An Anatomy of Firms' Political Speech*

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March 22, 2025

Abstract

We study the distribution of political speech across U.S. firms, using large language models to measure political engagement in firms' communications. Our analysis reveals five facts: (1) Political engagement is rare. (2) It is concentrated among large firms. (3) Firms specialize in specific topics and outlets. (4) Large firms engage in a broader set of topics and outlets. (5) The 2020 surge in political engagement was associated with increased engagement by medium-sized firms and a shift in political topics. These findings suggest fixed costs to political engagement and the dominance of large firms' views in the political space.

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The data for this paper were accessed between July 2022 and January 2023 through CIQ (2022), SEC (2022), and Twitter (2022).

1 Introduction

Firms often attempt to influence the design of government policies. These attempts have traditionally taken the form of lobbying or campaign contributions aimed at influencing regulations or industrial policies (e.g., Stigler, 1971; Grossman and Helpman, 1994; Bombardini and Trebbi, 2020, and references therein). Recently, however, firms appear to be increasingly using platforms such as earnings conference calls or social media to engage in political discussions on a broader range of topics, which extend beyond the regulations related to firms' businesses. At a time of high concentration in goods and labor markets (e.g., Philippon, 2019; De Loecker *et al.*, 2020; Manning, 2021; Kwon *et al.*, 2024), understanding which firms loom large in the political landscape becomes especially important.

In this paper we study the distribution of political speech across U.S. firms. We begin by developing a measure of political engagement based on firms' communications. Our baseline measure focuses on earnings calls, during which managers of publicly listed firms hold webcasts or teleconferences to discuss financial results with investors, analysts, and other market participants. The nature of discussions in earnings calls often facilitates more candid and open exchanges (Hassan *et al.*, 2024), making them particularly suitable for studying political engagement. We complement this analysis with the more formal communication found in 10-K filings and the more informal communication found in social media posts on Twitter.

To construct our measure of political engagement, we proceed in two steps. In the first step, we identify statements from firm communications that potentially contain political opinions, using keywords related to 18 political issues that the Pew Research Center has been tracking since 1997. In the second step, we train large language models to determine whether these statements actually contain political opinions. Overall, our resulting data set shows low but rising levels of firm political engagement, with a sharp surge in the year 2020.

Having constructed our new data set, we turn to our main goal of characterizing the distribution of political engagement across firms, through five facts. The first fact is that political engagement is rare: More than 60 percent of the firms do not issue any political statements during the 15 years of our sample, while only 5 percent of firms engage in political speech in more than 20 percent of their earnings calls. Even among firms that engage politically, the persistence of engagement over time is low.

The second fact is that political engagement is concentrated among large firms. We first show that the distribution of political engagement is highly concentrated, with 10 percent of the firms accounting for approximately 40 percent of the total political engagement over this period. We then document that political engagement is more prevalent among large firms, whether measured by assets, sales, or employment. In particular, a one-standard-deviation increase in firm size is associated with about a 0.8-percentage-point increase in the probability of political participation (or 20 percent of the mean of political participation).

The third fact is that firms tend to specialize in specific topics and use specific outlets. In terms of topics, roughly 70 percent of firms engage in a single topic, and only 3 percent of firms engage in more than three topics. In terms of outlets, half of firms that engage politically do so using only one outlet (earning calls, 10-Ks, or Twitter), and only 12 percent of firms use all three outlets.

The fourth fact is that large firms tend to engage in a broader set of topics and outlets. Among firms that engage politically, the smallest 10 percent of firms engage on average in 1.4 topics, while the largest 10 percent of firms engage in 1.8 topics. The corresponding averages for the number of outlets used are 1.4 and 2.1 outlets.

The fifth fact is that the 2020 surge in political engagement was associated with an increase in the engagement of medium-sized firms and a change in the mix of political topics. We show that the largest 10 percent of firms by size account for about 22 percent of all political engagement until 2020, but their share declines to about 17 percent thereafter. This decline is accounted for by the rise in participation of firms between the 10th and the 50th percentile of size. In terms of topics, the surge of political engagement is explained, in large part, by an increasing number of firms that express views about the environment, race relations, health policy, and criminal justice.

Our findings inform theories of firms' participation in political debates. In particular, the fact that political engagement is rare and concentrated among large firms suggests the existence of fixed costs, which also play an important role in the literature on firm dynamics, investment, and participation in international markets (e.g., Hopenhayn, 1992; Caballero and Engel, 1999; Melitz, 2003). In the case of political engagement, these fixed costs could arise if publicly expressing political opinions requires firms to invest in specialists to assess the political views of its customers, employees, or investors. This fixed-cost view is also consistent with the evidence that large firms tend to engage in a wider set of topics and outlets, as studied in the literature on multi-product firms; and with the fact that the 2020 surge in firms' political engagement—arguably a period in which the net benefits of political engagement increased—was associated with a rise in the engagement of medium-sized firms.

What are the broader implications of these findings for society? While we do not take a particular stance on where the political views of firms originate—whether they reflect an attempt to increase the appeal to customers, workers, or investors, or a direct attempt to influence policy and regulation—our findings suggest that those views represented by large firms will be more predominant in the political space. In this sense, firms amplify the views of particular constituencies in a way that differs from more traditional forms of political representation.

Related literature. Our paper is related to four strands of literature. First, we contribute to the long-standing debate on the role of firms in society. A traditional view, often attributed to Friedman (1962) holds that the role the firm is to maximize profits for its shareholders. Especially of late, this view has been challenged by those who maintain that firms should embrace a broader role, integrating social and political issues into their objectives (e.g., Broccardo *et al.*, 2022; Hart and Zingales, 2022). Our contribution to this discussion is to document that political speech is a margin through which large firms engage with society.

Second, we also relate to the emerging literature that analyzes corporate political speech. This literature has also documented a surge in corporate political speech in 2020, and linked it to the political preferences of firms' workers (Barari, 2024; Adrjan *et al.*, 2023), consumers (Conway and Boxell, 2024), and investors (Cassidy and Kempf, 2024; Kempf and Tsoutsoura, 2024).[1] We contribute to this literature by studying how the frequency, topics, and outlets of firm political engagement vary across the firm size distribution. By analyzing the universe of publicly traded firms and all their forms of public communication, we highlight the large

[1] A related literature studies the recent alignment of corporate actions with environmental, social, and governance (ESG) goals (see Gillan *et al.*, 2021, for a review of ESG research in corporate finance).

degree of concentration of speech across firms and the role played by firms that are large in their own markets.

Third, we contribute to the literature studying the role of the distribution of firms in domestic and international markets. Part of this literature focuses on granularity and the importance of large firms. Gabaix (2011) argues that firm-level shocks translate into aggregate fluctuations. Di Giovanni and Levchenko (2012) show that trade openness, by making large firms grow larger, increases the importance of granular shocks. Gaubert and Itskhoki (2021) show that idiosyncratic firm shocks can shape aggregate comparative advantage. Our contribution to this literature is to characterize a new dimension of concentration among firms—political engagement—while emphasizing that political engagement rises with firm size.

Fourth, we contribute to a large and expanding literature that uses textual data to provide new measurements of firms' behavior and characteristics, including financial conditions (Loughran and McDonald, 2011), monetary policy communication (Hansen *et al.*, 2018), political risks (Hassan *et al.*, 2019), geopolitical power dynamics (Clayton *et al.*, 2025), responsible sourcing (Alfaro-Ureña *et al.*, 2022), among many others (see Gentzkow *et al.*, 2019; Ash and Hansen, 2023, for comprehensive reviews). Our contribution is to develop a novel method to measure political engagement in different outlets of firm communication.

2 Data and Measurement

2.1 Data

We measure the prevalence of U.S. firms' political speech across three outlets of communication: earnings conference calls, regulatory filings, and social media posts. Our main analysis uses transcripts of earnings conference calls (hereafter "earnings calls"), in which managers of publicly listed firms hold webcasts or teleconferences to discuss financial results with investors, analysts, and other market participants, typically after the releases of regulatory disclosures. Even though earnings calls are not mandatory, they have become common practice adopted by most firms. According to the 2014 National Investor Relations

Institute survey, 97 percent of publicly traded firms in the U.S. hold earnings calls. Our sample consists of 283,920 earnings calls for 13,472 unique firms between 2008 and 2022, obtained from Capital IQ Transcripts (CIQ, 2022).

The second form of firm communication we study is firms' regulatory filings. Under Regulation S-K, publicly traded firms in the U.S. are required to file Form 10-K annually to disclose audited financial statements and provide comprehensive overviews of firm business conditions. We collect all electronically available Form 10-Ks filed by publicly traded firms in the U.S. between 1996 and 2022. 10-K filings are organized into standardized sections. We focus on the sections with greatest variation in language and therefore least susceptible to boilerplate legal statements and financial reporting: Item 1, which provides an overview of the firm's business; Item 7, which requires firm managers to discuss the firm's financial condition and results of operations; and Items 1A and 7A, which require firm managers to disclose general risk factors and market risk, respectively (Song and Stern, 2020). Our sample consists of 83,674 filings from 14,707 unique firms, obtained from EDGAR (SEC, 2022).

The third form of firm communication we consider is posts made by publicly traded firms on the social media platform Twitter (now X), which facilitates the dissemination of short messages, or "tweets," limited to 280 characters. We identify 3,110 publicly traded firms in the U.S. that have Twitter accounts and collect the complete set of tweets posted by these firms between 2014 and 2022 (Twitter, 2022).

Our main measure uses earnings calls, because the nature of its discussion facilitates more candid and open exchanges (Hassan *et al.*, 2024), making it particularly suitable for measuring political engagement. However, the three forms of communication complement each other as they differ in formality, content, and targeted audience. 10-K filings are regulatory documents designed to disclose comprehensive information to shareholders and regulators, featuring formal and legal language. Earnings calls typically accompany the release of 10-K and 10-Q filings. While firm managers prepare scripted presentations for these calls, the subsequent question-and-answer sessions with investors and analysts elicit more spontaneous interactions. Social media posts, particularly on platforms like Twitter, allow firms to engage informally with investors, customers, and employees.

2.2 Methodology

We develop a method for identifying political engagement and apply it across all three forms of firm communication. Our methodology consists of two steps. First, we identify statements from firm communication that potentially contain political engagement. This is designed to reduce the computational burden in the next step. Then, we classify whether each statement actually contains political engagement, using large language models fine-tuned for this purpose.

