability, we use unigrams instead of bigrams when estimating the topic model, following Yan et al. (2013) and Blei et al. (2003).

We estimate biterm topic models as opposed to the more common approach in the finance literature, which is Latent Dirichlet Allocation, or LDA (e.g., Bybee et al. (2024), Hansen et al. (2017)). LDA models the words in individual documents as drawn from abstract topics. Unfortunately, LDA performs poorly with short texts, such as tweets, because it requires a substantial amount of text within each document to estimate the parameters of the topic model. Biterm topic models, on the other hand, estimate topics over the entire corpus of tweets. They treat a single tweet as drawn from a single topic, as opposed to many, thus allowing for more precise inference of the tweet topic. Biterm topic models are frequently used in the NLP and economics literature when working with short texts, such as tweets (e.g., Qiang et al. (2022), Cookson et al. (2024c)).

The number of topics in a topic model is a subjective choice of the researcher. We estimate a 50-topic model because it is a round number that results in interpretable topics. For each tweet, we infer the most important topic for tweet k using a posterior implied by the estimated topic model:

$$\text{Topic Posterior}_{k,n} = \frac{\mathbb{P}\left(\text{Words Drawn from Topic } n\right)}{\sum_{m \in M} \mathbb{P}\left(\text{Words Drawn from Topic } m\right)}. \tag{4.5}$$

We then say that the tweet belongs to the topic with the largest posterior probability.

Because tweets are short snippets of text and typically refer to a single topic, this "most important" posterior measure does a good job of characterizing the content of individual tweets.

The full results from our biterm topic model estimation are shown in Table IA.4 in the Internet Appendix, available on the authors' websites. The topics are ordered by how frequently they are identified as the most important topic for an individual corporate tweet. We report the five most important unigrams for each topic.

Whereas topic models are often uninterpretable to a human reader, ours are highly interpretable. The words associated with each topic in Table IA.4 mostly belong to clearly distinguishable groups. We conjecture that this is because of the strong factor structure in partisan speech. Partisan speech, particularly on Twitter, is often issue-specific and thus well-suited for topic models.

We assign each topic a label by giving the list of unlabeled topics with the most important words associated with those topics to Chat-GPT. For ease of exposition, we further ask Chat-GPT to organize our 50 topics into a smaller set of meta-topics, which are shown in Table IA.5. For example, the meta-topic "Diversity, Equity, and Inclusion" (DEI) subsumes topics such as "workplace equality, diversity, and inclusivity," "LGBTQ Pride, support, and celebration," and "gender equality." The meta-topic "Sustainability and Environment" includes topics such as "energy sector," "climate action," and "clean energy, renewable power, and sustainability."

The list of topics in Internet Appendix Table IA.4 reveals that some tweets that we identify as partisan have a clear connection to the business of the company (e.g., companies discussing economic indicators or an oil & gas company discussing a pipeline project). Whether a topic is business-related depends not only on the subject but also on the industry of the tweeting firm. Therefore, we define, for each tweet topic, a set of industries whose core business is directly connected to the topic of the tweet. Our choices in classifying business-related tweets are reported in Internet Appendix Table IA.4. For example, the topic "Financial Reporting and Corporate Results" is labeled business-related for all firms. However, tweets belonging to the "health and medicine" topic are only labeled business-related if the sender is in the healthcare industry, measured using the two-digit SIC codes 80, 28, 51, and 63. Internet Appendix Figure IA.7 plots the fraction of Democratic and Republican tweets that are classified as business-related. For these tweets, we set the PSI-value of the tweet to 0.5, effectively treating them as nonpartisan.

4.3 Measure Validation

If our measure of partisan corporate speech accurately captures the use of partisan language by corporations, we would expect partisan corporate tweets to elicit stronger reactions from politicians than nonpartisan tweets. Therefore, as a validation test, we conduct a daily event study around corporate tweets identified by our methodology as partisan or nonpartisan. To measure politician responses, we collect all tweets sent by members of Congress in our sample that mention one of the firms in our dataset. Specifically, we combine (i) politician tweets that directly mention a corporate Twitter handle and (ii) politician tweets that reply to, quote, or retweet a corporate tweet.

Internet Appendix Table IA.2 reports the frequency of company mentions by members of Congress during the ten calendar days around a partisan corporate tweet relative to the control group of nonpartisan corporate tweets. The strictest specification in column (3) of Table IA.2 reports the coefficients from the following linear probability model:

$$\text{Mention}_{fkt} = \alpha_t + \alpha_k + \sum_{\tau=-5}^{\tau=+5} \beta_\tau \text{D}_{kt}^{\tau} \times \text{Partisan Tweet}_k + \sum_{\tau=-5}^{\tau=+5} \gamma_\tau \text{D}_{kt}^{\tau} + \varepsilon_{fkt}. \tag{4.6}$$

$Mention_{fkt}$ refers to an indicator equal to one if company f is mentioned by a politician on calendar day t around corporate tweet k. D_{kt}^{τ} stands for event-time dummies, with $\tau = 0$ indexing the calendar day on which the corporate tweet was sent. $PartisanTweet_k$ refers to an indicator equal to one if corporate tweet k is partisan (PSI-score $\leq$0.03 or $\geq$0.97) and zero if it is nonpartisan (PSI-score of 0.5). α_t and α_k are date and tweet fixed effects, respectively. The coefficients of interest are the coefficients on the interaction terms (β_τ), which capture the relative difference in the frequency of mentions by politicians between partisan and nonpartisan corporate tweets. By using nonpartisan tweets as a control group, we are effectively controlling for any increase in attention that may arise from sending any tweet.

Table IA.2 reveals a disproportionate increase in mentions by politicians around partisan corporate tweets relative to nonpartisan corporate tweets. The magnitude of the effect on event day $\tau = 0$ is 0.29 percentage points (see column (3)), which is a sizable effect relative to the unconditional mean of the dependent variable of 0.61%. These patterns are consistent with our measure of partisan corporate tweets, in fact, picking up the usage of partisan language.

5 Three Facts About Partisan Corporate Speech

This section analyzes the time and cross-sectional variation in partisan corporate speech, as well as stock returns around partisan corporate tweets, and summarizes the results in three stylized facts.

5.1 Aggregate Trends in Partisan Corporate Speech

Figure 1 plots the histograms of the partisan speech index (PSI) using all corporate tweets in every other year between 2012 and 2022. X-axis values closer to zero (one) indicate corporate language that is more similar to that of Democratic (Republican) members of Congress, respectively.

In the early years of the sample (i.e., 2012 to 2016), the distribution of PSI scores is tightly centered around 0.5, indicating that most corporate tweets are nonpartisan in tone. The distribution is relatively symmetric, with little mass in the tails, suggesting a low frequency of both Democratic- and Republican-sounding tweets.

After 2016, the distribution changes notably. There is a visible thickening in the tails of the distribution, reflecting an increase in the use of partisan language. This shift is especially pronounced in the left tail (closer to zero), corresponding to an increase in Democratic-sounding speech. The right tail (closer to one), corresponding to Republican-sounding speech, also grows but to a lesser extent.

By 2022, the distribution exhibits clear polarization in corporate speech: a large majority of tweets remain nonpartisan, but there is a growing share of tweets that use language closely aligned with one political party, particularly the Democratic Party.

To see the evolution in the volume of partisan corporate speech over our full sample period, Figure 2, Panel A plots the month-by-month percentages of all corporate tweets that are identified as highly partisan, defined as tweets with a PSI-value less than 0.03 or greater than 0.97. The figure confirms the findings from Figure 1: We observe a relatively low and stable frequency of partisan corporate tweets between 2012 and 2017, with partisan corporate tweets constituting approximately 0.5% of all corporate tweets. In November 2017, the volume of partisan corporate speech more than doubled, from ca. 0.5% to 1.2% of all corporate tweets. Then it continued to rise, reaching a peak of more than 6% in June 2022.

Panel B of Figure 2 breaks down partisan corporate speech into Democratic-sounding (blue line) and Republican-sounding (red line) tweets, which we refer to as "Democratic tweets" and "Republican tweets," respectively. While both types of partisan speech initially rise at similar rates, the trend shifts in early 2019, when Democratic-sounding speech begins to increase much more sharply than Republican-sounding speech. This disproportionate rise in Democratic speech aligns with patterns observed in media coverage of corporate political statements (e.g., Homroy and Gangopadhyay (2025)).

As illustrated in Internet Appendix Figure IA.2, the two time series display significant variation around major political and commemorative events. For example, a visible spike in the Democratic speech series can be observed in June 2020, shortly following the death of George Floyd. An example of a Democratic corporate tweet from this time is the following tweet by Duke Energy on June 8, 2020:

> "The heartbreaking loss of George Floyd's life and the powerful response to it are excruciating reminders of the progress we still need to make in our communities. We're pledging $1 million to nonprofit orgs committed to social justice and racial equity."

MNIR judges this tweet to be highly Democratic-sounding speech, with a PSI-value of approximately 6×10^{-5}.

The fifth-largest spike in the series of Democratic tweets is in March 2021. This is the month in which the state of Georgia passed a high-profile voting law that many perceived as restricting voting rights for political gain. Democratic-sounding corporate tweets from this month often refer to voting rights and/or to this law specifically. An example is the following tweet by Salesforce, Inc.:

> "A person's right to cast their ballot is the foundation of our democracy. Georgia HB 531 would limit trustworthy, safe & equal access to voting by restricting early voting & eliminating provisional ballots. That's why Salesforce opposes HB 531 as it stands. #gapol "

Other spikes in the series of Democratic tweets occur in June 2021 and June 2022, when many companies celebrated Pride month and advocated for LGBTQ rights. Moreover, in June 2022, many companies issued statements in response to the Supreme Court's decision to overturn Roe v. Wade. An example of such a statement is the following tweet by Hologic, Inc.:

> "Women's health and women's rights in the U.S. took a significant step backward with the overturning of Roe v. Wade. Our U.S. health insurance plans will continue to have access to comprehensive care, including abortion services and necessary travel expenses."

Calendar months in which Republican-sounding tweets regularly spike are November (Veterans Day) and May (Memorial Day) when many U.S. firms tweet patriotic messages and/or celebrate the military. For example, a tweet from Automatic Data Processing, Inc. on November 11, 2017, reads as follows:

> "At @ADP offices across the country, we are honoring our Veterans and their families for their service and sacrifice. Thank you for your contributions to the preservation of freedom and democracy! #militarystrong"

In November 2017, the month with the largest increase in the percentage of Republican tweets, many Republican-sounding tweets are related to the Tax Cuts and Jobs Act (TCJA) and tax reform more broadly. For example, The Boeing Company tweeted:

> "@Boeing CEO Dennis Muilenburg: "I would say that tax reform is the single most important thing we can do to generate job growth in the US."

The patterns in Figure 2 could be driven by a handful of companies that use Twitter very actively. To investigate this possibility, we also study the extensive margin of partisan tweeting. Internet Appendix Figure IA.4 plots the percent of firms, among those who send at least one tweet in a given calendar month, that send at least one Republican or Democratic partisan tweet, respectively. The results show that the relative increase in Democratic-sounding speech is not driven by a few companies. In 2021, the percentage of firms sending at least one Democratic-sounding tweet crosses the 60% threshold in some months, compared to the average of 12.5% of firms between 2012 and 2017.

Panel A of Internet Appendix Figure IA.6 presents the increase in Democratic- relative to Republican-sounding speech at the annual frequency. We compute the net Democratic tweet ratio ($NDTR$), defined as the percentage of Democratic tweets minus the percentage of Republican tweets, for a given firm and calendar year. Next, we regress the $NDTR$ on calendar-year dummies and firm fixed effects while clustering standard errors at the firm level. The figure reports the coefficient estimates and corresponding 95% confidence intervals for these calendar-year dummies.

The average $NDTR$ does not move around much until 2019, when we see the first visible shift toward more Democratic speech. It reaches a level in 2022 that is 3.6 percentage points (ppt) higher than in our baseline year 2012. This represents a sizable increase in the net Democratic tweet ratio, equivalent to more than 1.5 standard deviations.

5.1.1 Benchmarks and Robustness Tests

In Figure 3, we assess to what extent corporate speech may reflect the same patterns as other speech on Twitter. To do so, we analyze the trends in partisan speech for two alternative samples. The first benchmark consists of randomly selected tweets, plotted in Panel A of

Figure 3. Because it is infeasible to download the entire body of tweets within a reasonable time frame and because Twitter's API does not have the functionality to download random samples, we construct a random sample by querying Twitter for the first twenty tweets sent every hour of every day of the month. This procedure returns the first tweets sent at 2:00 PM, 3:00 PM, and every other hour of each day between January 1, 2012 and January 1, 2023. For a typical month, this approach results in slightly less than 15,000 tweets. We require that the language of the tweet is English and that the tweet originate from the United States.

Panel A of Figure 3 reveals two important insights. First, in terms of the average volume of partisan speech, the sender of the average tweet uses very little partisan speech—even less than the typical S&P 500 company. Second, even though the partisanship of the average tweet has increased over time, there are two distinct differences from the speech of U.S. corporations. First, we observe a more gradual increase in the overall quantity of partisan speech across time. Second, partisan speech is roughly evenly divided between Republican and Democratic-sounding speech, and both increased approximately at similar rates. Importantly, we do not observe the decoupling of the two series that we see for corporate speech on Twitter around the year 2019.

In Panel B of Figure 3, we repeat the same exercise for the tweets of Congress members. Unsurprisingly, the tweets of members of Congress are much more partisan on average than those by S&P 500 firms, as can be seen from the units on the y-axis. The volume of partisan speech by Congresspeople has also increased over time, but there is no similar divergence in the prevalence of Democratic and Republican-sounding speech starting in 2019, as the one we observe for corporations.

In the Internet Appendix, we present two important robustness tests. First, Internet Appendix Figure IA.3 shows that the patterns documented in Figure 2, Panel B are similar if we use alternative thresholds for the PSI-value to identify partisan tweets. Second, Internet Appendix Figure IA.5 plots the time series of Democratic and Republican-sounding speech using only politician speech from one year at a time. Although exact magnitudes differ from year to year, the broad patterns are very similar. This is an important test because it suggests that the time trend in partisan corporate speech is not driven by politician speech or the accuracy of our model changing over time; instead, corporations are changing their use of partisan phrases.

5.2 Firm Heterogeneity

To explore potential cross-sectional variation both in the average level and in the time-variation in partisan corporate speech, Figure 4 plots the average annual $NDTR$ separately for different subsamples of firms. The average $NDTR$ is shown by the firm's headquarters location (Panel A), Global Industry Classification Standard (GICS) sector (Panel B), the size of the firm's book assets (Panel C), market concentration in the firm's industry (Panel D), the CEO's party affiliation (Panel E), and the firm's workforce composition (Panel F). In Panels A and B, we restrict the sample to states and GICS sectors that contain at least 5% of all observations.

A striking finding from Figure 4 is the broad-based nature of the increase in Democratic-sounding speech. This trend is evident across all states (Panel A), with every state—including Texas—experiencing a rise in the $NDTR$ between 2019 and 2022. It also spans all GICS sectors (Panel B), affecting both consumer-facing sectors, such as "consumer discretionary," and business-focused sectors, such as "industrials" and "materials" (see also Panel A of Internet Appendix Figure IA.9 for a split between B2B and B2C industries). By the end of the sample period, the sectors with the highest $NDTR$ are materials and health care. We further observe the trend towards more Democratic-sounding speech across the full firm size distribution, although it is more pronounced for larger than for smaller firms (Panel C), as well for firms in industries with high and low levels of market concentration (Panel D). It is also present for firms run by both Democratic and Republican CEOs (Panel E), as well as for firms with a high and low share of Democratic workers (Panel F).[6]

We collect the findings from our analysis of partisan corporate speech in the following two facts:

Fact 1. *The volume of partisan corporate speech has increased significantly between 2012 and 2022.*

Fact 2. *Since 2019, the rise in Democratic-leaning language has outpaced the rise in Republican-leaning language, leading to more Democratic-leaning speech by U.S. corporations on average. This increase in Democratic-leaning language is broad-based, occurring across all sectors, states, and CEO political leanings.*

[6]Panel B of Internet Appendix Figure IA.9 reports the same split by workforce composition, using an alternative measure of partisan leaning based on workers' party registration status.

5.3 Content Analysis

To shed more light on the content of partisan corporate speech, this section presents results from a topic analysis, as well as an analysis aimed at separating tweets into those that contain actions or measurable commitments versus those that do not.

5.3.1 Topic Model

As described in Section 4.2, we estimate a biterm topic model and ask Chat-GPT to organize these topics into a smaller number of labeled meta-topics in order to better understand the content of partisan corporate tweets and how it has evolved over time.

Figure 5, Panel A reports the percentage of tweets across different meta-topics for Democratic-sounding tweets. Many Democratic-sounding tweets are related to DEI, sustainability and environment, and community and philanthropy. We see a strong increase in the prevalence of DEI-related tweets starting in late 2017, explaining a large part of the subsequent increase in the amount of Democratic speech. We also observe a moderate increase in tweets related to climate action, as well as an increase in the amount of corporate tweets celebrating Black History Month or Pride Month.

Panel B provides the topic breakdown for Republican-sounding tweets. A large fraction of Republican-sounding tweets are related to the energy sector and to business and the economy, even after applying our filters to exclude business-related tweets. Other Republican-sounding tweets comment on politics and legislation, such as the Tax Cuts and Jobs Act (TCJA) or the U.S. Mexico Canada Agreement (USMCA). We also observe an increase in patriotic and military celebrations over time, which are classified as Republican speech.

5.3.2 Speech versus Action

We further classify all corporate tweets into those that contain concrete actions and/or measurable commitments to a particular cause and those that do not. We will refer to the first type as "action tweets" and to the second type as "nonaction tweets." Examples of action tweets include companies pledging a certain dollar amount in charitable donations, committing to reducing greenhouse gas emissions by a certain percentage, or achieving a target gender quota within a pre-specified time frame. We perform the tweet classification using a transfer learning approach.

Transfer learning is a method in machine learning where a pre-trained model developed on one task is reused as the starting point for a model on a second task. This approach has become especially popular in natural language processing (NLP) due to its effectiveness in leveraging large-scale pre-trained models like BERT (Bidirectional Encoder Representations from Transformers), RoBERTa (Robustly Optimized BERT Pretraining Approach), GPT (Generative Pre-trained Transformer), etc., and their ability to understand and generate human language.

