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 2011 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 political alignment. Finally, we propose a theoretical framework and provide suggestive empirical evidence that these trends are 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. (2023)). 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 (CNBC (2019)), racial justice (Forbes (2020)), and voting rights (The New York Times (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' response to evolving stakeholder preferences regarding how corporations should behave, or the political preferences of corporate executives? Empirically addressing these questions has been challenging, as existing studies often rely on media coverage, introducing selection bias by capturing only statements that generate public attention or 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 2011 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 occured 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 an increase in 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, occurring across all sectors—including consumer- and business-oriented industries—as well as across geographies, firm sizes, and firms led by both Republican and Democratic CEOs.

Fact 3 is that, on average, partisan corporate tweets are followed by negative abnormal stock returns. However, the market response varies significantly depending on stakeholder alignment. Partisan tweets that align with the political preferences of investors exhibit 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 findings suggest that firms may not be intentionally using partisan language but rather engaging with topics that have become politically polarized. 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 non-pecuniary considerations—have played a role. First, in the time series, the growth of Democratic-leaning corporate speech closely correlates 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 Democratic slant of 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 value not only financial returns but also alignment with firms' political stances. Firms, in turn, seek to maximize their stock price while accounting for potential disutility from taking positions that conflict with stakeholder preferences. The model provides a unified explanation for our three stylized facts: (i) the rise of partisan corporate speech, (ii) its strong Democratic skew, and (iii) the negative stock price reaction following partisan statements, as well as heterogeneity by investor alignment. The core mechanism driving these results is that firms must attract capital from both aligned and non-aligned investors, forcing prices to reflect the willingness of the least aligned investors to hold the stock. This dynamic rationalizes why partisan speech, despite catering to some investors, leads to valuation declines.

Besides valuation effects, our model simultaneously explains the increase in partisan corporate speech overall and the disproportionate Democratic share of partisan corporate speech. As investor utility depends more strongly on firm stances, there is more scope for political controversy. Consequently, firms are more likely to be entangled in political disputes where they must voice partisan stances. These stances are disproportionately likely to be Democratic, because there are wealthy investors who strongly value firms that align with them and strongly dislike holding nonaligned firms in their portfolio. Thus, while taking Democratic political stances decreases firm valuation, taking Republican stances would result in an even larger decline in the firm's stock price.

Our study contributes to several strands of the literature. First, we contribute to a small but 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 during our sample period. 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. (2023); Homroy and Gangopadhyay (2023)) and others observing negative reactions (e.g., Bhagwat et al. (2020)). On the consumer side, Boxell and Conway (2024) finds that individuals adjust their consumption decisions in response to firms' stances on controversial social issues. 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. To the best of our knowledge, 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.[1]

[1] 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, we contribute to a growing literature on the political polarization 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, as Fos et al. (2023) show. The results in this paper suggest that U.S. companies are increasingly developing partisan identities (especially Democratic identities), as measured by their speech on social media. Our measure of partisan speech may be useful for the academic literature studying the role of partisan alignment between various stakeholders and the firm.

Third, we also contribute to a 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.[2] 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.

Two contemporaneous papers develop measures of partisan *corporate* speech that are similar to ours. One is Barari (2024), who studies the degree to which brands use bigrams on Twitter and Instagram commonly used by Republican and Democratic politicians on the same platforms. Our approach has two key differences. First, we are able to 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. 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 the approach we use 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

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

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)).

2 Data and Measure

2.1 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 the content of information dissemination on Twitter is fully under the control of the company, whereas press releases have to 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 are 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 company brand. Second, some companies have a separate Twitter account for their U.S. or North America 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 dropping the New York Times, News Corp, Tegna Inc., Fox Corp, and Scripps Network

[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.

Interactive Inc.

We also obtain Twitter handles for the official Twitter accounts for all members of Congress between 2011 and 2022. There are 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 for 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 also collect metrics designed to measure user engagement with the tweet: the number of times the tweet was retweeted, replied to, or quoted.

Table 1, Panel A, provides summary statistics for our sample of corporate tweets by year, 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. A few firms send a very large number of tweets per day, and many of these 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 full 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

[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.

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") as well as 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 a single word, whereas bigrams include two words, an example of which is "big data."

2.2 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.

2.3 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 2020 presidential election. 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. (2023), who link U.S. executives covered by ExecuComp to voter registration data.

2.4 Stock Returns

To measure changes in stock market valuations around tweets, we use 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.

3 Measure of Partisan Corporate Speech

Our measure of partisan corporate speech is designed to capture corporations' use of language that is highly indicative of usage by Democratic or Republican politicians. Intuitively, if a corporate tweet uses language that is highly predictive of being used by a Democrat (Republican), then we will label this tweet as Democratic(Republican)-sounding, respectively. To take this idea to the data, we use multinomial inverse regression (MNIR), a method from natural language processing (NLP) that has also been applied to detect partisan speech in Congress (Gentzkow et al. (2019)). We first estimate MNIR on tweets sent by Republican and Democratic politicians to find bigrams that are highly associated with usage by either party. We then use the resulting estimates to detect partisan tweets by corporates. We also use topic models to group partisan corporate tweets by their subject matter. We describe both methods in more detail below.

3.1 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:

$$\boldsymbol{c}_{it} \sim \mathrm{MN}\left(m_{it}, \boldsymbol{q}_t^{P(i)}\left(\boldsymbol{x}_{it}\right)\right). \tag{3.1}$$

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 that 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" from tweets that use these two words in completely different parts of the text.

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

We estimate the above model over bigrams used in tweets by members of Congress with a verified Twitter account between 2011 and 2022. Following Gentzkow et al. (2019), we analyze speech at the level of politician–time, with t corresponding to a given 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 both speech and party affiliation.

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. (2019)). We judge that truly partisan phrases should be used relatively frequently and by a broad range 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:

$$q_{jt}^R = \frac{1}{|R|}\sum_{i \in R} \boldsymbol{q}_t^{P(i)}(\boldsymbol{x}_{it})' \cdot e_j, \tag{3.2}$$

where e_j is a vector of zeros with a single entry of 1 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:

$$p_{jt}^R = \frac{q_{jt}^R}{q_{jt}^R + q_{jt}^D}. \tag{3.3}$$

For bigrams that are not used at least forty times by at least twenty different Twitter accounts in year t, we set $q_{jt}^R = \frac{1}{2}$.

We display the ten bigrams most associated with Republican and Democratic politicians' speech in 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 (2011–2013) yield some less intuitive bigrams, such as "pls rt" or "join us." This is likely due to Twitter usage among Congresspeople increasing over time. Importantly, in our robustness tests below we will show that our main stylized facts are not very sensitive to the precise time period on which our MNIR was estimated.

Finally, in order to obtain a measure of the partisanship of a corporate tweet, we apply the estimates from the MNIR that was estimated on 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

$$p_k^R = \frac{\prod_{j \in J^\star} q_{jt}^R}{\prod_{j \in J^\star} q_{jt}^R + \prod_{j \in J^\star} q_{jt}^D}, \tag{3.4}$$

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. Figure 1 plots the histograms of PSI-values using all corporate tweets in every other year between 2011 and 2022.

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 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 business operations of the firm. 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 3.2 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 constitute a relatively small share of all corporate tweets. The distribution of partisan tweets is also highly right-skewed, with a significantly larger mean than median.

Table 3 lists the most important partisan bigrams by U.S. companies within the set of partisan corporate tweets. We measure importance in a manner consistent with the method in Table 2: the expected change in the posterior of the set of all bigrams contained in partisan corporate tweets in a given calendar year if we were to remove a single bigram. The bigrams whose removal results in the largest increase (decrease) in the expected posterior are listed under the most important Democratic (Republican) bigrams.

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," "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 includes a few puzzling bigrams, such as "wall system," "warp speed," or "watch whole." Despite some noise in our measurement, we will be able to show that our measure of partisan corporate speech picks up meaningful and plausible variation across major events, such as the death of George Floyd.

3.2 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. (2023), 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 resulted in interpretable topics. For each tweet, we infer the most important topic for tweet k using a posterior implied by the estimated topic model:

$$\text{Topic Posterior}_{k,n} = \frac{\mathbb{P}\left(\text{Words Drawn from Topic } n\right)}{\sum_{m \in M} \mathbb{P}\left(\text{Words Drawn from Topic } m\right)}. \tag{3.5}$$

We then say that the tweet belongs to the topic that has 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.3 in the Internet Appendix. 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.3 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 estimation and inference using topic models.

We assign the topic labels in Internet Appendix Table IA.3 by giving the list of unlabeled topics with the associated most important words for those topics to Chat-GPT. We ask Chat-GPT to assign these topics a topic label. We further ask Chat-GPT to group these topics into a smaller number of meta-topics, which are shown in Table IA.4.

The list of topics in Internet Appendix Table IA.3 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. We therefore 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 can be seen in Internet Appendix Table IA.3. For instance, 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 as business-related if the sender is in the health care industry, measured using the two-digit SIC codes 80, 28, 51 and 63. Internet Appendix Figure C.5 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 Three Facts About Partisan Corporate Speech

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

4.1 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 2011 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.

Between 2011 and 2015, the mass of the distribution is centered around 0.5, indicating that most tweets by corporations do not use very partisan language. The distribution is relatively symmetric, indicating that Democratic- and Republican-sounding speech are roughly equally common. Between 2017 and 2021, we observe a pronounced increase in both tails of the distribution, with a particularly strong thickening of the left tail between 2019 and 2021. Overall, a comparison of the distributions in 2021 versus 2011 reveals a substantial rise in partisan corporate speech.

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 2011 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 doubles, from ca. 0.5% to 1.2% of all corporate tweets. It then continues to rise, reaching a peak of over 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.[5] 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 (see, e.g., Homroy and Gangopadhyay (2023)).

As illustrated in Internet Appendix Figure B.1, 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 partisan Democratic speech; it has 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.:

[5] We plot the two series using alternative PSI-value cutoffs in Internet Appendix Figure B.2.

> "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."

4.1.1 Benchmarks and Robustness Tests

In Figure 3, we assess to what extent corporate speech may reflect the same patterns in partisanship as other speech on Twitter. To do so, we document 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, 2011 and January 1, 2023. For a typical month, this approach results in slightly less than 15,000 tweets.

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 average 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 an increase in Republican-sounding speech earlier in the sample period, between 2014 and 2017. Second, after 2017, partisan speech is roughly evenly divided between Republican and Democratic-sounding speech, and both increase approximately at the same rate. Importantly, we do not observe the decoupling of the two series that we see for corporate speech on Twitter.

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. 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 provide two important robustness tests. First, Internet Appendix Figure B.2 shows that the patterns documented in Figure 2, Panel A are similar if we use alternative thresholds for the PSI-value to identify partisan tweets. Second, Internet Appendix Figure B.3 plots the time series of Democratic and Republican-sounding speech using only politician speech from one year at a time. Although the 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.

Third, a potential concern about our main findings from Figure 2 could be that the percentage of Democratic and Republican tweets could be driven by a handful of companies that use Twitter very actively. To see whether we obtain similar results if we weight each firm in our sample equally, we first 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. We then regress the net Democratic tweet ratio on calendar year dummies and cluster standard errors at the firm level. Panel A of Internet Appendix Figure B.4 reports the coefficient estimates and corresponding 95% confidence intervals for the calendar year dummies. The average net Democratic tweet ratio is significantly higher in 2012 than in 2011 (our baseline year), but it 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 almost 5 percentage points (ppt) higher than our baseline year 2011. This represents a sizable increase in the net Democratic tweet ratio, equivalent to more than 1.5 standard deviations. We therefore conclude that the increase in Democratic-sounding speech is not driven by a few companies sending an extremely large number of tweets.