2.2.1 Step 1: Identifying candidate statements on political engagement

We begin by using keyword search to identify firm statements that may express political opinions. A key challenge is selecting the right keywords, as firms often use different vocabularies in formal and informal communications. To address this, we begin with a small set of core political terms ("seed words") and then train word2vec models to expand the list. By training separate word2vec models on earnings calls, 10-K filings, and tweets, we capture politics-related language used in each communication outlet. This approach closely relates to Bloom *et al.* (2021), who use word2vec to discover technology-related vocabulary and study the diffusion of disruptive technology.[2]

To construct the seed words, we follow the list of political issues from the American Trends Panel by the Pew Research Center, which has surveyed the political priorities of Americans since 1997. These political issues, detailed in Appendix Table A.1, fall into two categories. The first include 10 recurring issues that have appeared for at least a decade: *crime*, *drug policy*, *education*, *environment*, *health policy*, *immigration*, *military*, *race relations*, *social security*, and *terrorism*. The second include 8 topical issues added to the survey as they come into the spotlight: *abortion*, *criminal justice*, *free speech*, *gun policy*, *LGBTQ*, *political system*, *poor and needy*, and *religion*.

For each political issue, we define a core set of seed words in Appendix Table A.2. Seed words are limited to those most relevant to each political topic to minimize researcher bias.[3]

[2] A proof-of-concept of this step was conducted using NL Analytics, a text analytics tool based on works including Bloom *et al.* (2021) and Hassan *et al.* (2019).

[3] Moreover, Appendix Figure A.1 conducts robustness by dropping seed words one by one and showing that the times series of political engagement remain stable regardless of specific seed words choices.

Next, we expand the keyword set using word2vec (machine learning models that help identify related words based on how they appear in text, Mikolov *et al.*, 2013). This step reduces false negatives by capturing additional political terms. Because firms use different vocabulary across communication outlets, we train separate word2vec models for each type of firm communication. To do so, we extract 3-sentence snippets surrounding seed words and use them as the training samples. Appendix C.1 details the training procedure. Word2vec uses information on both the ordering and the frequency of words to identify political terms closely related to seed words. For instance, "George Floyd" is identified by the trained word2vec as being highly related to "systemic racism" (a seed word under *race relations*) in earnings calls.

Finally, we refine the expanded keyword set to reduce false positives. First, we use only bigrams and trigrams to ensure that the keywords are specific to the intended context. Second, we perform an exhaustive audit to remove keywords unrelated to politics or those with ambiguous meanings (e.g., "carbon dioxide" may relate to climate change but is often used in other contexts).

2.2.2 Step 2: Classifying firm political engagement

Most statements identified through a keyword search do not involve political engagement but rather focus on firm business and political risks. For instance, both statements below contain the keyword "renewable energy" under the political topic of the environment, but only the second statement relates to political engagement:

> *Statement 1*: As I said at the beginning, sustained profitability is our overriding objective. We have built a platform that provides a broad array of energy efficiency and **renewable energy** solutions for a diversified base of clients to deliver sustainable profitability. The power of this platform is now becoming evident in our financials. (Electric City, 2011Q1 earnings call)
>
> *Statement 2*: Some heavily funded investors from California were driving this to try to get what they think is important for this state, and that's the constitutional amendment for renewable energy. So it tends to be—we like to refer to it as

hedge funds in California who want to capture our Constitution and turn it into **renewable energy** for their benefit. So they haven't destroyed the California economy enough? (CMS Energy, 2012Q4 earnings call)

Whether a statement contains political engagement depends on the context in which keywords are used, rather than on the mere occurrence of keywords. To classify political speech, we leverage recent developments in large language models: BERT (Bidirectional Encoder Representations from Transformer, Devlin *et al.*, 2018) and GPT (Generative Pre-trained Transformer, Achiam *et al.*, 2023). Unlike earlier models that assign a fixed embedding vector for each word, these recent models use a neural network architecture known as the transformer to generate word embeddings that are influenced by surrounding words—differentiating, for instance, "renewable energy" in the first statement as business-related and in the second statement as politics-related.

BERT and GPT each have advantages: BERT is bidirectional, using both preceding and subsequent texts to generate accurate embeddings. GPT is trained on almost the entire internet. However, it is sequential and only uses preceding texts, and it remains proprietary.

Therefore, we use both models: Our main measure is based on BERT because of its transparency and reproducibility (Dell, 2024). BERT is open-source, which allows us to fine-tune it for classifying political speech. At the same time, we conduct robustness using GPT, which allows us to compare political engagement across communication outlets.

Model 1: BERT. BERT only requires a small fine-tuning sample to achieve high classification accuracy, thanks to the large amount of training data and its attention mechanism (Devlin *et al.*, 2018). Our training sample consists of 3,500 statements drawn from those identified through the keyword search in Step 1, balanced across industries and political topics. Each statement is annotated by two coders, who were provided with the firm's industry and the criteria for classifying political opinions: "In this statement, a firm is expressing a statement about current political or social events." In cases of disagreement, a third coder reads the statement to break the tie. To ensure that our findings are not influenced by the size of the training sample or annotator bias, we compare our baseline results to GPT-based measure (described below).

Appendix C.2 details the fine-tuning procedure. We start with the uncased and base version of BERT with 110 million parameters, obtained through the platform Hugging Face, and train it with our labeled sample of firm statements. To avoid overfitting, we follow the procedure in Hansen *et al.* (2023) to choose the hyperparameters used in the process.

We use the fine-tuned BERT to classify whether each of the firm statements from Step 1 contains political speech or not. To ensure the accuracy of the measure, we classify a statement as political only if the model assigns it a probability greater than 95%. Additionally, statements where the main topic discussed coincides with a firm's business description in Compustat is excluded, to differentiate political engagement from political risk exposure.

Model 2: GPT. GPT is a generative large language model trained on a large corpus of internet and digitized text (Achiam *et al.*, 2023). To classify whether a statement is political engagement, we query GPT-4o mini under a zero-shot learning setting, using the prompt: "Your task is to classify whether a statement from a company's <earnings call/annual report/tweet> contains political or social statements. Respond with 1 if the statement contains political or social statements; and respond with 0 if the statement does not contain political or social statements. Only respond with 1 or 0."

Model performance. Appendix Table A.3 reports the performance of each model based on a test sample of 377 statements (15 percent of the labeled sample). The baseline BERT model has an accuracy of 86 percent and F1 score of 0.89, vastly outperforming a dictionary-based method. SEC-BERT (Loukas *et al.*, 2022), a version of BERT pre-trained on the specialized language of SEC filings, does not lead to a performance improvement. The next row in the table shows that fine tuning BERT with our human-labeled training data leads to a 83 percentage point accuracy improvement compared to a training data where all statements are labeled as nonpolitical, demonstrating the importance of the fine tuning. Finally, compared to GPT, BERT is superior in identifying political speech (89 percent vs. 17 percent), but GPT is better at identifying nonpolitical speech (99 percent vs. 85 percent).

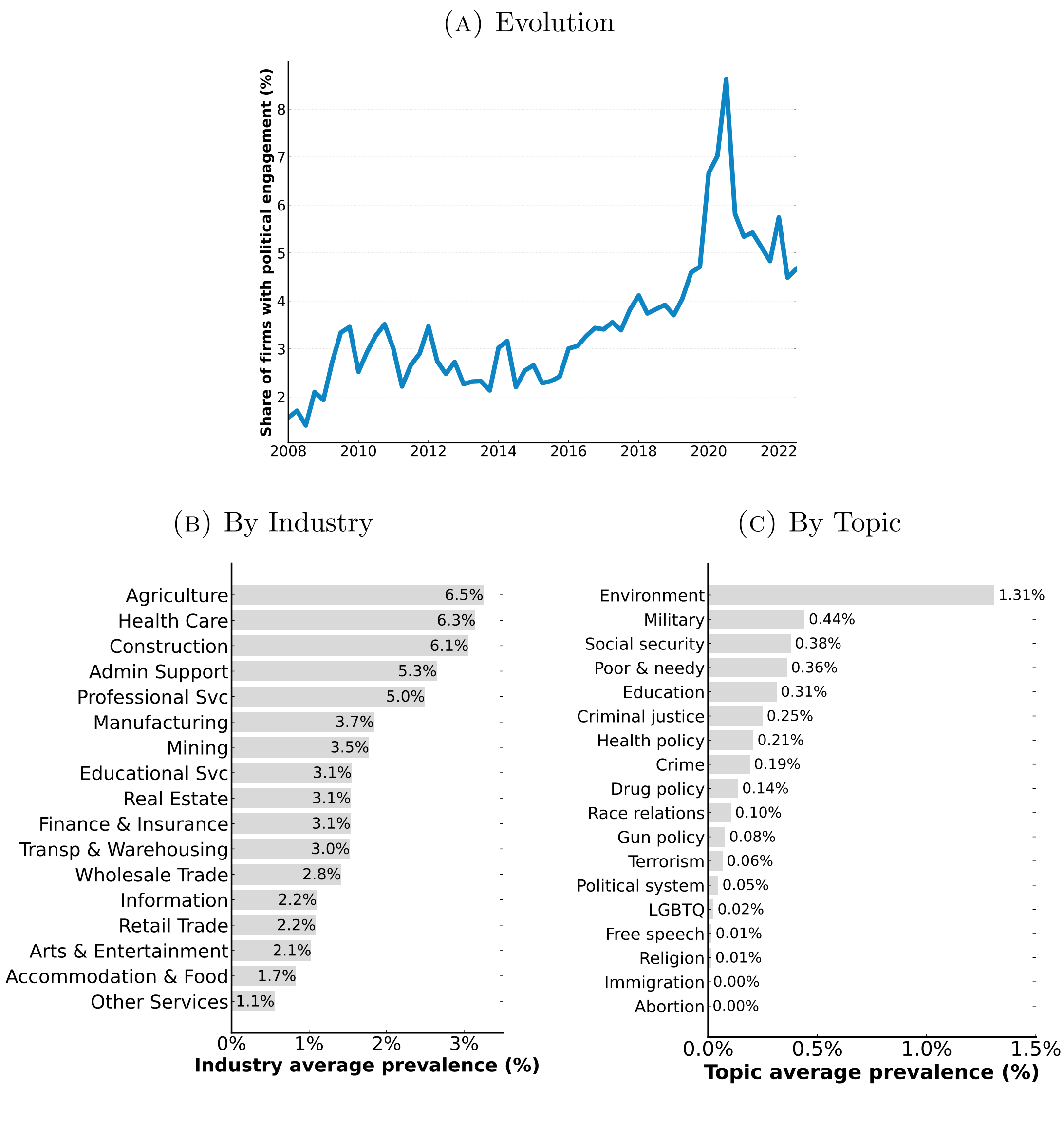
2.3 Aggregate patterns

Before characterizing the distribution of political engagement across firms, which is the main goal of our paper, we first use our new data set to document three aggregate patterns. Panel (A) of Figure 1 reports the average frequency of political engagement, measured by the share of firms that made political statements in their quarterly earnings calls between 2008 and 2022. Before 2016, the average frequency was relatively stable, hovering around 3 percent. Starting in 2016, the frequency of engagement gradually increased. In the summer of 2020—coinciding with the George Floyd protests and the COVID-19 pandemic and lockdowns—the frequency of engagement increased sharply, reaching an average of 9 percent. While it fell quickly thereafter, participation remained higher than during the earlier part of the sample, stabilizing at about 5 percent.