The overall procedure involves fine-tuning the RoBERTa model, developed and maintained by HuggingFace, with our Twitter data. We begin by tokenizing our dataset using RoBERTa's tokenizer. Following this, the tokenized data is used to train the model. During the fine-tuning process, the model learns from the labeled data, which consists of 9,268 tweets that have been manually classified into action (821) and nonaction tweets by two human research assistants.

The final trained model has a recall statistic of 0.95 (meaning that the model misses 5% of "actions" in the labeled dataset), precision of 0.90 (meaning that, out of all action labels predicted by the model, 90% are correctly predicted and 10% are false positives), and accuracy of 0.985 (the proportion of all labels that are predicted correctly, including action and non-action). Once the model is fine-tuned, we use it to predict whether the remaining corporate tweets that have not been labeled by humans fall into the action or non-action category.

An example of an action tweet would be the following tweet sent by PVH Group: *"PVH is committed to work toward goals of #ParisAgreement. As pledged in 2017 and reaffirmed in our #FWDFashion corporate responsibility strategy - we aim to power our offices, warehouses and stores with 100% renewable electricity by 2030. #wearestillin"*

Internet Appendix Figure IA.8 reports the percentage of all Democratic and Republican tweets that are classified as action tweets over time. Action tweets are relatively rare for both Democratic and Republican tweets, representing less than 7% of all partisan tweets on average. However, we observe an increase in the prevalence of action tweets over time: the share of action tweets among Democratic tweets increases from ca. 3% to 11%, and the share of action tweets among Republican tweets increases from 1% to 4%.

5.4 Firm Valuation Changes Around Partisan Corporate Speech

This section analyzes stock returns around partisan corporate tweets and summarizes the findings in our third stylized fact.

5.4.1 Average Stock Return Around Partisan Tweets

An important remaining question is the stock price implications of partisan corporate speech. We study daily cumulative abnormal returns (CARs) around partisan tweets, using the Fama and French (1993) and Carhart (1997) four-factor model to estimate abnormal returns and winsorizing them at the 1% and 99% levels within event time. After excluding events with multiple partisan tweets with different partisan leanings by the same company on a given date (2,091 tweets), subsequent tweets by the same company on the same topic (31,469 tweets), events with concurrent earnings announcements in the trading window (–1,+1) around the tweet (428 tweets) and tweets with missing returns during a symmetric 21-day event window around the event (944 tweets), we are left with a sample of 8,990 partisan tweets by 541 companies, of which 5,793 (3,197) have a Democratic (Republican) slant, respectively. We restrict the sample to the first tweet by a company on a given topic, estimated using our biterm topic model described above, in order to focus on a set of tweets that is more likely to convey new information to market participants, as companies often send out identical or very similar tweets on multiple occasions.

Figure 6, Panel A plots the average cumulative abnormal return around partisan tweets. On the day of the tweet itself, the average stock return is close to zero. However, a noticeable decline in the stock price occurs over the ten days following the average partisan tweet, reaching approximately –20 basis points (bps) on event day +10, statistically significant at the 5% level. When we extend the post-event window to 30 days after the tweet, we find that stock prices continue to decline until about 13 trading days after the tweet before leveling off, reaching a CAR of almost negative 30 bps (see Internet Appendix Figure IA.11). In other words, the full stock-price impact takes time to materialize, consistent with the delayed stock-price impact of legislation documented in previous work (e.g., Cohen et al. (2013)). We do not observe a significant trend in the stock price prior to the tweet event.

In Panel B of Figure 6, we separate tweets into those whose partisan slant is more versus less surprising given the company's past tweet history. Specifically, we compute a tweet's partisan-slant surprise as the absolute difference between the tweet's PSI-value and the average PSI-value of the company's tweets in the 36 months prior to the event. Tweets with a high surprise are those in the top quartile of partisan-slant surprises across all partisan tweets in a given calendar month. All other tweets are considered "low surprise." Consistent with the news content of partisan-slant surprises being higher, we observe a stronger decline in the stock price in the high-surprise subsample.

Table 4 confirms these results, reporting estimates of the average CAR measured over different windows for all partisan tweets (columns (1) to (3)) and for partisan tweets with high surprise (columns (4) to (6)). Standard errors are clustered at the firm level. The CAR over trading days (0,+10) following the event is –21.3 basis points for the average partisan tweet (column (3)) and –29.5 basis points for the average partisan tweet with high surprise (column (6)). Internet Appendix Table IA.6 shows that the level of statistical significance remains similar if we cluster standard errors at the calendar day of the tweet or the calendar month of the tweet, respectively. Moreover, the magnitude of our estimates is very similar if we do not winsorize returns, although they do become noisier (see Panel C of Table IA.6).

5.4.2 Heterogeneity in Stock Returns Around Partisan Corporate Tweets

The average returns shown in Figure 6 and Table 4 could mask a substantial degree of heterogeneity. To uncover potential sources of heterogeneity, we regress abnormal returns around partisan corporate tweets on measures of stakeholders' alignment with the partisan slant of the tweet. In particular, we construct measures of the CEO's, workers', and investors' alignment with the tweet. CEO alignment is equal to one if the partisan tweet matches the party affiliation of the CEO and zero otherwise. For Democratic (Republican) corporate tweets, workers' partisan alignment is defined as the percentage of Glassdoor reviews from blue (red) states. Investor alignment is more difficult to measure. Because much of Democratic-sounding speech focuses on combating climate change and promoting social equality (see Figure 5, Panel A)—goals that broadly align with those of sustainable investing—we use (minus) the percentage of company stock held by funds with a sustainability mandate for Democratic (Republican) corporate tweets, respectively, as a proxy for investor alignment. We further control for the firm's market capitalization and the degree of institutional ownership, and we include GICS sector $\times$ month fixed effects in order to compare tweets sent by firms in a similar industry and at a similar point in time. The results from these regressions are presented in Table 5, where all independent variables are standardized to have a mean of zero and a standard deviation of one.

The results in Table 5 indicate substantial heterogeneity by the degree of stakeholder alignment with the firm. CARs during a (0,+1) window around a partisan tweet with high surprise are 13.4 basis points higher for a one-standard-deviation higher alignment with workers (column (4)). The effect of worker alignment is even larger over the event window (0,+3) but then becomes statistically insignificant at ten trading days post-event. This pattern suggests that high-surprise partisan tweets that are better aligned with the partisan leaning of the firm's workforce tend to be associated with a more positive stock price reaction, indicating a potential cash flow effect.

Partisan alignment with investors also appears to matter for the stock price reaction, and its effect tends to grow with the event window horizon. For high-surprise partisan tweets, a one-standard-deviation higher investor alignment is associated with 23.6 basis points higher CAR over event days 0 to +10 (column (6)). Hence, although the average stock price reaction is negative, it is less negative if a greater share of investors is aligned with the tweet. Finally, there is no significant heterogeneity in the stock price reaction by the CEO's partisan alignment or by the size of the firm's market capitalization.

We sum up our findings from our analysis of stock returns in our third fact:

Fact 3. *The average partisan corporate tweet is followed by negative abnormal returns. Subsequent stock returns are less negative if there is greater alignment between the tweet and the preferences of the firm's shareholders.*

6 Potential Drivers of the Rise in Democratic-leaning Corporate Speech

Having established our three stylized facts, this section explores potential explanations for the disproportionate rise in Democratic-sounding corporate speech during the period 2019–2022.

6.1 CEOs' Personal Preferences

One possible explanation is that the rise in Democratic-leaning corporate speech reflects the personal political preferences of CEOs. However, the empircal evidence casts doubt on this agency-based narrative. First, the increase in Democratic speech is not limited to firms led by Democratic-leaning CEOs; it is also prevalent in firms with Republican-leaning CEOs (see Panel E of Figure 4). Second, the rise is, if anything, more pronounced in more competitive industries, where managerial discretion is more constrained by market forces (see Panel D of Figure 4). Together, these patterns suggest that external pressures, rather than CEOs' personal preferences, are likely driving the trend, consistent with the perception of most U.S. adults in mid-2020 (Anderson and McClain (2020)). In the following, we discuss the potential role of three external factors: employee, consumer, and investor preferences.

6.2 Employee Preferences

A potential driver of partisan corporate speech is pressure from employees. Surveys indicate that a substantial share of employees expect their employers to take public stances on social and political issues (e.g., Edelman (2019)), and Colonnelli et al. (2023) demonstrate in a field experiment in Brazil that firms' ESG practices influence talent allocation. Consistent with employees playing a role in corporate political speech, firms with a higher concentration of workers in Democratic-leaning states tend to use more Democratic-sounding language on average (see Panel F in Figure 4).

Unfortunately, the lack of longitudinal data makes it difficult to determine whether and to what extent employee expectations have changed over time, as most available surveys and experiments provide only cross-sectional snapshots. Some of our findings suggest that employee preferences alone cannot fully explain the observed trend. For instance, Democratic-leaning corporate speech has increased sharply even among firms headquartered in Republican-leaning states and those with a low share of employees in blue states (see Panels A and F in Figure 4). Additionally, we find no strong differential pattern between firms operating in industries with high versus low labor market tightness (see Panel C of Internet Appendix Figure IA.9).

6.3 Consumer Preferences

Another possible explanation is that firms are responding to consumer preferences. Recent years have seen a rise in politically motivated boycotts and consumer activism, with research documenting how consumers adjust their purchasing behavior in response to firms' political positions (e.g., Boxell and Conway (2024)). Consistent with this view, we find a somewhat stronger increase in Democratic-leaning speech among business-to-consumer (B2C) firms (see Panel A of Internet Appendix Figure IA.9).

However, the consumer-driven explanation has limitations. The increase in Democratic-sounding speech is not confined to B2C firms—it is also pronounced in business-to-business (B2B) industries. For instance, the GICS "Materials" sector, which includes firms in construction materials, chemicals, and packaging, exhibits one of the highest levels of Democratic-leaning speech by the end of the sample period. These firms primarily serve other businesses rather than individual consumers, making it difficult to reconcile the broad-based shift with a consumer-driven story alone.

6.4 Investor Preferences

Finally, the increase in Democratic-sounding speech may be driven by a shift in investor preferences. The rise of sustainable investing represents a fundamental shift in the asset management industry, which occurred at a similar time as the rise in Democratic-sounding corporate speech and may have exerted broad pressure on firms across sectors and geographies.

Panel A of Figure 7 shows a striking correlation between the growth of Democratic corporate speech and the explosion of assets under management (AUM) in sustainable funds, as reported by UNCTAD. Notably, the surge in Democratic-leaning speech lags the growth in sustainable AUM by approximately one year, consistent with firms adapting their communication in response to evolving investor demands. Given that large institutional investors tend to be broadly diversified across industries, this could explain why the trend is widespread rather than confined to specific sectors and locations.

To further test the investor channel, we examine the role of BlackRock, the world's largest asset manager, and its public advocacy for corporate social responsibility. Larry Fink, BlackRock's Chairman and CEO, has been a vocal proponent of firms taking a more active role in addressing social and political issues. His 2018 annual letter to CEOs emphasized the importance of corporate purpose, sparking widespread debate among business leaders and policymakers (Sorkin (2019)). His 2019 letter, titled "Purpose & Profit," went even further, explicitly calling on CEOs to engage in contentious social and political debates:

> "As a CEO myself, I feel firsthand the pressures companies face in today's polarized environment and the challenges of navigating them. Stakeholders are pushing companies to wade into sensitive social and political issues – especially as they see governments failing to do so effectively. As CEOs, we don't always get it right. And what is appropriate for one company may not be for another. One thing, however, is certain: the world needs your leadership. As divisions continue to deepen, companies must demonstrate their commitment to the countries, regions, and communities where they operate, particularly on issues central to the world's future prosperity."

Given BlackRock's influence, Fink's 2019 letter provides a suitable empirical setting to test whether a shift in investors' publicly stated preferences could have increased the pressure on U.S. companies to speak out on partisan issues. First, we examine whether January 2019 coincides with a notable shift in the distribution of partisan corporate speech. To do so, we compute the average quarterly net Democratic tweet ratio ($NDTR$) across our sample firms and perform a structural break analysis using the method proposed by Bai and Perron (1998) and Bai and Perron (2003). The Bai and Perron (BP, hereafter) method allows researchers to test for structural breaks at unknown points in time and to identify both the number of breaks and their corresponding dates of occurrence. In our context, we test for breaks in the mean quarterly $NDTR$.

The BP method identifies two structural breaks in the mean $NDTR$ (see Internet Appendix Table IA.3), with estimated break points in 2018Q4 and 2020Q4 (see Internet Appendix Figure IA.6, Panel B). In other words, Larry Fink's January 2019 letter coincides with a statistically significant shift in corporate partisan slant, supporting our hypothesis that investor preferences may be a key driver of the observed patterns in partisan corporate speech.

Second, we exploit cross-sectional variation in the degree of BlackRock ownership to assess whether firms with higher BlackRock ownership responded more strongly to Fink's 2019 letter. This is a demanding test because, given BlackRock's influence, its statements likely also influence the behavior of firms in which it holds a smaller stake. Despite this caveat, we find meaningful variation between firms with different levels of BlackRock ownership. Panel B of Figure 7 plots the quarterly $NDTR$ for firms with high versus low BlackRock ownership. To ensure that our results are not driven by total institutional ownership, we sort all firms into quartiles based on their total institutional ownership in a given quarter and then sort firms into high versus low BlackRock ownership groups by splitting at the median within each quartile. Before 2019Q1, the average partisan slant is close to zero and very similar across both sets of firms. In 2019Q1, the quarter in which the letter was published, we see a sizable difference emerge, which persists until almost the end of our sample period.

The same pattern is not present when we look at firms with high ownership by other institutional investors. In Internet Appendix Figure IA.10, we first sort all firms into quartiles based on their BlackRock ownership in a given quarter, and then sort firms into high versus low total institutional ownership groups by splitting at the median within each quartile. If anything, firms with high other institutional ownership increased the amount of Democratic speech by less.

To provide a more formal test of whether the difference emerging between firms with high versus low BlackRock ownership is statistically significant, we use a difference-in-differences design by estimating the following equation:

$$\text{NDTR}_{it} = \alpha_t + \alpha_i + \text{BRK Holdings}_{i,t-1} + \text{BRK Holdings}_{i,t-1} \times Post_t + \gamma' X_{i,t-1} + \epsilon_{it}, \quad (6.1)$$

where NDTR_{it} refers to the net Democratic tweet ratio for firm i in quarter t, $\text{BRK Holdings}_{i,t-1}$ refers to the lagged percentage of the firm's outstanding stock held by BlackRock, sorted into quartiles within a given calendar quarter, and $Post_t$ is an indicator variable equal to one for quarters including and following 2019Q1, and zero otherwise. $X_{i,t-1}$ is a vector of lagged control variables, which includes the percentage of the firm's stock owned by institutional investors and the log of the firm's total book assets, both sorted into quartiles within calendar quarter, as well as the interaction between both of these variables and the $Post$ indicator. α_i refers to firm and α_t to quarter fixed effects; we also estimate alternative specifications with sector $\times$ quarter and state $\times$ quarter fixed effects. We estimate equation (6.1) on data from three years before to three years after 2019Q1, i.e., from 2016Q1 to 2022Q1.

Table 6 reports the results. Consistent with the findings from Figure 7, Panel B, firms with higher BlackRock ownership exhibit a stronger increase in Democratic speech following

Larry Fink's 2019 letter. Specifically, our most conservative estimates in column (2) imply that going from the first to the fourth quartile of BlackRock ownership corresponds to a 0.48 (=0.161×3) ppt higher $NDTR$ post 2019Q1. Again, we find the opposite effect for ownership by other institutional investors, as firms with high 13F ownership exhibit a significantly smaller increase in Democratic speech.

While the economic magnitude of these effects is not very large, it likely represents a lower bound for the potential impact of Larry Fink's letter on partisan corporate speech. The reason is that BlackRock is a large shareholder in almost all companies in our sample. For example, in Panel B of Figure 7, the average ownership stake by BlackRock in the *Low BRK Holdings* group is still 4.1%. BlackRock is thus likely to have substantial influence also in the *Low BRK* category.

Overall, the patterns around Larry Fink's 2019 letter suggest that shifts in the stated preferences of large institutional investors could have played a role in the greater engagement by U.S. companies on social and political issues. This result may appear at odds with our earlier findings that stock prices tend to react negatively to partisan corporate speech, as standard intuition suggests that catering to investors' nonpecuniary preferences should increase stock prices. In the next section, we provide a theoretical framework in which a shift in investors' nonpecuniary preferences over partisan corporate speech can jointly explain the rise in partisan corporate speech, the decline in firm valuations around the average partisan tweet, as well as the documented heterogeneity by investors' partisan alignment.

7 Model

This section proposes a theoretical framework that can jointly explain our three stylized facts. Motivated by the empirical evidence in the previous section, our model features heterogeneous investors who derive positive nonpecuniary utility when their portfolio firms take political actions aligned with their preferences and negative utility when they take nonaligned actions. Our model provides a unified explanation for the rise in corporate political statements and the predominance of Democratic-leaning speech. It also accounts for the negative average effect of political statements on firm valuations. An extension of our model predicts that these adverse valuation effects should diminish when investors are more aligned with a firm's political stance. The key distinction from prior work is that, in our model, firms have to raise capital from both aligned and nonaligned investors. This force causes prices to adjust to incentivize the nonaligned investor to invest in positive quantities. We discuss our model's relation to prior work at length in Section 7.6 below. All proofs are given in Section G of the Internet Appendix.

The model features two types of investors, a Democratic investor and a Republican investor, indexed by $j \in \{D, R\}$. For simplicity, we refer to them as investors, though they should be understood as representing investor groups. Both investors hold shares in a single firm.

The model unfolds over three periods, visualized in Figure 8. The model is initialized at time zero. At time one, a political controversy may arise, forcing the firm to take an action $a \in \{a_D, a_R\}$. The political controversy and the firm's response should be interpreted broadly: a matter of public disagreement enters the political discourse, and the firm must align its stance with the preferences of either Democratic or Republican investors. If no controversy arises, the firm takes no action. After observing the realization of the controversy and the firm action, investors determine how much to invest in the firm and at what price.

At time two, the firm distributes a liquidating dividend, Y per share, to investors. Our model centers on heterogeneity in the nonpecuniary utility investors obtain from firms' political stances. To highlight this feature, we deliberately keep the environment stark, requiring only that investors prefer to hold shares in firms whose positions they support and that heterogeneity exists across investors. Accordingly, we assume a deterministic firm payout and model investors as risk-neutral.

