Partisan Corporate Speech

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Abstract

We develop a novel measure of partisan corporate speech using techniques from natural language processing. Using all tweets sent by companies in the S&P 500, we document a large increase in the amount of partisan corporate speech between 2011 and 2022. From 2019 onwards, this increase is disproportionately driven by companies using more Democratic-sounding speech. Additional tests suggest the recent growth in sustainable investing may have contributed to the surge in Democratic speech. Stock returns are close to zero around the average partisan tweet, but exhibit substantial heterogeneity by degree of stakeholder alignment.

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1 Introduction

Recently, prominent U.S. companies and their CEOs have taken a public stance on social and political issues on which Democrats and Republicans are deeply divided, including gun laws (CNBC (2019)), voting rights (The New York Times (2021)), and racial equality (Forbes (2020)). However, to date, we lack a systematic approach to measuring the prevalence of partisan corporate speech. In particular, it is challenging to separate the rise of partisan corporate speech from increased media attention and public response to such speech.

In this paper, we propose a novel measure of partisan corporate speech, using natural language processing applied to corporate statements shared on social media. We ask three fundamental questions. First, has corporate speech become more partisan over time? Second, what topics do companies discuss when they make partisan statements? Third, what could be potential drivers of the observed time trends in partisan corporate speech?

To answer these questions, we collect all tweets sent by S&P 500 companies with verified Twitter accounts between 2011 and 2022. To detect partisan corporate speech, we measure the degree of similarity in the language used by companies and the language used by members of the U.S. Congress on social media. Specifically, we estimate multinomial inverse regressions (MNIR) on tweets sent by Republican and Democratic members of Congress, and use the resulting estimates to identify corporate tweets that sound very similar to tweets sent by Republican or Democratic politicians.

We observe a significant increase in the frequency of partisan corporate speech on Twitter. Prior to 2017, partisan corporate speech on Twitter is very rare (less than 0.5% of all corporate tweets on average) and roughly evenly divided between Democratic and Republican-sounding speech. The first noticeable increase in partisan corporate speech occurs at the end of 2017, when the amount of both Republican and Democratic-sounding corporate speech more than doubles. Starting in early 2019, we observe a decoupling between the two time series: Democratic-sounding speech strongly increases, whereas Republican-sounding speech remains relatively flat. Randomly selected Twitter speech as well as Twitter speech by

Congresspeople do not exhibit the same patterns, suggesting that the trends we observe in corporate speech are not driven by aggregate trends in speech on Twitter.

To better understand the content of partisan corporate speech, we decompose partisan corporate tweets into distinct topics using biterm topic modeling. Using this approach, we find that most of the increase in Democratic-sounding speech is driven by increased discussion of diversity, equity, and inclusion (DEI), climate change, and celebrations such as Black History Month or Pride Month. Republican-sounding speech relates to the economy, energy, patriotism, and the military. This topic analysis is helpful because it indicates that companies may not necessarily use partisan sounding language on purpose; they may simply choose to speak out on topics that are highly partisan. We further find that relatively few partisan corporate tweets contain measurable actions or commitments, which we refer to as "action tweets." Less than 7% of all partisan corporate tweets involve specific corporate actions, such as donations, or measurable targets.

The disproportionate increase in Democratic-sounding speech is present across virtually all sectors, including consumer and business-oriented industries, as well as across all geographies, all firm size quartiles, and across firms with Republican and Democratic CEOs. Firms in industries with high market concentration show a slower increase, indicating that the trend may not be driven by firms with high market power. Within industries, we see that larger firms, as well as firms with greater ownership by funds with environment, social, and governance (ESG) objectives, exhibit a stronger increase in Democratic speech.

What can explain the widespread increase in the usage of Democratic-sounding speech among U.S. corporations? We provide some suggestive evidence that shifts in investor demand may have contributed to the trend. First, in the time series, there is a strong correlation between aggregate flows into funds with environment, social, and governance (ESG) objectives and the average Democratic slant of U.S. firms. Second, in the cross-section of firms, greater ownership by ESG funds is associated with a stronger increase in Democratic speech. Third, using a difference-in-differences design, we document an increase in the Democratic slant of firms with high BlackRock ownership around Larry Fink's influential 2019 letter to CEOs, which called for executives to lead on divisive issues. While these results provide strong suggestive evidence, more research is needed to establish a causal relationship between the rise of ESG investing and the usage of Democratic-sounding speech among U.S. corporations.

Finally, we also study stock prices around partisan corporate tweets. Using stock return data at both daily and intraday frequencies, we find close to zero changes in the firm's stock price immediately around the average partisan corporate tweet. However, we observe substantial heterogeneity in the stock price response as a function of the degree of stakeholder alignment. In particular, partisan tweets that are aligned with the preferences of investors and employees exhibit a more positive stock price reaction. Moreover, we see that the average partisan tweet tends to be followed by negative abnormal returns over the subsequent 10 trading days—a phenomenon that warrants further investigation.

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)). Boxell and Conway (2024) study how 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 and Barari (2024) are the first to apply natural language processing techniques to data from corporate Twitter accounts to identify partisan corporate speech ex ante.[1]

Second, we contribute to a growing literature on the political polarization of corporate America. Fos et al. (2023) show that executive teams have become more politically homogeneous over the past decade. Moreover, a growing number of studies document how political partisanship shapes individuals' views of the economy and their economic decisions, including in high-stakes, professional environments, such as credit analysts (Kempf and Tsoutsoura (2021)), asset managers (Cassidy and Vorsatz (2024), Kempf et al. (2023)), loan officers (Dagostino et al. (2023)), and entrepreneurs (Engelberg et al. (2024)). 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.

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.

[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.

[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).

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

[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.

filter leads to dropping the New York Times, News Corp, Tegna Inc., Fox Corp, and Scripps Network Interactive Inc. Collectively, these companies represent approximately 500,000 tweets, the vast majority of which come from the New York Times Twitter account.

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 time frame. 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 $\sim$4.4 million corporate tweets and $\sim$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

[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.

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 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 Stock Returns

To measure changes in stock market valuations around tweets, we use both second-by-second stock returns based on the Trade and Quote data (TAQ) during a window spanning 10 minutes before and after each tweet, as well as daily stock returns from CRSP. We access the TAQ and the CRSP data through the WRDS intraday and daily event study interface, respectively. WRDS imposes standard filters on the underlying TAQ data, such as requiring that no more than 20 percent of the underlying prices are missing within a 600-second window around the event. To estimate abnormal returns at the daily frequency, we use the Fama and French (1993) and Carhart (1997) four-factor model. We winsorize intraday returns at the 10% level and daily abnormal returns at the 1% level.

2.4 Holdings Data

We download quarterly data on mutual fund holdings from the CRSP mutual fund database and data on holdings by institutions filing SEC Form 13F from the Thomson Reuters 13F database. We merge the mutual fund holdings data to fund-level information from Morningstar Direct, using standard methods (see, e.g., Ma and Tang (2019)). Importantly, we obtain a fund-level ESG metric, which is the number of sustainability globes assigned to a fund by Morningstar.

3 Measure of Partisan Corporate Speech

Our measure of partisan corporate speech is designed to capture how similar the language used in a corporate tweet is to language used 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), 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 estimated model to detect partisan tweets by corporates.

After estimating MNIR, we also implement topic modeling. We 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^R_{jt}, using Bayes rule:

$$p^R_{jt} = \frac{q^R_{jt}}{q^R_{jt} + q^D_{jt}}. \tag{3.3}$$

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

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^R_{jt} 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 increasing over time.

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

$$p^R_k = \frac{\prod_{j \in J^\star} q^R_{jt}}{\prod_{j \in J^\star} q^R_{jt} + \prod_{j \in J^\star} q^D_{jt}}, \tag{3.4}$$

where $J^\star$ denotes the set of bigrams used in the corporate tweet. We refer to variable p^R_k as the "partisan speech index" (PSI) and define a tweet as partisan speech if p^R_k or $p^D_k = 1 - p^R_k$ 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 further 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 a partisan corporate tweet 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. Among the most important Democratic partisan bigrams are "racial wealth," "lgbtq equal," "act climat," and "pay gap." The most important Republican bigrams include "american energi," "progrowth taxreform," and "tune foxbusi." Table 3 also reveals, as it would be expected, that our approach is not free of measurement error.

Interestingly, the measurement error appears to be somewhat greater for Republican corporate speech: whereas the bigrams in the Democratic columns in Table 3 are very intuitive, especially in the more recent years, the Republican columns contain a few puzzling bigrams, such as "wall system," "warp speed," or "watch whole." However, in Section 4 below, we will show that our measure of partisan corporate speech picks up meaningful and plausible variation across major events, such as the death of George Floyd, and across firms with different workforce and investor compositions.

While our measure of partisan corporate speech comes with some measurement error, it also has distinct advantages. First, it does not require any subjective judgment regarding which topics or phrases are partisan, because it is entirely data-driven. Second, it can pick up more subtle partisan clues, such as those embedded in celebrations of Veterans Day or Black History Month, which are not overtly political but nonetheless strong predictors of partisan leaning. This feature is particularly important in the context of corporate speech, because corporations are less likely to make overt partisan statements than individuals. Third, it is an ex ante measure that does not require observing any ex post reaction to the tweet.

3.2 Topic Models

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. However, our results do not appear to be particularly sensitive to the number of 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 A.2 in the Appendix. The topics are ordered by how frequently they are 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 A.2 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 Table A.2 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 A.3.

The list of topics in Table A.2 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 Table A.2. 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. Appendix Figure A.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 Results

4.1 Trends in Partisan Corporate Speech

In Figure 1, we plot histograms of the partisan speech index 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, the distribution in 2021 is closer to a uniform distribution than the distribution in 2011, consistent with a rise in partisan corporate speech.

To see the evolution in the amount of partisan corporate speech over our full sample period, Figure 2 plots the month-by-month percentages of all corporate tweets that are identified as partisan. Panel A shows the percentage of all corporate tweets with a PSI value less than 0.03 (blue line) or greater than 0.97 (red line), respectively.[5] In our subsequent discussion, we refer to these tweets as "Democratic tweets" and "Republican tweets," respectively.

Figure 2, Panel A 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 when we combine Democratic and Republican-sounding speech. In November 2017, the amount of both Democratic and Republican corporate speech more than doubles, from ca. 0.3% to 0.7% and from 0.2% to 0.5% of all corporate tweets, respectively. In early 2019, the two lines begin to diverge, with

[5] We plot the two series using alternative posterior cutoffs in Appendix Figure A.1.