Appendix Figure A.2 reports the average frequency of political engagement using different measurement methods and across communication outlets. Panel (A) shows that the times series measured by GPT closely resembles that of BERT. Panel (B) uses the GPT measure to compare political engagement across communication outlets. Similar to the earnings calls, political engagement in 10-Ks spiked around 2020 before quickly declining, whereas political engagement in tweets rose throughout the sample.

Panels (B) and (C) of Figure 1 document the large variation in the industries to which participating firms belong and in the topics that firms engage with. Regarding industries, those with the highest average frequency of engagement are agriculture, health care, construction, and administrative support, while those with the lowest average frequency are arts and entertainment, accommodation and food, and other services. Appendix Figure A.3 accounts for industry size and shows that among firms that engaged politically, industries with highest contribution to political engagement are manufacturing, finance and insurance, and information. Regarding topics, those with the highest average frequency of engagement are *environment*, *military*, *social security*, and *poor and needy*.

Figure 1: The Average Frequency of Political Engagement: Evolution, Industries, and Topics



Notes: Panel (A) reports the share of firms with political engagement over the sample period 2008–2022. Panels (B) and (C) report the share of firms with political engagement in each industry and discussing each political topic, respectively.

3 Political Engagement across the Firm Distribution

In this section, we characterize the distribution of political engagement across firms throughout our entire sample. Section 3.1 focuses on the frequency of engagement, while Section 3.2 studies the topics and outlets of engagement.

3.1 The frequency of political engagement

We begin by documenting two facts about the distribution of political engagement frequency: it is rare and concentrated among large firms.

Fact 1: Political engagement is rare among firms.

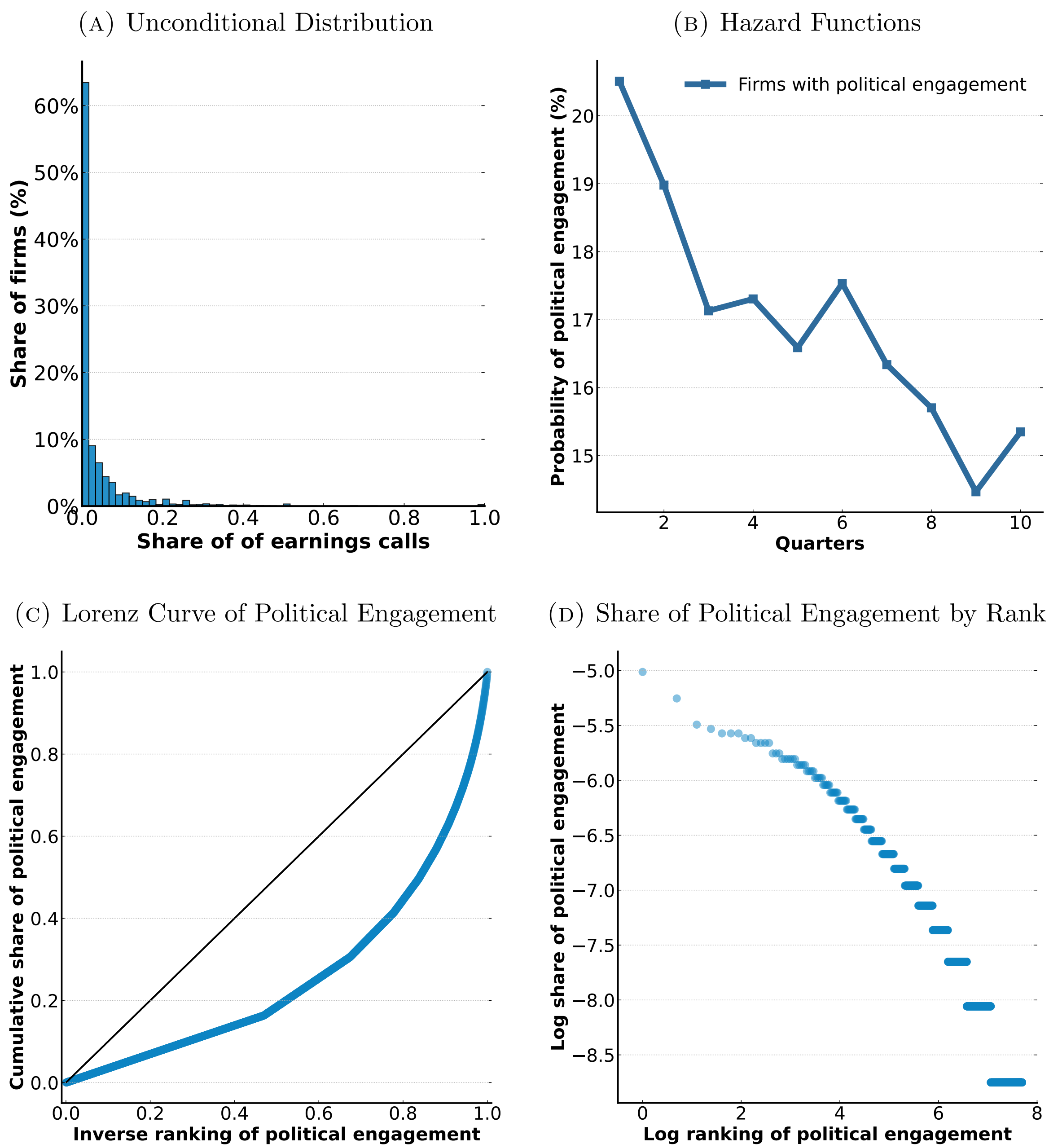
Panel (A) of Figure 2 reports the distribution of engagement frequency. For each firm, we compute the share of earnings calls in which the firm engages politically and then display the distribution of those shares. A key feature that stands out is that political engagement is rare. More than 60 percent of firms do not issue any political statements during the 15 years of our sample, while 5 percent of firms engage in political speech in more than 20 percent of their earnings calls.

Appendix Table A.4 shows that this result holds in both pre-2020 and post-2020 and when using GPT instead of BERT to classify political engagement (although in this case, we detect more engagement, with 48 percent of firms not issuing political statements). Appendix Table A.4 also shows that engagement is rare in 10-K filings and on Twitter, with 57 and 65 percent of firms not issuing political statements in these outlets.[4]

Complementing our findings about the unconditional distribution, Panel (B) of Figure 2 depicts the hazard function of political engagement, after having issued a political statement. The figure shows that the persistence of political engagement is low. Only 20 percent of firms that have engaged in a given quarter engage again in the following quarter. The share falls steadily, reaching 15 percent 10 quarters after having engaged.

[4]We calculate the share of political engagement on Twitter among firms with a Twitter account between 2014 and 2022. However, 50 percent of firms in our sample did not have a Twitter account during that time.

Figure 2: The Distribution and Concentration of Political Engagement



Notes: Panel (A) is a histogram of the average fraction of earnings calls that contain political engagement over the sample period of 2008–2022. Panel (B) reports the probability of subsequent earnings calls containing political engagement for firms that have engaged politically with no missing earnings calls in the sample. The bottom panel ranks a firm by its political engagement share, measured as the number of its earnings calls with political engagement as a share of total firm-quarter pairs containing political engagement among all firms in the sample period 2008–2022. Panel (C) plots the cumulative share of political engagement against firms inversely ranked by political engagement share. We invert the ranking in this panel to be consistent with the convention of Lorenz curves, so that the leftmost points correspond to least politically engaged firms. Panel (D) reports the scatter plot of a firm's log political engagement share against its log ranking of political engagement for all sample firms.

Fact 2: Political engagement is concentrated among large firms.

A counterpart to the infrequency of political engagement is its concentration. To study the concentration of political engagement, we define the total amount of participation as the total number of quarter-firms that feature firm political engagement, summed across all periods and firms. We then compute each firm's engagement share as the number of its earnings calls with political engagement out of this total. Panel (A) of Figure 2 shows the Lorenz curve corresponding to these firm-level shares and indicates that the most engaged firms account for a disproportionate share of total engagement. For instance, the top 10 percent of firms, ranked by engagement shares, account for 40 percent of total engagement.

Panel (B) of Figure 2 reports the scatter plot of the rank-size relation. Following the firm granularity literature, we use this relation to study the top of the distribution. Complementing this figure, Appendix Table A.5 shows that, using the approach in Eaton *et al.* (2011), the distribution exhibits a fat right tail: the slope for the top 1 percent of firms is -0.2.[5] As another metric of concentration, consider the collective share of mentions of the top 50 most engaged firms, which is 15 percent, while that of the top 100 most engaged firms is 24 percent.[6] We conclude that political engagement is highly concentrated among firms, and to an extent comparable, at least, to concentration in output markets.

Given the high concentration of political engagement, it is natural to ask what types of firms participate the most. We now document that political engagement is concentrated among large firms. Appendix Figure A.4 presents binned scatter plots depicting the relationship between political engagement and firm size, measured by log real assets. Panel (A) presents the relationship using the raw data, pooling across firms and quarters. It indicates a positive association between political engagement and firm size. Panel (B) demeans these variables at the 4-digit NAICS sector level (equivalent to using a sector fixed effect in a regression context) and confirms that the relation between political engagement and size also holds within sectors. This relationship is quantitatively significant, showing that the share

[5] Appendix Table A.5 reports that the coefficients are -0.32 and -0.4 when we run the regressions using the top 5 and top 10 percent of firms. Panel (B) of this table shows that, under this metric, the concentration of engagement is roughly half that of sales for the firms in our sample.