7.1 Investors

We model investors as valuing both consumption and alignment with the political stances of the firms in their portfolios:

$$U_j\left(C_j, x_j, a\right) = C_j + \mathcal{A}_j(a) g\left(x_j, \delta_j\right) \tag{7.1}$$

Investor j's utility depends on consumption (C_j), alignment with the firm's political action ($\mathcal{A}_j(a)$), and the size of their holdings in the firm ($x_j \geq 0$) with price P per share. One share pays out dividend Y, denominated in units of the consumption good, which enters into C_j. For simplicity, we suppress time discounting. The investor's objective is to choose x_j to maximize utility, subject to a budget constraint dependent on investor wealth (W_j).

$$x_j P \leq W_j \tag{7.2}$$

This investment decision implicitly determines both consumption and the investor's portfolio exposure to firms whose political stances align or conflict with their preferences. The investment decision is made at time one after investors observe whether a political controversy realizes and the firm's action if an action is taken.

The function g governs the interdependence between the investors' portfolio holdings and the degree to which they internalize the firm's political stance. In the baseline model, we assume a functional form linearly increasing in x_j.

$$g\left(x_j, \delta_j\right) = \delta_j x_j \tag{7.3}$$

These preferences reflect some investors' reluctance to hold firms in their portfolios that take political actions they oppose. The parameter $\delta_j > 0$ captures the extent to which investors value alignment with firm actions in their utility. In the limit as $\delta_j \to 0$, investors make decisions purely based on financial considerations, ignoring firm stances. As δ_j increases, investors place greater importance on holding positions in firms whose actions align with their preferences.

To complete our characterization of preferences, the final step is to define the functional form for $\mathcal{A}_j\left(a\right)$. We seek a function that captures both the positive effects of partisan alignment and the negative effects of misalignment. For simplicity, we parameterize this function as

$$\mathcal{A}_j\left(a\right) = \begin{cases} 1 & \text{If a political controversy occurs and } a = a_j \\ 0 & \text{If no political controversy occurs} \\ -1 & \text{If a political controversy occurs and } a \neq a_j, \end{cases} \tag{7.4}$$

where a_j denotes the investor's preferred policy.

We make the intentionally simple modeling choice that firms must take a stand once a controversy arises. In practice, remaining neutral is often perceived as implicit support for one side or the other. When many firms publicly address a social issue while a few remain silent, observers frequently interpret the silence as tacit disagreement with those who have spoken out.

We model the arrival rate of controversies as

$$q = f\left(\delta_R, \delta_D\right), \tag{7.5}$$

where f is an increasing function of both δ_R and δ_D. This formulation reflects the idea that as investors become more concerned with firms' political actions, the potential for controversy increases. Conceptually, we model controversies as arising unpredictably—for example, triggered by widespread protests over racial equality that are themselves sparked by events outside the firm's control.

Market clearing is given by

$$x_D + x_R = x, \tag{7.6}$$

where x denotes the total shares of the firm's stock outstanding. In equilibrium, prices must adjust so that all shares are held and market clearing holds with equality. We do not model an outside asset, such as cash or government bonds, and assume that any unallocated wealth is passively held without affecting market equilibrium.

Assumption 1. *$W_j < xY$ for both $j \in \{R, D\}$ and $W_D + W_R > xY$.*

This assumption ensures no firm can finance itself by raising funds from Democrats or Republicans alone. It reflects the idea that when firms raise capital, neither Democratic nor Republican investors control a sufficiently large amount of wealth to finance firms exclusively. This assumption is particularly relevant given that our empirical setting features large firms in the S&P 500, and ownership of these firms is likely distributed across investors with diverse political preferences. In a richer model, this assumption could be reflected in investors' unwillingness to fully finance large firms due to their desire to limit exposure to idiosyncratic risk.[7]

7.2 Firms

The firm is assumed to maximize its share price, given by

$$V(P, a) = P \tag{7.7}$$

The firm's problem is to maximize V by choosing a in the event of a controversy. If no controversy occurs no action can be taken, which we denote by $a = \phi$. P is the time one price of the firm; i.e., at the time of the investors' investment decision. P is partially determined by the action a.

7.3 Equilibrium

We now turn to the equilibrium of our model. To do so, we first analyze equilibrium pricing and allocations under both political controversy and no controversy. To avoid redundancy, we consider the case where the firm takes action a_D; the case where it takes a_R is symmetric. To understand the model's predictions, we proceed in three steps. First, we characterize

[7] We conjecture that similar results to the ones we derive could be generated in a model where investors are highly risk averse. In this case, aligned investors would demand substantial compensation for bearing the additional risk associated with holding aligned firms and this force would cause the price to depreciate.

prices in various cases. Using these prices, we determine the equilibrium holdings and, in turn, the equilibrium price. Finally, we analyze how these equilibrium conditions shape the firm's optimal action.

Lemma 1. *In the absence of a political controversy, the price of a share is given by* Y*.*

If no political controversy arises, the impact of additional shares in the firm depends only on the marginal utility of consumption, scaled by the share's payout. The key theoretical implications of our specification of preferences arise in the presence of a political controversy.

Lemma 2. *After taking action* a_D*, if the firm could be fully financed by the* D *investor, the price of a share of the firm would be given by*

$$P = Y + \delta_D \tag{7.8}$$

This result follows from the first-order condition of the D investor. Conditional on the firm taking action a_D, the D investor derives additional utility from holding shares, as the firm's political stance aligns with her preferences. In this hypothetical equilibrium, the firm is fully financed by the D investor. As a result, the elevated price relative to the no-action benchmark reflects the D investor's internalization of the benefits of political alignment. This result aligns with the standard intuition that firms catering to investors' nonpecuniary preferences tend to see higher valuations. When firms take actions that align with investor preferences, their valuations increase.

Proposition 1. *There exists no equilibrium where the shares in the firm are fully held by a single investor.*

This result follows from the previous two lemmas, combined with Assumption 1. If shares are held by a single investor, there are three possible cases. First, in the absence of controversy, either investor type may hold the stock. In this case, $P = Y$, but Assumption 1 ensures that no individual investor is wealthy enough to finance this position alone, ruling out this possibility. Second, if a controversy arises and the firm takes an action, the shares may be held exclusively by the investor who agrees with the action. However, this would result in $P > Y$, which also contradicts Assumption 1. Finally, if the firm takes an action and shares are exclusively held by the investor who disagrees with it, Assumption 1 is not violated, as the price will be strictly below Y. However, the investor who agrees with the action would be willing to pay a price strictly greater than the prevailing price, preventing this from being an equilibrium. Thus, this result highlights that the key theoretical implication of Assumption 1 is that the stock must be held by both investor types in equilibrium.

Proposition 2. *If a controversy occurs and the firm takes action a_D, equilibrium, if it exists, is defined by the allocations*

$$x_D = \frac{W_D}{Y - \delta_R} \text{ and } x_R = x - \frac{W_D}{Y - \delta_R} > 0 \tag{7.9}$$

with

$$P = Y - \delta_R \tag{7.10}$$

this equilibrium is guaranteed to exist if

$$W_D < (Y - \delta_R)\, x \tag{7.11}$$

This proposition is key to understanding the intuition of our model. Once a firm takes action a_D, the D investor purchases shares until her budget constraint binds, leaving some shares outstanding. The R investor is marginal, and prices adjust downward until the R investor is willing to hold x_R shares. Thus, to satisfy market clearing, the price must adjust so that the investor who disagrees with the firm's stance is willing to hold the stock.

The model's solution is indeterminate if equation (7.11) is not satisfied. In this case, the aligned investor is wealthy enough to finance the firm at the discounted price $Y - \delta_R$, but not the full price Y. In the model extension described in Section 7.4 below, we can guarantee equilibrium existence under a weaker condition.

Unlike in most models of sustainable investing, investors who value firm political stances *do not* earn lower returns than those who do not. In our model, the return on investors' equity portfolio is given by

$$r = \frac{Y}{P} \tag{7.12}$$

All investors receive the same return on their wealth invested in equity, r. However, investors aligned with a firm's political stance can acquire shares at a lower price than they would otherwise be willing to pay.

To understand the equilibrium implications of our model, we now turn to comparative statics for the preference parameters δ_R and δ_D.

Proposition 3. *When $\delta_D > \delta_R$, the firm will find it optimal to take action a_D.*

The firm's objective is to maximize its share price P. If it takes action a_R, the share price is discounted by δ_D; if it takes action a_D, the discount is δ_R. A value-maximizing firm will therefore choose the action associated with the smaller discount—specifically, a_D if $\delta_D < \delta_R$. In this way, investor demand can pressure a value-maximizing firm into taking political actions aligned with the investor group that experiences greater disutility over nonaligned firm behavior.

To analyze our model's predictions regarding the change in firm valuation around the onset of political controversies and firms' political actions, we compare the prevailing price at time one, P, to the price of a claim to a share of the firm at time zero, P_0.

Corollary 1. *When a political controversy arises and the firm takes an action $a \in \{a_R, a_D\}$, the stock price declines. If the firm takes action a_D, the price falls by $(1-q)\delta_R$; if it takes action a_R, the decline is $(1-q)\delta_D$.*

In the model, a political controversy inevitably alienates part of the firm's investor base, regardless of the firm's chosen action. Alienated investors demand a lower price to hold a nonaligned stock as compensation for the disutility of investing in firms whose political actions they oppose. This creates a no-win situation: any action the firm takes will offend some investors and result in a financial cost through lower valuations.

7.4 Model Extension with Quadratic Benefit of Alignment

In an extension of the model, we solve a version where there is quadratic utility of alignment or nonalignment. In this extension, we define the function g as follows.

$$g\left(x_j, \delta_j\right) = \frac{\delta_j}{2} x_j^2 \tag{7.13}$$

What matters for the logic of this extension is that investors experience significant disutility from holding large, concentrated stakes in firms whose actions are politically misaligned. While they may hold small positions in such firms through passive investment vehicles, they are likely to be highly averse to taking large, direct stakes in individual companies whose actions conflict with their preferences.

By modeling this explicitly, we capture the idea that the impact of partisan actions may depend on the extent to which firms must raise capital from nonaligned investors. This insight is formalized in the following corollary.

Proposition 4. *The negative price effects of political controversies decrease with the alignment of the firm's action with its investor base.*

The logic of this result is intuitive. When a firm takes actions misaligned with a subset of its investors, the impact depends on how much capital it must raise from those alienated investors. As the required funding from this group increases, the negative effect on the firm's valuation becomes more pronounced. This result only holds in the quadratic case because the marginal cost of financing a stake in the firm is increasing in stake size. Intuitively, investors are highly averse to holding substantial equity positions in firms whose political actions they disagree with. In contrast, with linear utility marginal disutility is constant and investors are not increasingly averse to additional holdings when their stake is already large.

7.5 Relation to Empirical Findings

Our model allows us to jointly rationalize the three stylized facts that we report: (i) the substantial increase in the volume of partisan corporate speech between 2012 and 2022, (ii) the disproportionate increase in Democratic-sounding corporate speech, and (iii) the negative average stock price reactions associated with partisan corporate speech, as well as the documented heterogeneity by investor alignment. We interpret the rise of sustainable investing as reflecting an increase in δ_D; i.e., the degree to which investors who sympathize with traditionally Democratic-leaning policies, such as actions to mitigate climate change and increasing the representation of women and minorities, care about the alignment of their preferences with the actions of firms in their portfolio.

We first turn to Fact 1, the overall rise in partisan corporate speech. In our model, the arrival rate of controversies, q, increases with δ_D. As δ_D grows, this increases the total number of controversies and, thus, the total number of instances in which firms take political stances. Therefore, if δ_D increased during our sample period, this could explain the overall rise in partisan corporate speech.

To explain Fact 2, we invoke Proposition 3. This proposition shows that an increase in δ_D can also explain the disproportionate increase in Democratic speech, because the prospect of a significant price decline can discipline managers. Such price declines occur when firms take actions that conflict with the preferences of an investor group that strongly values alignment with the firms' political actions. To avoid these losses, managers are incentivized to act in ways that align with the group's preferences. If we interpret the rise of sustainable investing as a substantial increase in δ_D, Proposition 3 can rationalize the choice of many corporate managers to take actions associated with Democratic positions.

Proposition 3 also rationalizes the patterns observed in Panel E of Figure 4. In this figure, we observe an increase in Democratic-sounding speech even for firms led by Republican CEOs. Proposition 3 demonstrates how investor pressure can compel firms to take actions that may not align with the personal preferences of the firm manager.

Finally, to explain Fact 3, we turn to Corollary 1. This fact documented a striking feature of the data: stock prices tend to decline following partisan tweets. This result goes against standard intuition that catering to investor preferences should increase firm valuations. Our model gives a simple intuition for this result. When a firm takes either action a_D or a_R, it alienates part of its investor base. Those investors become less willing to hold the stock. For the firm to finance itself, the price must adjust downward so that all investors are willing to hold the stock. Importantly, this is still an optimal action for the firm, because its valuation would decline even more if it took the opposite action.

We also find that firms that take actions that are more aligned with the preferences of their investor base experience smaller stock price declines. Our model also explains this via Proposition 4. If the action is more aligned with investors, fewer investors will be alienated and the stock price impact will be reduced.

7.6 Relation to Existing Theoretical Literature

Our model follows in a tradition of studying the impact of nonpecuniary preferences on asset prices (Pástor et al. (2021)). Within this stream of literature, our work is most closely related to that of Wu and Zechner (2024), hereafter WZ, who also examine an environment where investors value political stances and value-maximizing firms take positions to align with investor preferences. However, unlike WZ, our model predicts that corporate political stances unambiguously reduce firm value. In contrast, WZ finds that firm stances aligned with investor preferences can enhance firm valuations.

The key reason for this difference is that in our model, only nonaligned investors are marginal, due to the wealth constraint. This forces the price to reflect the first-order condition of the nonaligned investor to sustain an equilibrium. Otherwise, the two model structures have many similarities and it is possible to derive a condition similar to equation (7.10) in the risk-neutral case of the WZ model.

8 Conclusion

This paper provides one of the first large-scale empirical analyses of partisan corporate speech, using a novel measure based on natural language processing of corporate social media communication. We use this measure to establish three key stylized facts. First, partisan corporate speech has increased significantly over the past decade, with a particularly sharp rise after 2017. Second, this increase has been disproportionately driven by Democratic-leaning statements, a trend that spans industries, geographies, and firms led by both Democratic and Republican CEOs. Third, partisan corporate statements are, on average, followed by negative abnormal stock returns, with significant heterogeneity depending on the political alignment of the firm's investor base.

To explain these patterns, we explore potential drivers of the rise in Democratic-sounding speech. While employee and consumer preferences may play a role, we also find novel empirical support for an investor-demand channel. The surge in Democratic corporate speech coincides with the rapid expansion of sustainable investing, and firms with high BlackRock ownership exhibit a particularly strong shift toward Democratic language following Larry Fink's 2019 letter to CEOs, which urged CEOs to engage more in contentious social and political debates. Our theoretical model formalizes this mechanism, demonstrating how shifts in investors' nonpecuniary preferences can lead firms to adopt partisan positions, even when doing so negatively impacts stock prices.

Our study opens several avenues for future research. First, while we document a strong correlation between investor preferences and partisan corporate speech, establishing causality remains an important challenge. Second, an open question is whether partisan corporate speech has financial consequences beyond short-term stock price reactions. Future research could examine how partisan statements influence customer loyalty, employee retention, and firm reputation over extended time horizons. Third, while we focus on publicly traded firms with a heterogeneous investor base, private companies and startups may face different incentives when engaging with social and political issues. Investigating whether partisan speech patterns differ between public and private firms could provide deeper insights into the role of capital markets in shaping corporate political engagement.

Fourth, because our data ends in early 2023, we cannot examine whether and how corporate speech patterns have responded to increasing political backlash, especially against ESG and DEI initiatives, as well as broader shifts in the political climate. Examining how firms navigate a shifting political environment could shed light on the extent to which corporate political engagement is driven by structural economic factors versus short-term political pressures. Finally, as firms increasingly engage in partisan speech, understanding its broader economic and political implications becomes more critical. Future research could explore how partisan corporate speech affects regulatory outcomes, lobbying effectiveness, or election dynamics.