Democratic-sounding speech exhibiting a much stronger increase than Republican-sounding speech.

The time-series plot in Panel A displays significant variation around major events. 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 for 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. Many Democratic corporate tweets from this month explicitly refer to voting rights and/or to this law specifically. An example is the following tweet by Salesforce, Inc.:

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

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

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

In the time series of Republican-sounding tweets, we observe fewer pronounced spikes than in the series of Democratic tweets. The month with the largest increase in the percentage of Republican tweets is November 2017. Many of these tweets refer to Veterans Day, which falls on November 11. One such tweet, from Automatic Data Processing, Inc., 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"

Other Republican-sounding tweets in November 2017 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."

We also compute the difference between the two series plotted in Panel A of Figure 2. We define it as the share of Democratic-sounding tweets minus the share of Republican-sounding tweets in a given calendar month and label the resulting variable as the "net Democratic tweet ratio." When we test the hypothesis of two structural breaks in the time series of the net Democratic tweet ratio against the null hypothesis of no breaks using the test by Bai and Perron (1998), we can reject the null hypothesis at the 1% level and obtain January 2019 and December 2020 as the estimated break points. We will investigate a potential reason for for the first break point in January 2019 in Section 5.

In Panel B of Figure 2, we compute the net Democratic tweet ratio at the firm-year level, by taking the difference between the number of Democratic and Republican tweets and then dividing by all tweets sent by the company in a given calendar year. We then regress the net Democratic tweet ratio on calendar year dummies and cluster standard errors at the firm level. Panel B of Figure 2 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. The pattern in Panel B of Figure 2 also implies that the observed increase in partisan tweets in Panel A is not driven by a few companies sending an extremely large number of tweets, because, in Panel B, every firm-year is given equal weight irrespective of the number of tweets sent. In sum, we observe a massive shift in the partisan speech of the average S&P 500 company with an active Twitter account during our sample period.

4.1.1 Firm Heterogeneity

Figure 3 plots the average annual net Democratic tweet ratio separately by the firm's headquarter location (Panel A), the Global Industry Classification Standard (GICS) sector (Panel B), the size of the firm's book assets (Panel C), and CEO party affiliation (Panel D). In Panels A and B, we restrict the sample to states and GICS sectors that contain at least 5% of all observations. The surprising finding from Figure 3 is how pervasive the increase in Democratic-sounding speech is. It occurs across all states (Panel A), with every state experiencing an increase in the net Democratic tweet ratio between 2011 and 2022, including Texas. It also occurs across a broad range of sectors (Panel B), including both consumer-oriented industries, such as "consumer discretionary," and business-oriented industries, such as "industrials" and "materials."[6] The sectors with the highest net Democratic tweet ratios

[6] The large negative value for energy companies in 2011 is driven by these companies commenting negatively on the proposal to repeal tax subsidies for fossil fuels by the Obama administration.

at the end of the sample period are materials and health care. These pattern indicate the increase in partisan speech is unlikely to be solely driven by consumer preferences.

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). It is also present for firms run by both Democratic and Republican CEOs (Panel D), suggesting that the trend may not be driven by CEOs advancing their personal agendas.

How does partisan speech on Twitter vary within industry and geography? To answer this question, we regress the net Democratic tweet ratio measured at the firm-year level on a set of lagged firm characteristics: firm size (measured by the logarithm of total book assets); Tobin's Q (the ratio of the market value to the book value of the firm's assets); an indicator for Democratic CEOs (obtained from Fos et al. (2023) and constructed by linking CEOs to voter registration data provided by L2, Inc.); the percentage of all shares outstanding held by institutional investors as well as by ESG funds (defined as any fund with at least four Morningstar sustainability globes); and the share of the firm's employees located in blue states (constructed using the geographical distribution of employee reviews on glassdoor.com). In columns (1) and (3), we further control for the industry Herfindahl Index (constructed using revenue data and 2-digit SIC codes from Compustat) and an indicator for B2C industries. In column (1), we include year fixed effects, in column (2) industry $\times$ year fixed effects (defined using 2-digit SIC codes), and in column (3) state $\times$ year fixed effects (defined using the firm's headquarter location reported in Compustat).

Table 4, Panel A reports the results. All independent variables are standardized to have a mean of zero and a standard deviation of one. Within industry, the three independent variables with the largest effects on the level of the net Democratic tweet ratio are firm size, the share of employees located in blue states, and ownership by ESG funds (see column (2)). Specifically, one-standard-deviation larger book assets, share of employees in blue states, and ESG ownership correspond to a 0.37 ppt, 0.19 ppt, and 0.15 ppt higher net Democratic tweet ratio, respectively. We further find that Democratic speech is less prevalent in industries with high market concentration and more prevalent in B2C industries (see columns (1) and (3)). Firms run by Democratic CEOs tend to use more Democratic speech, consistent with Di Giuli and Kostovetsky (2014), but this relationship is not statistically significant when we focus on within-state variation (see column (3)).

In Panel B of Table 4, we estimate a cross-sectional regression and use firm characteristics measured at year-end 2018 to predict the change in the firm's Democratic tweet ratio between 2018 and 2022. The variables that consistently predict a stronger increase in Democratic speech across all specifications are firm size and ESG ownership, whereas the industry Herfindahl index and the indicator for B2C industries consistently predict a smaller increase in Democratic speech. The coefficient on ESG holdings in column (2) of Panel B implies that one-standard-deviation higher ESG ownership is associated with a 0.27 ppt larger increase in the net Democratic tweet ratio.

The results in Table 4 are informative because they indicate that catering to the preferences of institutional investors may have played a role in the growth of Democratic-sounding corporate speech. This result is somewhat surprising because shareholders have not been featured very prominently in companies' arguments for speaking up on social and political issues. We return to this issue in Section 5 below. The negative relation with market concentration across both panels and the absence of a relation with the party affiliation of the CEO in Panel B suggests that the phenomenon is unlikely driven by U.S. CEOs advancing their personal political agendas.

4.1.2 Benchmarks and Robustness Tests

In Figure 4, 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 4. 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 4 reveals two important insights. First, in terms of the level of partisan speech, the sender of the average tweet uses very little partisan speech—even less than the average S&P 500 company on Twitter. 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 4, 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 amount 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 Appendix, we provide two important robustness tests. First, Appendix Figure A.1 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, Appendix Figure A.2 plots the time series of partisan corporate 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.

4.1.3 Topics

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. In Appendix Table A.2, we report 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 Appendix Table A.3.

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.

4.1.4 Action Labels

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"*

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

5 The Role of Investor Demand

The growth in Democratic-sounding corporate speech coincided with an explosion of interest in investing along environmental, social and governance (ESG) criteria. Moreover, the results in Table 4 show that ownership by ESG funds positively predicts both the level and, more strongly, the increase in Democratic corporate speech between 2018 and 2022. These patterns raise the question of whether the increase in Democratic-sounding speech, which often focuses on environmental and social issues (see Figure 5, Panel A), could have been a response to a shift in investor preferences and, specifically, the growth of ESG investing. In this section, we explore this possibility. We begin by studying the relationship between flows into ESG funds and firms' net Democratic tweet ratios. Next, we study changes in the partisan slant of corporate speech around the influential letter by Larry Fink, Chairman and CEO of BlackRock, in January 2019, which was by many observers perceived as a paradigm shift due to its explicit call for companies to lead on controversial social and political issues.

5.1 Sustainable Investing and the Partisan Slant of Corporate Speech

The time series reveals a striking correlation between assets managed by funds with a sustainability mandate and the average net Democratic tweet ratio (NDTR) of U.S. firms. Appendix Figure A.4 plots the aggregate assets under management (AUM) of U.S. sustainable funds by year, using information provided by UNCTAD (2021). Interestingly, the explosive increase in assets managed by sustainable funds happens right around the time where corporate speech becomes more Democratic-sounding. Between 2010 and 2020, the correlation between the AUM of sustainable funds and the following year's average net Democratic tweet ratio is above 0.97. We are not aware of studies documenting such a dramatic and sudden shift in the preferences of consumers or employees, which tend to change more slowly.

We also find a strong correlation between ESG fund flows and Democratic slant in the cross-section of firms. To quantify the impact of ESG fund flows, we first calculate a firm-level exposure to ESG fund flows. We proceed in three steps. First, we multiply quarterly dollar flows into mutual funds by the percentage of the fund's total assets held in the stock of firm i at the end of the prior quarter. Second, we classify funds by the number of sustainability globes assigned by Morningstar. Specifically, we group funds with four or five globes ("High sustainability") and those with three or fewer globes ("Low sustainability"). We sum the total firm-level flows across all mutual funds within these two categories. Third, we divide this firm-by-quarter quantity by the firm's market capitalization at the end of the prior quarter and express it in percent. We call the resulting variables "High Sustainability Fund Flows" (HSFF) and "Low Sustainability Fund Flows" (LSFF), respectively.

We then regress the firm's net Democratic tweet ratio (also expressed in percent) between zero and four quarters ahead on the firm-level flows:

$$\mathrm{NDTR}_{i,t+k} = \beta_1 \mathrm{HSFF}_{it} + \beta_2 \mathrm{LSFF}_{it} + \nu_i + \gamma_t. \tag{5.1}$$

In all specifications, we include both firm (ν_i) and quarter (γ_t) fixed effects. The results from this regression are reported in Table 5. We estimate this regression at the quarterly frequency using flows from U.S. equity funds that were assigned a Morningstar sustainability globe rating between mid-2018 and 2021:

Our results imply that flows into stocks from funds with high Morningstar sustainability ratings are associated with a statistically significantly greater Democratic slant one, three, and four quarters in the future. Specifically, flows into sustainable funds equalling one percent of a firm's market capitalization are associated with a 61 basis points higher net Democratic tweet ratio one quarter ahead. The magnitudes vary between 89 and 41 basis points for quarters three and four, respectively. Conversely, flows into funds with lower sustainability rankings are never significantly positively correlated the net Democratic tweet ratio. If anything, flows into funds with lower sustainability ratings are associated with a significantly lower NDTR three quarters ahead.