[6] Gabaix (2011) meanwhile, shows that sales of the top 50 largest firms in the US are about 25 percent of GDP.

of firms that engage politically ranges from less than 3.5 percent for firms with the lowest levels of real assets to 5.5 percent for the largest firms.

To document the systematic association between political engagement and firm size, we estimate variants of the following regression:

$$\text{engagement}_{it} = \alpha_s + \alpha_t + \beta \log \text{size}_{it} + \gamma X_{it} + \epsilon_{it}, \tag{1}$$

where engagement_{it} is a dummy variable that takes the value of 1 if firm i engages in period t and 0 otherwise; size_{it} is a measure of size, either real assets, real sales, or employment; X_{it} is a vector of firm-level controls; and α_s and α_t denote sector and time-fixed effects. We two-way cluster standard errors by firm and quarter. In the vector of firm-level controls, we include variables typically used in the corporate finance literature: firm age, leverage, and real sales growth. In addition we control for total firm lobbying (Kim, 2018, at the annual frequency), to control for a firm's general tendency to engage in politics. Appendix B provides a detailed definition of all variables used in the empirical analysis.

Table 1 reports the results from estimating equation (2) and indicates a strong and robust association between political engagement and firm size. In particular, across all model specifications, a one-standard-deviation increase in firm size is associated with approximately a 0.8-percentage-point increase in the probability of political participation (or 20 percent of the mean of political participation), which is statistically significant at the 1 percent level. Among the other variables used as controls in (2), firm age, sales growth, and lobbying do not exhibit a statistically significant relationship with political participation, while leverage shows a negative relationship with political participation that is statistically significant at the 10 percent level.

Appendix Table A.6 shows that the association between political engagement and firm size is observed in both the pre-2020 and post-2020 periods, with a stronger slope in the latter. It also shows that this association is stronger when using GPT to classify political engagement. Finally, it shows that the slope is twice as large for engagement in 10-K filings and on Twitter.

TABLE 1: Political Engagement, Firm Size, and Other Firm-Level Variables

	Share of political engagement (percent)					
	(1)	(2)	(3)	(4)	(5)	(6)
Log real assets	0.841***	0.787***				
	(0.163)	(0.172)				
Log real sales			0.767***	0.759***		
			(0.159)	(0.167)		
Log employment					0.858***	0.802***
					(0.173)	(0.183)
Log age		-0.069		-0.066		-0.130
		(0.109)		(0.109)		(0.113)
Leverage		-0.226*		-0.216*		-0.216*
		(0.117)		(0.117)		(0.123)
Real sales growth		-0.000		-0.000		0.000
		(0.000)		(0.000)		(0.000)
Lobbying		0.103		0.119		0.125
		(0.086)		(0.089)		(0.091)
Observations	162080	144027	159655	143634	153578	136913
R^2	0.036	0.038	0.036	0.038	0.036	0.038
Industry FE	yes	yes	yes	yes	yes	yes
Quarter FE	yes	yes	yes	yes	yes	yes
Double-clustered SE	yes	yes	yes	yes	yes	yes

Notes: This table reports results from estimating variants of

$$\text{engagement}_{it} = \alpha_s + \alpha_t + \beta \log \text{size}_{it} + \gamma X_{it} + \epsilon_{it}, \tag{2}$$

where engagement$_{it}$ is a dummy variable that takes the value of 1 if firm i engages in quarter t and zero otherwise; size$_{it}$ is either real assets, real sales, or employment; X_{it} is a vector of firm-level controls, including firm age, leverage, real sales growth, and lobbying spending; and α_s and α_t denote sector and time fixed effects. All firm variables are standardized across the sample. Standard errors are clustered by firm and quarter. * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$).

3.2 The topics and outlets of political engagement

We now study the distribution of topics and outlets of political engagement. We document that firms tend to specialize in specific topics and outlets and that this specialization is less prevalent among large firms, who tend to engage in a wider range of topics and outlets. We describe each of these facts in more detail next.

Fact 3: Firms tend to specialize in specific topics and outlets.

Panel (A) of Figure 3 reports the number of topics that firms engage in during our sample period. Roughly 70 percent of firms engage in a single topic, and only 3 percent of firms engage in more than three topics. That is, when firms choose to engage, they specialize in a narrow set of topics.[7] Appendix Table A.7 shows that we also find specialization in terms of topics when using GPT to classify political engagement, with only 6 percent of firms engaging in three or more topics.

Panel (B) of Figure 3 shows that firms also specialize in the set of outlets they use for political engagement. In this analysis, we focus on the period from 2014 to 2022, during which, as discussed in Section 2, we have data available on three outlets of political engagement: earnings calls, 10-Ks, and Twitter. As indicated in columns 1, 4, and 7 of Panel (B), half of firms that engage politically do so using only one outlet. 12 percent of firms use all three outlets.

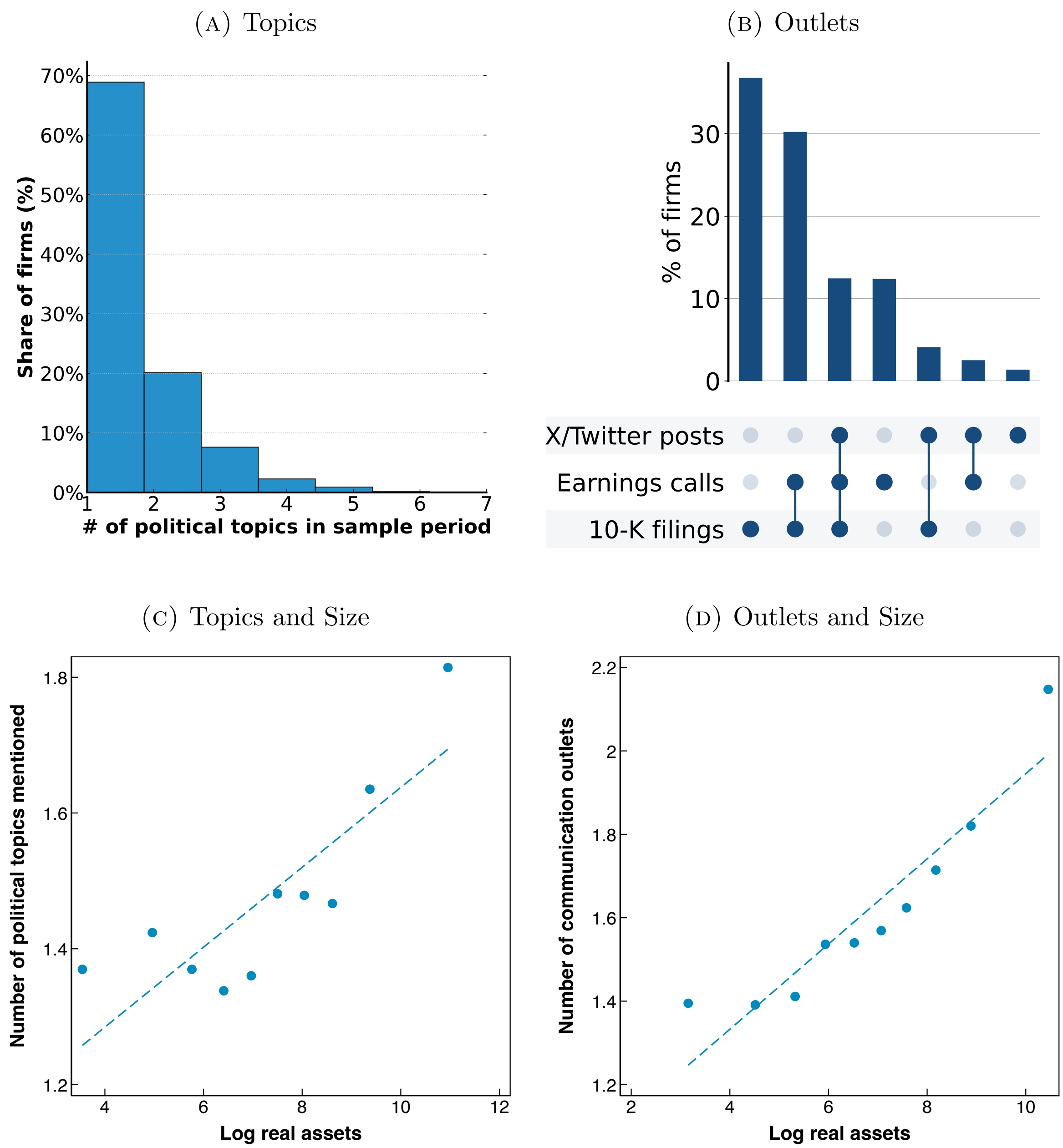
Complementing this finding, Panel (B) of Appendix Figure A.5 shows that this specialization in outlets is also present when we focus on firm-years as the unit of observation. Appendix Table A.7 documents that firms' specialization in political topics varies across different outlets, with greater specialization in 10-K filings (where only 3 percent of firms engage in three or more topics) and less specialization on Twitter (where 17 percent of firms engage in three or more topics). Finally, Appendix Table A.9 shows that this specialization among outlets occurs despite the fact that the probability of engaging politically in earnings calls is associated with a higher probability of engaging in other outlets.

Fact 4: Large firms tend to engage in a wider set of topics and outlets.

The bottom panel of Figure 3 documents how specialization across topics and outlets varies across the firm size distribution. Panel (C) shows that large firms tend to engage in more topics than small firms. We divide firms into size deciles, measured by log real assets, and report the average number of political topics mentioned by firms in each size decile. Among

[7] To complement this finding, Panel (A) of Appendix Figure A.5 reports the distribution of the average number of topics mentioned per earnings call featuring political engagement. The vast majority of these documents (more than 85 percent) involve only one topic. Only 6 percent of these documents involve two or more topics.