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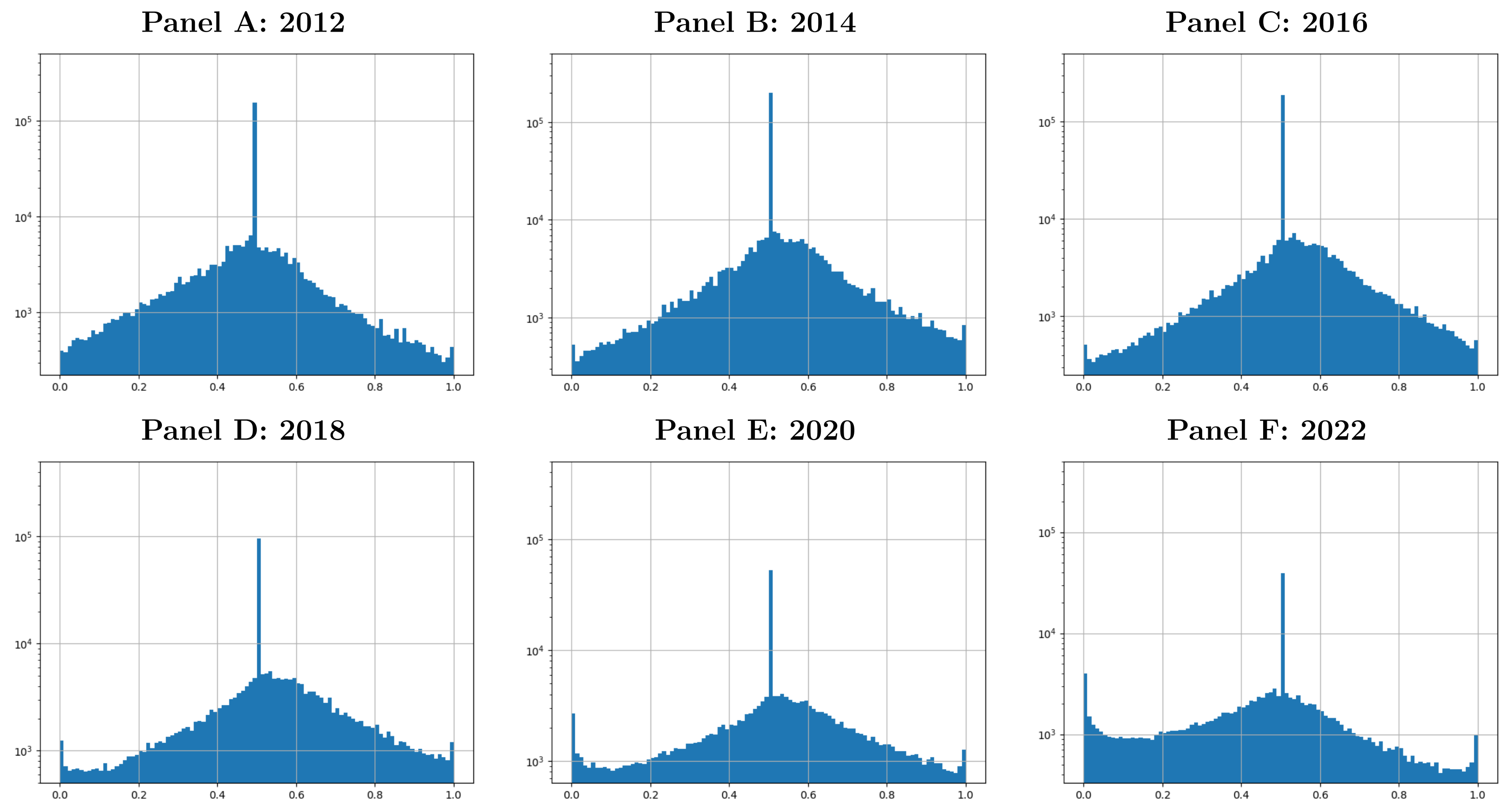
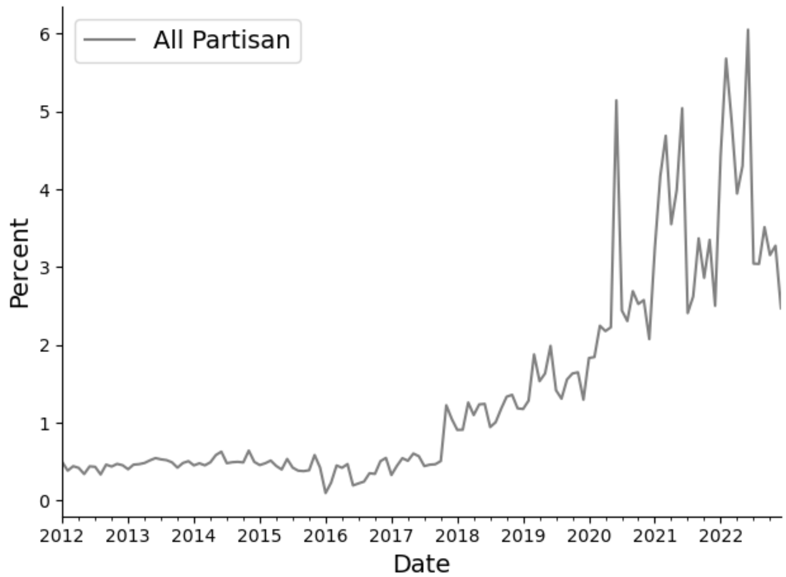
Figure 1
Distribution of PSI-scores for Corporate Tweets



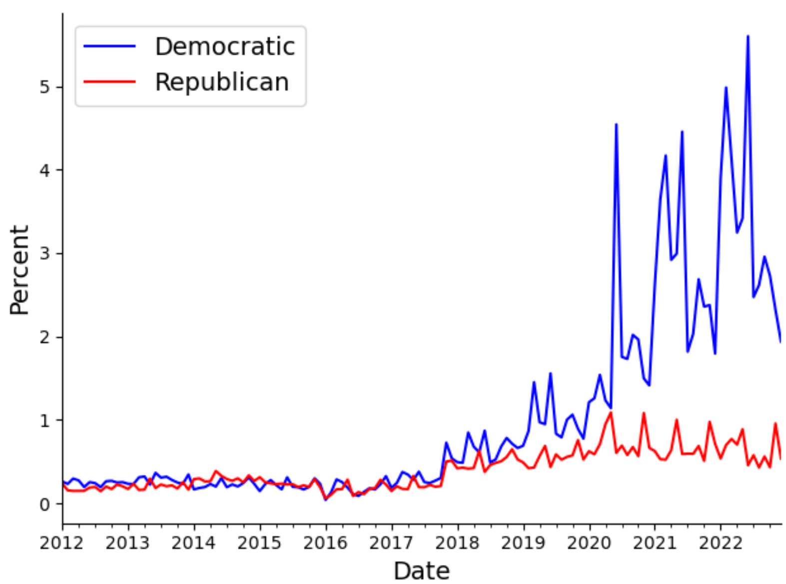
The figure displays the histograms of PSI-scores for corporate tweets sent biannually throughout our sample. A PSI-value near zero uses strongly Democratic-sounding language and a PSI-value near one uses strongly Republican-sounding language. The y-axis shows the logged number of tweets with a PSI-value falling within a particular bin.

Figure 2
Partisan Corporate Speech Over Time

Panel A: Partisan Corporate Speech



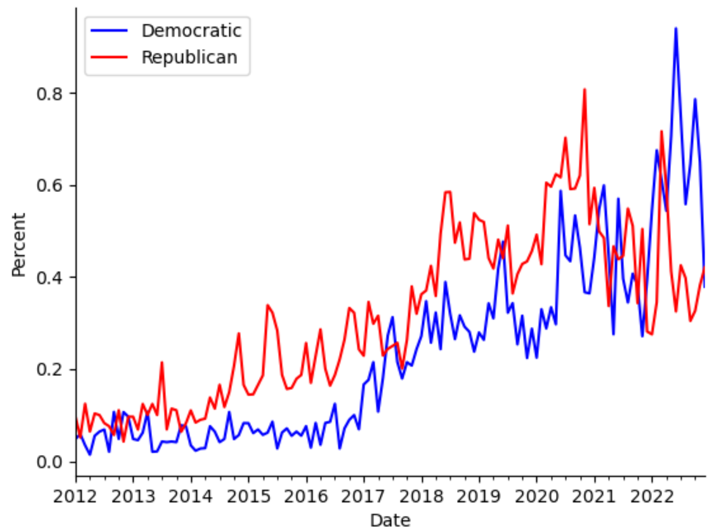
Panel B: Democratic vs. Republican-Sounding Speech



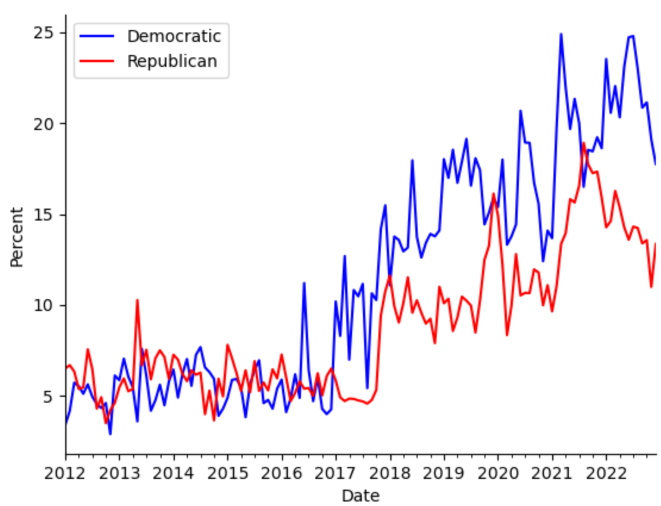
Panel A of this figure plots the percentage of partisan tweets by calendar month. Panel B separates partisan tweets into Democratic (blue line) and Republican (red line) partisan tweets, respectively. Democratic (Republican) tweets are those with a PSI-value ≤ 0.03 (≥ 0.97), respectively.

Figure 3
Benchmarks

Panel A: Random Sample of Tweets

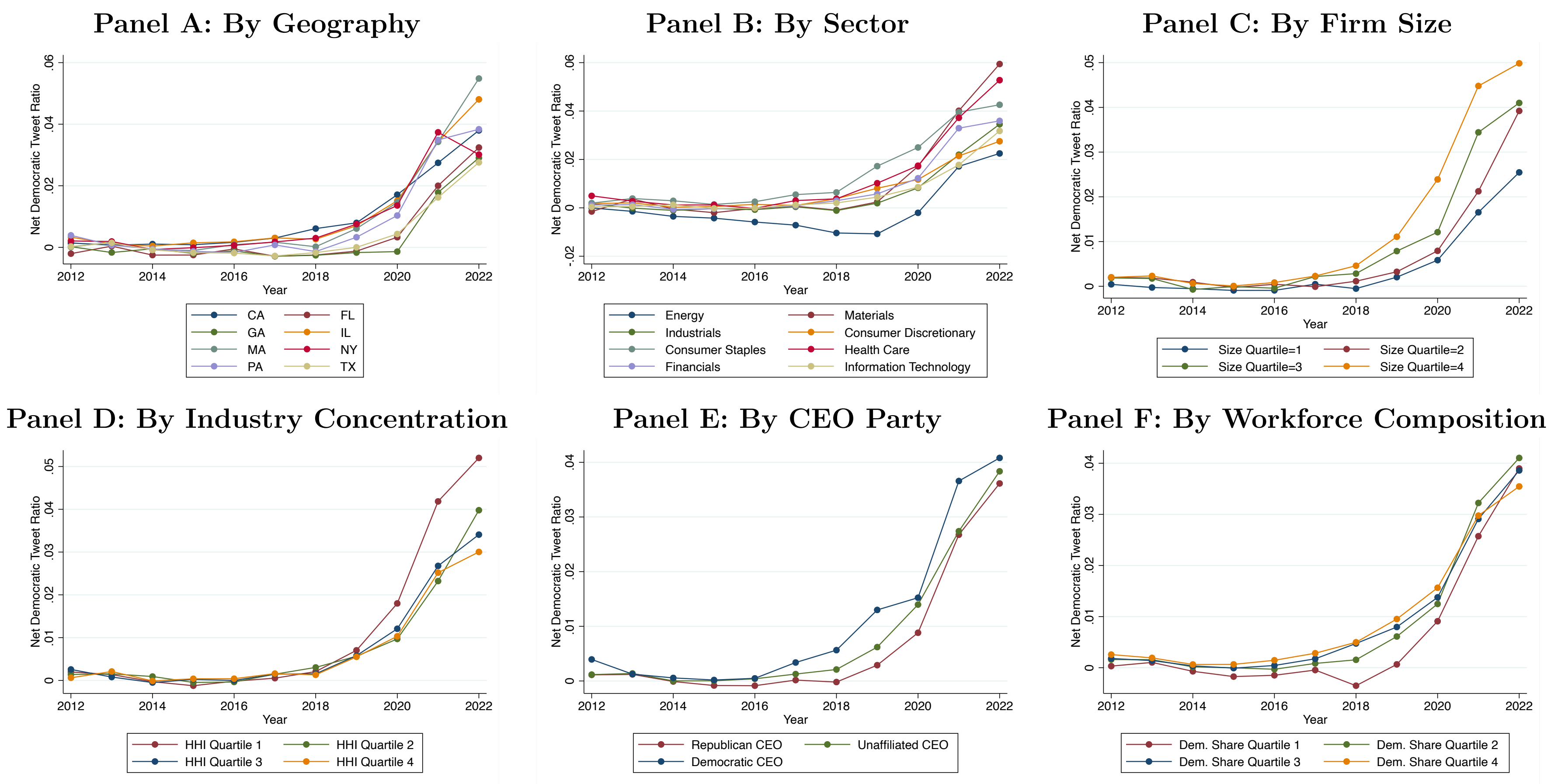


Panel B: Tweets by Members of Congress



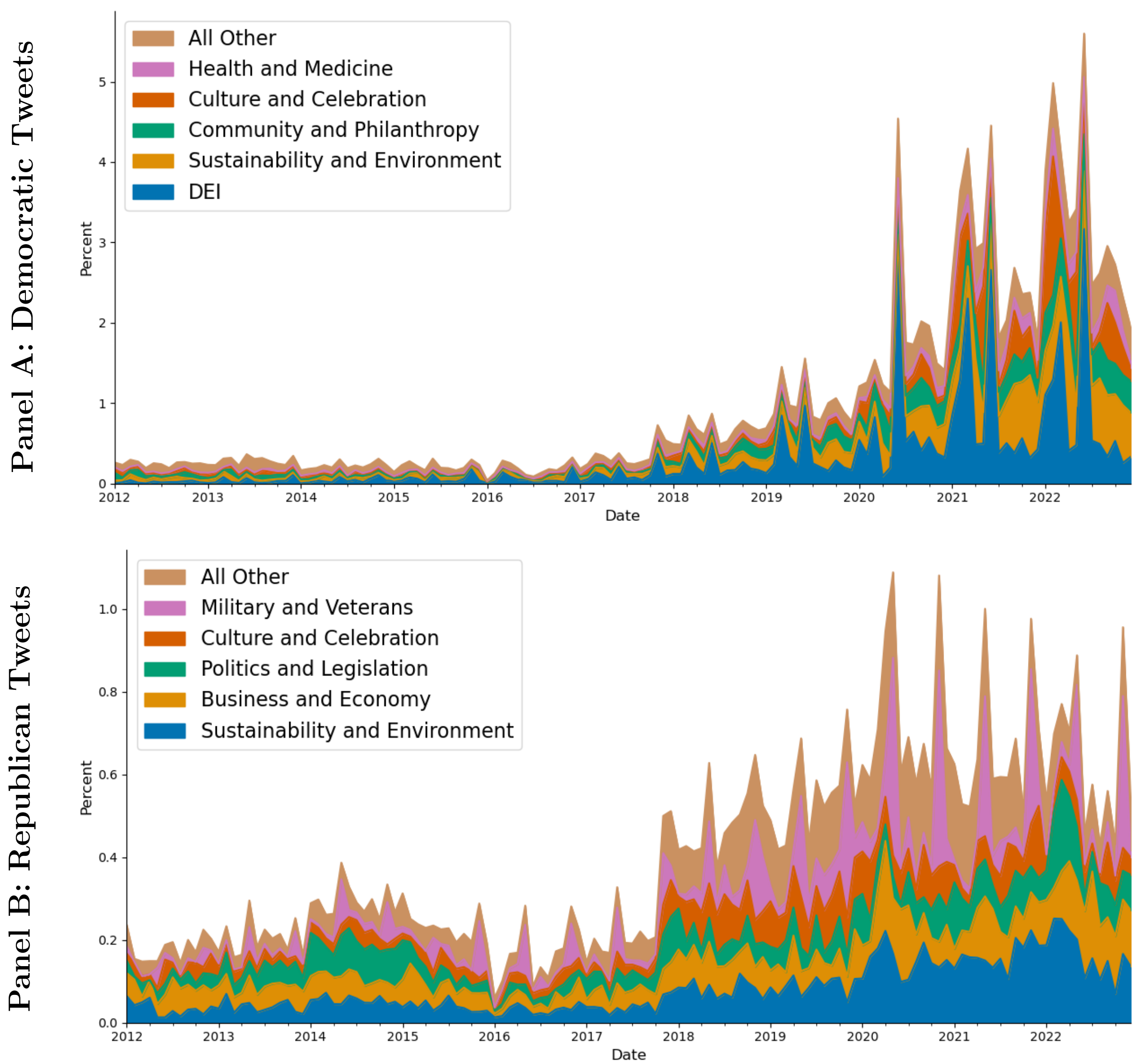
This figure displays the percentage of partisan tweets for two distinct samples. Panel A plots, for each calendar month, the percentage of partisan tweets in a randomly selected sample of tweets on Twitter. To construct this random sample, we download approximately 15,000 tweets per month by querying Twitter's API for the first twenty tweets sent at each day-hour-pair for every day in each month. Panel B plots the percentage of partisan tweets among all tweets sent by all members of Congress between 2012 and 2022 with an active Twitter account.

Figure 4
Net Democratic Tweet Ratio by Subsample



The figure plots the average net Democratic tweet ratio, defined as the percentage of Democratic tweets minus the percentage of Republican tweets by a company in a given calendar year, by the state of the firm's headquarters (Panel A), by the firm's GICS sector (Panel B), by the firm's size quartile, measured using total book assets (Panel C), by market concentration in the firm's industry, measured using the Herfindahl Index of revenue shares in a given 2-digit SIC industry (Panel D), by the party affiliation of the CEO (Panel E), as well as by the composition of the firm's workforce (Panel F). In Panels A and B, for ease of exposition, we restrict the sample to states and GICS sectors that contain at least 5% of all observations. Quartiles are formed within a given calendar year.