These results must be interpreted with caution. For instance, omitted variables, such as economy-wide demand for sustainability, could drive both flows into high sustainability funds and firm-level increases in NDTR. We view the above results as consistent with, but not necessarily indicative of, a causal impact of sustainable investing on corporate partisan speech.

5.2 The 2019 Larry Fink Letter

The annual letters to CEOs by BlackRock's Chairman and CEO Larry Fink regularly receive widespread attention in both the popular and financial press. By calling on companies to make "a positive contribution to society," Larry Fink's letter from January 2018 represented a first "inflection point" in the debate over the social responsibility of business and, according to observers, "set off a yearlong conversation among business leaders and policymakers" (The New York Times (2019)). His 2019 letter, titled "Purpose & Profit" and published in January 2019, went even further by more explicitly calling for CEOs to lead on divisive social and political issues. Fink wrote:

> "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 as the world's largest asset manager, Fink's letter provides a suitable empirical setting to test whether a shift in investor demand could have increased the pressure on U.S. companies to speak out on partisan issues. Note also that the January 2019 letter coincides with the earliest breakpoint in the monthly time series of the average net Democratic tweet ratio estimated in Section 4.1. To explore this possibility, Figure 6, Panel A 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 Panel B, 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*. This finding is consistent with the results from Table 4, which shows that total institutional ownership is, if anything, negatively correlated with the change in the net Democratic tweet ratio between 2018 and 2022.

To 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:

$$\text{NDTR}_{it} = \alpha_t + \alpha_i + \text{BRK Holdings}_{i,t-1} + \text{BRK Holdings}_{i,t-1} \times Post_t + \gamma' X_{i,t-1} + \epsilon_{it}, \quad (5.2)$$

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 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 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 industry $\times$ quarter and state $\times$ quarter fixed effects. We estimate Equation (5.2) 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 6, Panel A, 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 0.84 (=0.281×3) ppt higher net Democratic tweet ratio post 2019Q1. Interestingly, firms with high BlackRock ownership exhibited, if anything, less Democratic slant prior to Fink's 2019 letter. Again, this relationship does not hold for firms with high ownership by other institutional investors: those show 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 Figure 6, 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. However, more research is needed to establish a causal link between investor demand and partisan corporate speech.

6 Stock Price Reaction

An important remaining question is what are the stock price implications of partisan corporate speech. Ex-ante, the direction of the stock price response to partisan tweets is not obvious. On one hand, partisan corporate tweets could be a signal of the financial strength of the company, or even causally increase the stock price, e.g., because they increase loyalty towards the firm in the labor market, product market, or financial markets. On the other hand, partisan statements could be made to distract from financial problems, or affect the stock price negatively in a causal manner, e.g., because managers fail to anticipate stakeholders' reaction to the statement.

To shed light on this question, we study cumulative stock returns at both daily and intraday frequencies around partisan corporate tweets. Companies often send out identical or similar tweets on multiple occasions, which could make it challenging to detect a significant stock price reaction. To focus on partisan tweets that are more likely to convey new information, in this part of our analysis we restrict the sample of tweets to the first tweet of a given company on a given topic, estimated using our biterm topic model described above.

We further remove tweet events with multiple partisan tweets by the same firm on the same calendar day. These filters reduce the sample from 45,764 partisan tweets to 10,734 partisan tweets.

The precise time stamps of the tweets allow us to conduct a second-by-second analysis of returns in a 20-minute window around each tweet. Analyzing returns in such a narrow window around the tweet helps rule out that the observed stock price response may be confounded by other events. After conditioning on tweets sent during trading hours with a sufficiently high number of return observations, we obtain a sample of 5,751 partisan tweets. The results from this exercise are displayed in Panels A and B of Figure 7. Panel A plots cumulative returns around all partisan tweets and Panel B around partisan tweets with a high surprise. To construct a measure of surprise, we compute the absolute difference between the tweet's PSI-value and the average PSI-value of the company's tweets during the preceding 36 months. Tweets with a high surprise are those with an absolute difference above the median in a given calendar year. In Panel A, we observe negative returns leading up to the average partisan tweet, but close-to-zero returns following the tweet. When we focus on partisan tweets with high surprise in Panel B, stock prices tend to increase in the first minutes following the tweet, but the effect is economically small and starts to revert towards the end of the event window.

An important limitation of the intraday analysis is that it can only capture a very short-term response by investors. Restricting the window to twenty minutes around the tweet misses the potential effects of announcements that are disseminated to market participants via other channels and then echoed on Twitter some time before or after, or responses from stakeholders that may materialize over the following days. We therefore also study cumulative abnormal returns at daily frequency, using the Fama and French (1993) and Carhart (1997) 4-factor model to estimate abnormal returns. In addition to conditioning again on the first tweet by a company on a given topic, we also exclude tweets with missing returns during the 21-day event window as well as tweets that coincide with an earnings announcement, leaving us with 9,490 tweets to study.

Figure 7, Panels C and D, plot the cumulative abnormal returns around all partisan tweets (Panel C) and partisan tweets with high surprise (Panel D). We observe again a close-to-zero response on the day of the average partisan corporate tweet (Panel C), as well as on the day of the average partisan tweet with high surprise (Panel D). However, at the daily frequency, we observe negative abnormal returns following the average partisan tweet, reaching almost –20 basis points (bps) on event day 10, statistically significant at the 5% level. Although it remains unclear whether these negative abnormal returns reflect endogenous timing or the causal effect of partisan tweeting, they are nevertheless informative because they indicate that partisan tweets on average tend to be a negative signal for the firm's stock price performance.

The average returns in Figure 7 could mask a substantial degree of heterogeneity. To uncover potential sources of such heterogeneity, we regress abnormal returns around Democratic- and Republican-sounding tweets on the same lagged firm characteristics as in Table 4. The results from these regressions are presented in Table 7, where all independent variables are standardized to have a mean of zero and a standard deviation of one.

The results in Table 4 indicate substantial heterogeneity by the degree of stakeholder alignment with the firm. Cumulative abnormal returns during a (0,+1) window around Democratic-sounding tweets are 6.6 basis points higher for a one-standard deviation increase in ESG holdings, and 7.5 basis points higher for a one-standard deviation increase in the share of employees located in blue states (see column (1)). Importantly, the sign on the coefficients for these two independent variables reverses when we look at Republican-sounding tweets, with the difference in coefficients between columns (1) and (3) being statistically significant at the 1% and 5% level, respectively.

Overall, the evidence from our stock return analysis suggests that the average partisan corporate tweet has not triggered large immediate stock price movements, although we observe substantial heterogeneity in daily returns by the degree of stakeholder alignment with the partisan slant of the tweet. Partisan corporate speech is followed by negative abnormal returns during the subsequent 10 trading days, which could reflect endogenous timing or a delayed negative causal effect of partisan corporate speech. Either way, during our sample period, partisan corporate statements on average seem to have been a negative signal about the company's stock price performance.

7 Conclusion

We apply new techniques in natural language processing to all tweets sent by S&P 500 companies between 2011 and 2022 to identify partisan speech by corporations. Our measure of partisan corporate speech detects instances when corporations use language similar to that of Republican or Democratic politicians on Twitter. We show that the amount of partisan corporate speech on Twitter has increased dramatically in recent years across all sectors and all states. We further show that the increase is disproportionally driven by Democratic-sounding speech; in particular, statements related to climate change as well as diversity, equity, and inclusion.

Additional tests indicate that the increase in Democratic-sounding speech could be related to the growth in sustainable investing. We find a strong correlation between ownership by funds with sustainability mandates and the Democratic slant of corporate speech both in the time series and in the cross-section. Moreover, we observe an increase in Democratic speech among firms with high BlackRock ownership around the time of the influential letter by Larry Fink in January 2019, which called for companies to lead on controversial social and political issues.

Using an event study approach, we document close to zero average returns around the average partisan corporate tweet, although returns vary significantly by degree of stakeholder alignment. Moreover, abnormal returns over the 10 days following the tweet tend to be negative, indicating that partisan tweets may be a negative signal about future stock performance.