Figure 3: Specialization in Topics and Outlets



Notes: Panel (A) is a histogram of the total number of political topics that firms discuss. Panel (B) is a histogram of the combinations of communication outlets that firms use, ranked from the most used to the least used: earnings calls only, 10-Ks only, earnings calls and Twitter, earnings calls and 10-Ks, Twitter only, all three outlets, and 10-Ks and Twitter. Panel (C) reports the binned scatter plot of the number of political topics mentioned by firms that have engaged at least once in the sample period against firm size. Panel (D) reports the binned scatter plot of the number of communication outlets used by firms that have engaged at least once in the sample period against firm size. In both panels, each dot represents a decile of firm size, measured by log real assets.

firms that engage politically, the smallest 10 percent of firms discuss an average of 1.4 topics, while the largest 10 percent of firms discuss an average of 1.8 topics. Appendix Table A.8 presents these results in a regression format, showing that the positive association between the number of political topics and firm size is also present when using GPT to classify political engagement, as well as in 10-K filings and on Twitter.

To further study the relationship between the topics of political engagement and firm size, we estimate a multinomial logit model in which we allow for firm size to have different effects on the likelihood of choosing each topic. Appendix Figure A.6 presents the results, showing that large firms tend to engage in the same topics as the average firm.

Panel (D) of Figure 3 shows that large firms tend to use more outlets for political engagement than small firms do. Among firms that engage politically, the smallest 10 percent of firms use, on average, 1.4 outlets, while the largest 10 percent of firms use 2.1 outlets. To complement this analysis, Appendix Table A.9 estimates a linear probability model to understand the joint distribution of engagement across outlets. The results indicate that firms that engage in earnings calls are more likely to also engage in 10-Ks and tweets and that large firms are more likely to engage in both 10-Ks and tweets.

4 Accounting for the Surge of Political Engagement

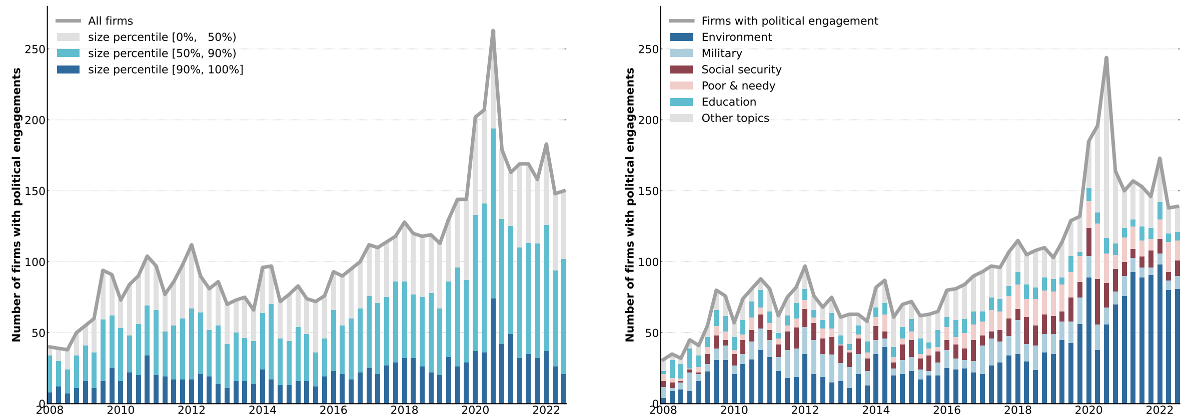
So far, our analysis has concentrated on characterizing the distribution of political engagement across firms throughout our entire sample. We now focus on studying how the distribution of engagement changed during the surge of political engagement documented in Section 2.3, which occurred in the summer of 2020. We summarize our findings as follows:

Fact 5: The 2020 surge in political engagement was associated with an increase in the engagement of medium-sized firms and a change in the mix of political topics.

Panel (A) of Figure 4 illustrates the role of firm size in the surge of political engagement. In this figure, we compute the share of the total number of firms engaging (solid line) that is accounted for by three groups of the firm-size distribution within quarters: firms (1) below

FIGURE 4: Accounting for the Surge of Political Engagement

(A) Firm Size (B) Topics



Notes: Panel (A) reports the number of firms in each size bin that engage politically in each quarter. Size bins are calculated using firm size in each quarter. Panel (B) subsets to firms that engage politically and reports the number of firms that engage in a given political topic in each quarter.

the median, (ii) between the 50th and the 90th percentile, and (iii) above the 90th percentile. The figure shows that there has been a shift in the importance of smaller firms in accounting for total overall political engagement, especially in the wake of summer 2020. While the share of total engagement by the largest 10 percent of firms hovered around 22 percent until 2020, it declined to 17 percent by 2022. In contrast, the engagement of the next 40 percent of largest firms has increased—from 40 percent in 2015, to 48 percent in 2020, and finally to 50 percent in 2022. Note that firms in all groups engaged more over time, but the engagement of middle-sized firms grew more, as shown in Appendix Table A.10.

Panel (B) shows the topics in which firms engage over time, plotting separately the top five topics (throughout our entire sample) and grouping the rest in a category called "other topics." Two key patterns emerge. First, over the whole sample, the composition of topics is relatively stable. The top five topics—*environment*, *military*, *social security*, *poor and needy*, and *education*—account for the lion's share of engagement, with a participation rate usually higher than 90 percent. Since 2016, however, there has been a gradual increase in the participation of other topics. This increase was especially salient in 2020. As shown in Appendix Table A.11, among these other topics, the three main topics behind this growth are *race relations*, *health policy*, and *criminal justice*.

5 Conclusions

We have documented new patterns of political engagement among U.S. firms and, in particular, demonstrated that the outsize role that large firms play in goods and labor markets is mirrored in the fact that they account for a large share of political speech. Such speech may reflect profit-maximizing firms trying to reach more consumers or it may reflect firms adopting a broad, "stakeholder" view of their operations. We do not take a stand on what the explanation is. While the speech patterns we document here are in line with the U.S. legal tradition of allowing firms to express political views, our findings also suggest additional caution in evaluating the role that large firms play in society.

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Appendix

A Additional Tables and Figures

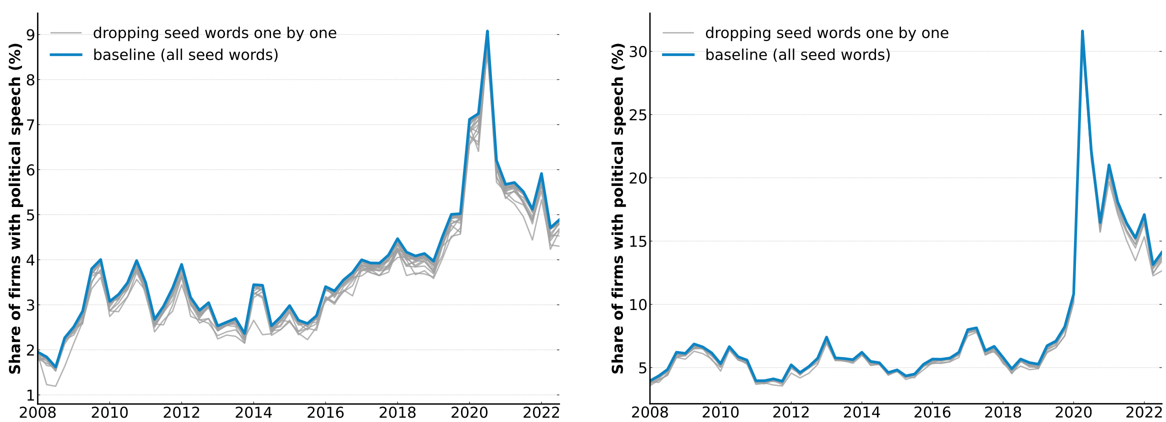
Table A.1: Pew Political Issues

Recurring issues			Topical issues	
Crime	Immigration	~~Budget deficit~~	Abortion	LGBTQ
Drug policy	Military	~~Economy~~	Criminal justice	Political system
Education	Race relations	~~Global trade~~	Free speech	Poor and needy
Environment	Social security	~~Jobs~~	Gun policy	Religion
Health policy	Terrorism			

Notes: This table reports political issues from the American Trends Panel by the Pew Research Center from 1997 to 2022. Recurring issues refer to political issues that have appeared in the survey for at least 10 years, and topical issues are added to the survey as they come into the spotlight. Economy-related issues are removed to focus on purely political topics.

Figure A.1: Varying seed words

(a) BERT Measure (b) GPT Measure



Notes: This figure reports the times series of average political engagement in earnings calls, dropping one seed words at a time from Table A.2. The blue lines represent the baseline measures with all seed words, and the gray lines drop one seed word each.

Table A.2: Seed Words for Political Issues

Political issue	Seed words
abortion	abortion, reproductive rights
crime	crime prevention, juvenile crime, death penalty, death row, capital punishment, gun violence, violent crime
criminal justice	police, criminal justice, black lives matter, capitol riot, defund police
drug policy	marijuana legalization, drug addiction, drug overdose, vaping, opioid epidemic
education	education, student loan, student debt, title ix
environment	climate change, global warming, extreme weather
free speech	free speech, cancel culture, first amendment rights, offensive speech, censorship, misinformation, fake news
gun policy	gun, rifle, gun policy, second amendment, open carry, assault rifle, gun violence, background checks
health policy	health policy, mental health
immigration	immigrant, refugee, immigration policy, immigration enforcement, deportation, daca
lgbtq	lgbtq, diversity equity inclusion, gender identity, transgender, trans rights, gender affirming, pronouns, nonbinary
military	national defense, war iraq, war ukraine, veteran, afghan troops
political system	supreme court, separation church state, gerrymandering, democracy, voting rights, electoral college
poor and needy	safety net, universal basic income, homeless, homelessness, poor needy, economic inequalities, income inequality, low income americans
race relations	discrimination, prejudice, systemic racism, national belonging, racism, who black, who white, whiteness, white fragility, white supremacy
religion	religious, religious liberty, religious groups, christian nation, bible
social security	medicare, social security
terrorism	terrorism, terror attacks, terrorist, cyber warfare