4.2 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 net Democratic tweet ratio separately for different subsamples of firms. The average NDTR is shown by the firm's headquarter location (Panel A), Global Industry Classification Standard (GICS) sector (Panel B), the size of the firm's book assets (Panel C), 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 net Democratic tweet ratio between 2019 and 2022. It also spans all GICS sector (Panel B), affecting both consumer-facing sectors, such as "consumer discretionary," and business-focused sectors, such as "industrials" and "materials" (see also Panel C of Internet Appendix Figure D.7 for a split between B2B and B2C industries).[6] By the end of the sample period, the sectors with the highest net Democratic tweet ratios 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 high and low share of Democratic workers (Panel F).[7]

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

Fact 1. *The volume of partisan corporate speech has increased significantly between 2011 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. The increase in Democratic-leaning language post 2019 is broad-based, occurring across all sectors, states, and CEO political leanings.*

[6] The large negative value for energy companies in 2011 reflects their opposition to the Obama administration's proposal to repeal fossil fuel tax subsidies.

[7] Panel B of Internet Appendix Figure D.7 reports the same split by workforce composition, using an alternative measure of partisan leaning based on workers' party registration status.

4.3 Content Analysis

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

4.3.1 Topic Model

We also estimate a biterm topic model in order to better understand the subject of partisan corporate tweets and how they have evolved over time. Internet Appendix Table IA.3 reports the full list of 50 topics estimated using our biterm topic model described in Section 3.2. For ease of exposition, we further aggregate these topics by asking Chat-GPT to organize them into a smaller set of meta-topics. 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." We report our exact mapping of topics into broader topic categories in Internet Appendix Table IA.4.

Figure 5, Panel A, reports the percentage of tweets across different topic categories 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 an 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 big 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.

4.3.2 Speech vs. 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 "non-action tweets." Examples of action tweets include companies pledging a certain dollar amount in charitable donations, or 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 non-action 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. Out of the full sample of corporate tweets, the model identifies around 1% as "action" tweets.

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 C.6 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%.

4.4 Stock Price Reactions Around Partisan Corporate Speech

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

4.4.1 Average Stock Price Reaction

An important remaining question is what are 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 (2,334 tweets), events with concurrent earnings announcements in the trading window (–1,+1) around the tweet (1,415 tweets), subsequent tweets by the same company on the same topic (31,332 tweets), and tweets with missing returns during a symmetric 21-day event window around the event (1,001 tweets), we are left with a sample of 9,249 partisan tweets by 545 companies, of which 5,861 (3,388) 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 similar tweets on multiple occasions.

Figure 6, Panel A plots the average CAR around partisan tweets. The average stock return on the day of the average partisan tweet is close to zero. However, a noticeable decline in the stock price 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 E.9). 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)).

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 surprise 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 all 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 –21.5 basis points for the average partisan tweet (column (3)) and –28.4 basis points for the average partisan tweet with high surprise (column (6)). Internet Appendix Table IA.5 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 Internet Appendix Table IA.5).

4.4.2 Heterogeneity in Stock Returns Around Partisan Corporate Tweets

The average returns studied in Figure 6 and Table 4 could mask a substantial degree of heterogeneity. To uncover potential sources of such 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, respectively. To measure investor alignment, we use (minus) the percentage of company stock held by funds with a sustainability mandate for Democratic (Republican) corporate tweets, respectively. We further control for the firm's market capitalization and the degree of institutional ownership, and we include GICS sector × 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 the average partisan tweet are 4.5 basis points higher for a one-standard deviation higher alignment with workers (column (2)), and 15.0 basis points higher if the tweet comes with a high partisan surprise (column (4)). The effect of worker alignment is even larger over window (0,+3) but then becomes economically smaller and statistically insignificant at ten trading days post event. This pattern suggests that 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, at least initially, 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 horizon. For high-surprise partisan tweets, a one-standard-deviation higher investor alignment is associated with 21.9 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 for tweets with a higher share of investors being in partisan alignment. Finally, there is no significant heterogeneity in the stock price reaction by the CEO's partisan alignment or by firm size.

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 of around 20 basis points. Subsequent stock returns are less negative if there is greater partisan alignment between the tweet and the political preferences of the firm's shareholders.*

5 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.

5.1 CEOs' Personal Preferences

One possible explanation is that the rise in Democratic-leaning corporate speech reflects the personal preferences of CEOs. However, the evidence does not strongly support 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 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 values, are likely driving the trend, is consistent with the perception of U.S. adults in mid 2020 (Pew Research (2020)). In the following, we discuss three key external factors: employee, consumer, and investor preferences.

5.2 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., **?** (**?**)), 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).

However, 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. Moreover, 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. Additionally, we find no strong differential pattern between firms operating in industries with high versus low labor market tightness (see Panel A of Internet Appendix Figure D.7).

5.3 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, we find a somewhat stronger increase in Democratic-leaning speech among business-to-consumer (B2C) firms (see Panel C of Internet Appendix Figure D.7).

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.

5.4 Investor Preferences

Finally, the increase in Democratic-sounding speech—much of which focuses on environmental and social issues (see Figure 5, Panel A)—may be driven by a shift in investor preferences. The rise of sustainable investing represents a fundamental shift in the asset management industry, potentially exerting 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.

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 (The New York Times (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' 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 of 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 NDTR.

The BP method identifies two structural breaks in the mean NDTR (see Internet Appendix Table IA.2), with estimated break points in 2018Q4 and 2020Q4 (see Internet Appendix Figure B.4, 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 net Democratic tweet ratio 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.

Interestingly, the same pattern is not present when we look at firms with high ownership by other institutional investors. In Internet Appendix Figure D.8, 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 formal test whether the difference emerging between firms with high versus low BlackRock ownership is statistically significant, we implement a difference-in-differences analysis, by estimating the following equation:

$$\text{NDTR}_{it} = \alpha_t + \alpha_i + \text{BRK Holdings}_{i,t-1} + \text{BRK Holdings}_{i,t-1} \times Post_t + \gamma' X_{i,t-1} + \epsilon_{it}, \quad (5.1)$$

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 (5.1) 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 net Democratic tweet ratio post 2019Q1. Again, we find the opposite effect for ownership by other institutional investors: 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 behind 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' non-pecuniary 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.

6 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 non-pecuniary 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, and it 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 6.5 below.

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 non-pecuniary 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.

6.1 Investors

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

$$U_j\left(C_j, x_j, a\right) = C_j + x_j^2 \frac{\delta_j}{2} \mathcal{A}_j(a) \tag{6.1}$$

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).

$$x_j P \leq W_j \tag{6.2}$$

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.

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 the function $\mathcal{A}_j(a)$. 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

$$\mathcal{A}_j(a) = \begin{cases} 1 & \text{If a political controversy occurs and } a = a_j \\ 0 & \text{If no political controversy occurs} \\ -1 & \text{If a political controversy occurs and } a \neq a_j, \end{cases} \tag{6.3}$$

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

$$q = f(\delta_R, \delta_D), \tag{6.4}$$

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.

Market clearing is given by

$$x_D + x_R = x \tag{6.5}$$

where x denotes the total shares in the firm 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.

6.2 Firms

Firms are run by managers that belong to one of two types, $\theta \in \{D, R\}$. The manager knows her type, but investors do not. The manager's utility is given by

$$V_\theta (P, a) = P + \frac{\zeta}{2} \mathcal{A}_\theta (a) \tag{6.6}$$

This specification is deliberately similar to that of investors. The manager seeks to maximize the firm's stock price P but also has personal preferences over the firm's action a. As with investors, we denote the manager's preferred action as a_θ. The function $A_\theta(a)$ remains as previously defined. The degree to which the manager's utility depends on the choice of a is governed by $\zeta \geq 0$.

The manager's problem is to maximize V_θ 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.

The reward or penalty for taking action a_θ reflects the private benefit or cost to the manager of the firm adopting positions that conflict with the manager's preferences. For example, a Republican CEO may be reluctant to take Democratic-aligned actions. While our arguments below hold even if $\zeta = 0$ and there is no role for agency frictions, we include this parameter to emphasize that investor pressure can induce managers to take positions that diverge from her own preferences.

6.3 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 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 firm'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*

$$P = Y + \delta_D x \tag{6.7}$$

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 their 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 full internalization of the benefits of political alignment. This result aligns with the standard intuition that firms catering to investors' non-pecuniary 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. For simplicity, we thus invoke Assumption 1.

Proposition 2. *In the event of a controversy, if the firm takes action a_D, equilibrium is defined by the allocations*

$$x_D = \frac{W_D}{P} \text{ and } x_R = x - \frac{W_D}{P} > 0 \tag{6.8}$$

with

$$P \in (0, Y) \text{ satisfying } P = Y - \delta_R \left(x - \frac{W_D}{P} \right), \tag{6.9}$$

where P is increasing in W_D and decreasing in δ_R.

This proposition is key to understanding the intuition of our model. Once a firm takes action a_D, the D investor purchases shares until their 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 magnitude of this effect depends on two factors. First, W_D: as W_D increases, D investors hold a larger share of the firm's outstanding stock, while R investors hold a smaller share. With reduced holdings, R investors exert less price pressure, mitigating the decline in the share price. The second factor is δ_R, which governs R investors' aversion to holding shares in a firm whose stance they oppose. As δ_R increases, R investors require greater compensation to hold the stock, leading to a larger decline in the firm's price.

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

$$r = \frac{Y}{P} \tag{6.10}$$

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.

In sum, each parameter δ_D, δ_R, W_D, and W_R can affect investor demand and, by extension, firm behavior. To better understand these forces, we consider two limiting cases in which we can quantify firm behavior. In the first, we consider the setting where D investors' wealth becomes larger and larger, while R investors' wealth tends towards zero.

Proposition 3. *As $W_D \to xY$ and $W_R \to 0$, a firm with type $\theta = R$ will find it optimal to take action a_D when*

$$\delta_D x > \zeta \tag{6.11}$$

This expression captures the trade-off corporate managers face between price impact and the cost of taking actions misaligned with their personal preferences. Notably, it depends on δ_D, which reflects the extent to which D investors avoid holding stocks of firms whose actions they oppose.

The second set of parameters that determines equilibrium are δ_D and δ_R. We now turn to understanding how varying these parameters can affect firm choices.

Proposition 4. *As $\delta_D \to \infty$ and $\delta_R \to 0$, the firm will find it optimal to take action a_D, even if $\theta = R$, when*

$$Y - \frac{W_R}{x} > \zeta \tag{6.12}$$

Our observation that the firm's decision to take action a_R critically depends on δ_D is not confined to the limiting case where the D investor is significantly wealthier than the R investor. Even if wealth shares remain fixed, firms may find it optimal to take action a_D if Democratic aversion to holding stocks that take action a_R becomes arbitrarily large while R investors remain indifferent. As Democratic investors become increasingly unwilling to hold firms that take action a_R, the R investor will hold a growing share of the stock. The expression $\frac{W_R}{x}$ represents the stock price in the limit where prices adjust to allow the R investor to hold the entire stock. If the difference between this price and the price conditional on taking action a_D is sufficiently large, the firm will find it optimal to take action a_D in all cases.

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 occurs and the firm takes an action $a \in \{a_R, a_D\}$, the price of the stock declines.*

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.

Corollary 2. *The negative price effects of political controversies decline with the alignment of the firm's action with its investor base.*

Our model further predicts that the stock price decline varies depending on how well the firm's action aligns with its investor base. When the action aligns more closely with investors—meaning a larger share, weighted by wealth, agrees—the decline is smaller. This result follows from our earlier arguments, which emphasize that a key concern for firms is the extent to which investors are unwilling to hold stocks misaligned with their political preferences.