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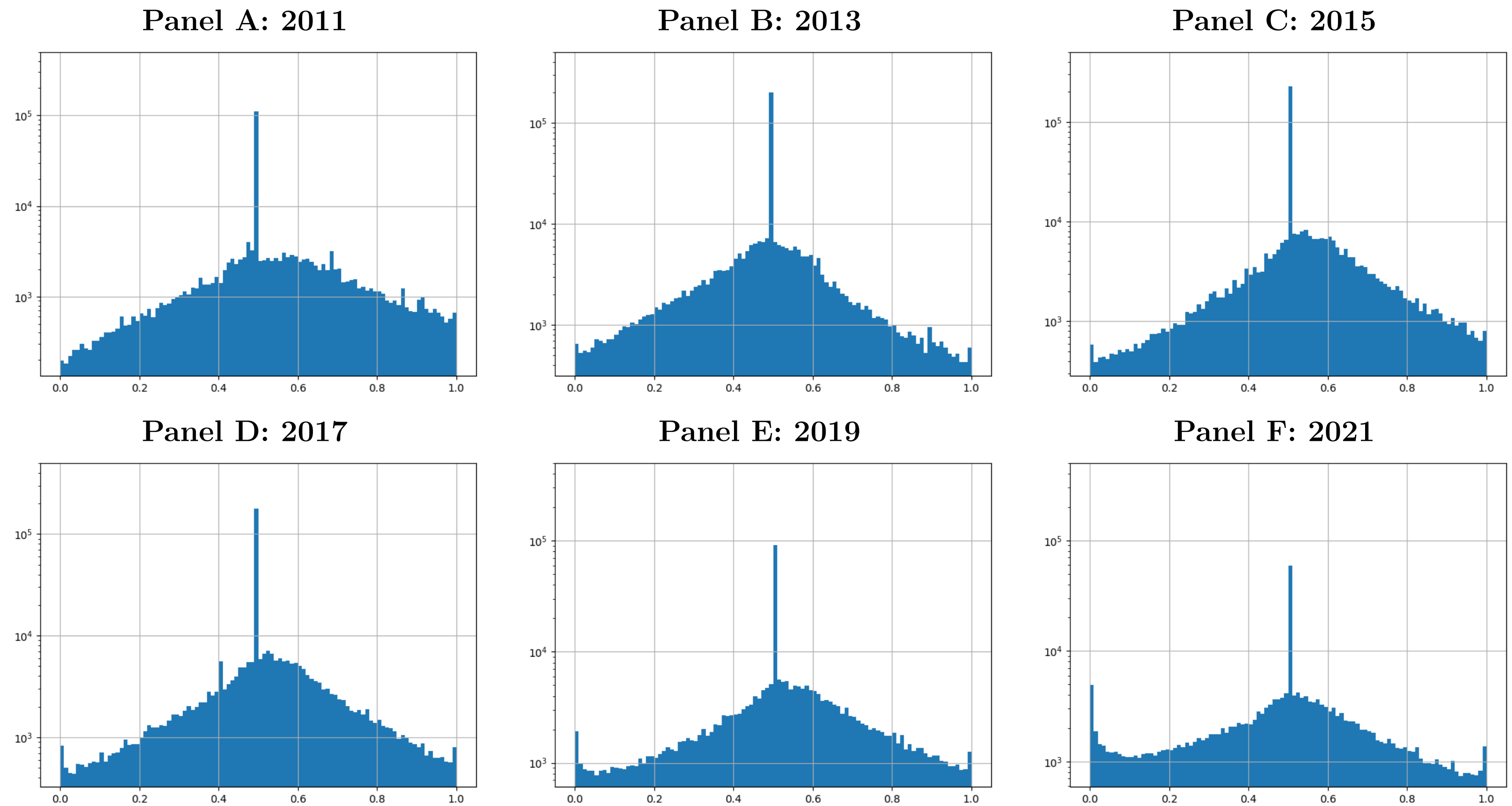
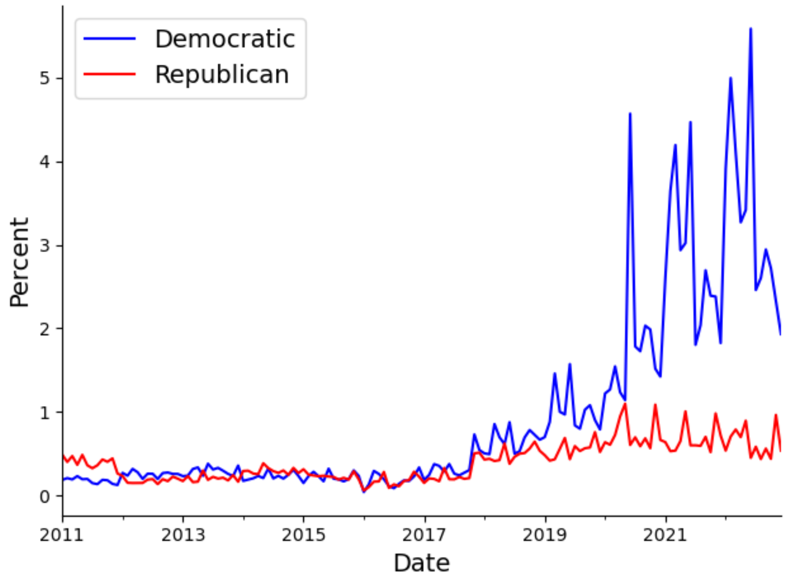
Figure 1
Distribution of PSI-scores for Corporate Tweets



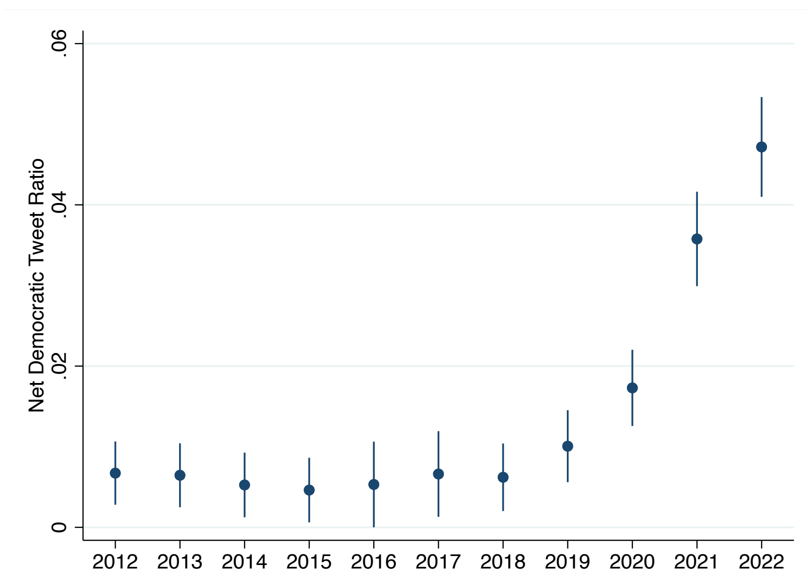
The figure displays the histograms of PSI-scores for corporate tweets sent biannually throughout our sample. A PSI-value near zero uses strongly Democratic-sounding language and a PSI-value near one uses strongly Republican-sounding language. The y-axis shows the logged number of tweets with a PSI-value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

Figure 2
Time Series of Partisan Corporate Tweets

Panel A: Percentage of All Tweets

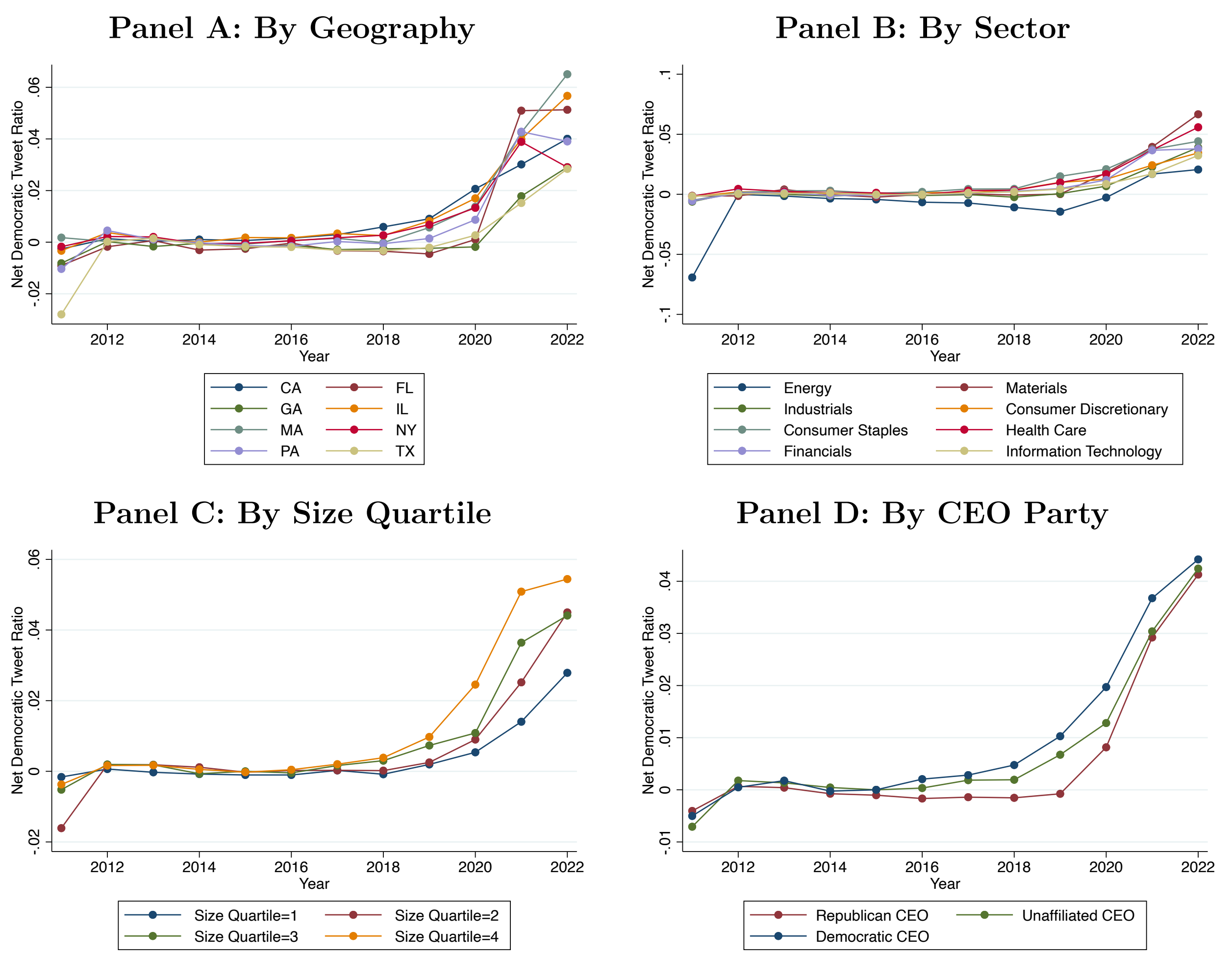


Panel B: Net Democratic Tweet Ratio



Panel A of this figure plots the percentage of partisan tweets by calendar month. The blue (red) line corresponds to Democratic (Republican) partisan tweets. Panel B displays the average net Democratic tweet ratio, defined as the percentage of Democratic tweets minus the percentage of Republican tweets by a company in a given calendar year. In both panels, Democratic (Republican) tweets are tweets with a PSI-value ≤ 0.03 (≥ 0.97), respectively. In Panel B, 95% confidence intervals are based on standard errors clustered at the firm level.