Table A.3: Performance of BERT and Alternative Models

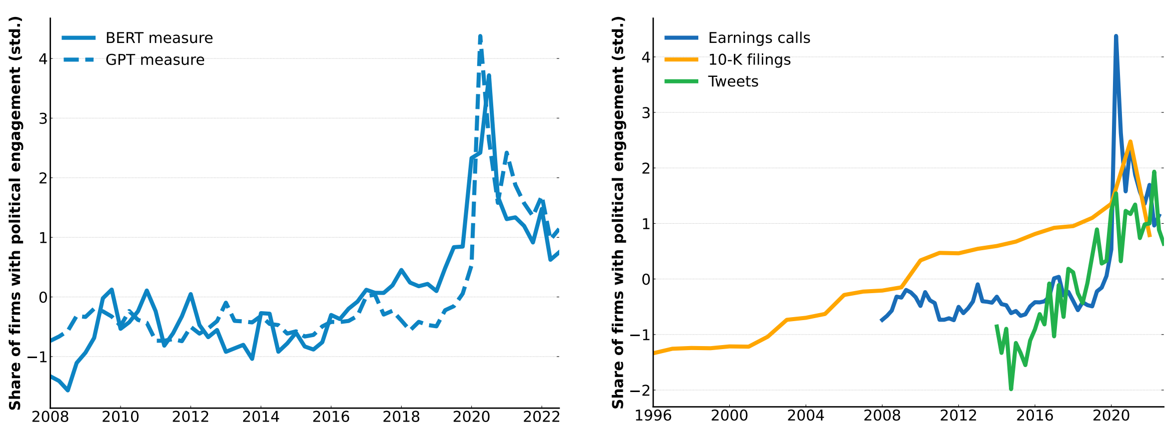
	NLP Model	F1 Score			Accuracy		
		Overall	Recall	Precision	Overall	Nonpolitical	Political
1	Baseline BERT	0.89	0.96	0.86	0.86	0.85	0.89
2	Dictionary	0.00	0.00	0.05	0.05	0.00	1.00
3	SEC-BERT	0.88	0.95	0.84	0.84	0.85	0.83
4	All zeros	0.92	0.90	0.95	0.95	1.00	0.00
5	GPT-4	0.94	0.93	0.95	0.95	0.99	0.17

Notes: This table reports the performance of natural language models detailed in Section C.3 in classifying political engagement. In this table, TP, FP, TN, FN, and n denote, respectively, true positives (correctly classified political statements), false positives (nonpolitical statements incorrectly classified as political), true negatives (correctly classified nonpolitical statements), false negatives (political statements incorrectly classified as nonpolitical), and the total number of statements from the test sample based on model classification. Recall is computed as $\text{TP}/(\text{TP}+\text{FN})$; precision is computed as $\text{TP}/(\text{TP}+\text{FP})$; the overall F1 score is computed as $2/(1/\text{Precision}+1/\text{Recall})$; and accuracy is computed as $(\text{TP}+\text{TN})/n$.

Figure A.2: Times Series: All Communication Outlets

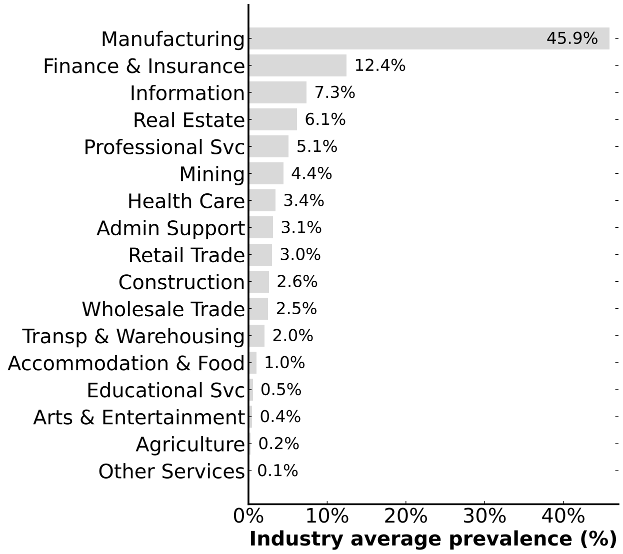
(A) Earnings Calls

(B) All Communication Outlets



Notes: This figure reports the times series of the share of firms with political engagement across different measurement methods and communication outlets. Panel (A) reports the times series of the share of firms with political engagement in earnings calls using the BERT measure (solid line) and GPT measure (dashed line). Panel (B) reports the times series of the share of firms with political engagement under the GPT measure in earnings calls (blue line), 10-K filings (yellow line), and tweets (green line). All series are standardized.

Figure A.3: Contribution to Political Engagement by Industry



Notes: This figure reports each industry's political engagement as a share of total political engagement, conditional on firms with political engagement.

Table A.4: The Distribution of Engagement Frequency

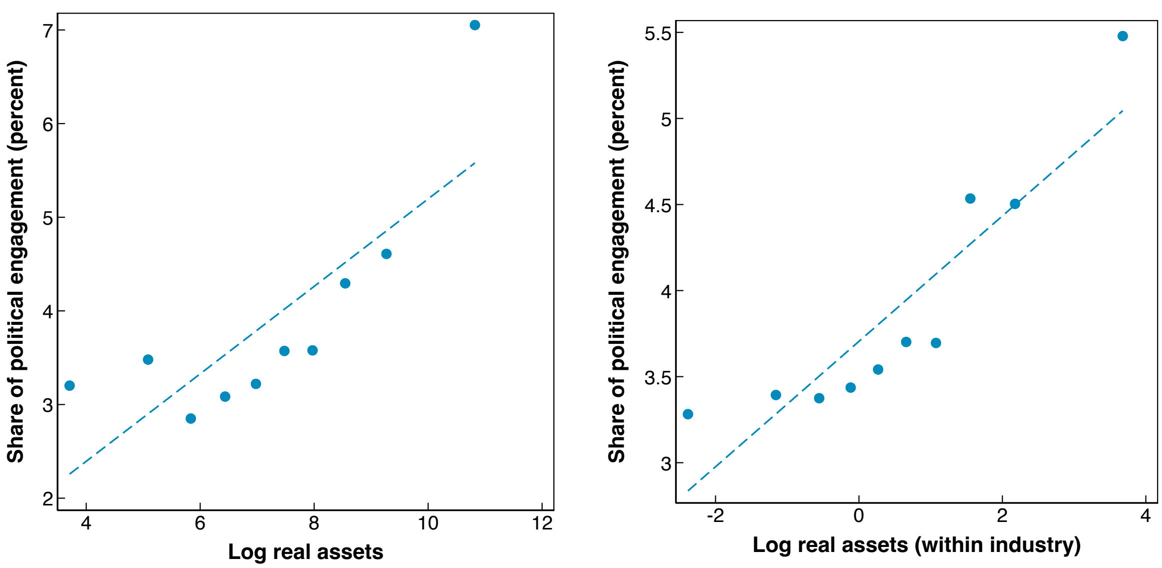
	Earnings calls				**10-Ks**	**Tweets**	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Share of firms with political speech							
in any document	37%	31%	31%	52%	43%	35%	18%
in > 20% documents	5%	4%	8%	12%	32%	13%	7%
Method	BERT	BERT	BERT	GPT	GPT	GPT	GPT
Sample	all firms	pre-2020	post-2020	all firms	all firms	Twitter presence	all firms

Notes: This table reports the share of firms with political speech for various measures. Columns 1 to 4 present the share of firms with political speech in earnings calls: Column 1 covers the period 2008–2022 using the BERT measure, Column 2 covers the 2008–2019 subsample using the BERT measure, Column 3 covers the 2020–2022 subsample using the BERT measure, and Column 4 covers the 2008–2022 period using the GPT measure. Column 5 present the share of firms with political speech in 10-K filings for 1996–2022. Columns 6 to 7 present the share of firms with political speech on Twitter for 2014–2022: Column 6 calculates this share relative to firms with Twitter accounts, and Column 7 calculates it as a share of all firms with earnings calls.

Figure A.4: Political Engagement and Firm Size

(A) Raw Data

(B) Within Sector



Notes: This figure reports binned scatter plots of the share of firms that engage politically against firm size. Each dot represent a decile of firm size, measured by log real assets. Panel (A) reports the relationship for all firms and quarters. Panel (B) reports the relationship between the share of firms that engage politically against firm size relative to industry average, measured by the residuals after regressing log real assets on 4-digit NAICS industry fixed effects.

Table A.5: Concentration of Political Engagement: Comparison with Sales

(A) Political Engagement

	Log share of engagement		
	(1) Top 1%	(2) Top 5%	(3) Top 10%
Log (1 - percentile of engagement)	-0.23***	-0.32***	-0.40***
	(0.01)	(0.01)	(0.01)
Observations	21	109	219
R^2	0.937	0.946	0.945
Pareto parameter	4.315	3.080	2.491

(B) Sales

	Log share of sales		
	(1) Top 1%	(2) Top 5%	(3) Top 10%
Log (1 - percentile of sales)	-0.56***	-0.80***	-0.88***
	(0.01)	(0.01)	(0.00)
Observations	76	381	762
R^2	0.964	0.976	0.981
Pareto parameter	1.800	1.256	1.135

Notes: This table reports data on the right tail of the distribution of political engagement (Panel A) and sales (Panel B), following the specification in Eaton *et al.* (2011). Let x^q denote the qth percentile of political engagement among all firm-quarter pairs such that $\Pr(x_{it} \leq x^q) = q$. This table reports the coefficient β_1 estimated from

$$\log x_{it}^q = \beta_0 + \beta_1 \log(1 - q_{it}),$$

where x_{it}^q denotes the share of political engagement (or sales) of firm i in quarter t, q_{it} denotes the percentile of of firm political engagement (or sales) in quarter t. The Pareto parameter α is calculated from $\beta_1 = -1/\alpha$. * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$).