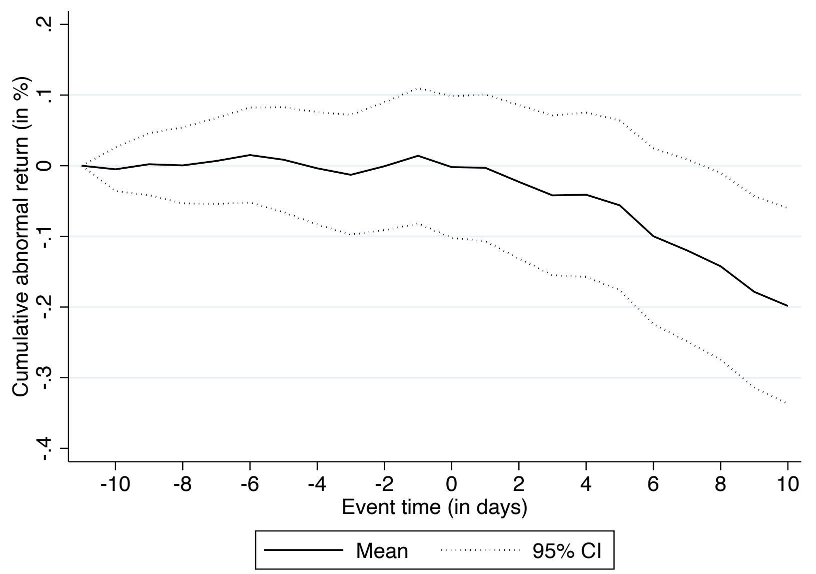
Figure 5
Topic Analysis of Partisan Corporate Tweets



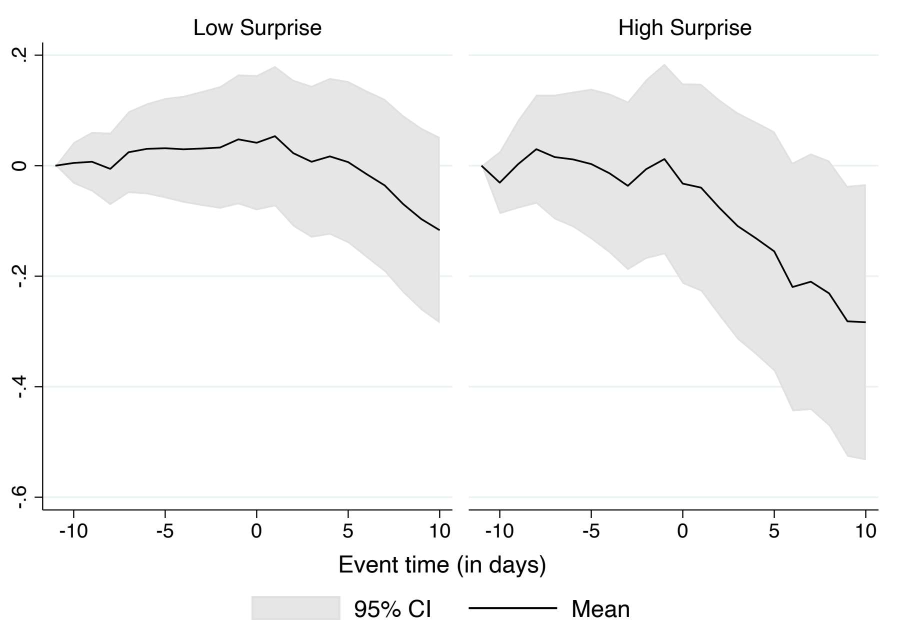
The figure displays the evolution of partisan corporate speech, grouped by meta-topic. Panel A shows the frequency of Democratic tweets broken down by the five most common meta-topics used in Democratic tweets. Panel B does the same for Republican tweets. Democratic (Republican) tweets are those with a PSI-value ≤ 0.03 (≥ 0.97). Topics are estimated using a biterm topic model and then grouped into larger meta-topics using Chat-GPT. The mapping from topics to meta-topics is provided in Internet Appendix D.

Figure 6
Stock Returns Around Partisan Corporate Tweets

Panel A: All Partisan Tweets



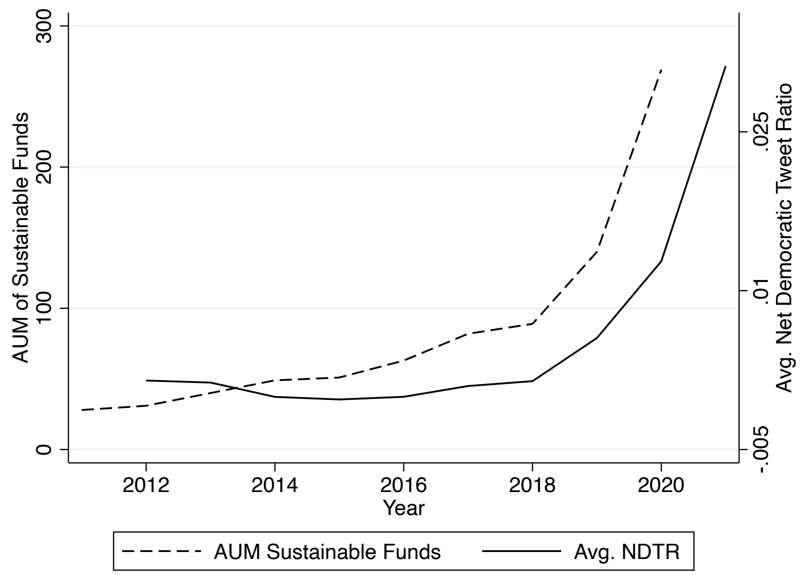
Panel B: By Surprise



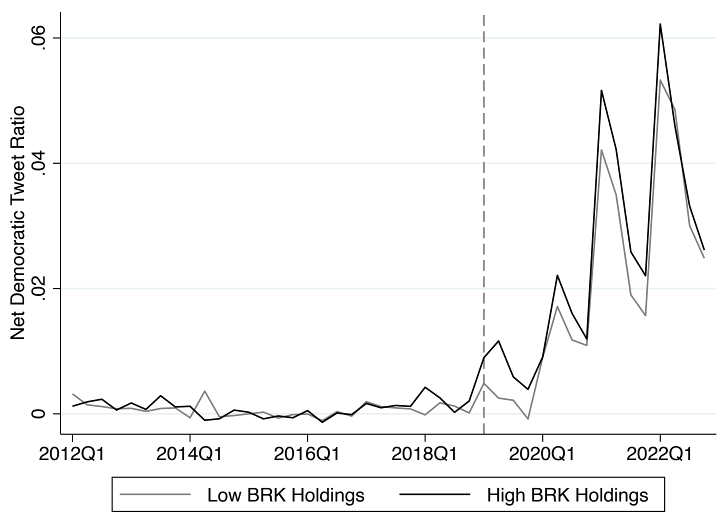
The figure displays cumulative daily stock returns around partisan corporate tweets. Panel A plots returns for the full sample of tweets, whereas Panel B reports returns separately for the subsamples with high versus low partisan-slant surprise. Daily abnormal returns are calculated using the Fama and French (1993) and Carhart (1997) four-factor model estimated over trading days $t = -300$ to $t = -50$ relative to the tweet.

Figure 7
Partisan Corporate Speech and Investor Composition

Panel A: AUM of Sustainable Funds and Corporate Partisan Slant

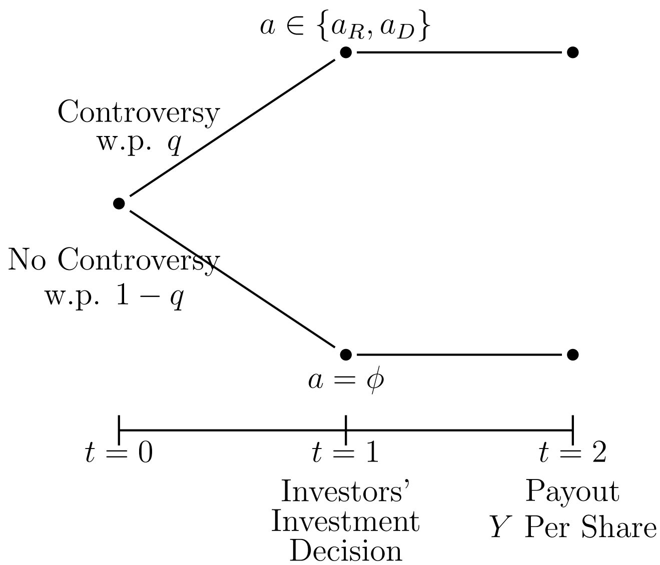


Panel B: BlackRock Ownership and Corporate Partisan Slant



Panel A displays the aggregate assets under management (AUM) of U.S. sustainable funds and the average net Democratic tweet ratio (NDTR) by calendar year. Aggregate AUM of sustainable funds (measured in $ billion) are obtained from UNCTAD. Panel B plots the average NDTR for firms with high versus low BlackRock ownership, sorted within total institutional ownership quartile. We first sort all firms into quartiles based on their total institutional ownership in a given quarter, and then sort firms into high versus low BlackRock ownership groups by splitting at the median within each quartile. The dashed vertical line corresponds to the first quarter of 2019.

Figure 8
Model Timing



This figure illustrates the model's timing. At $t = 1$, a controversy may or may not arise. If no controversy occurs, the firm takes no action. If a controversy arises, the firm chooses between two possible actions. Investors observe this decision and make their investment choice. At $t = 2$, the firm distributes a payout of Y per share to investors.

Table 1
Corporate Tweets: Summary Statistics

The table reports summary statistics for all tweets sent by firms in the S&P 500 via their verified Twitter accounts between 2012 and 2022. A firm appears in one of the three panels if the firm's Twitter account sent any tweet (Panel A), at least one Democratic tweet (Panel B) or at least one Republican tweet (Panel C) in that year, respectively. Democratic (Republican) tweets are those with a PSI-value ≤ 0.03 (≥ 0.97).

Year:	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
	Panel A: All Tweets										
Unique Firms	431	449	481	496	511	526	532	539	542	545	537
Average Tweets Per Firm	837.47	958.4	988.54	963.56	1263.84	756.02	649.33	572.09	484.73	450.4	349.34
Standard Deviation of Tweets Per Firm	1380.38	1449.37	1330.61	1107.42	9155.23	985.45	818.36	657.51	650.74	663.07	490.69
Minimum Number of Tweets	1	1	1	1	1	1	1	1	1	1	1
Median Number of Tweets	466	559	615	631	558	468	405	348	285	270	220
Maximum Number of Tweets	21699	20139	18959	11602	206275	11146	11060	4616	6616	8678	4967
	Panel B: Democratic Tweets										
Unique Firms	244	252	246	249	264	300	374	399	451	475	490
Average Tweets Per Firm	3.66	4.84	4.33	4.21	3.61	4.51	6.09	7.71	10.14	14.83	13.05
Standard Deviation of Tweets Per Firm	4.3	9.5	8.45	6.57	6.29	7.05	8.55	11.73	16.44	21.78	19.63
Minimum Number of Tweets	1	1	1	1	1	1	1	1	1	1	1
Median Number of Tweets	2	2	2	2	2	3	3	4	5	9	8
Maximum Number of Tweets	43	118	97	53	77	78	59	129	162	249	224
	Panel C: Republican Tweets										
Unique Firms	182	211	249	283	275	264	367	356	363	321	256
Average Tweets Per Firm	3.56	4.15	5.62	3.94	3.27	3.72	4.59	4.73	5.32	5.07	4.61
Standard Deviation of Tweets Per Firm	8.18	13.37	26.8	8.85	6.39	7.73	7.58	7.7	13.57	18.54	17.81
Minimum Number of Tweets	1	1	1	1	1	1	1	1	1	1	1
Median Number of Tweets	2	2	2	2	2	2	3	2	3	2	2
Maximum Number of Tweets	75	182	412	114	94	103	81	85	210	240	219

Table 2
Most Partisan Bigrams by Year

The table shows the ten bigrams most associated with use by Republican or Democratic politicians on Twitter by year, where the most partisan bigrams are calculated as the change in the expected posterior if, without telling the listener, the bigram was removed from the vocabulary. The most important Democratic partisan bigrams would result in the largest *increase* in the above quantity and the most Republican partisan bigrams would result in the largest decrease.

Democratic	Republican	Democratic	Republican	Democratic	Republican
2022		2021		2020	
gun violenc	american energi	vote right	men women	public health	small busi
health care	gas price	climat chang	biden administr	health care	presid realdonaldtrump
climat chang	secur border	gun violenc	law enforc	million american	law enforc
im proud	energi independ	build better	small busi	gun violenc	american peopl
vote right	energi product	child care	secur border	climat chang	men women
across countri	unleash american	work famili	open border	preexist condit	nanci pelosi
work famili	open border	im proud	god bless	social secur	god bless
social secur	law enforc	across countri	tax spend	john lewi	thank realdonaldtrump
lower cost	border patrol	health care	race theori	save live	unit state
mental health	god bless	right vote	critic race	across countri	look forward
2019		2018		2017	
gun violenc	men women	gun violenc	tax reform	health care	tax reform
climat chang	secur border	preexist condit	men women	work famili	tax code
background check	border secur	climat chang	law enforc	middl class	cut job
health care	nation secur	health care	secur border	climat chang	men women
preexist condit	american peopl	work famili	cut job	preexist condit	repeal obamacar
im proud	law enforc	social secur	look forward	million american	north korea
prescript drug	pass usmca	trump administr	small busi	aca repeal	law enforc
trump administr	nanci pelosi	im proud	border secur	health insur	american peopl
across countri	look forward	across countri	american peopl	puerto rico	look forward
million american	presid realdonaldtrump	civil right	nation secur	repeal aca	repeal replac
2016		2015		2014	
gun violenc	hillari clinton	climat chang	iran deal	minimum wage	loi lerner
climat chang	obama administr	gun violenc	men women	immigr reform	obama admin
donald trump	obama admin	vote right	nation secur	equal pay	men women
health care	men women	women health	look forward	climat chang	rand paul
vote right	law enforc	work famili	obama administr	middl class	presid obama
regist vote	god bless	middl class	small busi	equal work	obama administr
town hall	tax code	exim bank	presid obama	rais minimum	small busi
background check	nation secur	better infrastructur	obama admin	health care	listen live
work famili	via dcexamin	congress must	wotus rule	civil right	look forward
congress must	tax reform	civil right	listen live	million american	god bless
2013		2012			
immigr reform	delay obamacar	senat inouy	gas price		
gun violenc	obama admin	middl class	tax hike		
student loan	listen live	student loan	ron paul		
health care	obama administr	post photo	small busi		
town hall	defund obamacar	pls rt	repeal obamacar		
health insur	repeal obamacar	health care	listen live		
afford care	men women	women health	job creator		
sexual assault	ir target	town hall	tcot gop		
comprehens immigr	balanc budget	social secur	tax reform		
background check	tax code	regist vote	presid obama		

Table 3
Most Important Partisan Bigrams Used by Corporations by Year

The table shows the ten most partisan bigrams, where the most partisan bigrams are calculated as follows. We call the most important partisan bigrams the set of partisan bigrams that appear most frequently in partisan tweets (tweet-level $PSI \leq 0.03$ or ≥ 0.97) that are themselves partisan (bigram-level $q_{jr}^{R} \leq 0.03$ or ≥ 0.97). This calculation excludes business-related tweets.

Democratic	Republican	Democratic	Republican	Democratic	Republican
2022		**2021**		**2020**	
lgbtq equal	tune foxbusi	lgbtq equal	tune foxbusi	lgbtq equal	tune foxbusi
score hrc	level inflat	celebr pride	vaccin passport	celebr lgbtq	benefit employe
right campaign	employ ad	celebr lgbtq	employ ad	workplac polici	american energi
authent selv	foreign busi	protect planet	flip switch	fight racial	food home
health inequ	benefit employe	happi pride	support life	black latinx	warp speed
build equit	inflat highest	authent selv	benefit employe	lgbtq youth	foxbusi discuss
women color	wall system	lgbtqia communiti	watch whole	happi pride	oper warp
racial wealth	dozen job	latinx communiti	busi confid	lgbtqia communiti	effect manag
equit societi	rep roy	racial wealth	suppli world	authent selv	busi confid
close racial	letter chairman	right campaign	potus whitehous	build equit	join morningsmaria
2019		**2018**		**2017**	
lgbtq equal	tune foxbusi	happi pride	tune foxbusi	lgbtq equal	tune foxbusi
workplac polici	morningsmaria foxbusi	pay gap	benefit employe	pay gap	benefit employe
pay gap	benefit employe	lgbtq equal	effect manag	workplac polici	morningsmaria foxbusi
happi pride	flip switch	lgbtq youth	watch whole	right campaign	tax regulatori
lgbtq youth	american energi	celebr lgbtq	american oil	bring clean	busi optim
celebr lgbtq	fuel oil	child poverti	morningsmaria foxbusi	futur make	taxreform mean
authent selv	avail job	teacher help	join mariabartiromo	lgbtq youth	progrowth taxreform
right campaign	gas line	bring clean	confer chair	teacher help	via dcexamin
lgbtq right	food home	member lgbtq	avail job	happi pride	discuss taxreform
bring clean	busi confid	right campaign	christma came	score hrc	flip switch
2016		**2015**		**2014**	
pay gap	potus whitehous	bring clean	tune foxbusi	bring clean	tune foxbusi
futur make	tune foxbusi	futur make	avail job	pair shoe	american energi
bring clean	flip switch	score hrc	employ ad	pay gap	benefit employe
score hrc	american energi	teacher help	flip switch	teacher help	reward employe
sustain infrastructur	us employ	equalpay equal	us employ	impact aca	foxbusi discuss
teacher help	morningsmaria foxbusi	happi pride	confid economi	right campaign	us unemploy
happi pride	oper control	cleaner greener	benefit employe	safer workplac	christma came
hunger america	diesel price	bold climat	american energi	score hrc	energi crisi
workplac polici	scienc chang	act climat	gas line	happi pride	busi confid
lgbtq youth	miss presid	amazon rainforest	christma came	peopl shape	employ ad
2013		**2012**			
hunger america	tune foxbusi	pair shoe	job council		
right campaign	confid hit	amazon rainforest	foxbusi discuss		
bring clean	modern trade	right campaign	tune foxbusi		
impact aca	via foxnew	hunger america	price index		
pair shoe	produc oil	pay full	benefit employe		
protect planet	reward employe	bring clean	make top		
happi pride	talk radio	score hrc	flip switch		
best one	watch whole	charg network	american energi		
moment action	big guy	protect planet	employ ad		
teacher help	american energi	improv work	diesel price		

Table 4
Average Stock Returns Around Partisan Tweets

The table reports results from OLS regressions of daily cumulative abnormal returns over various event windows around partisan corporate tweets, measured in percent, on a constant. In columns (4) to (6), we restrict the sample of partisan tweets to those in the top quartile of partisan-slant surprises. Standard errors, reported in parentheses, are clustered at the firm level.

	Cumulative Abnormal Return (in %)					
	(0,+1)	(0,+3)	(0,+10)	(0,+1)	(0,+3)	(0,+10)
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	-0.017	-0.056*	-0.213***	-0.052	-0.121*	-0.295***
	(0.022)	(0.034)	(0.057)	(0.042)	(0.063)	(0.105)
N	8,990	8,990	8,990	2,777	2,777	2,777
High surprise only?	No	No	No	Yes	Yes	Yes

Table 5
Heterogeneity in Stock Returns Around Partisan Tweets

The table reports results from OLS regressions of daily cumulative abnormal returns over various event windows around partisan corporate tweets, measured in percent, on firm characteristics. In columns (4) to (6), we restrict the sample of partisan tweets to those in the top quartile of partisan-slant surprises. CEO alignment is equal to one if the partisan tweet matches the party affiliation of the CEO, and zero otherwise. For Democratic (Republican) corporate tweets, *Share of workers aligned* is defined as the percentage of Glassdoor reviews from blue (red) states, respectively, and *Share of investors aligned* is equal to (minus) the percentage of company stock held by funds with a sustainability mandate, respectively. All independent variables are standardized to have a mean of zero and a standard deviation of one and are defined in Internet Appendix Table IA.1. Standard errors, reported in parentheses, are clustered at the firm level.