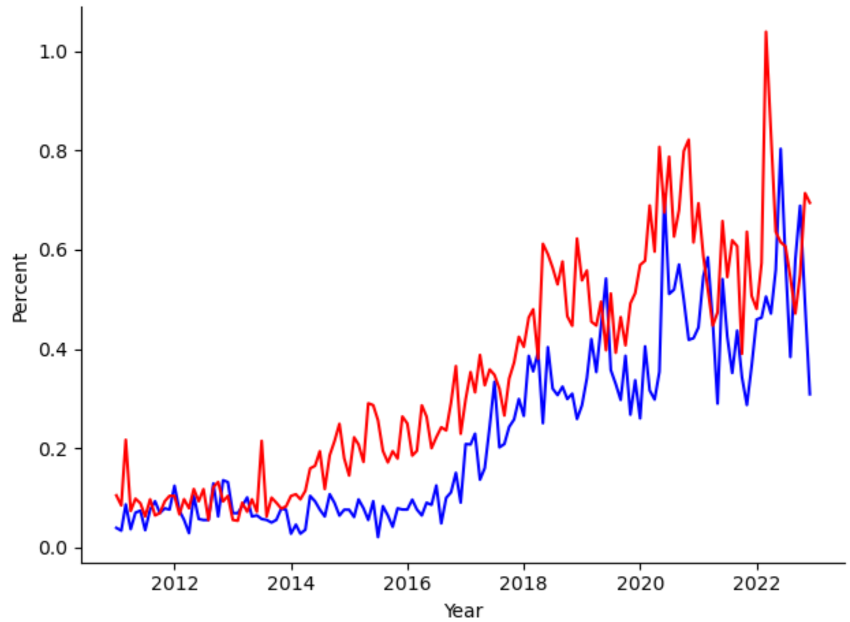
Figure 3
Net Democratic Tweet Ratio by Subsample



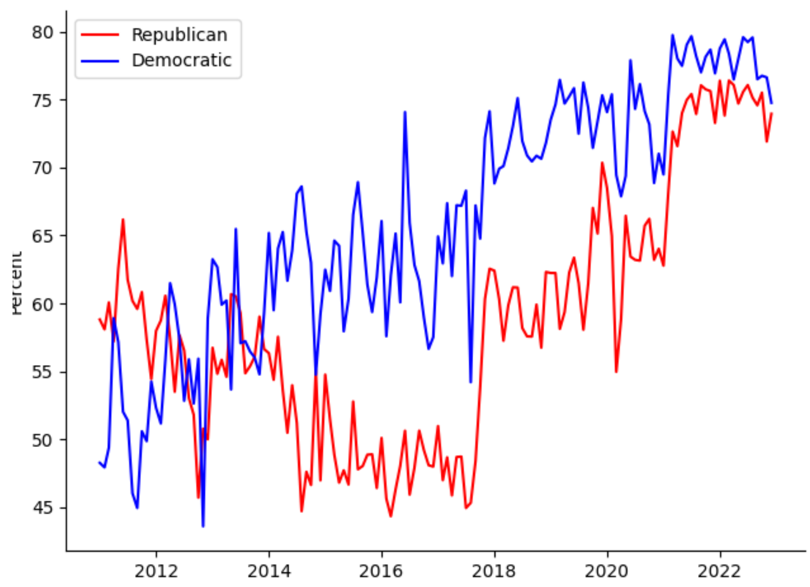
The figure plots the net Democratic tweet ratio, defined as the percentage of Democratic tweets minus the percentage of Republican tweets by a company in a given calendar year, by the state of the firm's headquarters (Panel A), by the firm's GICS sector (Panel B), by the firm's size quartile (Panel C), and by the party affiliation of the CEO (Panel D). Size quartiles are formed based on total book assets within a calendar year. 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. Party affiliations of CEOs are obtained from voter registration records provided by L2, Inc.

Figure 4
Time Series of Partisan Tweets for Other Samples

Panel A: Random Sample

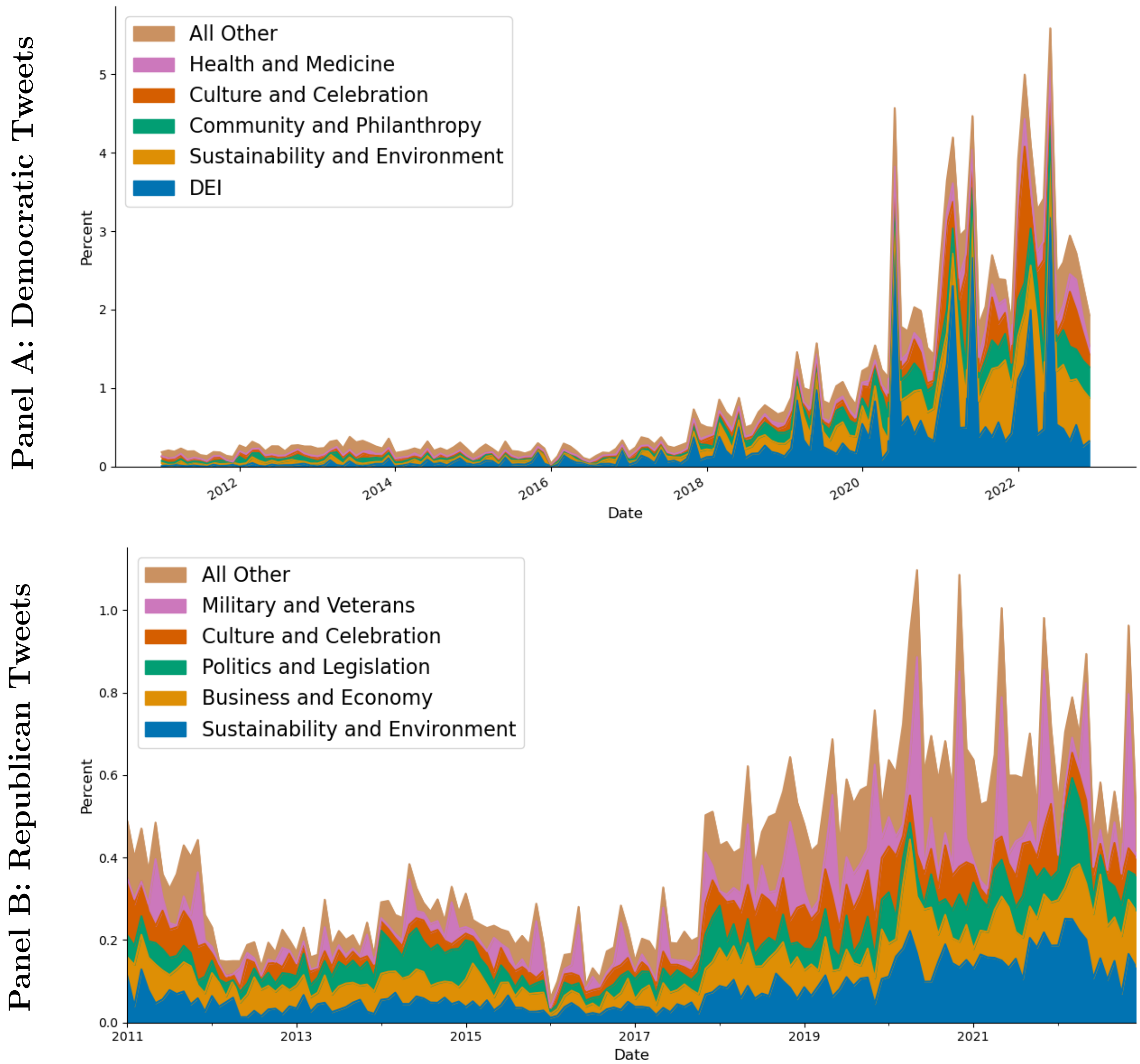


Panel B: Federal Legislators



This figure displays the time series 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.

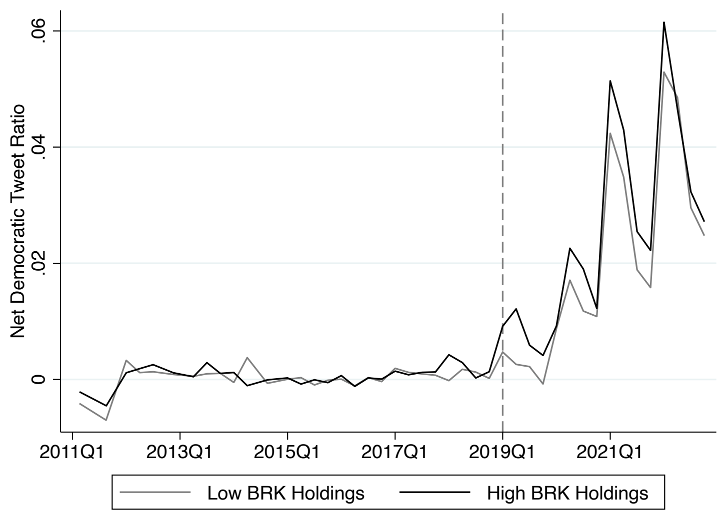
Figure 5
Partisan Corporate Tweets by Time and Meta-Topic



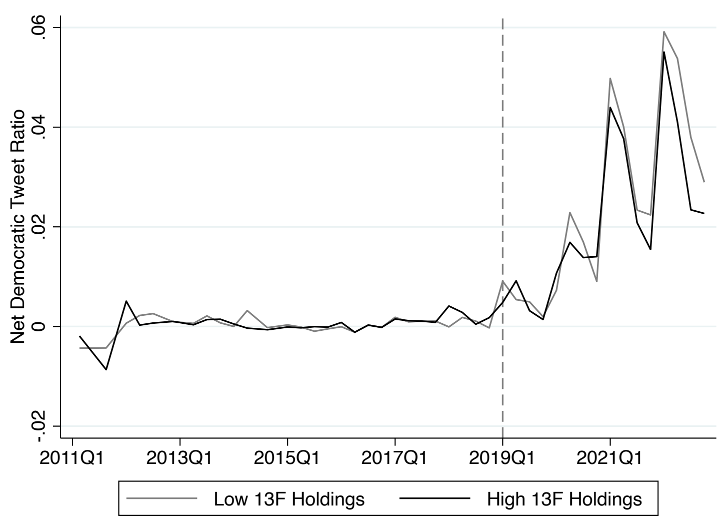
The figure displays the evolution of partisan corporate speech, grouped by meta-topic. Panel A shows the frequency of Democratic tweets broken down by the five most common meta-topics used in Democratic tweets. Panel B does the same for Republican tweets. Democratic tweets are tweets with a PSI-value ≤ 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 the Appendix.