TABLE A.6: Political Engagement, Firm Size, and Other Firm-Level Variables

	Earnings calls (BERT)			Pre-2020			Post-2020			Earnings calls (GPT)			10-Ks (GPT)			Tweets (GPT)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
Log real assets	0.787***			0.501***			1.821***			2.285***			4.604***			3.845***		
	(0.172)			(0.148)			(0.369)			(0.373)			(0.670)			(0.946)		
Log real sales		0.759***			0.483***			1.668***			2.267***			4.251***			3.093***	
		(0.167)			(0.152)			(0.344)			(0.387)			(0.623)			(0.853)	
Log employment			0.802***			0.506***			1.949***			2.455***			4.490***			4.067***
			(0.183)			(0.157)			(0.397)			(0.419)			(0.714)			(1.008)
Observations	144027	143634	136913	116094	115846	110330	27930	27785	26579	144027	143634	136913	47221	47098	45261	6064	6057	5972
R^2	0.038	0.038	0.038	0.037	0.037	0.037	0.053	0.053	0.054	0.094	0.093	0.094	0.166	0.166	0.161	0.097	0.096	0.096
Industry FE	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Quarter FE	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Double-clustered SE	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Firm controls	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes

Notes: This table reports results from estimating variants of a linear probability model:

$$\text{engagement}_{it}^{k} = \delta_s + \delta_t + \beta \cdot \log \text{size}_{it} + \gamma X_{it} + \varepsilon_{it},$$

where $\text{engagement}_{it}^{k}$ is a dummy variable that takes the value of 100% if firm i engages in quarter t in communication outlet $k \in$ {earnings calls, 10-Ks, tweets} and zero otherwise; size_{it} is either real assets, real sales, or employment; X_{it} is a vector of firm-level controls, including firm age, leverage, real sales growth, and lobbying spending; and α_s and α_t denote sector and time fixed effects. Columns 1 to 12 are based on quarterly data from 2008 to 2022 (or its sub-samples); Columns 13 to 15 are based on annual data from 1996 to 2022; and Columns 16 to 18 are based on quarterly data from 2014 to 2022. Standard errors are clustered by firm and time. * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$).

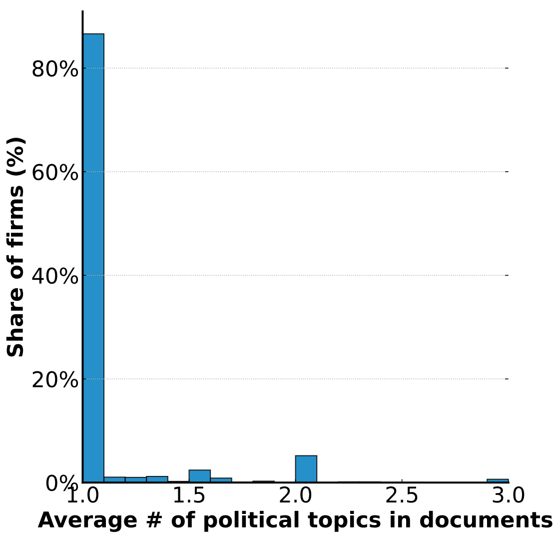
Table A.7: Specialization in Topics

Share of firms mentioning:	**1 Topic**	**2 Topics**	**3+ Topics**
In earnings calls			
BERT	69%	20%	3%
Pre-2020	74%	18%	2%
Post-2020	77%	16%	0%
GPT	47%	16%	6%
In 10-K filings			
GPT	40%	20%	3%
In tweets			
GPT	33%	20%	17%

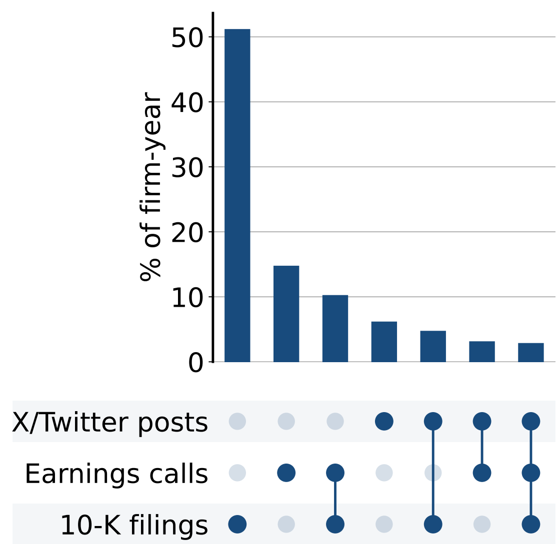
Notes: This table reports, among the firms engaging in political speech in a communication outlet (either earnings calls, 10-K filings, or tweets), the share of firms that discuss 1, 2, or more than 3 political topics.

Figure A.5: Alternative Measures of the Distribution of Topics and Outlets in Political Engagement

(a) Average Number of Topics per Firm Document with Political Engagement



(b) Outlets Used for Political Engagement per Firm-Year



Notes: Panel (A) is a histogram of the average number of political topics that firms discuss over the sample period that is available for communication outlets (2014–2022). Panel (B) is a histogram of the combinations of communication outlets that firms use per document, ranked from the most used to the least used: earnings calls only, Twitter only, 10-Ks only, earnings calls and Twitter, earnings calls and 10-Ks, 10-Ks and Twitter, and all three outlets. Political engagement in this panel is measured using the GPT measure.

Table A.8: Topics and Size

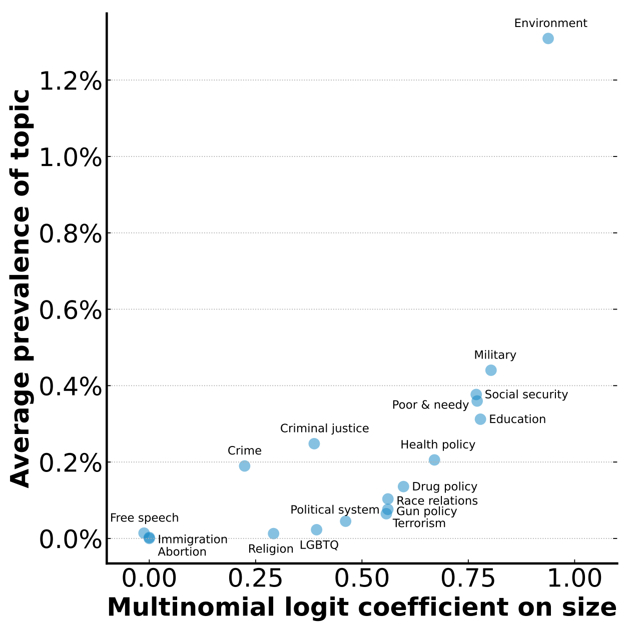
	Earnings call				10-K	Tweets
	(1)	(2)	(3)	(4)	(5)	(6)
Size (log real assets)	0.058***	0.029***	0.028***	0.142***	0.144***	0.368***
	(0.008)	(0.008)	(0.008)	(0.010)	(0.007)	(0.024)
Observations	2196	1639	1134	3127	5343	867
R^2	0.022	0.008	0.010	0.061	0.075	0.212
Measure	BERT	BERT	BERT	GPT	GPT	GPT
Sample	all firms	pre-2020	post-2020	all firms	all firms	Twitter presence

Notes: This table reports results from estimating variants of

$$N_i = \alpha + \beta \text{size}_i + \varepsilon_i,$$

where N_i is the number of political topics firm i has discussed over the sample period, and size_i is the average size of firm i over the sample period, measured with log real assets. * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$).

Figure A.6: Size and the Probability of Engaging in Each Topic



Notes: This figure reports the scatter plot of the average shares of firms that engage in a given political topic against the coefficients β for the topic estimated from the multinomial logit regression:

$$\log \frac{\Pr(\text{topic} = j)}{\Pr(\text{topic} = \text{immigration})} = \beta_j \text{size}_{it} + \varepsilon_{it}$$

for firm i in quarter q and topics j specified in Table A.11, excluding "immigration" as the reference topic and "abortion" with zero engagement. Firm size is measured with log real assets.

Table A.9: Distribution of Engagement across Outlets

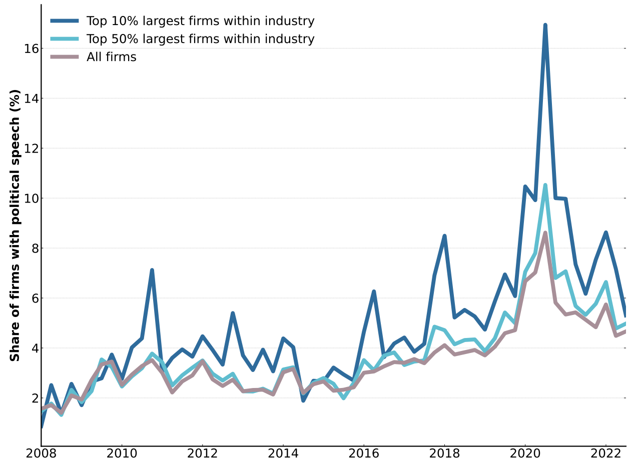
	Political speech (10-Ks)		Political speech (tweets)	
	(1)	(2)	(3)	(4)
Political engagement (earnings calls)	0.389	-2.286	5.797***	3.510***
	(1.898)	(2.282)	(0.587)	(0.489)
Size (log real assets)		2.460***		2.324***
		(0.486)		(0.206)
Log age		-0.097		0.588***
		(0.657)		(0.151)
Leverage		1.061		-1.191**
		(2.716)		(0.516)
Real sales growth		0.004***		-0.000
		(0.001)		(0.000)
Lobbying		0.332		0.953***
		(0.199)		(0.213)
Observations	18812	15701	149562	112470
R^2	0.144	0.160	0.055	0.114
Double-clustered SE	yes	yes	yes	yes
Industry FE	yes	yes	yes	yes
Quarter FE	yes	yes	yes	yes

Notes: This table reports estimates from the linear probability model

$$\text{engagement}_{it}^{k} = \delta_s + \delta_t + \beta \cdot \text{engagement}_{it}^{\text{earnings}} + \gamma X_{it} + \varepsilon_{it}, \text{ for } k \in \{\text{10-Ks, tweets}\},$$

where $\text{engagement}_{it}^{k}$ is a binary variable that takes the value of 100% if firm i engages in political speech in quarter t through outlet $k \in \{\text{10-Ks, tweets}\}$; $\text{engagement}_{it}^{\text{earnings}}$ is a binary variable that takes the value of 1 if the firm i engages in political speech in quarter t in its earnings call; X_{it} is a vector of firm-level controls, including firm age, leverage, real sales growth, and lobbying spending; and α_s and α_t denote sector and time fixed effects. Political engagement in this table is measured using the GPT measure. Columns 1 and 2 use annual data from 2008 to 2022, and Columns 3 and 4 use on quarterly data from 2014 to 2022. Standard errors are clustered by firm and time. * ($p < 0.10$), ** ($p < 0.05$), *** ($p < 0.01$).

Figure A.7: Increase of Political Engagement by Firm Size



Notes: This figure reports the share of firms with political engagement for all firms, firms whose size relative to industry average (4-digit NAICS) is in the top 50 percentile in each quarter, and firms whose size relative to industry average is in the top 10 percentile in each quarter.