6.4 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 2011 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 4. 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 4 can rationalize the choice of many firm managers to take actions associated with Democratic positions.

Proposition 4 also rationalizes the patterns observed in Panel E of Figure 4. In this figure, we observe an increase in Democratic partisan speech across firms, even when the firm has a Republican CEO. Proposition 4 demonstrates how investor pressure can compel firms to take actions, even if those actions do 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 Corollary 2. If the action is more aligned with investors, fewer investors will be alienated and the stock price impact will be reduced.

6.5 Relation to Existing Theoretical Literature

Our model follows in a tradition of studying the impact of non-pecuniary 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 (2023), 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, both aligned and non-aligned investors must hold strictly positive amounts of the stock in equilibrium. This forces the price to reflect the first-order condition of the non-aligned investor to sustain an equilibrium. Otherwise, the two model structures have many similarities and it is possible to derive a condition similar to Equation 6.9 in the risk-neutral case of the WZ model.

The additional meaningful departure from WZ is that we model investor disutility associated with holding non-aligned firms as quadratic instead of linear. This modeling choice is what ultimately results in a more negative announcement effect for firms whose political actions are less aligned with firm stakeholders. Our other results are unchanged when we instead use a linear functional form.

7 Conclusion

This paper provides one of the first large-scale empirical analysis 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 find the strongest empirical support for an investor-driven 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. Future work could explore quasi-experimental settings to further isolate the impact of ESG mandates on corporate political speech. 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 in political discourse. 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 at the end of 2022, 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. Have firms adjusted their public positioning in response to growing scrutiny from political elites in Republican-led states? Has the partisan tone of corporate speech changed following the second election of Donald Trump? 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 even election dynamics.

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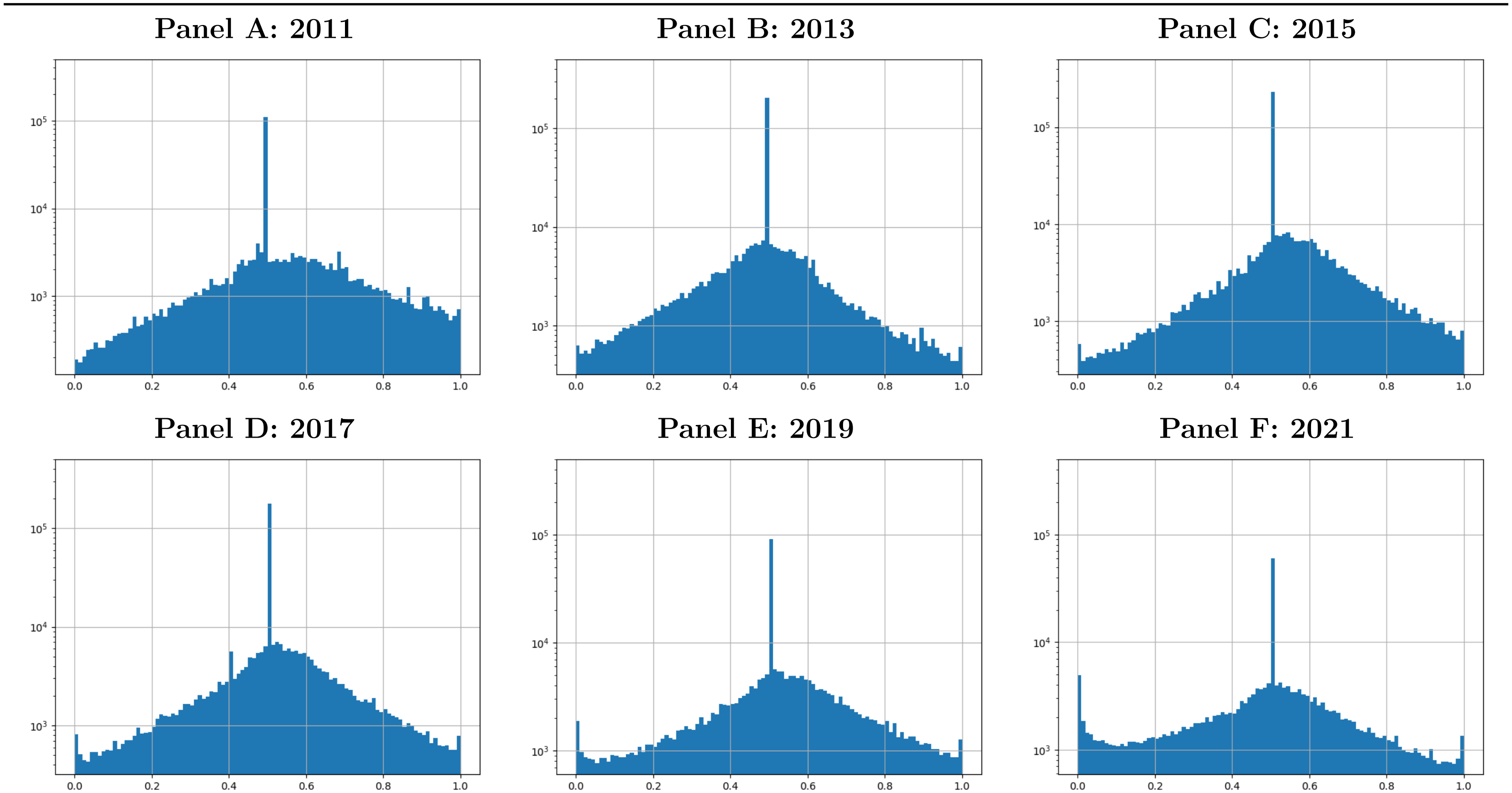
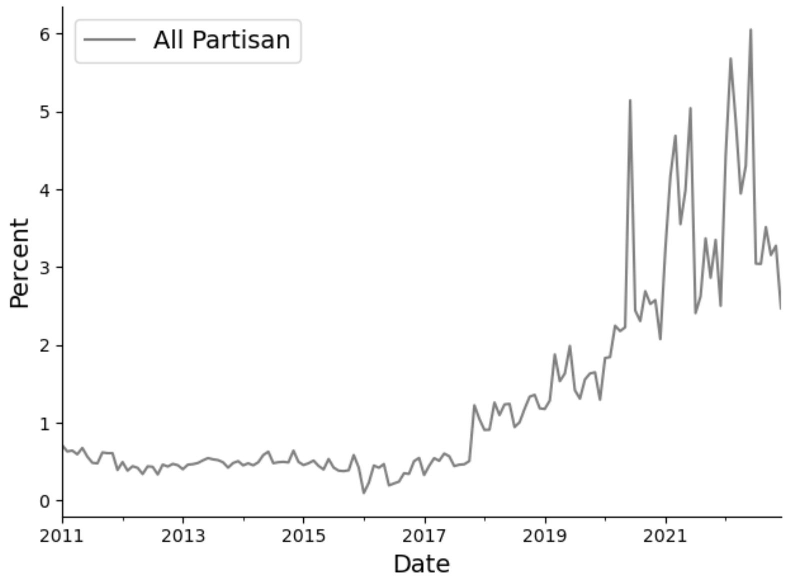
Figure 1
Distribution of PSI-scores for Corporate Tweets



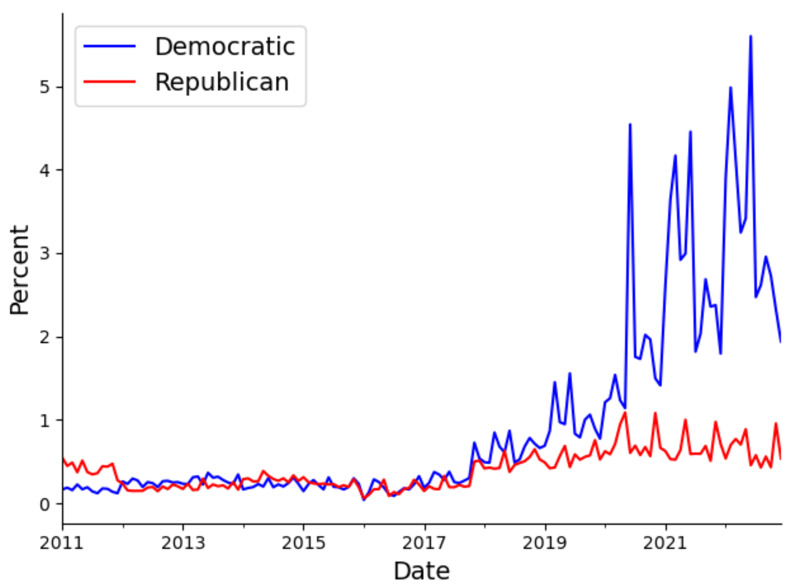
The figure displays the histograms of PSI-scores for corporate tweets sent biannually throughout our sample. A PSI-value near zero uses strongly Democratic-sounding language and a PSI-value near one uses strongly Republican-sounding language. The y-axis shows the logged number of tweets with a PSI-value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

Figure 2
Partisan Corporate Speech Over Time

Panel A: Partisan Corporate Speech



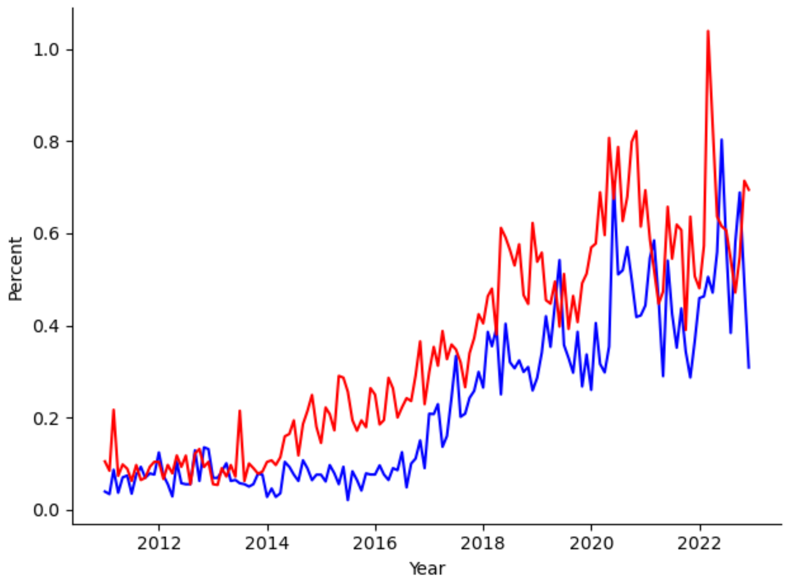
Panel B: Democratic vs. Republican-Sounding Speech



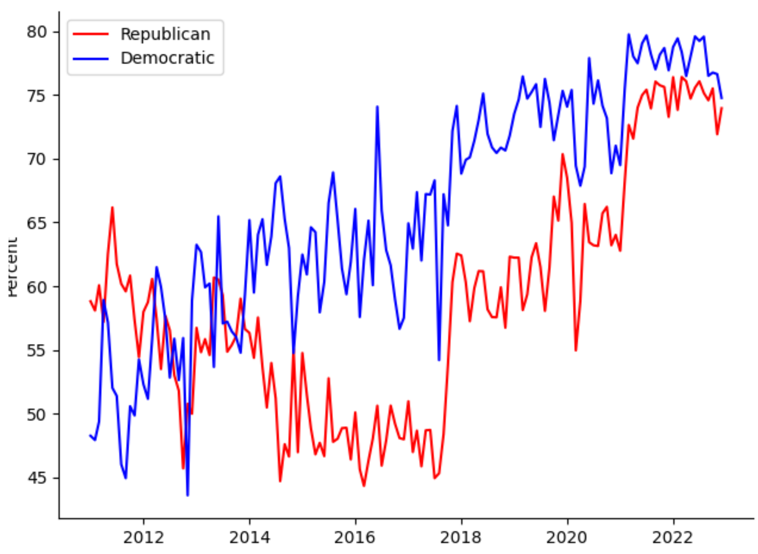
Panel A of this figure plots the percentage of partisan tweets by calendar month. Panel B separates partisan tweets into Democratic (blue line) and Republican (red line) partisan tweets, respectively. Democratic (Republican) tweets are tweets with a PSI-value ≤ 0.03 (≥ 0.97), respectively.