	Cumulative Abnormal Return (in %)					
	(0,+1)	(0,+3)	(0,+10)	(0,+1)	(0,+3)	(0,+10)
	(1)	(2)	(3)	(4)	(5)	(6)
Share of workers aligned	0.033	0.069**	0.068	0.134**	0.223***	0.196
	(0.025)	(0.032)	(0.061)	(0.057)	(0.077)	(0.125)
CEO aligned	0.022	0.014	0.007	0.039	0.006	0.011
	(0.023)	(0.033)	(0.057)	(0.051)	(0.066)	(0.115)
Share of investors aligned	0.046**	0.049	0.090	0.102**	0.096	0.236**
	(0.023)	(0.031)	(0.058)	(0.045)	(0.063)	(0.112)
Log market cap	-0.041	-0.076	-0.102	-0.002	-0.067	0.018
	(0.032)	(0.049)	(0.083)	(0.067)	(0.097)	(0.156)
IO	-0.012	-0.046	-0.051	0.020	-0.028	-0.112
	(0.027)	(0.041)	(0.077)	(0.060)	(0.092)	(0.160)
N	8,065	8,065	8,065	2,604	2,604	2,604
R^2	0.065	0.076	0.094	0.142	0.163	0.161
Sector × month FE	Yes	Yes	Yes	Yes	Yes	Yes
High surprise only?	No	No	No	Yes	Yes	Yes

Table 6
Corporate Partisan Slant Around Larry Fink's 2019 Letter to CEOs

The table reports results from a difference-in-differences analysis around Larry Fink's 2019 Letter to CEOs. The dependent variable is the firm's net Democratic tweet ratio in a given calendar quarter, measured in percent. *Post* is an indicator equal to one for quarters 2019Q1 and onwards, and zero otherwise. The time period is restricted to three years before and after 2019Q1. Size quartiles are defined based on total book assets. Standard errors, reported in parentheses, are clustered at the firm level.

	Net Democratic Tweet Ratio		
	(1)	(2)	(3)
BRK Holdings Quartile	-0.110	-0.016	-0.114
	(0.070)	(0.065)	(0.075)
Post=1 × BRK Holdings Quartile	0.215**	0.161*	0.218**
	(0.092)	(0.096)	(0.100)
13F Holdings Quartile	0.099	0.013	0.122
	(0.078)	(0.084)	(0.077)
Post=1 × 13F Holdings Quartile	-0.249***	-0.170*	-0.337***
	(0.088)	(0.088)	(0.098)
Size Quartile	-0.296*	-0.373**	-0.266*
	(0.152)	(0.170)	(0.155)
Post=1 × Size Quartile	0.476***	0.606***	0.468***
	(0.083)	(0.106)	(0.089)
N	11,737	11,466	11,101
R^2	0.408	0.493	0.450
Firm FE	Yes	Yes	Yes
Quarter FE	Yes	No	No
Sector × Quarter FE	No	Yes	No
State × Quarter FE	No	No	Yes

INTERNET APPENDIX

This internet appendix presents additional results to accompany the paper "Partisan Corporate Speech." The contents are as follows:

Internet Appendix A provides variable descriptions.

Internet Appendix B presents results from a validation test of our measure of partisan corporate speech.

Internet Appendix C provides additional results on aggregate trends in partisan corporate speech.

Internet Appendix D reports additional results from our analysis of the content of partisan corporate speech.

Internet Appendix E presents additional results on firm heterogeneity.

Internet Appendix F presents additional results from the analysis of stock returns around partisan corporate tweets.

Internet Appendix G contains the appendix to accompany our theoretical model.

A Variable Descriptions

Table IA.1
Variable Descriptions

Variable	Description
Dependent variables	
Partisan tweet	Indicator equal to one if the tweet's PSI-value is $\leq$0.03 or $\geq$0.97, and zero otherwise.
Net Democratic tweet ratio ($NDTR$)	The difference in the number of Democratic-sounding tweets and the number of Republican-sounding tweets, divided by the total number of tweets sent by the firm in a given time period. Democratic (Republican)-sounding tweets are those with a PSI-value $\leq$0.03 ($\geq$0.97).
CAR (0,+τ)	Daily cumulative abnormal return, measured over trading days 0 to $+\tau$ around a corporate tweet. Abnormal returns are calculated using the Fama and French (1993) and Carhart (1997) four-factor model estimated over days $t = -300$ to $t = -50$ and requiring a minimum of 100 non-missing observations, and they are winsorized at the 1% and 99% levels within event time.
Independent variables	
Firm size quartile	The firm's total book assets as of the most recent fiscal year-end, sorted into quartiles within a given calendar year (for annual data) or quarter (for quarterly data). Data obtained from Compustat Annual.
Industry concentration quartile	Herfindahl index computed using the revenue shares of firms within a given 2-digit SIC industry, sorted into quartiles within a given calendar year. Data obtained from Compustat Annual using the most recent fiscal year-end.
Democratic worker share quartile	The percentage of employee reviews from blue states, sorted into quartiles within a given calendar year. The locations of employee reviews are obtained from the Glassdoor website, and a state classified as blue if the statewide vote share for the Democratic candidate in the 2016 presidential election exceeded that of the Republican candidate by more than five percentage points. Data on vote shares are obtained from the FEC website at `https://www.fec.gov/documents/1890/federalelections2016.xlsx`.
High (low) partisan-slant surprise	Indicator equal to one if the tweet is (not) in the top quartile of partisan tweets in a given calendar quarter, based on the absolute difference between the tweet's PSI-score and the average PSI-score of all tweets sent by the same company during the previous 36 months.
CEO aligned	Indicator equal to one if the partisan tweet matches the party affiliation of the CEO, zero if it does not match the party of the CEO, and 0.5 otherwise. Party affiliations of CEOs are obtained from Fos et al. (2025), who use voter registration data to infer partisan leanings.

Continued on next page

Table IA.1 – continued

Variable	Description
Share of workers aligned	The percentage of employee reviews from blue (red) states if the tweet has a Democratic (Republican) slant, respectively. The locations of employee reviews are obtained from the Glassdoor website, and states are classified as blue versus red based on the statewide vote shares in the 2016 presidential election. In order to be classified as a blue versus red state, the difference in the party voter shares has to be in excess of five percentage points. Data on vote shares are obtained from the FEC website at `https://www.fec.gov/documents/1890/federalelections2016.xlsx`.
Share of investors aligned	(Minus) The percentage of the firm's outstanding shares owned by funds with a sustainability mandate if the tweet has a Democratic (Republican) slant, respectively. Information on fund mandates and stock holdings are obtained from Morningstar.
Log market cap	Logarithm of the firm's market capitalization as of the most recent fiscal year-end. Data obtained from Compustat Annual.
IO	Percentage of the firm's shares outstanding held by institutional investors in the Thomson Reuters 13F database.
BRK holdings quartile	Percentage of the firm's shares outstanding held by BlackRock, sorted into quartiles within a given calendar quarter. Data obtained from Thomson Reuters 13F.
13F holdings quartile	Percentage of the firm's shares outstanding held by institutional investors in the Thomson Reuters 13F database, sorted into quartiles within a given calendar quarter.

B Measure Validation

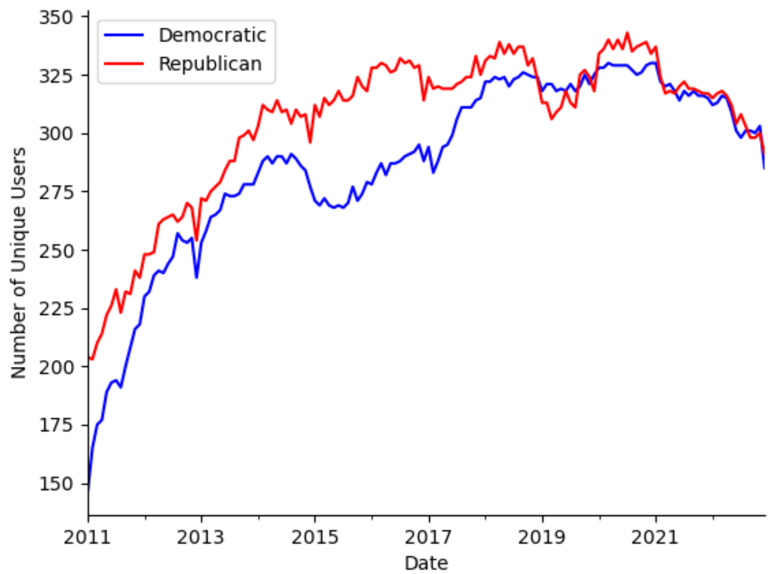
Table IA.2
Company Mentions by Members of Congress Around Partisan Corporate Tweets

The table reports results from a linear probability model that regresses an indicator equal to one if the company is mentioned in a tweet by a member of Congress on a given day, and zero otherwise, on event-time dummies, as well as interactions between the event-time dummies and an indicator *Partisan Tweet*, which is equal to one for partisan corporate tweets (PSI-score of $\leq$0.03 or $\geq$0.97) and zero for nonpartisan corporate tweets (PSI-score= 0.5). For readability, the dependent variable is multiplied by 100 in all columns. Standard errors are clustered at the firm level.

	Mentioned by Member of Congress		
	(1)	(2)	(3)
$\tau = -4 \times$ Partisan Tweet	0.150	-0.033	0.055
	(0.098)	(0.065)	(0.064)
$\tau = -3 \times$ Partisan Tweet	0.092	-0.091*	-0.003
	(0.099)	(0.054)	(0.055)
$\tau = -2 \times$ Partisan Tweet	0.127	-0.056	0.032
	(0.099)	(0.057)	(0.051)
$\tau = -1 \times$ Partisan Tweet	0.197*	0.014	0.103
	(0.115)	(0.067)	(0.071)
$\tau = 0 \times$ Partisan Tweet	0.378***	0.195**	0.283***
	(0.138)	(0.097)	(0.104)
$\tau = +1 \times$ Partisan Tweet	0.253**	0.069	0.158**
	(0.111)	(0.070)	(0.068)
$\tau = +2 \times$ Partisan Tweet	0.186*	0.003	0.091
	(0.108)	(0.069)	(0.067)
$\tau = +3 \times$ Partisan Tweet	0.071	-0.112*	-0.023
	(0.090)	(0.057)	(0.054)
$\tau = +4 \times$ Partisan Tweet	0.183**	-0.001	0.088
	(0.087)	(0.056)	(0.057)
$\tau = +5 \times$ Partisan Tweet	0.095	-0.088	
	(0.090)	(0.056)	
N	30,463,202	30,463,202	30,463,202
R^2	0.003	0.032	0.160
Day FE	No	Yes	Yes
Firm FE	No	Yes	No
Tweet FE	No	No	Yes

C Additional Results on Aggregate Trends in Partisan Corporate Speech

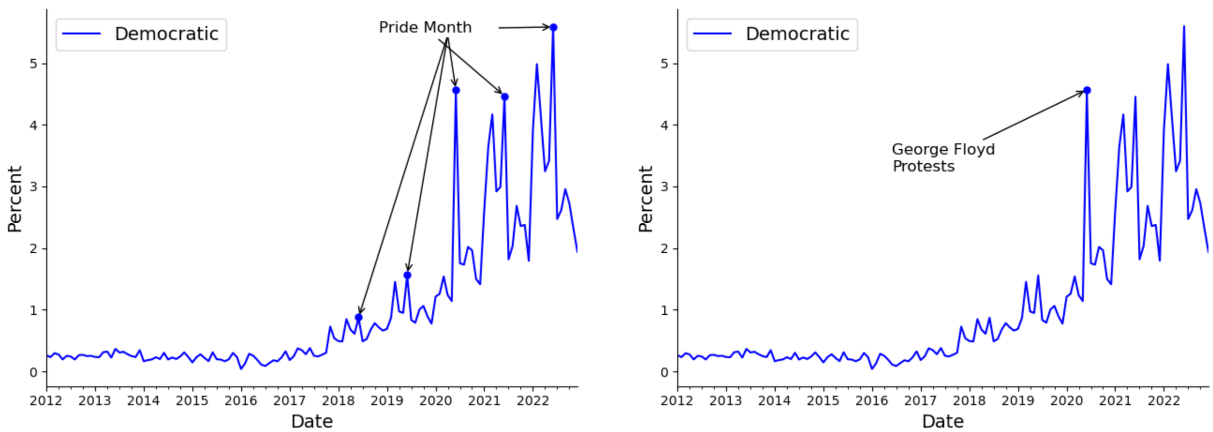
Figure IA.1
Number of Active Accounts Over Time by Party Affiliation



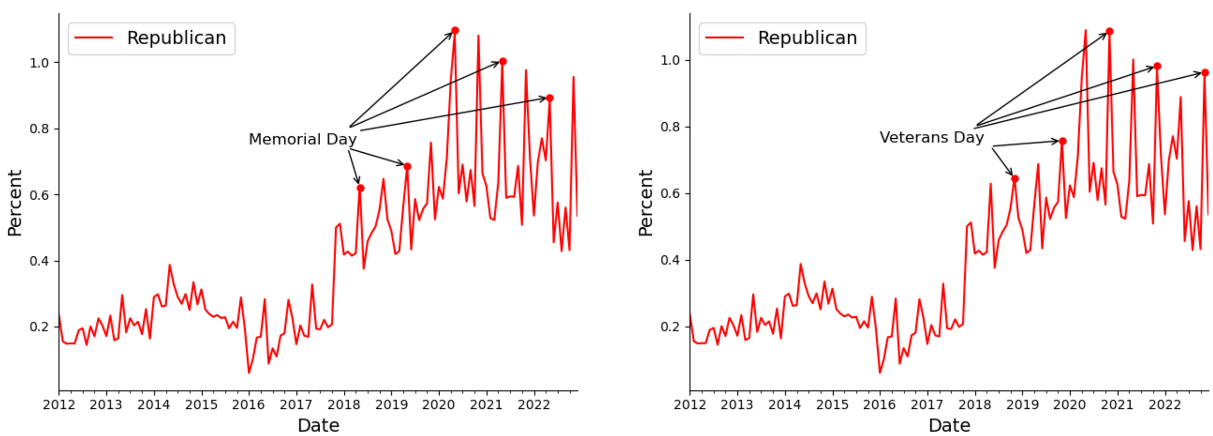
The figure shows the number of active accounts belonging to a Congressional member by calendar month and party affiliation of the member.

Figure IA.2
Partisan Corporate Speech: Key Events

Panel A: Democratic-Sounding Speech



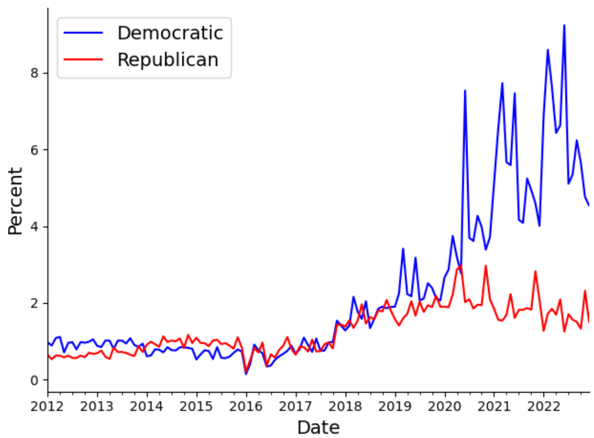
Panel B: Republican-Sounding Speech



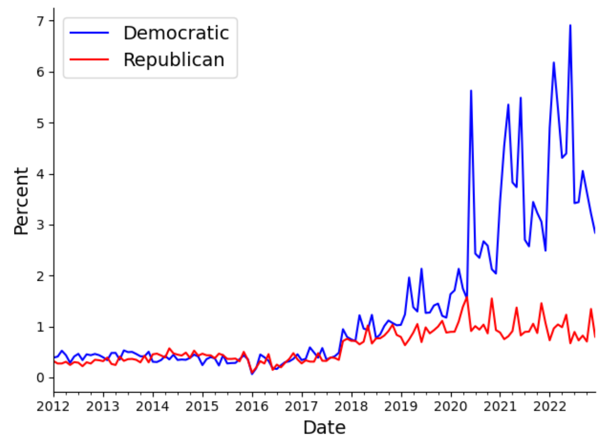
This figure displays our series of partisan speech, split into Democratic (Panel A) and Republican (Panel B) speech, and labels the months in which the two series have notable spikes.

Figure IA.3
Alternative Thresholds to Identify Partisan Speech

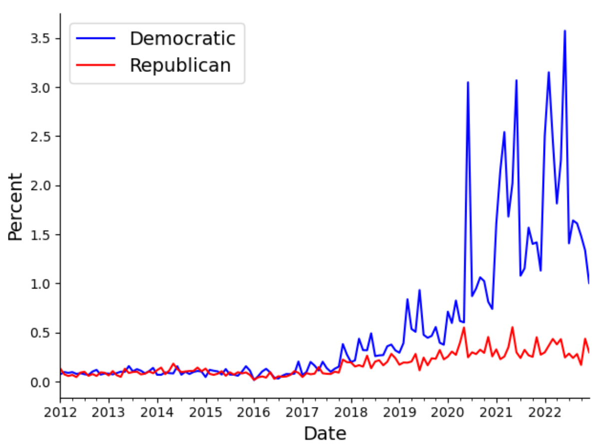
Panel A: Cutoffs 0.1, 0.9



Panel B: Cutoffs 0.05, 0.95

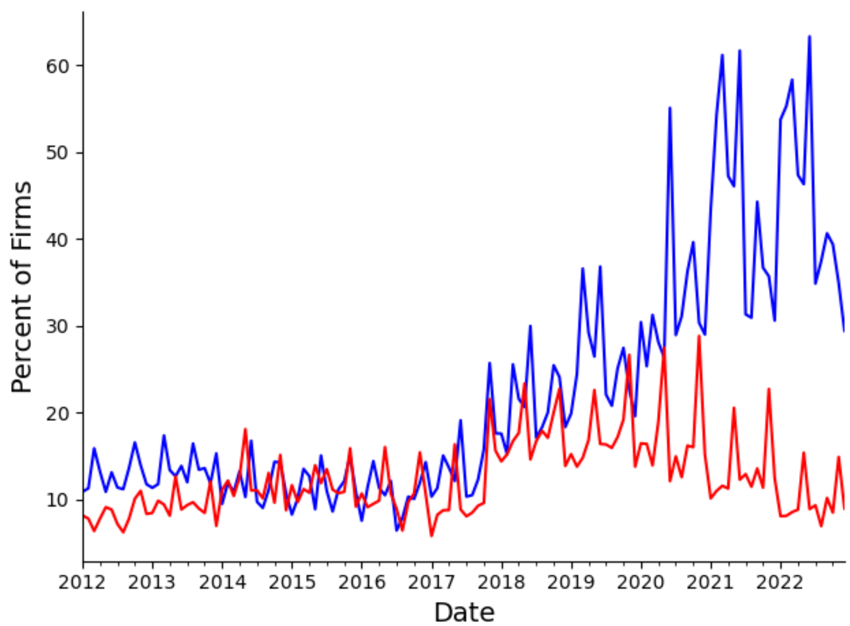


Panel C: Cutoffs 0.01, 0.99



The figure repeats Figure 2, Panel B in the main paper, using different thresholds of PSI-values at which a tweet is characterized as Democratic- or Republican-sounding.