Figure 6
Partisan Corporate Speech and Institutional Ownership

Panel A: By BlackRock Ownership

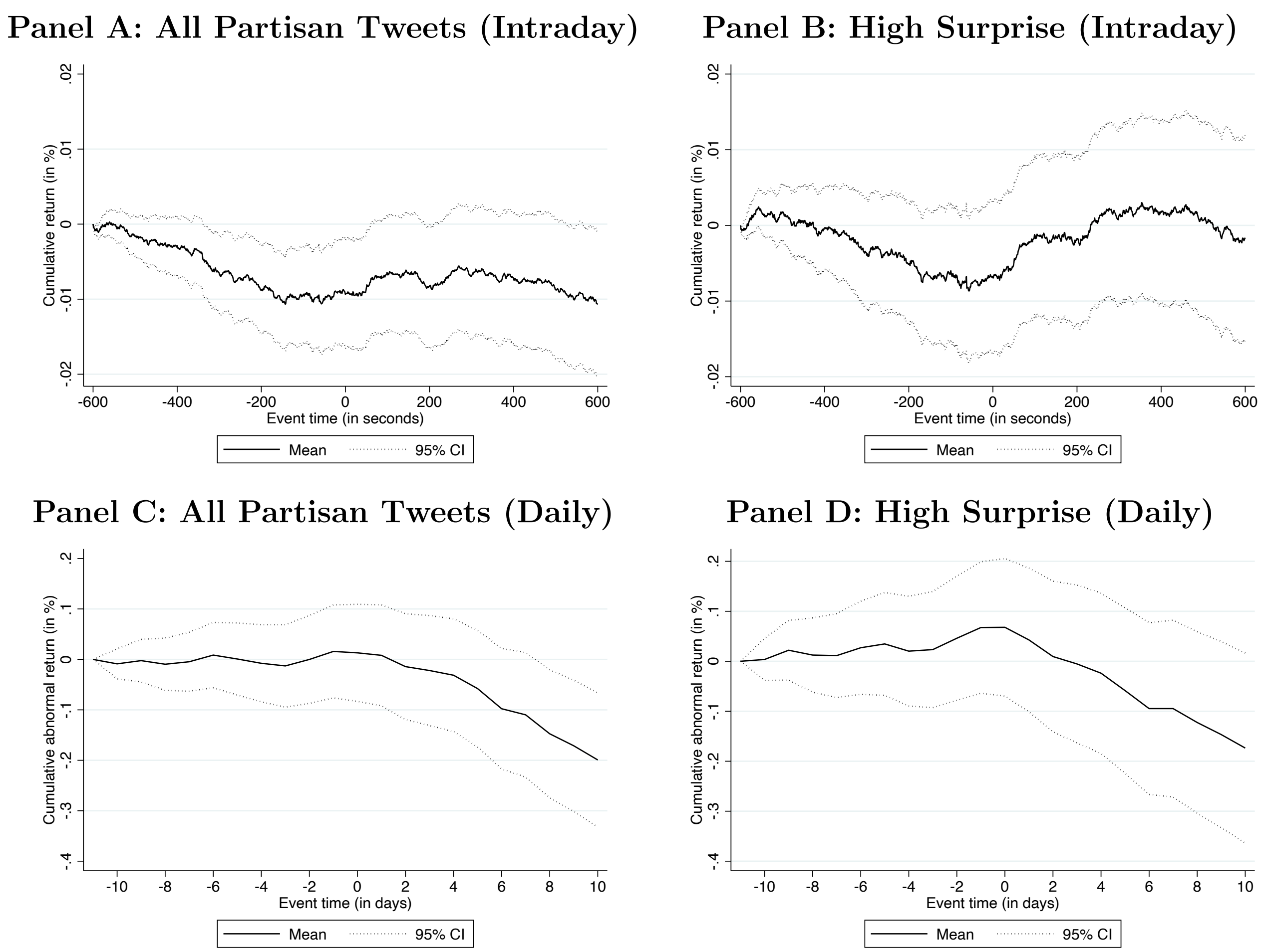


Panel B: By 13F Ownership



Panel A of this figure plots the average net Democratic tweet ratio 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. Panel B plots the average net Democratic tweet ratio for firms with high versus low institutional ownership, sorted within BlackRock ownership quartile. 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.

Figure 7
Stock Returns Around Partisan Corporate Tweets



The figure displays cumulative stock returns at intraday and daily frequencies around partisan corporate tweets. Panels A and B display cumulative stock returns in a twenty-minute window around partisan corporate tweets. The x-axis is measured in event-time seconds and the y-axis is measured in percentage points. Panel A plots intraday returns around all partisan tweets and Panel B around tweets with high surprise, defined by computing the absolute difference between the tweet's PSI-value and the average PSI-value of the company's tweets during the preceding 36 months and splitting the sample at the median within calendar year. Panels C and D plot daily returns for both the full sample and the subsample with high 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. Across all panels, we restrict the sample to the first tweet by a given company on a given topic.

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	124	245	253	246	249	265	300	375	399	452	475	490
Average Tweets Per Firm	3.39	3.76	4.96	4.45	4.27	3.66	4.53	6.14	7.82	10.18	14.9	13.04
Standard Deviation of Tweets Per Firm	4.36	4.41	9.62	8.77	6.63	6.3	7.05	8.64	11.91	16.51	21.81	19.62
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	191	180	211	249	281	273	265	368	358	364	323	258
Average Tweets Per Firm	5.04	3.56	4.13	5.58	3.93	3.28	3.75	4.61	4.7	5.35	5.1	4.6
Standard Deviation of Tweets Per Firm	6.79	8.11	13.37	26.8	8.88	6.41	7.73	7.57	7.69	13.56	18.48	17.74
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

This table shows the ten bigrams most associated with use by Republican or Democratic politicians on Twitter by year, measured by the change in the expected PSI of a congressional speaker if that particular bigram was removed from the corpus of tweets.

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 bigrams that most affect the PSI scores of partisan corporate tweets, measured by the change in the expected PSI score of a corporate tweet if that bigram were dropped from the corpus of corporate tweets. The most important Democratic bigrams would result in the largest *increase* in the expected PSI score and the most Republican bigrams would result in the largest decrease. In this calculation we exclude 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
Heterogeneity in the Partisan Slant of Corporate Speech

The table reports results from OLS regressions of (changes in) the firm's net Democratic tweet ratio on lagged firm characteristics. The net Democratic tweet ratio is defined as the difference in the number of Democratic tweets (PSI-value $\leq$0.03) and the number of Republican tweets (PSI-value $\geq$0.97), divided by the total number of tweets sent by the firm in a given calendar year. In Panel A, the dependent variable is the level of the net Democratic tweet ratio in a given firm-year, measured in percent. In Panel B, the dependent variable is the change in the net Democratic tweet ratio between 2022 and 2018, also measured in percent, and firm characteristics are measured as of year-end 2018. Independent variables are defined in Appendix Table A.1. All independent variables are standardized to have a mean of zero and a standard deviation of one. Standard errors, reported in parentheses, are clustered at the firm level.

Panel A: Net Democratic Tweet Ratio

	Net Democratic Tweet Ratio		
	(1)	(2)	(3)
Log assets	0.258***	0.370***	0.284***
	(0.057)	(0.071)	(0.062)
Tobin's Q	-0.105*	-0.151	-0.130*
	(0.062)	(0.100)	(0.072)
Democratic CEO	0.097**	0.113**	0.085
	(0.048)	(0.053)	(0.052)
IO	-0.063	-0.042	-0.095
	(0.059)	(0.061)	(0.086)
ESG holdings	0.154**	0.150**	0.050
	(0.064)	(0.060)	(0.060)
Employees blue states	0.148**	0.188**	0.206*
	(0.074)	(0.094)	(0.119)
HHI	-0.179***		-0.135***
	(0.046)		(0.049)
B2C industry	0.239***		0.200***
	(0.059)		(0.061)
N	4,877	4,762	4,588
R^2	0.224	0.331	0.273
Year FE	Yes	No	No
Industry × Year FE	No	Yes	No
State × Year FE	No	No	Yes

Continued on next page

Table 4 – Continued

Panel B: Change in the Net Democratic Tweet Ratio 2018–2022

	Δ Net Democratic Tweet Ratio		
	(1)	(2)	(3)
Log assets	0.578*	1.156***	0.747***
	(0.295)	(0.377)	(0.269)
Tobin's Q	-0.179	-0.402	-0.139
	(0.174)	(0.369)	(0.170)
Democratic CEO	0.134	0.290	-0.010
	(0.191)	(0.208)	(0.186)
IO	-0.636	-0.020	-1.081**
	(0.469)	(0.505)	(0.436)
ESG holdings	0.362***	0.274**	0.409***
	(0.138)	(0.137)	(0.146)
Employees blue states	-0.455*	-0.360	-0.009
	(0.269)	(0.303)	(0.375)
HHI	-0.813***		-0.764***
	(0.169)		(0.181)
B2C industry	0.502*		0.428*
	(0.259)		(0.258)
N	424	416	398
R^2	0.072	0.210	0.267
Industry FE	No	Yes	No
State FE	No	No	Yes

Table 5
ESG Fund Flows and the Partisan Slant of Corporate Speech

The table reports results from OLS regressions of the firm's net Democratic tweet ratio, measured in percent k quarters ahead, on fund flows into individual stocks via U.S. equity domestic mutual funds. Fund flows into a stock are calculated as the dollar flows into a given fund muliplied by the lagged percentage of the fund's total net assets invested in that stock. Flows into the stock are then summed over all mutual funds in two sustainability categories. "High Sustainability Fund Flows" corresponds to funds with four and five sustainability globes assigned by Morningstar, and "Low Sustainability Fund Flows" to funds with three or fewer sustainability globes. We then divide the aggregated flows by the market cap of the stock at the end of the prior quarter, and express the resulting object in percent. Standard errors are clustered at the firm level and are reported in parentheses.

	Net Democratic Tweet Ratio t+k				
	0Q	1Q	2Q	3Q	4Q
	(1)	(2)	(3)	(4)	(5)
High Sustainability Fund Flows	0.274	0.612***	0.208	0.891***	0.413*
	(0.194)	(0.196)	(0.216)	(0.206)	(0.218)
Low Sustainability Fund Flows	0.109	-0.103	-0.020	-0.368**	0.102
	(0.134)	(0.153)	(0.156)	(0.154)	(0.144)
Firm FE	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes
N	3,745	3,727	3,702	3,653	3,578
R^2	0.394	0.429	0.429	0.443	0.447

Table 6
Partisan Corporate Speech 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. All other variables are defined in Appendix Table A.1. Standard errors, reported in parentheses, are clustered at the firm level.