Figure 3
Benchmarks

Panel A: Random Sample of Tweets

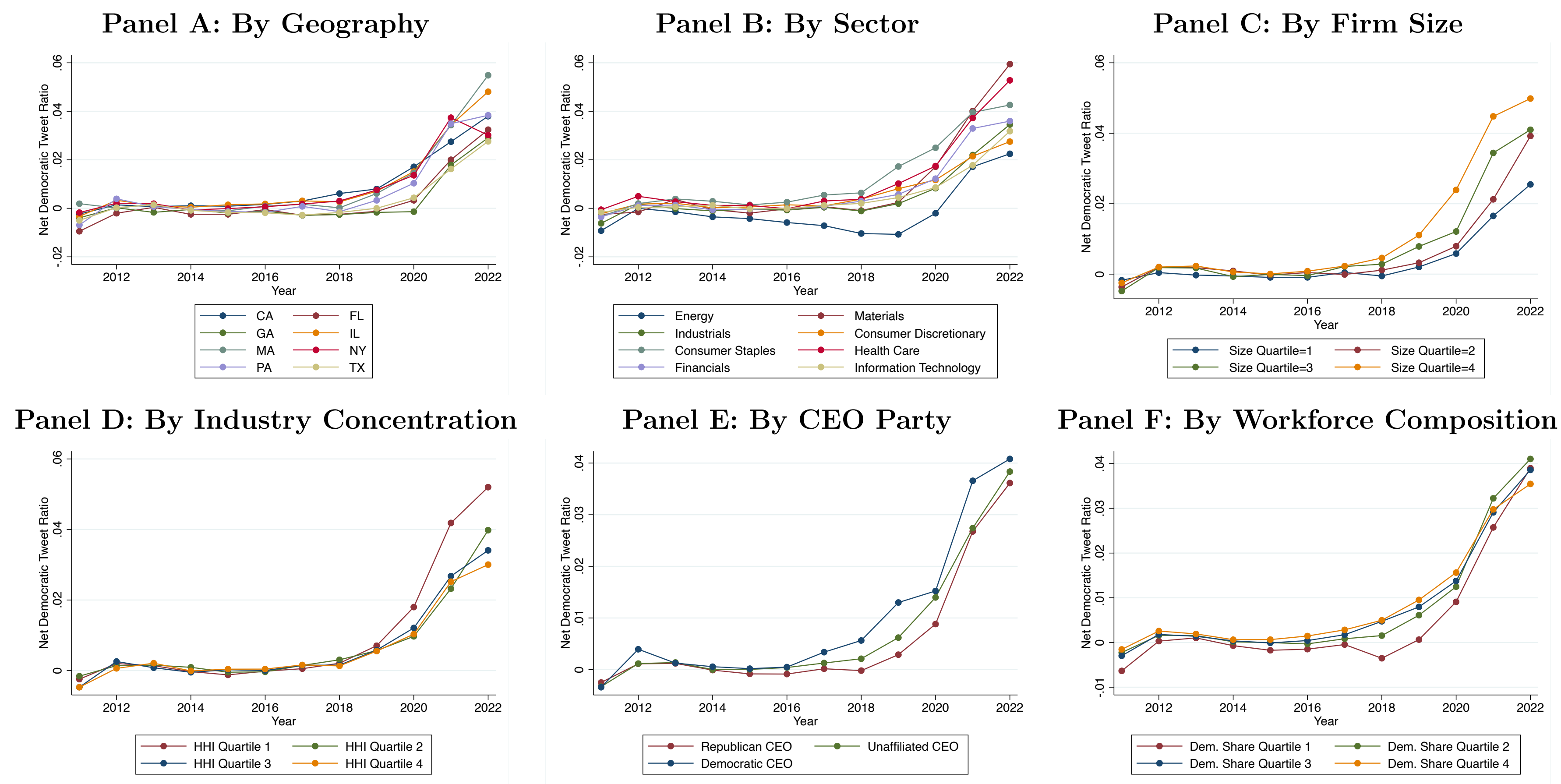


Panel B: Tweets by Members of Congress



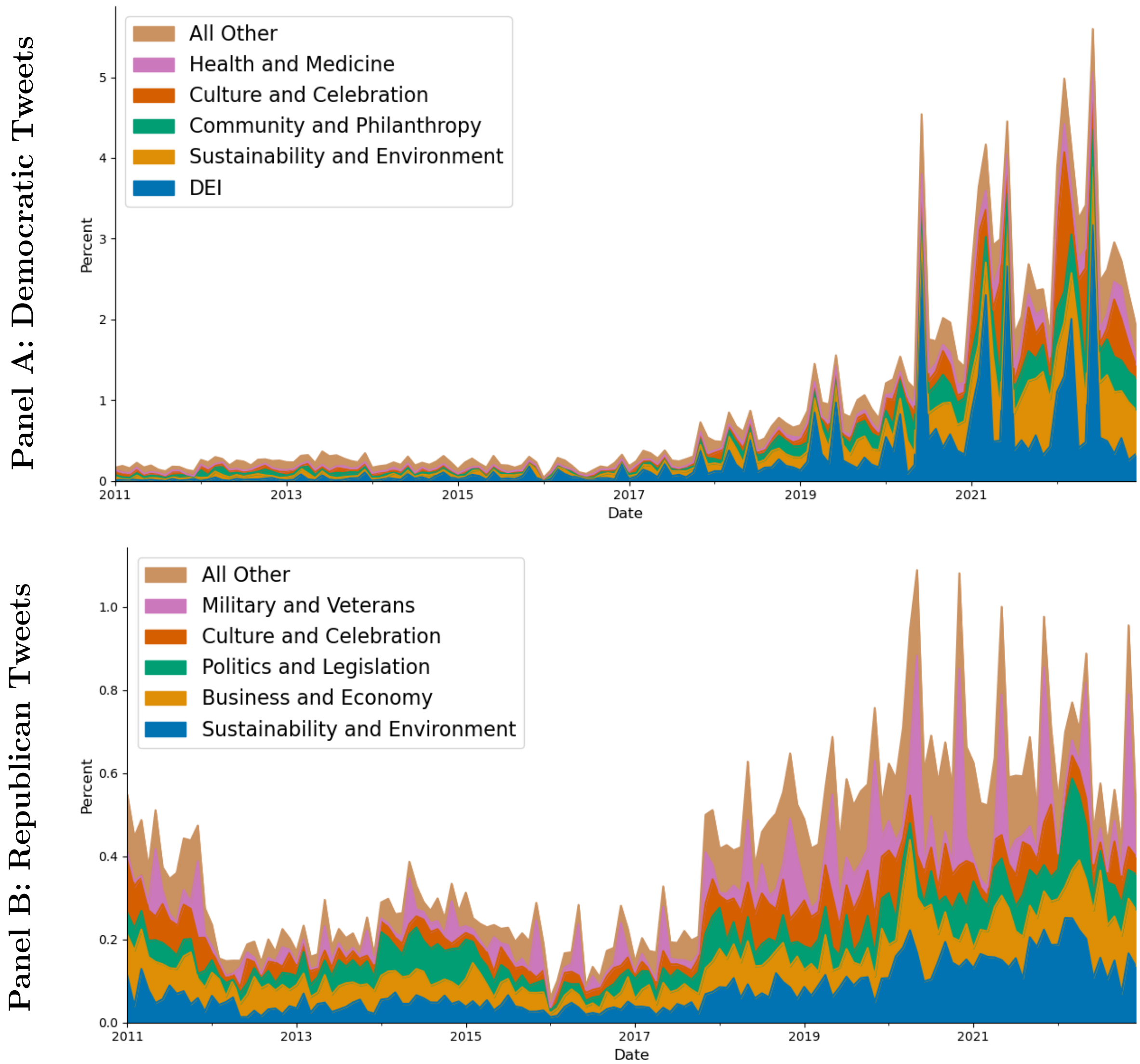
This figure displays the percentage of partisan tweets for two distinct samples. Panel A plots, for each calendar month, the percentage of partisan tweets in a randomly selected sample of tweets on Twitter. To construct this random sample, we download approximately 15,000 tweets per month by querying 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 2011 and 2022 with an active Twitter account.

Figure 4
Net Democratic Tweet Ratio by Subsample



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 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.

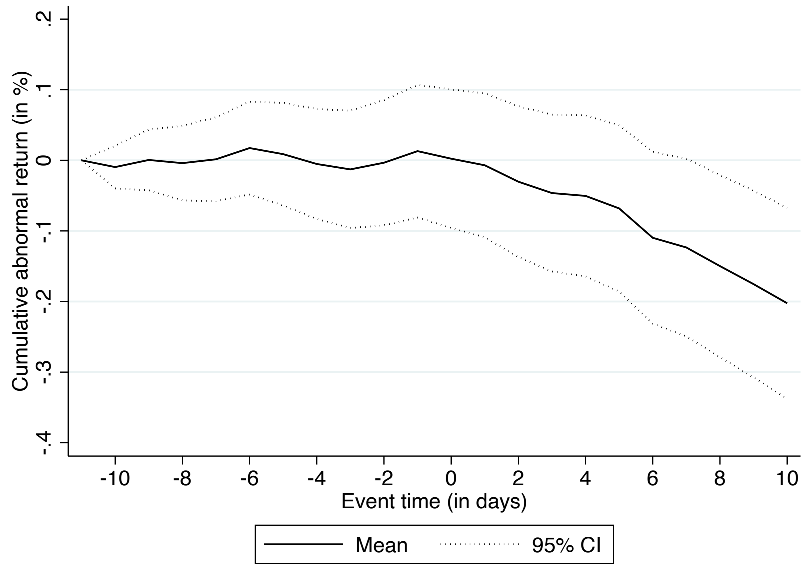
Figure 5
Topic Analysis of Partisan Corporate Tweets



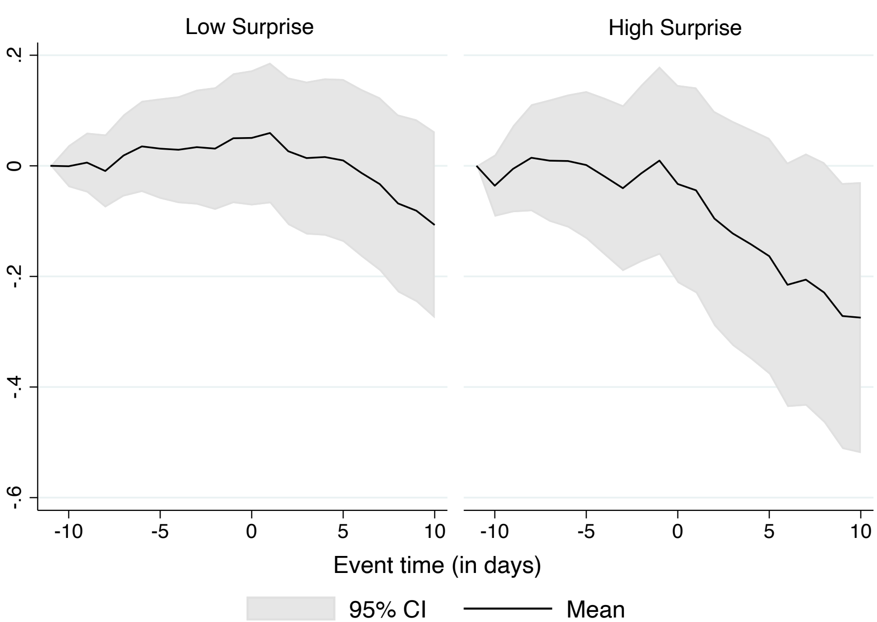
The figure displays the evolution of partisan corporate speech, grouped by meta-topic. Panel A shows the frequency of Democratic tweets broken down by the five most common meta-topics used in Democratic tweets. Panel B does the same for Republican tweets. Democratic tweets are tweets with a PSI-value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