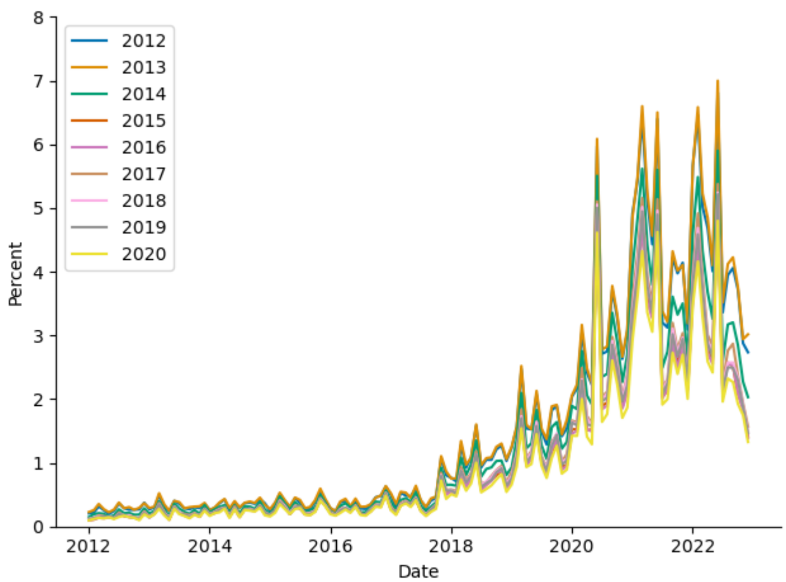
Figure IA.4
Partisan Corporate Speech: Extensive Margin



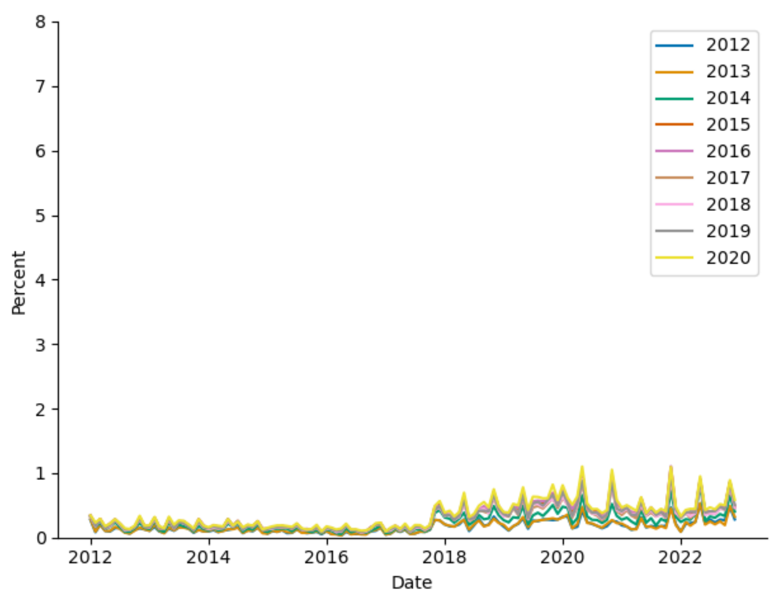
The figure repeats Figure 2, Panel B in the main paper, displaying only the extensive margin. The plotted series is the percent of firms, among those sending at least one tweet within a given month, that send at least one Republican or Democratic partisan tweet, respectively.

Figure IA.5
Varying the Timing of Politician Speech

Panel A: Democratic-Sounding Speech



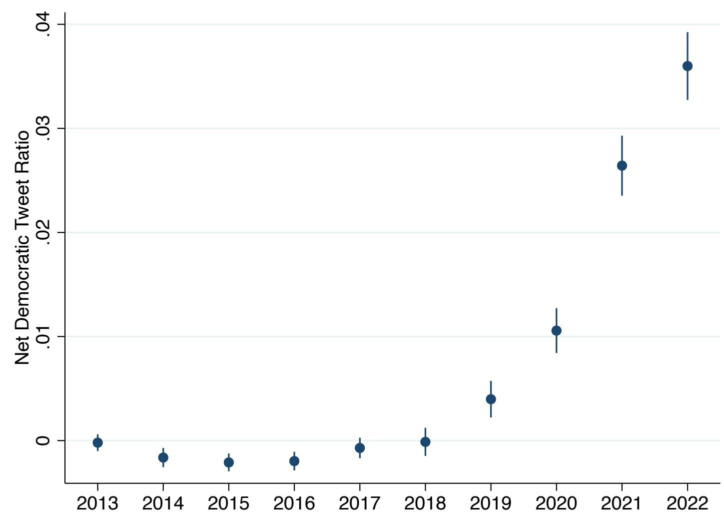
Panel B: Republican-Sounding Speech



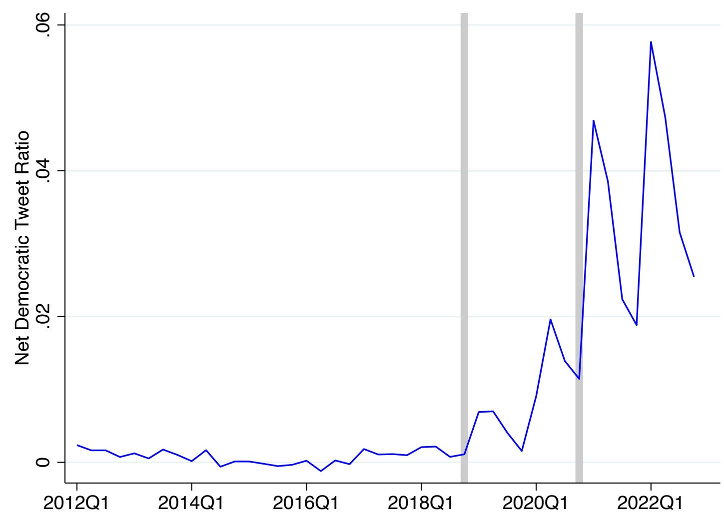
The figure displays the time series of partisan corporate speech using politician speech from only one calendar year at a time in the construction of our parisan bigram scores. Specifically, we estimate the posterior probabilities for all bigrams sent by Congresspeople in a given calendar year and then apply these year-by-year probabilities to the entire sample of corporate tweets. Each year-by-year measure corresponds to a different line. Panel A shows the resulting series for Democratic-sounding speech and Panel B for Republican-sounding speech, using PSI-values of 0.03 and 0.97 as cutoffs, respectively.

Figure IA.6
Average Net Democratic Tweet Ratio: Annual and Quarterly Frequencies

Panel A: Annual Frequency



Panel B: Quarterly Frequency



The figure displays time trends in the average net Democratic tweet ratio ($NDTR$), defined as the percentage of Democratic tweets minus the percentage of Republican tweets, by calendar year (Panel A) and by quarter (Panel B), respectively. In Panel A, we estimate an OLS regression of a firm's annual $NDTR$ on calendar year dummies and firm fixed effects and plot the estimated coefficients, together with the corresponding 95% confidence intervals that are based on standard errors clustered at the firm level. In Panel B, we plot the mean quarterly $NDTR$, and the gray vertical bars indicate the estimated break points on the mean quarterly $NDTR$ using the procedure by Bai and Perron (1998) and Bai and Perron (2003).

Table IA.3
Structural Break Test on the Mean Net Democratic Tweet Ratio

The table presents results from the estimation of the number of break points on the mean quarterly NDTR using the procedure by Bai and Perron (1998) and Bai and Perron (2003). We report the results from a sequential F-test to determine the number of breaks, in which the null hypothesis of m breaks is tested against the alternative of one more break $(m+1)$.

Number of breaks (m)	F-test Statistic	5% Critical Value
0	151.48	8.58
1	11.40	10.13
2	4.53	11.14
3	4.43	11.83
4	4.35	12.25

D Additional Results From Content Analysis

Table IA.4
Partisan Speech Topic Model

This table reports each of the fifty topics from the biterm topic model estimated on corporate tweets between 2011 and 2022 with a PSI-value ≥ 0.9 or ≤ 0.1. For each topic, we provide (i) the Chat-GPT assigned topic label, (ii) the five unigrams most associated with that topic, and (iii) the list of 2-digit SIC codes for which a tweet belonging to the topic is classified as business-related. Topics are ordered in decreasing frequency, with the most common topics at the top of the table.

	Topic Label	5 Most Important Unigrams					Business
1	Emergency preparedness and response	custom	power	hurrican	weather	line	49, 63, 95, 96
2	Veterans and military service	thank	veteran	honor	serv	day	37, 38, 97
3	Workplace equality, diversity, and inclusivity	equal	index	proud	corpor	work	
4	Energy sector	gas	oil	energi	natur	us	13, 29, 46, 49
5	Credit rating agencies	rate	moodi	assign	million	bond	All
6	Business and employment	busi	employe	job	small	new	69, 68, 67, 66, 65, 64, 63, 62, 61, 60
7	Economic indicators and market trends	us	market	rate	price	high	69, 68, 67, 66, 65, 64, 63, 62, 61, 60
8	Awards, recognition, and achievements	award	year	compani	name	honor	
9	Legislative and political actions	us	act	vote	protect	support	
10	Sustainability and climate change	futur	sustain	energi	chang	innov	
11	Financial reporting and corporate results	quarter	result	second	earn	report	All
12	Celebration and recognition of cultural heritage	celebr	month	american	black	histori	
13	Celebrations, well-wishing, and expressing happiness	year	happi	celebr	day	wish	
14	Health and medicine	covid19	vaccin	test	learn	get	80, 28, 51, 63
15	Climate action	climat	emiss	chang	sustain	reduc	
16	Financial assistance	help	save	student	loan	plan	69, 68, 67, 66, 65, 64, 63, 62, 61, 60
17	News and statements by political figures	say	presid	trump	us	state	
18	Technology, data, and network solutions	data	center	network	5g	new	All
19	Education	student	program	learn	educ	help	
20	Community support and philanthropy	communiti	support	help	provid	program	
21	Home, lifestyle, and shopping	get	home	make	one	new	All
22	Entertainment and media consumption	watch	new	live	game	episod	78, 79
23	Security, risk management, and data protection	secur	risk	data	protect	learn	All
24	Health and healthcare	health	care	help	patient	access	80, 28, 51, 63
25	Event or webinar invitation	join	us	today	regist	pm	
26	Sustainability and environmental protection	sustain	help	protect	learn	planet	
27	Markets, investments, and finance	market	global	read	discuss	invest	69, 68, 67, 66, 65, 64, 63, 62, 61, 60

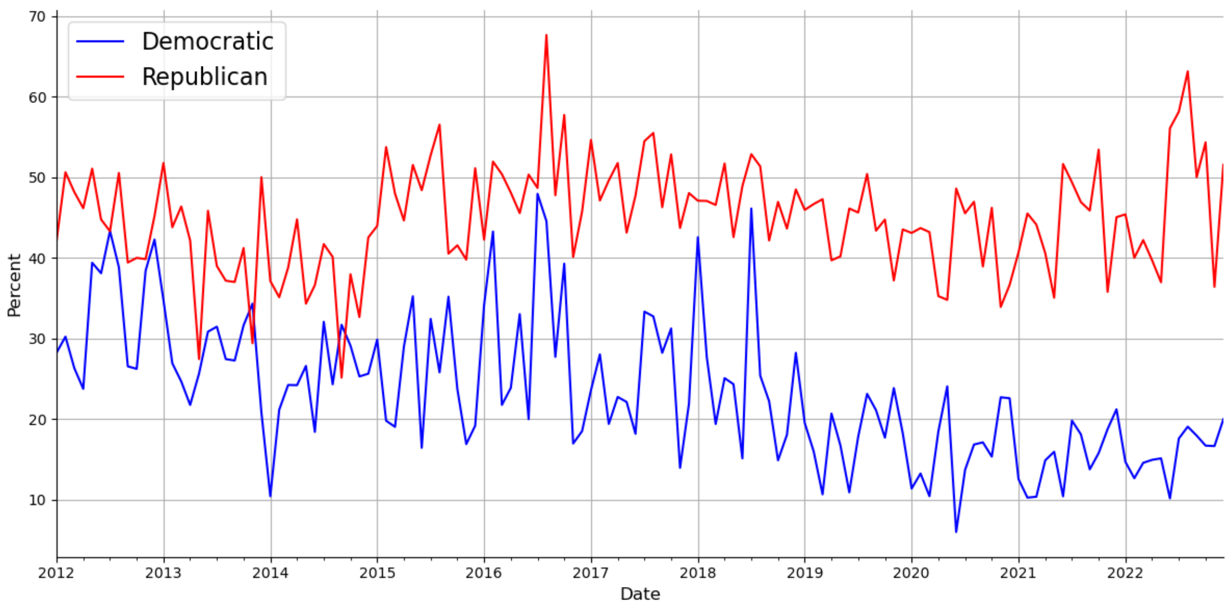
	Topic Label	5 Most Important Unigrams					Business
28	Positive sentiments	great	time	see	realli	thank	
29	Military and defense	defens	missil	system	air	us	37, 38, 97
30	Martin Luther King, Jr.	honor	king	dr	right	today	
31	Hard drives and external storage solutions	drive	hard	seagat	storag	new	All
32	Numbers and statistics	year	million	us	1	sinc	All
33	Discussions, interviews, and content featuring executives	discuss	ceo	watch	presid	join	
34	Navy and aerospace	us	uss	ship	carrier	navi	37, 38, 97
35	US China Relations	new	china	trade	us	global	
36	LGBTQ Pride, support, and celebration	pride	lgbtq	communiti	celebr	support	
37	Gender Equality	women	day	celebr	intern	equal	
38	Cities and location	new	red	citi	san	get	All
39	Water safety and cleanliness	water	safe	safeti	help	clean	95, 96
40	Food, hunger relief, and charitable actions	food	help	donat	hunger	us	
41	Inclusivity, diversity, and workplace culture	inclus	divers	employe	work	communiti	
42	Spanish Language	de	la	en	el	para	All
43	Community, racial equity, and social change	communiti	racial	chang	health	equiti	
44	New technologies, products, and solutions	learn	new	technolog	product	read	All
45	Teamwork, appreciation, employment, and community engagement	team	thank	great	employe	week	
46	Business and retail news	via	new	wsj	retail	sale	All
47	Energy, home, and environmental sustainability	energi	home	use	save	gas	
48	Clean energy, renewable power, and sustainability	energi	clean	power	electr	renew	
49	Positive impact	make	work	help	world	us	
50	Contests	win	get	chanc	us	day	

Table IA.5
Meta-Topic Classification

This table reports the associated meta-topic for each topic listed in Table IA.4. Meta-topic groupings and meta-topic labels are assigned by asking Chat-GPT to organize the fifty topics estimated by our biterm topic model into a smaller set of meta-topics.

Topic	Description	Meta-Topic
1	Emergency preparedness and response	Emergency and Security
2	Veterans and military service	Military and Veterans
3	Workplace equality, diversity, and inclusivity	DEI
4	Energy sector	Sustainability and Environment
5	Credit rating agencies	Business and Economy
6	Business and employment	Business and Economy
7	Economic indicators and market trends	Business and Economy
8	Awards, recognition, and achievements	Culture and Celebration
9	Legislative and political actions	Politics and Legislation
10	Sustainability and climate change	Sustainability and Environment
11	Financial reporting and corporate results	Business and Economy
12	Celebration and recognition of cultural heritage	Culture and Celebration
13	Celebrations, well-wishing, and expressing happiness	Culture and Celebration
14	Health and medicine	Health and Medicine
15	Climate action	Sustainability and Environment
16	Financial assistance	Business and Economy
17	News and statements by political figures	Politics and Legislation
18	Technology, data, and network solutions	Technology and Innovation
19	Education	Education and Knowledge Sharing
20	Community support and philanthropy	Community and Philanthropy
21	Home, lifestyle, and shopping	Lifestyle and Entertainment
22	Entertainment and media consumption	Lifestyle and Entertainment
23	Security, risk management, and data protection	Emergency and Security
24	Health and healthcare	Health and Medicine
25	Event or webinar invitation	Education and Knowledge Sharing
26	Sustainability and environmental protection	Sustainability and Environment
27	Markets, investments, and finance	Business and Economy
28	Positive sentiments	Culture and Celebration
29	Military and defense	Military and Veterans
30	Martin Luther King, Jr.	Culture and Celebration
31	Hard drives and external storage solutions	Technology and Innovation
32	Numbers and statistics	Education and Knowledge Sharing
33	Discussions, interviews, and content featuring executives	Education and Knowledge Sharing
34	Navy and aerospace	Military and Veterans
35	US China Relations	Politics and Legislation
36	LGBTQ Pride, support, and celebration	DEI
37	Gender Equality	DEI
38	Cities and location	Locations and Language
39	Water safety and cleanliness	Emergency and Security
40	Food, hunger relief, and charitable actions	Community and Philanthropy
41	Inclusivity, diversity, and workplace culture	DEI
42	Spanish Language	Locations and Language
43	Community, racial equity, and social change	DEI
44	New technologies, products, and solutions	Technology and Innovation
45	Teamwork, appreciation, employment, and community engagement	Culture and Celebration
46	Business and retail news	Business and Economy
47	Energy, home, and environmental sustainability	Sustainability and Environment
48	Clean energy, renewable power, and sustainability	Sustainability and Environment
49	Positive impact	Community and Philanthropy
50	Contests	Culture and Celebration