Table A.10: Contribution to Political Engagement Growth 1997–99 to 2020–22, by Size

Firm size percentile	**Avg engagement (%)**	**Growth (p.p.)**
Small $[0\%, 50\%)$	1.31	0.37
	(11.36)	
Medium $[50\%, 90\%)$	1.75	1.05
	(13.12)	
Large $[90\%, 100\%]$	0.84	0.32
	(9.10)	

Notes: The first column reports the average share of firms that engage politically (as percent) for each size bin, with the standard deviation of firm engagement reported in parenthesis. The second column reports the political engagement growth for each size bin (in percentage points), defined as the difference between the average share of firms that engage politically in 2020–2022 and this share in 1997–1999.

Table A.11: Contribution to Political Engagement Growth 1997–99 to 2020–22, by Topic

Topic	**Avg engagement (%)**	**Growth (p.p.)**
1. Environment	1.79	1.46
	(13.25)	
2. Race relations	0.09	0.48
	(3.08)	
3. Health policy	0.19	0.17
	(4.34)	
4. Criminal justice	0.22	0.15
	(4.73)	
5. LGBTQ	0.02	0.07
	(1.42)	
6. Social security	0.36	0.05
	(6.01)	
7. Poor and needy	0.33	0.02
	(5.71)	
8. Immigration	0.00	0.00
	(0.56)	
9. Abortion	0.00	0.00
	(0.00)	
10. Education	0.27	-0.01
	(5.20)	
11. Religion	0.01	-0.01
	(1.09)	
12. Gun policy	0.07	-0.02
	(2.70)	
13. Crime	0.17	-0.02
	(4.14)	
14. Terrorism	0.07	-0.04
	(2.67)	
15. Free speech	0.01	-0.04
	(1.16)	
16. Political system	0.05	-0.07
	(2.33)	
17. Drug policy	0.12	-0.15
	(3.48)	
18. Military	0.39	-0.23
	(6.22)	

Notes: The first column reports the average share of firms that engage in a political topic (as percent), with the standard deviation of topic-specific firm engagement reported in parenthesis. The second column reports the growth in topic engagement (in percentage points), defined as the difference between the average share of firms that engage in a topic in 2020–2022 and in 1997–1999. Topics are ranked by the growth in topic engagement.

B Data Construction

This appendix provides details on the firm financial variables used in the empirical analysis, based on quarterly Compustat data. The definition of the variables follows that in Kahle and Stulz (2017) and Ottonello and Winberry (2020).

Variables

1. *Size*: the log of total real assets (`atq`), deflated using the BLS implicit price deflator.

2. *Real sales*: sales (`saleq`) deflated using the BLS implicit price deflator.

3. *Real sales growth*: log differences in real sales.

4. *Employment*: number of employees (`emp` from Compustat Annual).

5. *Age*: number of years since CRSP listing.

6. *Leverage*: the ratio of total debt (sum of `dlcq` and `dlttq`) to total assets (`atq`).

7. *Return on equity*: the ratio of income before extraordinary items (`ibq`) to market capitalization (`cshoq` times `prccq`).

C Details for natural language processing

This appendix provides additional details on our natural language processing procedures. Section C.1 provides additional details for word2vec models used for identifying firm statements that potentially contain political opinions. Section C.2 provides additional details for BERT models used for classifying whether a statement contains political opinions.

C.1 Details for word2vec

We train a separate word2vec model on each corpus of firm communication: earnings calls, 10-K filings, and tweets. For each corpus, the training sample consists of all 3-sentence snippets surrounding the seed words defined in Table A.2. We perform standard preprocessing to remove cases, punctuation, and stop words, but keep numbers because they remain informative for political discussions (e.g., "CO2 emissions").

We use the skip-gram implementation of word2vec, through the Python package `gensim`. The vocabulary includes unigrams, bigrams, and trigrams. After the model is trained, we extract 20 words that are most related to the seed word, ranked by cosine similarity.

We perform two refinements to the expanded keyword set to avoid including keywords unrelated to political contexts. First, we use only bigrams and trigrams to ensure that the keywords are specific to the intended context. Second, we perform an exhaustive audit to remove keywords unrelated to politics or those with ambiguous meanings (e.g., "carbon dioxide" may relate to climate change but is often used in other contexts).

C.2 Details for BERT

This section provides details on the fine tuning of BERT for classifying political engagement.

C.2.1 Annotating the training sample

To form the training sample for fine-tuning BERT, we draw 3,500 statements from those identified through a keyword search, ensuring representation across industries and political issues. We employ a team of research assistants to annotate whether a statement contains political opinions. For each statement, we provide the annotator with the industry of the firm along with the following criteria for classifying whether the statement contains political opinions: "In this statement, a firm is expressing a statement about current political or social events." Each statement is annotated by two members of the research team. In cases of disagreement, a third member reads the statement to break the tie.

Out of 3,268 statements for which we received valid annotations, 130 were classified as political opinions. To form the training sample, we balanced the representation of statements, randomly drawing from those that do not contain a political opinion to match the number of statements that do. The rare nature of political speech in earnings calls poses a problem of small training samples, discussed in Abowd *et al.* (2021) in the context of linking survey and administrative data. We draw the training sample by political topics to ensure sufficient training in each topic, and verify that the training sample is representative in terms of firm size.[8] In addition, we conduct robustness by constructing an alternative measure based on GPT, another large language model that is trained on almost the entire internet.

C.2.2 Training BERT

Having constructed the training sample, we now use it to fine-tune BERT for identifying political engagement. We start with the uncased and base version of BERT with 110 million parameters, obtained through Hugging Face.[9]

To fine tune the model, we need to specify hyperparameters that determine the rate of learning and how the training sample is read in. To avoid overfitting, we follow the procedure in Hansen *et al.* (2023) for hyperparameter selection. First, we set aside 15 percent of the human-labeled sample as the holdout test sample, which is not seen by the model during the hyperparameter-selection step and will be used to evaluate the performance of BERT compared with other language models.

Using the remaining 85 percent of the sample as the training sample, we perform a grid search over combinations of the hyperparameters: learning rates $\beta_{\text{lr}} \in \{2\times 10^{-5}, 3\times 10^{-5}, 5\times 10^{-5}\}$, epochs $\beta_{\text{e}} \in \{10, 15, 20\}$, and batch sizes $\beta_{\text{bs}} \in \{16, 32\}$. We use a 5-fold cross-validation and select the hyperparameters that yield the highest average F1 score across the 5 training splits. The resulting hyperparameters are $\beta_{\text{lr}} = 5 \times 10^{-5}$, $\beta_{\text{e}} = 10$, and $\beta_{\text{bs}} = 32$.

At this stage, we assess the performance of BERT using the holdout test sample, which the model has not "seen." We compare the fine-tuned BERT with other natural language models and

[8]The average size (and standard deviation) of firms with political speech in the training sample is 16,991 (75,644) million dollars in total assets, and that of firms with nonpolitical speech is 17,206 (38,833).

[9]https://huggingface.co/google-bert/bert-base-uncased

report the results in Section C.3.

C.2.3 Using BERT to classify political engagement

The final model we use to classify political engagement is re-estimated on the entire human-labeled sample, which includes both the training and test data. We use this model to classify the candidate statements that the keyword search from Section 2.2.1 identifies as potentially political.

The output from BERT is the probability distribution over each class label (i.e., political or nonpolitical). The higher the probability, the more confident the model is that a statement contains political opinions. To ensure the accuracy of the measure, we classify a statement as political engagement if the probability is above a 0.95 threshold. If the main topic discussed in the statement coincides with a firm's business description in Compustat, we classify the statement to be nonpolitical engagement, in order to differentiate our measure of political engagement from measures of political risks.

C.3 Model evaluation

We use assess model performance in classifying statements in the holdout test sample. We compare the performance of BERT with a wide range of alternative language models:

1. *Dictionary*: We use the dictionary of political keywords constructed in Section 2.2.1. By construction, all statements identified through the keyword search in Section 2.2.1 are classified as positive under the dictionary model.

2. *SEC-BERT*: Rather than using BERT-BASE pre-trained on generic English language texts, we use SEC-BERT pre-trained on SEC filings (Loukas *et al.*, 2022). We fine-tune SEC-BERT with the same training sample used in baseline BERT. This allows us to assess the importance of pre-training the model to the specialized language of financial documents.

3. *All zeros*: Instead of using our human-labeled training sample, we fine-tune BERT with a training sample where all statements are classified as negative, corresponding to the median outcome. This allows us to assess the importance of the training sample.

4. *GPT-4*: We query GPT-4 under a zero-shot learning setting, using the prompt: "Your task is to classify whether a statement from a company's earnings call contains political or social

statements. Respond with 1 if the statement contains political or social statements; and respond with 0 if the statement does not contain political or social statements. Only respond with 1 or 0."

Table A.3 presents the performance of each model, evaluated on two metrics: accuracy and F1 socre. Accuracy is the proportion of correctly classified statements out of the total test sample; and F1 score is the harmonic mean of the model's precision and recall, measuring its ability to correctly identify both political (true positives) and nonpolitical (true negatives) statements. The test sample consists of 377 statements, 7 percent of which contain political opinions. Row 1 reports that the baseline BERT model has an accuracy of 86 percent and F1 score of 0.89. Row 2 shows that a simple dictionary-based method performs poorly in classifying political engagement. Row 3 shows that SEC-BERT, a version of BERT pre-trained on the specialized language of SEC filings does not lead to a performance improvement and slightly underperforms the baseline BERT. Row 4 demonstrates the importance of the human-labeled training sample for fine tuning BERT. The accuracy of correctly classifying a true positive increases by 83 percentage points with our training sample compared to that with an all-zero training sample. Finally, Row 4 compares BERT with GPT-4. BERT substantially outperforms GPT-4 in identifying true political speech, with an accuracy of 89 percent compared to that of 17 percent for GPT-4; in contrast, GPT-4 outperforms BERT in identifying true nonpolitical speech, with an accuracy of 99 percent compared to that of 85 percent for BERT.

Given the relative strength of BERT and GPT, we measures political engagement using both models. We use BERT as our baseline measure for its open-source nature to ensure transparency and reproducibility, while also verifying that our findings are robust to using the alternative GPT measure.