Figure 6
Stock Returns Around Partisan Corporate Tweets

Panel A: All Partisan Tweets



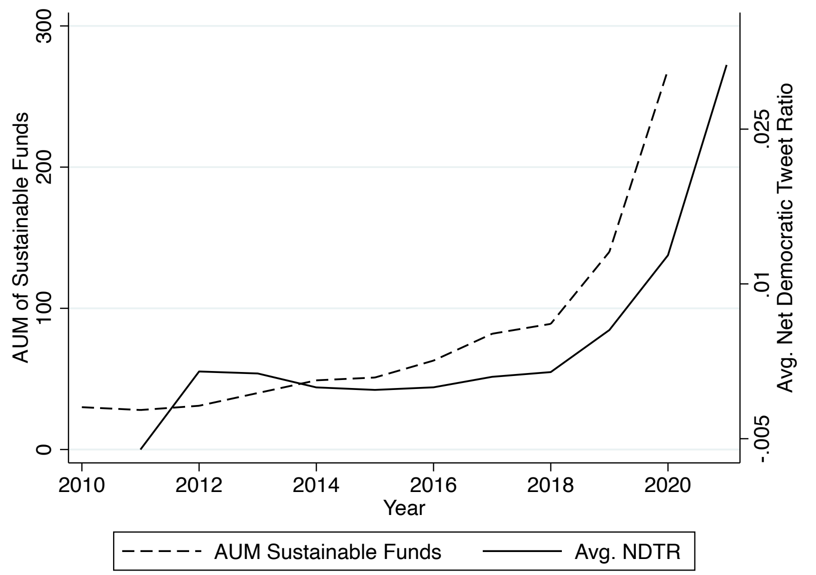
Panel B: By Surprise



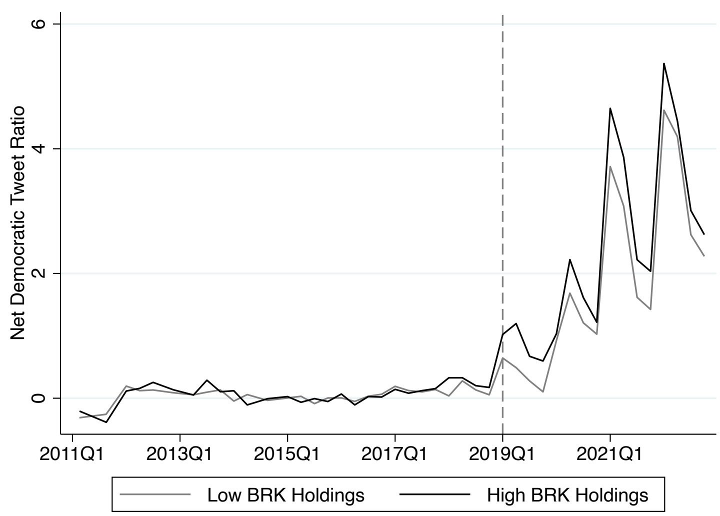
The figure displays cumulative daily stock returns around partisan corporate tweets. Panel A plots returns for the full sample of tweets, whereas Panel B reports returns separately for the subsamples with high versus low partisan-slant surprise. Daily abnormal returns are calculated using the Fama and 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

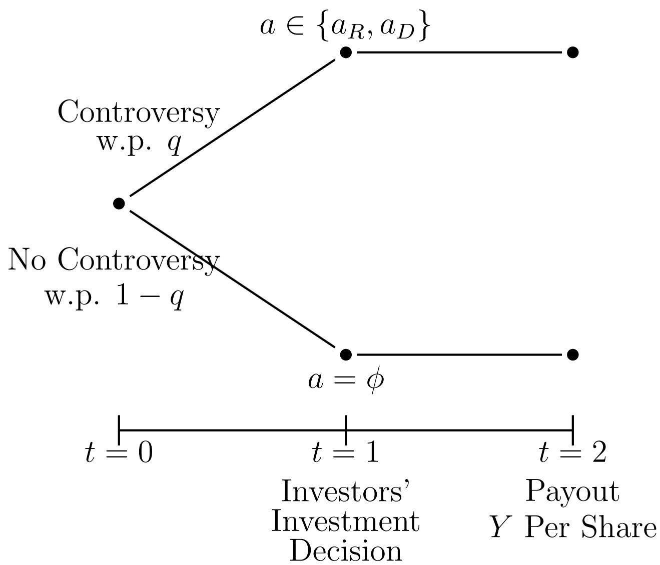


Panel B: BlackRock Ownership and Corporate Partisan Slant



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 2011 and 2022. A firm appears in one of the three panels if the firm's Twitter account sent any tweet (Panel A), a Democratic tweet (Panel B) or a Republican tweet (Panel C) in that year, respectively.

Year:	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
	Panel A: All Tweets											
Unique Firms	380	431	449	481	496	511	526	532	539	542	545	537
Average Tweets Per Firm	638.55	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	1211.95	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	1
Median Number of Tweets	309	466	559	615	631	558	468	405	348	285	270	220
Maximum Number of Tweets	17831	21699	20139	18959	11602	206275	11146	11060	4616	6616	8678	4967
	Panel B: Democratic Tweets											
Unique Firms	121	244	252	246	249	264	300	374	399	451	475	490
Average Tweets Per Firm	3.24	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	4.04	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	1
Median Number of Tweets	2	2	2	2	2	2	3	3	4	5	9	8
Maximum Number of Tweets	26	43	118	97	53	77	78	59	129	162	249	224
	Panel C: Republican Tweets											
Unique Firms	192	182	211	249	283	275	264	367	356	363	321	256
Average Tweets Per Firm	5.3	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	7.41	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	1
Median Number of Tweets	3	2	2	2	2	2	2	3	2	3	2	2
Maximum Number of Tweets	64	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 follows. We first calculate the probability of a bigram's usage as the frequency of the bigram in the sample of congressional tweets divided by the total number of bigrams used. We then multiply the posterior of the bigram with the probability of usage and sum over the set of all bigrams. We then recalculate this quantity, dropping a single bigram from the set of bigrams. 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.

Democrat	Republican	Democrat	Republican	Democrat	Republican
2022		2021		2020	
gun violenc	woke agenda	vote right	god bless	public health	look forward
vote right	pelosi biden	gun violenc	critic race	million american	nation secur
im proud	law enforc	build better	tax spend	john lewi	thank realdonaldtrump
climat chang	socal inflat	climat chang	secur border	gun violenc	unit state
lower cost	energi independ	work famili	open border	preexist condit	god bless
work famili	secur border	child care	american peopl	vote right	men women
social secur	openbord polici	right vote	law enforc	care act	nanci pelosi
clean energi	disinform board	im proud	men women	right vote	law enforc
across countri	gas price	john lewi	small busi	social secur	american peopl
brown jackson	american energi	civil right	openbord polici	civil right	small busi
2019		2018		2017	
gun violenc	pass usmca	gun violenc	nation secur	work famili	small busi
climat chang	look forward	preexist condit	unit state	middl class	nation secur
background check	nanci pelosi	climat chang	north korea	preexist condit	repeal obamacar
preexist condit	unit state	social secur	cut job	town hall	american peopl
im proud	law enforc	work famili	secur border	health insur	law enforc
vote right	nation secur	vote right	american peopl	climat chang	north korea
el paso	border secur	civil right	small busi	aca repeal	men women
prescript drug	secur border	im proud	law enforc	million american	cut job
civil right	men women	regist vote	men women	puerto rico	tax code
town hall	american peopl	famili separ	tax reform	repeal aca	tax reform
2016		2015		2014	
gun violenc	tax code	vote right	look forward	kidnap rt	obama administr
climat chang	payment iran	climat chang	obama administr	minimum wage	last night
vote right	small busi	gun violenc	nuclear deal	immigr reform	small busi
regist vote	last night	town hall	obama admin	equal pay	presid obama
join us	nation secur	civil right	rand paul	middl class	men women
town hall	law enforc	exim bank	small busi	civil right	obama admin
civil right	obama admin	right vote	nation secur	care bringbackourgirl	rand paul
right vote	men women	women health	men women	climat chang	loi lerner
background check	obama administr	work famili	iran deal	rais minimum	reid desk
social secur	hillari clinton	middl class	polici summit	equal work	obamacar enrolle
2013		2012		2011	
immigr reform	presid obama	middl class	tcot gop	pls rt	gop tcot
billion snap	men women	post photo	repeal obamacar	town hall	small busi
gun violenc	tax code	pls rt	listen live	via addthi	gas price
student loan	pres obama	town hall	job creator	social secur	budget amend
town hall	look forward	student loan	small busi	end medicar	rt speakerboehn
afford care	obama administr	regist vote	tax hike	middl class	tcot gop
health insur	listen live	social secur	gas price	reduc deficit	cut spend
vote right	small busi	women health	jobsact help	post photo	job creator
comprehens immigr	delay obamacar	join us	senat inouy	job plan	roll call
background check	obama admin	afford care	sopa pipa	big oil	balanc budget

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 first calculate the probability of a bigram's usage as the frequency of the bigram in the sample of partisan corporate tweets divided by the total number of bigrams used. We then multiply the posterior of the bigram with the probability of usage and sum over the set of all bigrams. We then recalculate this quantity, dropping a single bigram from the set of bigrams. 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. This calculation excludes business-related tweets.

Democrat	Republican	Democrat	Republican	Democrat	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		2011	
hunger america	tune foxbusi	pair shoe	job council	charg network	foxbusi discuss
right campaign	confid hit	amazon rainforest	foxbusi discuss	bring clean	fix economi
bring clean	modern trade	right campaign	tune foxbusi	pair shoe	spend extra
impact aca	via foxnew	hunger america	price index	achiev univers	scienc chang
pair shoe	produc oil	pay full	benefit employe	latino leader	fairi tale
protect planet	reward employe	bring clean	make top	amazon rainforest	polici drive
happi pride	talk radio	score hrc	flip switch	planet futur	employe benefit
best one	watch whole	charg network	american energi	workplac polici	gallon gas
moment action	big guy	protect planet	employ ad	month earn	job council
teacher help	american energi	improv work	diesel price	teacher help	via foxnew

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	-0.020	-0.059*	-0.215***	-0.054	-0.132**	-0.284***
	(0.022)	(0.033)	(0.056)	(0.043)	(0.063)	(0.102)
N	9,249	9,249	9,249	2,842	2,842	2,842
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, the share of workers aligned is defined as the percentage of Glassdoor reviews from blue (red) states, respectively, and the 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)
Log market cap	-0.040	-0.078*	-0.106	0.013	-0.048	0.008
	(0.031)	(0.047)	(0.082)	(0.064)	(0.092)	(0.147)
Share of workers aligned	0.045*	0.085**	0.063	0.150***	0.230***	0.161
	(0.026)	(0.034)	(0.062)	(0.057)	(0.078)	(0.123)
CEO aligned	0.029	0.019	0.025	0.034	-0.004	0.000
	(0.023)	(0.033)	(0.057)	(0.051)	(0.065)	(0.113)
Share of investors aligned	0.042*	0.043	0.087	0.100**	0.092	0.219**
	(0.022)	(0.030)	(0.057)	(0.045)	(0.062)	(0.111)
IO	0.001	-0.050	-0.059	0.031	-0.054	-0.135
	(0.027)	(0.041)	(0.076)	(0.057)	(0.083)	(0.155)
N	8,261	8,261	8,261	2,663	2,663	2,663
R^2	0.070	0.083	0.097	0.148	0.172	0.159
Sector $\times$ 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 provides additional results on aggregate trends in partisan corporate speech.