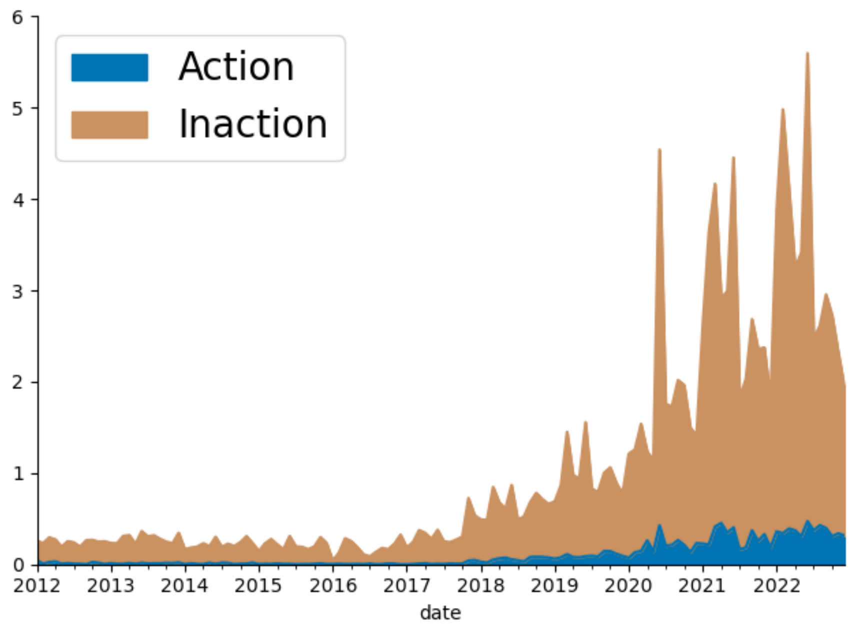
Figure IA.7
Proportion of Business-Related Partisan Tweets



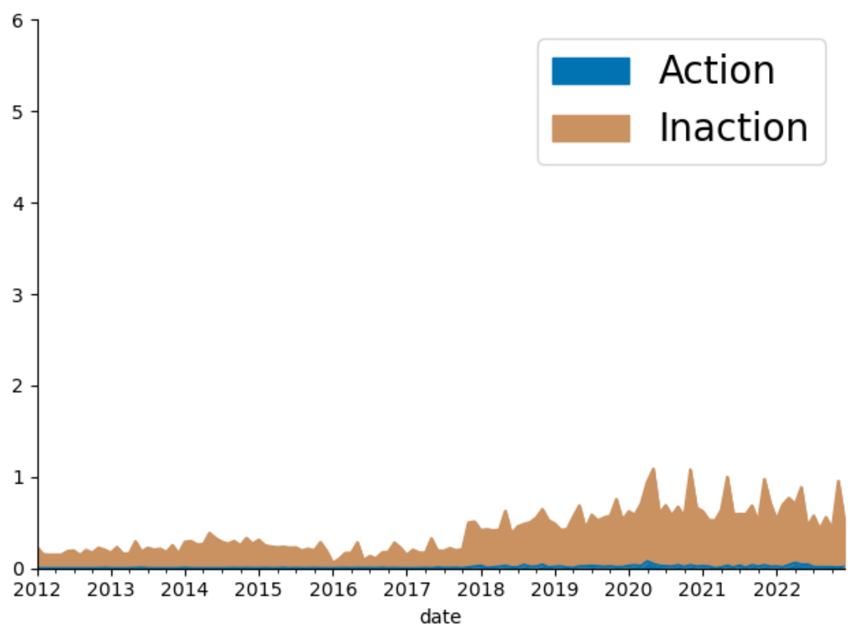
This figure displays the proportion of partisan corporate speech that is classified as business-related using the topics and industries listed in Table IA.4.

Figure IA.8
Action vs. Non-action Tweets

Panel A: Democratic Tweets



Panel B: Republican Tweets

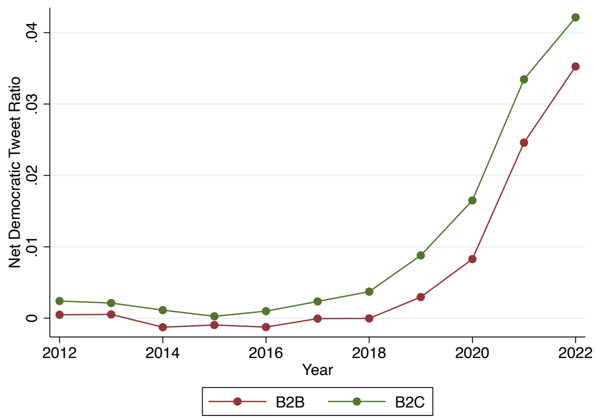


The figure displays the frequency of Republican and Democratic corporate tweets that describe an action (blue) versus those that do not (brown).

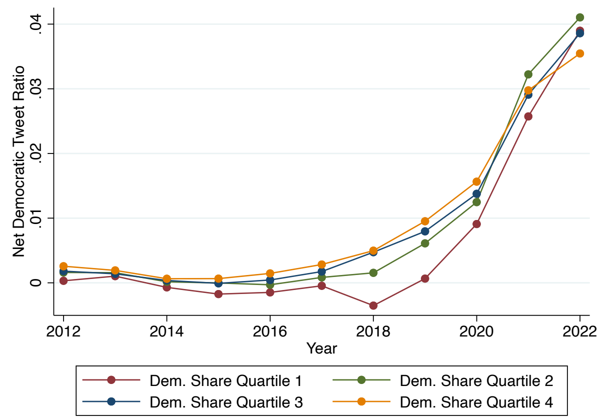
E Additional Results on Firm Heterogeneity

Figure IA.9
Additional Dimensions of Firm Heterogeneity

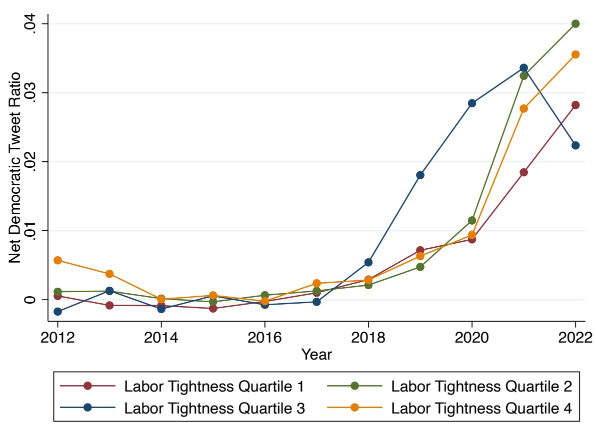
Panel A: By Customer Type



Panel B: By Workforce Composition

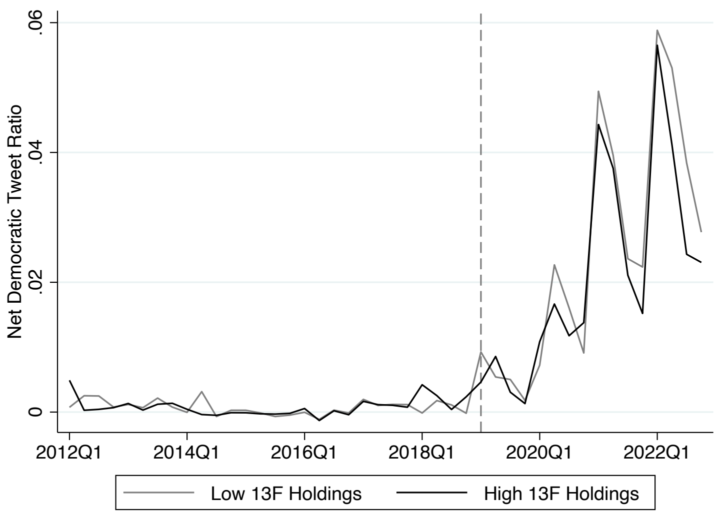


Panel C: By Labor Market Tightness



The figure plots the net Democratic tweet ratio, defined as the percentage of Democratic tweets minus the percentage of Republican tweets by a company in a given calendar year, by customer type (Panel A), by workforce composition (Panel B), and by labor market tightness (Panel C). In Panel A, Fama-French-48 industries are manually classified as B2B versus B2C based on their descriptions at `https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/det_48_ind_port.html`. In Panel B, we compute the share of Democratic workers at the firm-year level, defined as the number of Democratic workers divided by the number of Democratic and Republican workers, after combining resume data from Revelio Labs and commercial voter data by L2, Inc. In Panel C, labor market tightness is computed for a given North American Industry Classification System (NAICS) code and calendar year as the average number of job openings divided by the level of unemployment, as reported on the website of the Bureau of Labor Statistics. Quartiles are formed within a given calendar year.

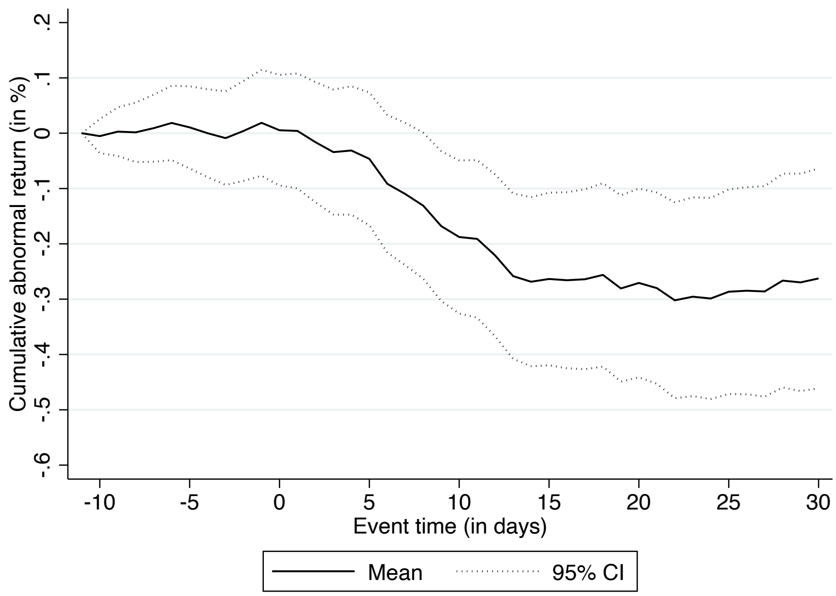
Figure IA.10
Partisan Corporate Speech and Institutional Ownership



The figure plots the average net Democratic tweet ratio for firms with high versus low institutional ownership, sorted within BlackRock ownership quartile. Institutional ownership is measured using holdings by 13F investors. We first sort all firms into quartiles based on their BlackRock ownership in a given quarter, and then sort firms into high versus low total institutional ownership groups by splitting at the median within each quartile. The dashed vertical line corresponds to the first quarter of 2019.

F Additional Results on Stock Returns Around Partisan Corporate Tweets

Figure IA.11
Stock Returns Around Partisan Corporate Tweets: Long Event Window



The figure repeats Figure 6, Panel A in the main paper, using a 30-day post-event window.

Table IA.6
Average Stock Returns Around Partisan Tweets: Robustness Tests

The table repeats Table 4 in the main paper, using alternative clustering strategies for standard errors (Panels A and B) and non-winsorized returns (Panel C).

Panel A: Clustering at the Tweet-date Level

	Cumulative Abnormal Return (in %)					
	(0,+1)	(0,+3)	(0,+10)	(0,+1)	(0,+3)	(0,+10)
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	-0.017	-0.056*	-0.213***	-0.052	-0.121**	-0.295***
	(0.022)	(0.033)	(0.052)	(0.041)	(0.057)	(0.087)
N	8,990	8,990	8,990	2,777	2,777	2,777
High surprise only?	No	No	No	Yes	Yes	Yes

Panel B: Clustering at the Calendar-month Level

	Cumulative Abnormal Return (in %)					
	(0,+1)	(0,+3)	(0,+10)	(0,+1)	(0,+3)	(0,+10)
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	-0.015	-0.068*	-0.215***	-0.052	-0.121*	-0.295***
	(0.023)	(0.040)	(0.078)	(0.042)	(0.061)	(0.099)
N	8,465	8,465	8,465	2,777	2,777	2,777
High surprise only?	No	No	No	Yes	Yes	Yes

Panel C: Non-winsorized Returns

	Cumulative Abnormal Return (in %)					
	(0,+1)	(0,+3)	(0,+10)	(0,+1)	(0,+3)	(0,+10)
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	-0.012	-0.056	-0.191***	-0.034	-0.121	-0.246**
	(0.026)	(0.041)	(0.067)	(0.052)	(0.075)	(0.125)
N	8,990	8,990	8,990	2,777	2,777	2,777
High surprise only?	No	No	No	Yes	Yes	Yes

G Model Appendix

Lemma 1. *In the absence of a political controversy, the price of a share is given by* Y*.*

Proof. Investor utility is given by

$$U_j\left(C_j, x_j, a\right) = C_j + x_j \delta_j \mathcal{A}_j(a)$$

Notice that

$$\frac{\partial C_j}{\partial x_j} = Y$$

where this follows from the payout of Y per share in the stock. This implies that

$$\frac{\partial U_j}{\partial x_j} = Y + \delta_j \mathcal{A}_j\left(a\right) = Y$$

where the second equality exploits that we are in the no-controversy case and so $\mathcal{A}_j\left(a\right) = 0$. This expression is identical for all j and determines the price of a share. □

Lemma 2. *After taking action* a_D*, if the firm could be fully financed by the* D *investor, the price of a share of the firm would be given by*

$$P = Y + \delta_D \tag{7.8}$$

Proof. In this case, we know that

$$\frac{\partial U_D}{\partial x_D} = Y + \delta_D A_D\left(a\right) = Y + \delta_D$$

where the second equality follows from $\mathcal{A}_D\left(a\right) = 1$ in the hypothesized equilibrium. This object will determine the price as the D investor is willing to hold x shares at this price and the R investor is unwilling to purchase any shares at this price, as $\frac{\partial U_R}{\partial x_R} = Y - \delta_R < P$. □

Proposition 1. *There exists no equilibrium where the shares in the firm are fully held by a single investor.*

Proof. To show this, we check each case and verify that in each case it is not possible for a single investor to hold the entire stock.

Case 1: no controversy

By lemma 1, we know that in this case $P = Y$. If a single investor held the entirety of the stock, that would require $x_j Y = xY$, but we know that $xY > W_j$ by Assumption 1. This is a contradiction and implies that the stock must be held by both investors in non-zero amounts.

Case 2: controversy and stock held by aligned investor

By lemma 2, we know that in this case the price is given by $P = Y + \delta_D$ (WLOG suppose that the aligned investor is the D type). This implies that $P > Y$. This again violates Assumption 1, because then $Px > Yx > W_D$.

Case 3: controversy and stock held by nonaligned investor

It is easy to show that in this case, the price is given by $P = Y - \delta_R$ (WLOG assume that the nonaligned investor is the R type). This does not immediately lead to a violation of Assumption 1, because now $P < Y$. However, this cannot be an equilibrium, because now the D type investor is willing to purchase shares from the R type investors at price $Y + \delta_D > P$.

This completes the proof, as there is no equilibrium that can be sustained where only a single investor type holds shares in the stock. □

Proposition 2. *If a controversy occurs and the firm takes action a_D, equilibrium, if it exists, is defined by the allocations*

$$x_D = \frac{W_D}{Y - \delta_R} \text{ and } x_R = x - \frac{W_D}{Y - \delta_R} > 0 \tag{7.9}$$

with

$$P = Y - \delta_R \tag{7.10}$$

this equilibrium is guaranteed to exist if

$$W_D < (Y - \delta_R)\, x \tag{7.11}$$

Proof. To show this, we first notice that any candidate equilibrium must have $x_R, x_D > 0$, by Proposition 1. This implies that the price must be set by the FOC of the R investor, if $P > Y - \delta_R$ then the R investor is not willing to have $x_R > 0$. If $P < Y - \delta_R$ then it cannot be an equilibrium because both investors would want to purchase more shares at that price. We next observe that any equilibrium must have $x_D = \frac{W_D}{P}$. Since the price is set by the FOC of the R investor, the D investor will purchase as many shares as they are able, until their budget constraint binds. x_R is then solved for using the market clearing condition.

□

Proposition 3. *When $\delta_D > \delta_R$, the firm will find it optimal to take action a_D.*

Proof. If the firm takes action a_D the price will be determined by the R's first-order condition

$$P = Y - \delta_R$$

If firm takes the action a_R then price will be determined by the D's first-order condition

$$P = Y - \delta_D$$

The firm will find it optimal to take action a_D if

$$Y - \delta_R > Y - \delta_D \Leftrightarrow \delta_D > \delta_R$$

which verifies the claim. $\square$

Corollary 1. *When a political controversy arises and the firm takes an action $a \in \{a_R, a_D\}$, the stock price declines. If the firm takes action a_D, the price falls by $(1-q)\delta_R$; if it takes action a_R, the decline is $(1-q)\delta_D$.*

Proof. The equilibrium price conditional on a controversy is $P < Y$ by Proposition 2. If a controversy does not occur, the price is given by Y, from Lemma 1. Before it is known whether a controversy will arise, the price will be given by

$$P_0 = qP + (1-q)\,Y \text{ where } P = Y - \delta_R < P_0 < Y \text{ since } 0 < q < 1$$

WLOG assume the action taken is a_D. The difference between P_0 and P is given by

$$\begin{aligned}
P_0 - P &= qP + (1-q)\,Y - P \\
&= (1-q)\,Y - (1-q)\,P \\
&= (1-q)\,(Y - P) \\
&= (1-q)\,(Y - (Y - \delta_R)) \\
&= (1-q)\,\delta_R
\end{aligned}$$

The case for $a = a_R$ is symmetric. $\square$

G.1 Model Extension

In the analysis below, we extend the model to allow for a quadratic cost of non-alignment. It can be shown that equilibrium is characterized by the allocations

$$x_D = \frac{W_D}{P} \text{ and } x_R = x - \frac{W_D}{P} > 0 \tag{G.1}$$

with prices satisfying

$$P = \frac{1}{2}\left(Y - \delta_R x + \sqrt{(Y - \delta_R x)^2 + 4\delta_R W_D}\right) \tag{G.2}$$

where $P \in (0, Y)$ is increasing in W_D and decreasing in δ_R. A sufficient condition to guarantee an equilibrium exists is $W_D < \delta_R x^2$.

Proposition 4. *The negative price effects of political controversies decrease with the alignment of the firm's action with its investor base.*

Proof. It is easy to verify that the difference between the initial price (P_0) and the price on controversy (P) is given by the expression

$$P_0 - P = (1 - q)(Y - P)$$

This expression is decreasing in P. From the expression above, we know that $P \in (0, Y)$ is increasing in W_D, this implies that the RHS is decreasing in W_D, which is the content of the claim. $\square$