	Net Democratic Tweet Ratio		
	(1)	(2)	(3)
BRK Holdings Quartile	-0.254**	-0.111	-0.262*
	(0.119)	(0.096)	(0.140)
Post × BRK Holdings Quartile	0.320**	0.281**	0.336**
	(0.139)	(0.132)	(0.157)
13F Holdings Quartile	0.188*	0.099	0.230**
	(0.103)	(0.113)	(0.110)
Post × 13F Holdings Quartile	-0.333***	-0.237**	-0.430***
	(0.117)	(0.118)	(0.140)
Size Quartile	-0.194	-0.225	-0.170
	(0.294)	(0.273)	(0.296)
Post × Size Quartile	0.462***	0.640***	0.497***
	(0.129)	(0.141)	(0.151)
N	11,737	11,466	11,101
R^2	0.311	0.408	0.355
Firm FE	Yes	Yes	Yes
Quarter FE	Yes	No	No
Industry × Quarter FE	No	Yes	No
State × Quarter FE	No	No	Yes

Table 7
Heterogeneity in Stock Returns Around Partisan Tweets

The table reports results from OLS regressions of daily cumulative abnormal returns, measured in percent, around partisan corporate tweets on firm characteristics. All independent variables are standardized to have a mean of zero and a standard deviation of one and are defined in Appendix Table A.1. Standard errors, reported in parentheses, are clustered at the firm level.

	Cumulative Abnormal Return (in %)					
	Democratic Tweets			Republican Tweets		
	(0,+1)	(0,+2)	(0,+3)	(0,+1)	(0,+2)	(0,+3)
	(1)	(2)	(3)	(4)	(5)	(6)
Log assets	-0.0429	-0.0772*	-0.0814*	-0.0612	-0.0970**	-0.125**
	(-1.31)	(-1.93)	(-1.67)	(-1.59)	(-2.09)	(-2.31)
Tobin's Q	-0.0671**	-0.0888**	-0.0976**	-0.0522	-0.0725	-0.0490
	(-2.02)	(-2.19)	(-2.05)	(-1.10)	(-1.07)	(-0.66)
Democratic CEO	-0.00361	-0.0177	-0.0590	0.00301	-0.0172	-0.0488
	(-0.12)	(-0.46)	(-1.43)	(0.09)	(-0.35)	(-0.90)
IO	-0.0404	-0.0383	-0.0551	0.0946***	0.0392	0.0705
	(-1.33)	(-0.97)	(-1.23)	(2.86)	(0.92)	(1.53)
ESG holdings	0.0659***	0.0604*	0.0698*	-0.0413	-0.0482	-0.0545
	(2.61)	(1.75)	(1.78)	(-1.28)	(-1.08)	(-1.04)
Employees blue states	0.0749**	0.114***	0.118***	-0.00182	0.00264	-0.0180
	(2.31)	(3.00)	(2.86)	(-0.05)	(0.06)	(-0.31)
HHI	-0.0228	-0.0442	-0.0184	-0.0430	-0.0514	-0.0517
	(-0.76)	(-1.15)	(-0.37)	(-1.23)	(-1.01)	(-0.92)
B2C industry	0.0348	0.0749**	0.0580	0.0352	0.0720	0.126**
	(1.32)	(2.17)	(1.38)	(0.91)	(1.47)	(2.22)
N	5,743	5,743	5,743	3,308	3,308	3,308
R^2	0.003	0.004	0.004	0.005	0.003	0.005

A Appendix

Table A.1
Variable Descriptions

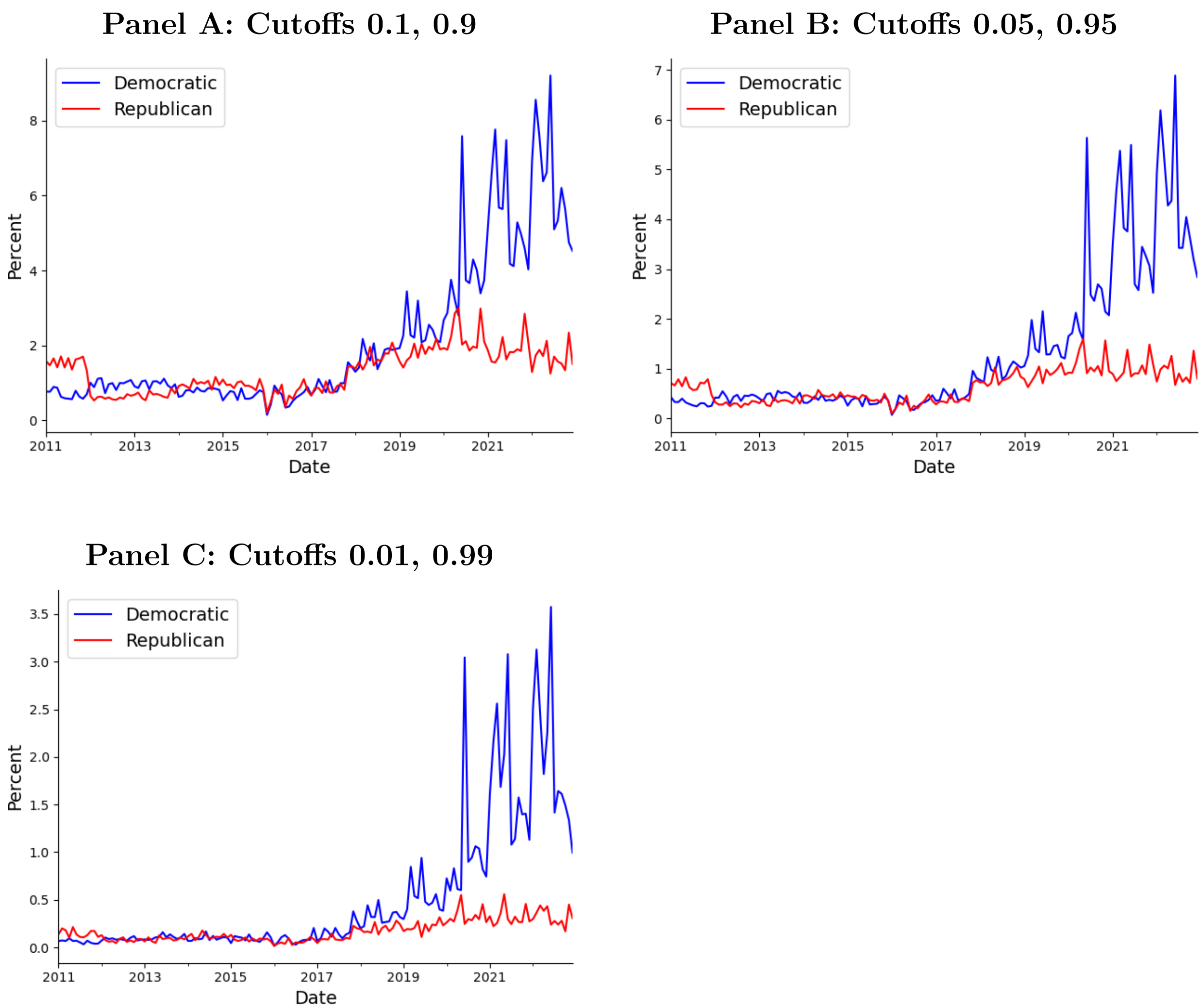
Variable	Description
Dependent variables	
Partisan tweet	Indicator equal to one if the tweet's PSI-value is $\leq$0.03 or $\geq$0.97, and zero otherwise.
Net Democratic tweet ratio ($NDTR$)	The difference in the number of Democratic-sounding tweets and the number of Republican-sounding tweets, divided 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 $+\tau$ around a corporate tweet. Abnormal returns are calculated using the Fama and French (1993) and Carhart (1997) four-factor model estimated over days $t = -300$ to $t = -50$ and requiring a minimum of 100 non-missing observations.
Independent variables	
Log assets	Logarithm of total book assets. Data obtained from Compustat Annual.
Tobin's Q	Ratio of the market to the book value of assets. Data obtained from Compustat Annual.
Democratic CEO	Indicator equal to one if the CEO is affiliated with the Democratic party, zero if she is affiliated with the Republican party, and 0.5 otherwise. Party affiliations are obtained from voter registration records provided by L2, Inc.
IO	Percentage of the firm's outstanding shares owned by institutional investors in the Thomson Reuters 13F database.
ESG holdings	Percentage of the firm's outstanding shares owned by funds with a Morningstar sustainability globe rating $\geq$4. Holdings are obtained from the CRSP Mutual Fund database.
HHI	Herfindahl index computed using the revenue shares of firms within a given 2-digit SIC industry. Data obtained from Compustat Annual.
B2C industry	Indicator equal to one if the firm's 4-digit SIC industry is B2C, and zero otherwise.
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.
Size Quartile	The firm's total book assets, sorted into quartiles within a given calendar quarter. Data obtained from Compustat Annual.

Continued on next page

Table A.1 – continued

Variable	Description
High Sustainability Fund Flows (HSFF)	Flows from high sustainability funds into a stock, calculated as the dollar flows into funds with four or five Morningstar sustainability globes multiplied by the lagged weight of the stock in each fund's portfolio. Stock-level flows are summed across all funds and then divided by the stock's market cap at the end of the previous quarter.
Low Sustainability Fund Flows (LSFF)	Flows from low sustainability funds into a stock, calculated as the dollar flows into funds with three or fewer Morningstar sustainability globes multiplied by the lagged weight of the stock in each fund's portfolio. Stock-level flows are summed across all funds and then divided by the stock's market cap at the end of the previous quarter.