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

Internet Appendix D presents additional results on firm heterogeneity.

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

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), respectively.
CAR (0,+τ)	Daily cumulative abnormal return, measured over trading days 0 to +τ 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% within event time.
Independent variables	
Firm size quartile	The firm's total book assets, 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.
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.
Log market cap	Logarithm of the firm's market capitalization as of the most recent fiscal year-end. Data obtained from Compustat Annual.
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. (2023), who use voter registration data to infer party.

Continued on next page

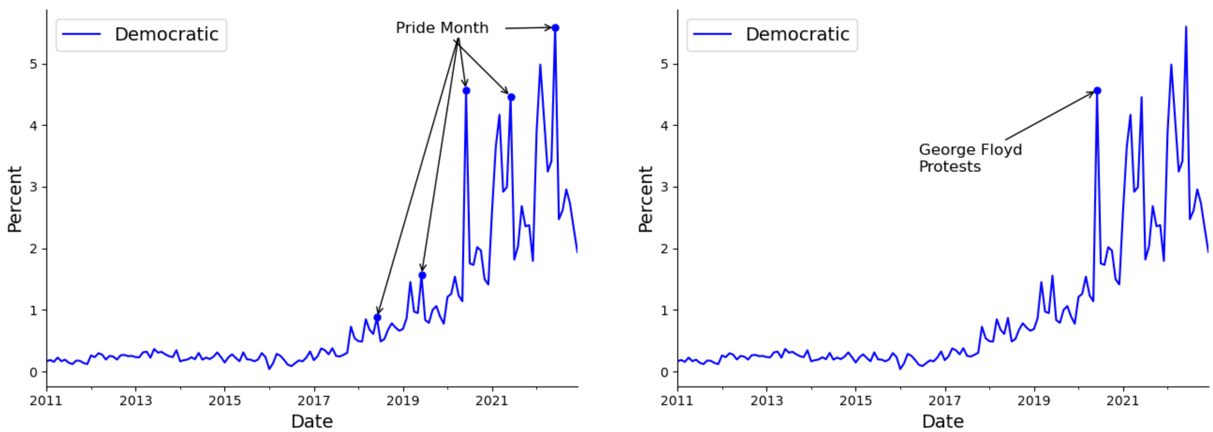
Table IA.1 – continued

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 according to Morningstar if the tweet has a Democratic (Republican) slant, respectively. Information on fund mandates and stock holdings are obtained from Morningstar.
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.

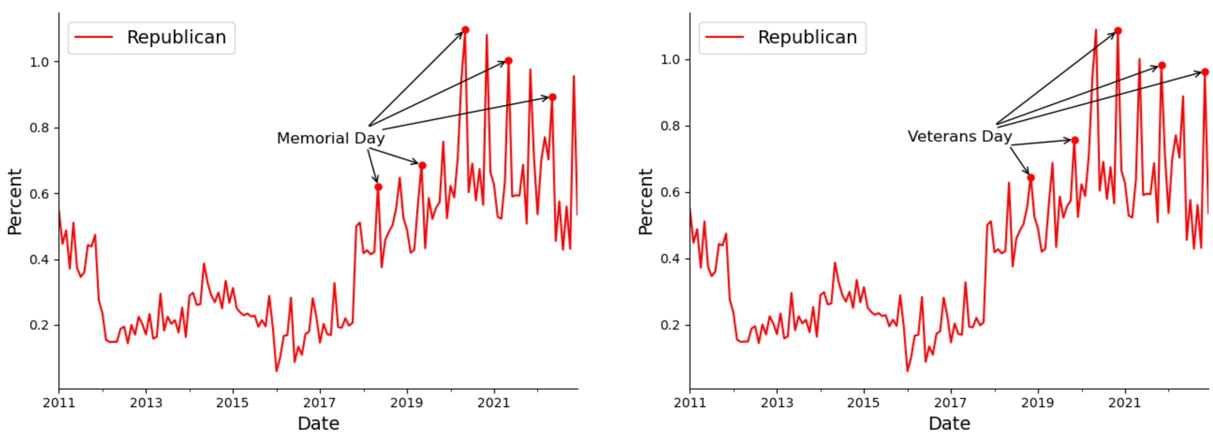
B Additional Results on Aggregate Trends in Partisan Corporate Speech

Figure B.1
Partisan Corporate Speech: Key Events

Panel A: Democratic-Sounding Speech

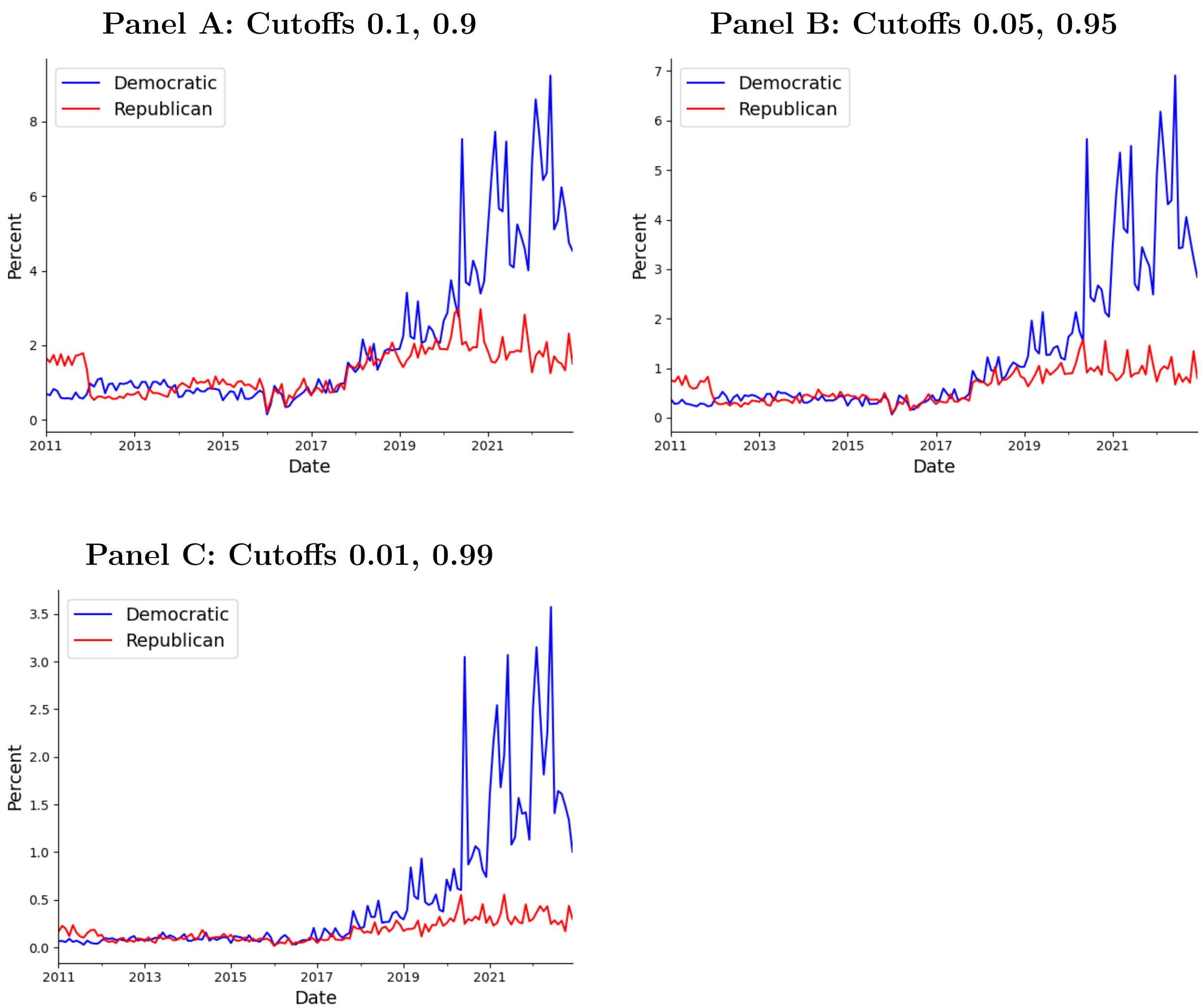


Panel B: Republican-Sounding Speech



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.

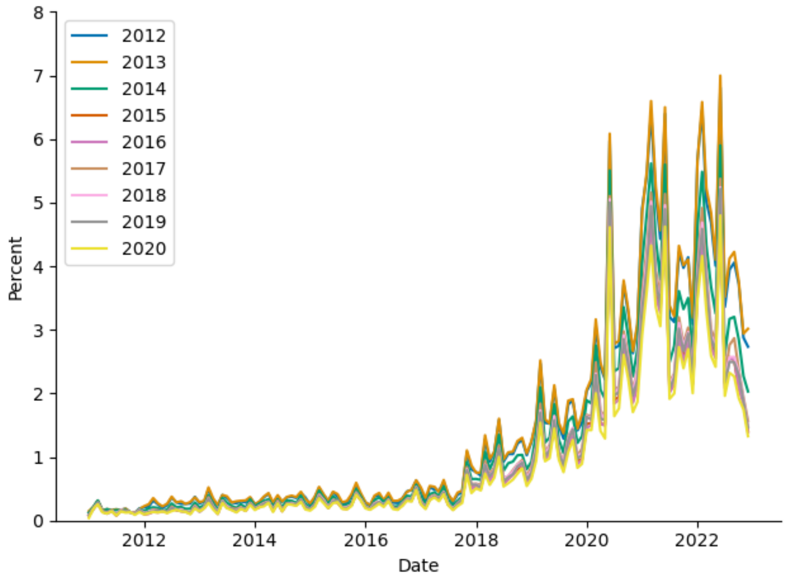
Figure B.2
Alternative Thresholds to Identify Partisan Speech



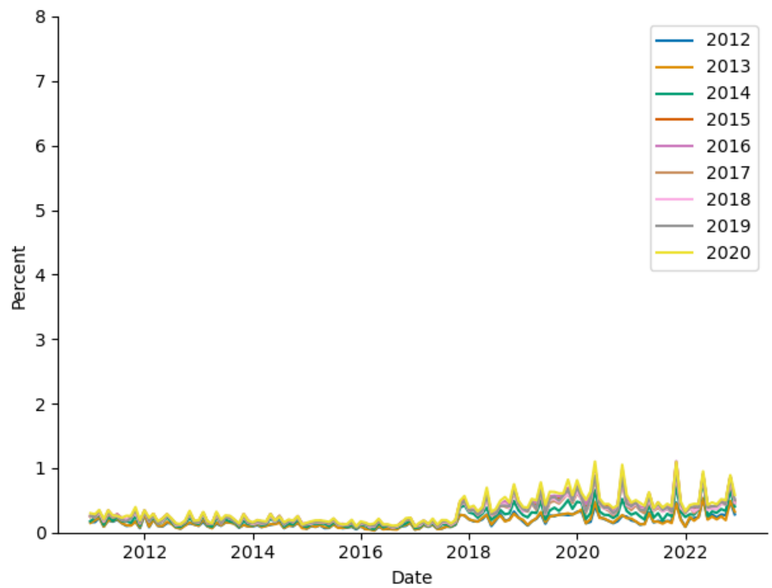
The figure shows the same series as in Figure 2, Panel A, but for different thresholds of PSI-values at which we characterize speech as Democratic- or Republican-sounding.

Figure B.3
Varying the Timing of Politician Speech

Panel A: Democratic Speech

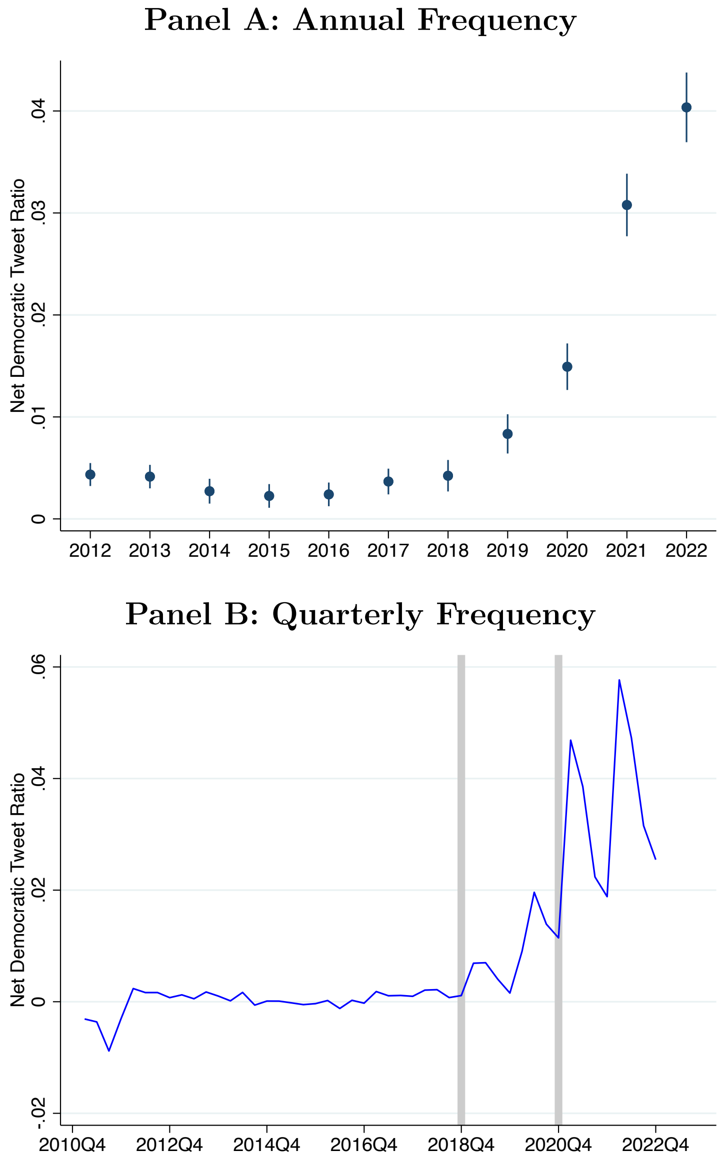


Panel B: Republican Speech



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 B.4
Average Net Democratic Tweet Ratio: Annual and Quarterly Frequencies



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 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.2
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	159.57	8.58
1	13.91	10.13
2	4.58	11.14
3	4.57	11.83
4	4.49	12.25

C Additional Results From Content Analysis

Table IA.3
Partisan Speech Topic Model

This table reports each of the fifty topics for the biterm topic model estimated on corporate tweets 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 would be classified as business-related. Topics are ordered in decreasing frequency, the most common are 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

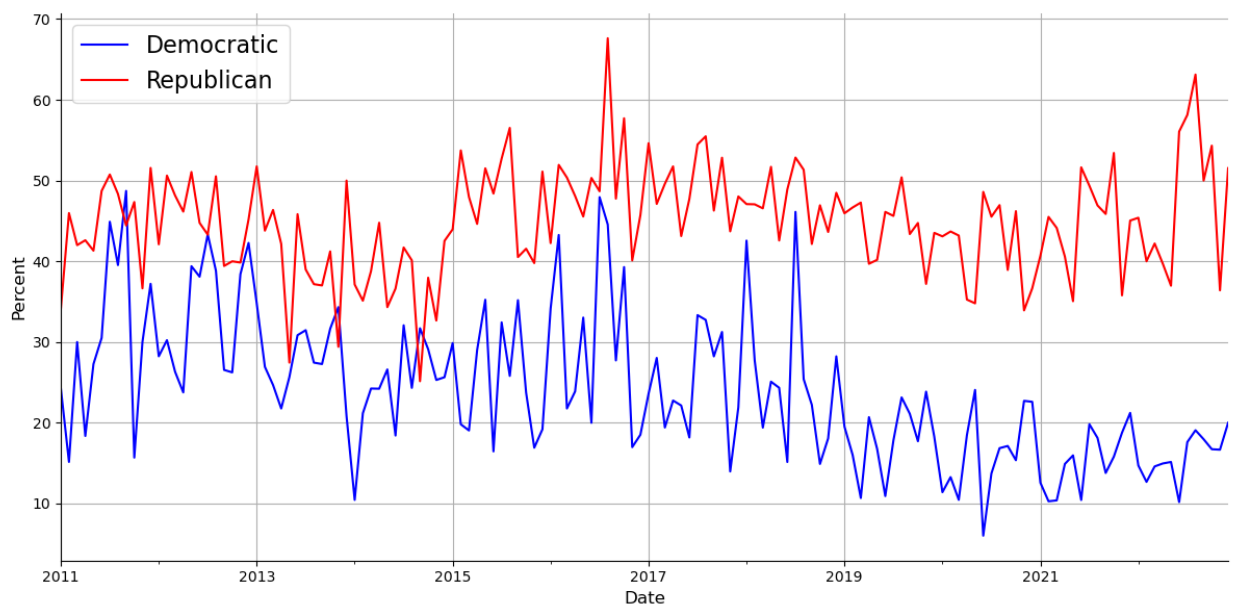
	Topic Label	5 Most Important Unigrams					Business
28	Positive sentiments	great	time	see	realli	thank	
29	Military and defense	defens	missil	system	air	us	37, 38, 97
30	Martin Luther King, Jr.	honor	king	dr	right	today	
31	Hard drives and external storage solutions	drive	hard	seagat	storag	new	All
32	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.4
Meta-Topic Classification

This table reports the associated meta-topic for each topic listed in Table IA.3. We chose these meta-topic groupings and associated meta-topic labels by asking Chat-GPT to organize our topics 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

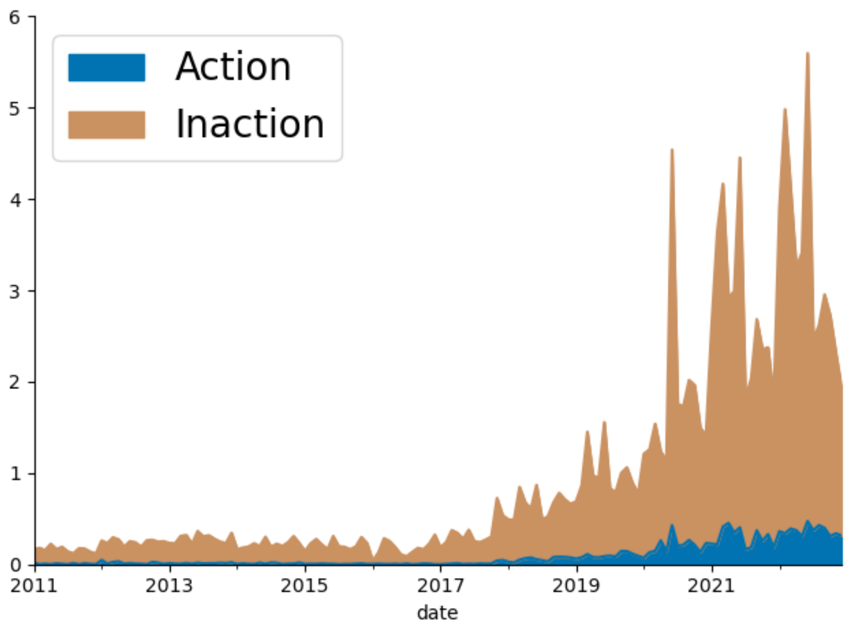
Figure C.5
Proportion of Business-Related Partisan Tweets



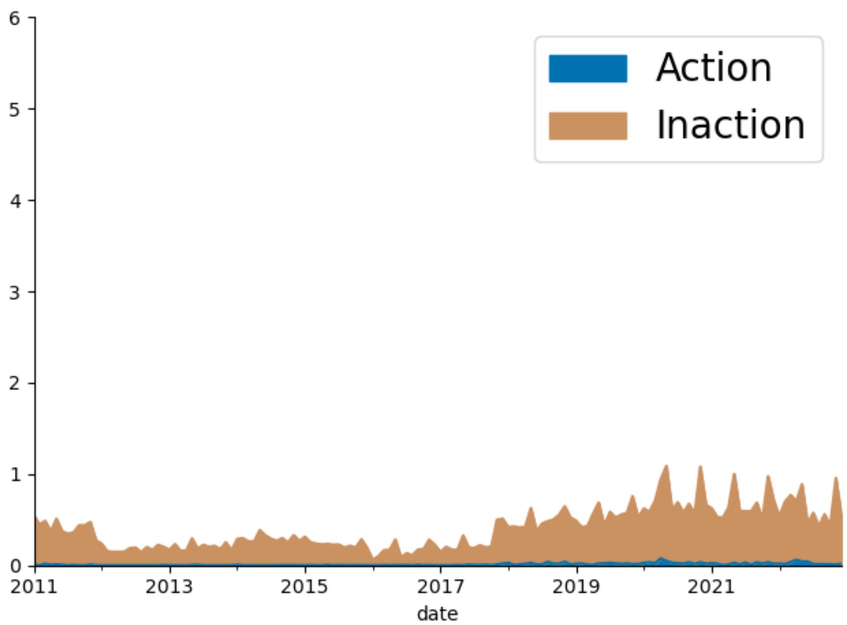
This figure displays the proportion of partisan corporate speech that we classify as business-related using the topics and industries listed in Internet Appendix Table IA.3.

Figure C.6
Action vs. Non-action Tweets

Panel A: Democratic Tweets



Panel B: Republican Tweets

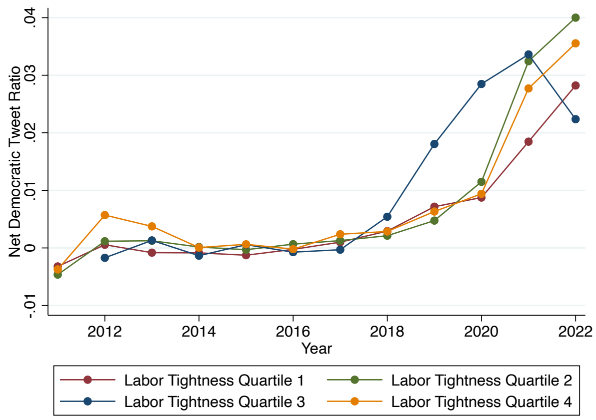


The figure displays the frequency of Republican and Democratic corporate tweets that describe an action (blue) versus those that do not (brown).