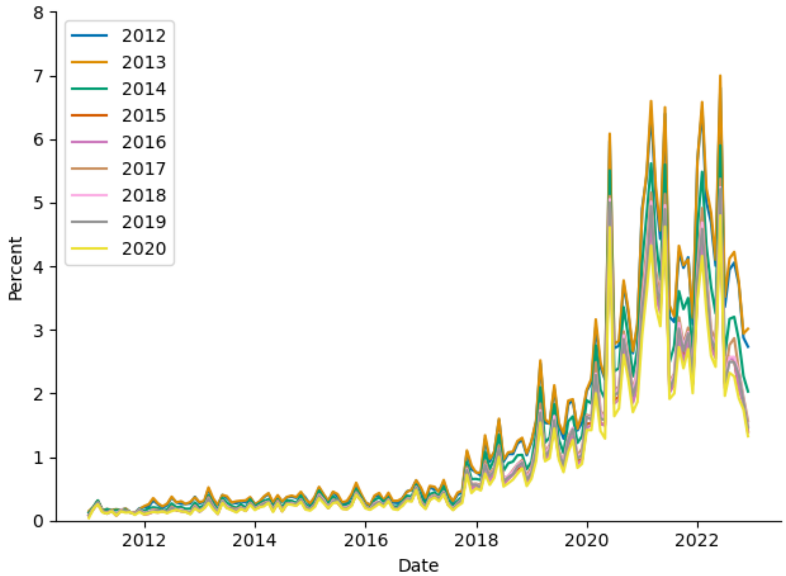
Figure A.1
Threshold Robustness Checks



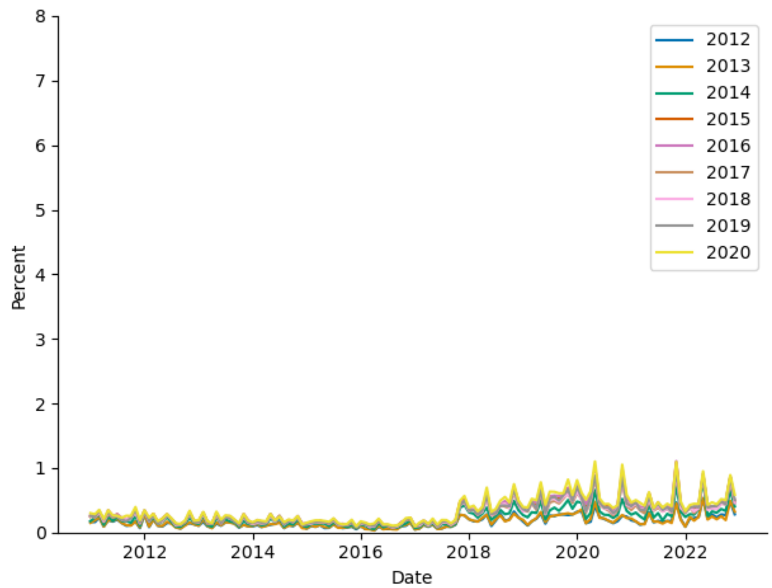
The figure shows the same series as in Figure 2, Panel A, but for different thresholds of PSI-values at which we characterize speech as Democratic or Republican.

Figure A.2
Using Politician Speech from a Single Year

Panel A: Democratic Speech



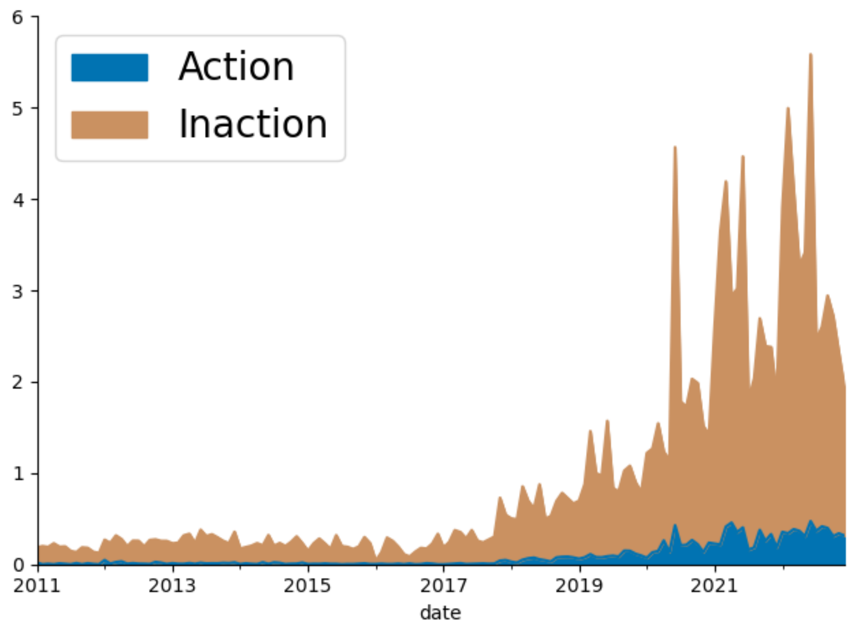
Panel B: Republican Speech



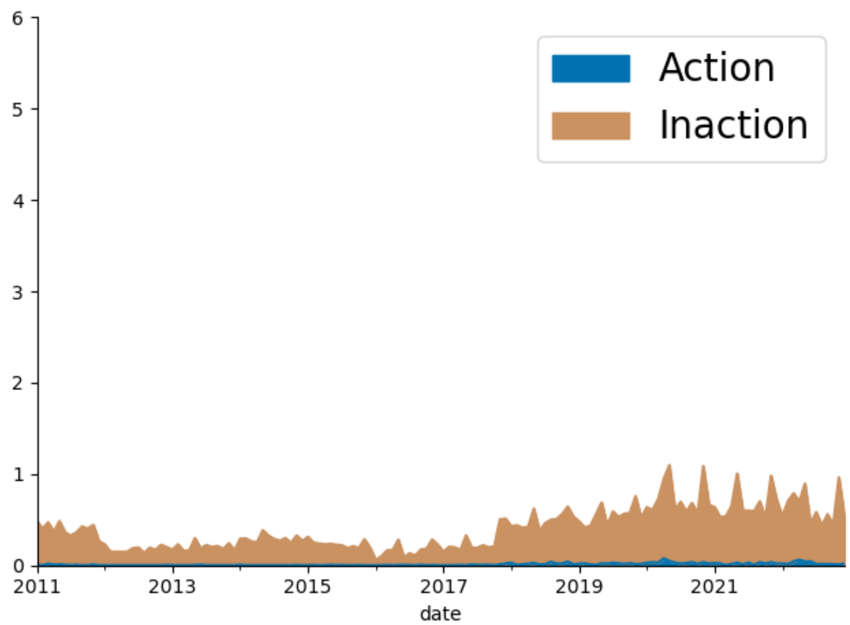
The figure displays the time series of partisan corporate speech using politician speech from only one calendar year at a time in the construction of our PSI. Specifically, we estimate the posterior probabilities for all bigrams sent by Congresspeople in a given calendar year and then apply these year-by-year 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 A.3
Action vs. Non-action Tweets

Panel A: Democratic Tweets

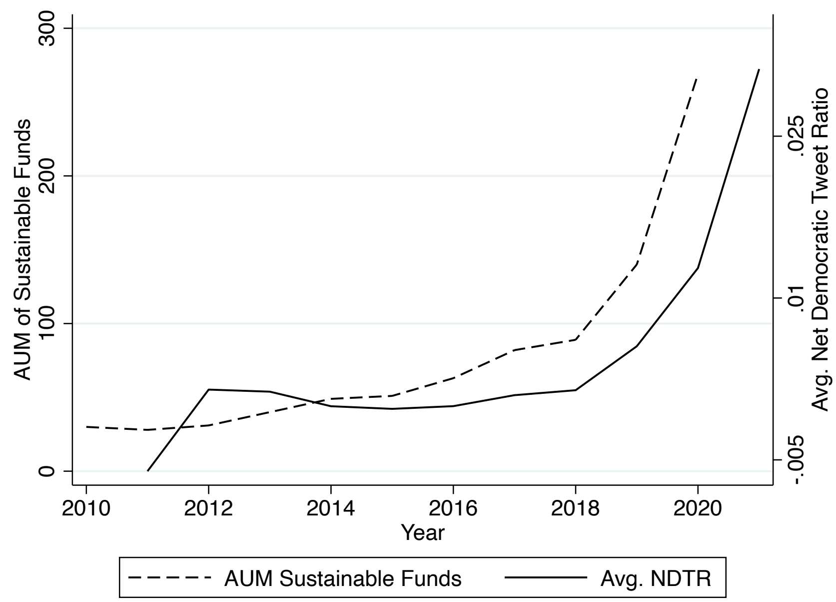


Panel B: Republican Tweets



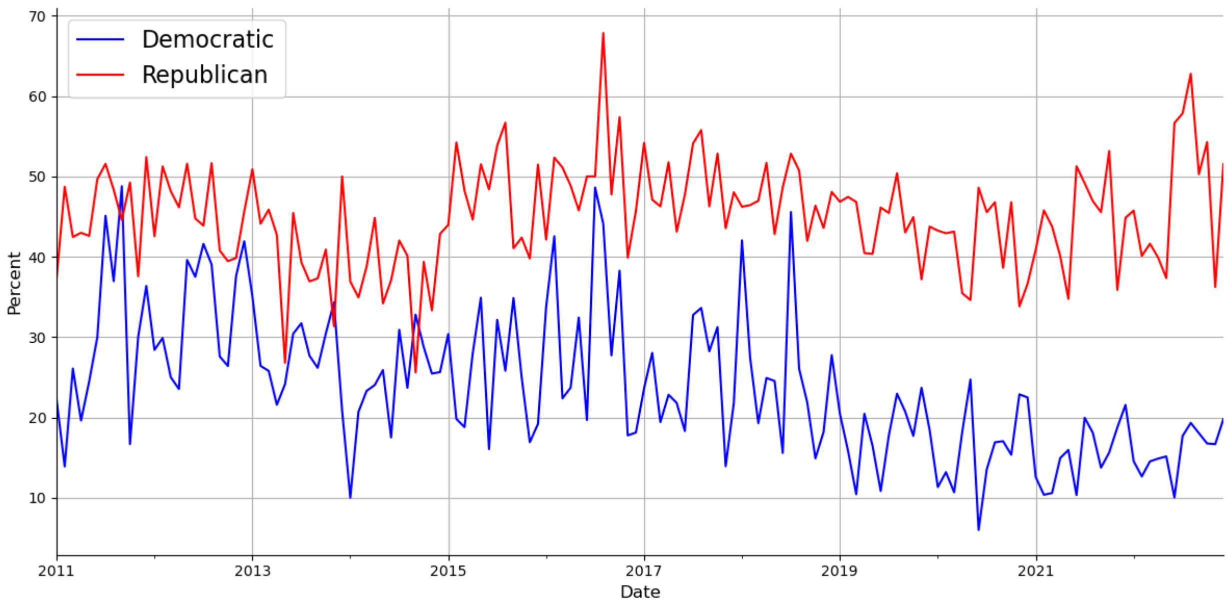
The figure displays the frequency of Republican and Democratic corporate tweets that describe an action (blue) versus those that do not (brown).

Figure A.4
AUM of Sustainable Funds and Corporate Partisan Slant By Year



The figure 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.

Figure A.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 Appendix Table A.2.

Table A.2
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
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	

	Topic Label	5 Most Important Unigrams					Business
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 A.3
Meta-Topic Classification

This table reports the associated meta-topic for each topic listed in Table A.2. 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