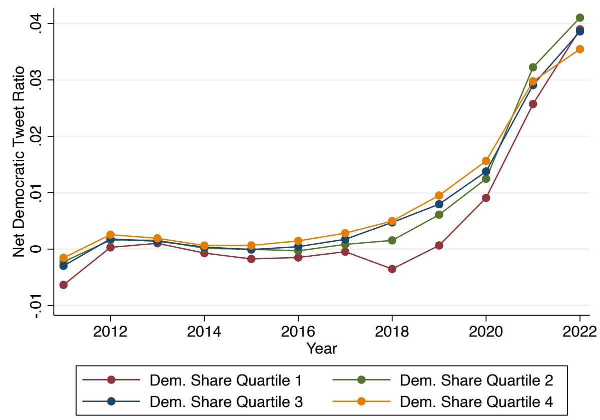
D Additional Results on Firm Heterogeneity

Figure D.7
Additional Dimensions of Firm Heterogeneity

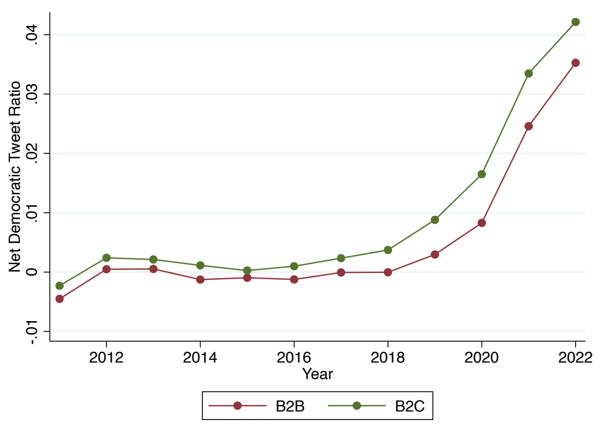
Panel A: By Labor Market Tightness



Panel B: By Workforce Composition

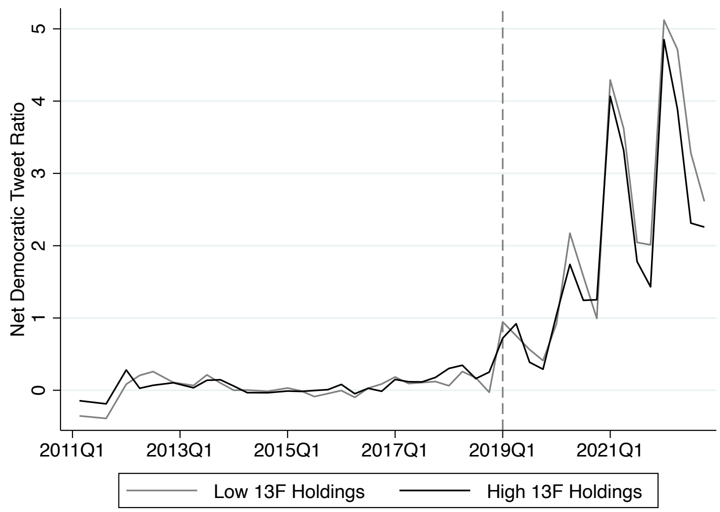


Panel C: By Customer Type



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 labor market tightness (Panel A), by workforce composition, measured using the voter registration status of the firm's workers (Panel B), and by customer type (Panel C).

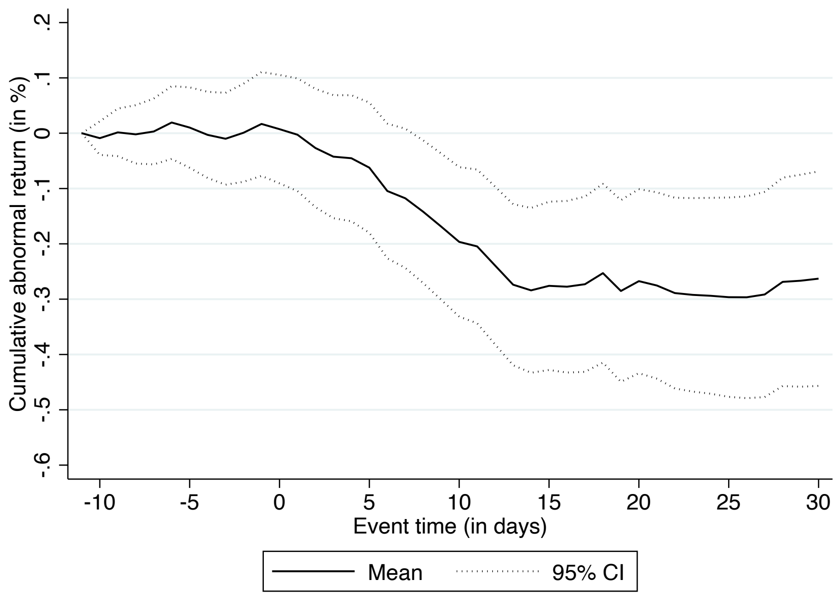
Figure D.8
Partisan Corporate Speech and Institutional Ownership



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.

E Additional Results on Stock Returns Around Partisan Corporate Tweets

Figure E.9
Stock Returns Around Partisan Corporate Tweets: Long Event Window



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

Table IA.5
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	-0.020	-0.059*	-0.215***	-0.054	-0.132**	-0.284***
	(0.022)	(0.032)	(0.052)	(0.041)	(0.058)	(0.086)
N	9,249	9,249	9,249	2,842	2,842	2,842
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	-0.016	-0.070*	-0.211***	-0.054	-0.132**	-0.284***
	(0.023)	(0.041)	(0.077)	(0.043)	(0.064)	(0.099)
N	8,681	8,681	8,681	2,842	2,842	2,842
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	-0.014	-0.061	-0.190***	-0.037	-0.133*	-0.231*
	(0.026)	(0.039)	(0.065)	(0.052)	(0.074)	(0.121)
N	9,249	9,249	9,249	2,842	2,842	2,842
High surprise only?	No	No	No	Yes	Yes	Yes

F Mathematical 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

$$U_j\left(C_j, x_j, a\right) = C_j + x_j^2 \frac{\delta_j}{2} \mathcal{A}_j(a)$$

Notice that

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

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

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

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. $\square$

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*

$$P = Y + \delta_D x \tag{6.7}$$

Proof. In this case, we know that

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

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

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.

<u>Case 1: no controversy</u>

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 $P = Y + \delta_D x$ (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 $P = Y - \delta_R x$ (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 $Y > P$. 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. *In the event of a controversy, if the firm takes action a_D, equilibrium is defined by the allocations*

$$x_D = \frac{W_D}{P} \text{ and } x_R = x - \frac{W_D}{P} > 0 \tag{6.8}$$

with

$$P \in (0, Y) \text{ satisfying } P = Y - \delta_R \left(x - \frac{W_D}{P} \right), \tag{6.9}$$

where P is increasing in W_D and decreasing in δ_R.

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 $P > Y - \delta_R x_R$ then the R investor is not willing to have $x_R > 0$. If $P < Y - \delta_R x_R$ 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. The equation for prices is given by plugging in x_R into the R investor's FOC.

To show that P is increasing in W_D, we use implicit differentiation.

$$\begin{aligned}
\frac{\partial P}{\partial W_D} &= \frac{\partial}{\partial W_D}\left(Y - \delta_R\left(x - \frac{W_D}{P}\right)\right)\\
\frac{\partial P}{\partial W_D} &= 0 - \delta_R\left(0 - \frac{\partial}{\partial W_D}\frac{W_D}{P}\right)\\
\frac{\partial P}{\partial W_D} &= \delta_R \frac{P - W_D\frac{\partial P}{\partial W_D}}{P^2}\\
\frac{\partial P}{\partial W_D}\frac{P^2}{\delta_R} &= \left(P - W_D\frac{\partial P}{\partial W_D}\right)\\
\frac{\partial P}{\partial W_D}\left(\frac{P^2}{\delta_R} + W_D\right) &= P\\
\frac{\partial P}{\partial W_D} &= \frac{P}{\frac{P^2}{\delta_R} + W_D} > 0
\end{aligned}$$

The final inequality follows from positive P. Notice that there is no equilibrium that can be sustained with non-positive P, because then the D type investor would be willing to purchase all shares and it would be feasible to do so, but then the resulting price would be determined by the FOC of the D type investor and would be, in particular, positive.
To show that P is decreasing in δ_R, we again use implicit differentiation.

$$\begin{aligned}
\frac{\partial P}{\partial \delta_R} &= \frac{\partial}{\partial \delta_R}\left(Y - \delta_R\left(x - \frac{W_D}{P}\right)\right)\\
\frac{\partial P}{\partial \delta_R} &= -\left(x - \frac{W_D}{P}\right) - \delta_R\frac{W_D\frac{\partial P}{\partial \delta_R}}{P^2}\\
\frac{\partial P}{\partial \delta_R} &= -\left(x - \frac{W_D}{P}\right) - \delta_R\frac{W_D\frac{\partial P}{\partial \delta_R}}{P^2}\\
\frac{\partial P}{\partial \delta_R}\left(1 + \delta_R\frac{W_D}{P^2}\right) &= -\left(x - \frac{W_D}{P}\right)\\
\frac{\partial P}{\partial \delta_R} &= -\frac{x_R}{1 + \delta_R\frac{W_D}{P^2}} < 0
\end{aligned}$$

□

Proposition 3. *As $W_D \to xY$ and $W_R \to 0$, a firm with type $\theta = R$ will find it optimal to take action a_D when*

$$\delta_D x > \zeta \tag{6.11}$$

Proof. First, notice that as $W_D \to xY$, $P \to Y$ if the firm takes action a_D. To see this, start from

$$\lim_{W_D \to xY} Y - \delta_R \left(x - \frac{W_D}{P} \right) = Y - \delta_R \left(x - \frac{xY}{P} \right)$$

Now, we can use the first-order condition to verify that this is satisfied for $Y = P$:

$$Y = Y - \delta_R \left(x - \frac{xY}{Y} \right) \Rightarrow Y = Y$$

which verifies the claim.

If instead, the firm takes the action a_R, it is immediate that the price instead is given by

$$P = Y - \delta_D x$$

The $\theta = R$ firm then takes action a_D if the following inequality is met:

$$Y - \frac{\zeta}{2} > Y - \delta_D x + \frac{\zeta}{2}$$
$$\delta_D x > \zeta$$

which verifies the claim □

Proposition 4. *As $\delta_D \to \infty$ and $\delta_R \to 0$, the firm will find it optimal to take action a_D, even if $\theta = R$, when*

$$Y - \frac{W_R}{x} > \zeta \tag{6.12}$$

Proof. As $\delta_R \to 0$, if the firm takes action a_D the price will be determined by the first-order condition

$$P = Y - \delta_R x_R = Y$$

As $\delta_D \to \infty$ and the firm takes the action a_R then price will be determined by the first-order condition

$$P = Y - \delta_D x_D$$

But for this to be an equilibrium it must be that $P > 0$, which implies that $x_D \to 0$. Therefore $x_R \to x$ and price will be determined by the equation

$$P = \frac{W_R}{x}$$

Returning to the firm's problem, this implies that the type R firm will find it optimal to take action a_D when

$$Y - \frac{\zeta}{2} > \frac{W_R}{x} - \frac{\zeta}{2}$$

which verifies the claim. □

Corollary 1. *When a political controversy occurs and the firm takes an action $a \in \{a_R, a_D\}$, the price of the stock declines.*

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

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

On the arrival of a controversy, the price will immediately descend from P_0 to P. □

Corollary 2. *The negative price effects of political controversies decline 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. We know that P is increasing in W_D, this implies that the RHS is decreasing in W_D, which is the content of the claim. □