Political Speech from Corporations is Sparse, Only Recently Liberal, and Moderately Representative: Evidence from Social Media

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April 18, 2023

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Abstract

How do corporations engage in political speech in the age of social media? Scaling partisan cues in \( \approx \) 2 million Twitter and Instagram posts from the 1,000 most popular corporate brands in the United States, I find that most corporate political speech is discernibly liberal, but concentrated in a handful of brands and occurring in uneven bursts across time. Moreover, this communication is not as dishonest as many popular narratives suggest: the majority of brands’ partisan speech is well-aligned with the political preferences of key stakeholders (e.g. employees, voters, and consumers) and at least somewhat informative about relevant firm activities (e.g. workplace practices, regulatory compliance, and climate policy). These results provide a measured counterbalance to popular narratives of ‘woke capitalism’, suggesting that liberal political speech from corporate America is, at worst, inconsistent rather than outright hypocritical.

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* I thank the Institute for Quantitative Social Science and Center for American Political Studies at Harvard University for funding this project. For their feedback and comments, I thank Ryan Enos, Gary King, Chelsea Green, Michael Hiscox, Kosuke Imai, Kala Viswanathan, In Song Kim, Justin de Benedictis-Kessner, Jennifer Hochschild, Tyler Simko, Hunter Rendleman, Kevin Troy, Elizabeth Thom, Stuart Soroka, members of the Imai Research Group, attendees of the Harvard Graduate Political Economy Workshop, attendees of the 2022 MPSA Annual Conference, the SurveyMonkey Research Insights Team, and attendees of the 2022 APSA Political Communication Pre-Conference. I especially thank Ryan Enos for early conversations and guidance.

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Significance

According to popular ‘woke capitalism’ narratives, companies are espousing liberal political values that are unrepresentative of consumers’, employees’, and other stakeholders’ views and misleading about their actual commitments to racial equity, climate justice, and other issues. Analyzing political signals in more than 2 million social media posts from the most popular corporate brands in America, this study finds evidence contrary to this claim. That is, most leading companies’ online speech is not particularly politically engaged, but when it is, it usually aligns with the political preferences of firm stakeholders and predicts a liberal company agenda. These results describe a growing alignment between the business sector and liberal interests in America, with the caveat that it is recent, moderate in magnitude, and sometimes inconsistent.

1 Introduction

The American public increasingly seeks political leadership from private corporations on issues ranging from abortion access to gun violence to climate change (1–3). At the same time, the rise of social media as an source of political information for many voters (4, 5), and the primary marketplace for many young consumers (6) provides a powerful platform for corporate brands to set the agenda on these issues. Critics, however, accuse corporate brands of hypocrisy in their speech – that is, systematically communicating progressive stances and values that are unrepresentative of stakeholders’ political preferences and misleading about company agendas, a phenomenon often dubbed ‘woke capitalism’ or ‘woke-washing’ (7, 8). Indeed, recent studies confirm that companies ‘green-wash’ their environmental externalities (3, 9) and ‘diversity-wash’ their hiring practices (10), with the effect of masking harmful climate policies and inequities in the workforce. Still, no single study to date provides a complete picture of the supply of corporate political communication across industries, time, stakeholders, and issues.

This paper leverages a novel dataset of more than 2 million brand social media posts to answer a series of descriptive questions around political speech in corporate America. First, to what extent do major corporations in the United States actually send political signals in their communications with the mass public? Second, where do these signals fall on the political spectrum? Is it overwhelmingly to the left as critics of ‘woke capitalism’ contend or does it lean more to the right like corporate behavior in other political arenas in the post-
Citizens United era (11)? Third, is speech representative of the preferences of important
stakeholders and informative about firm activities and priorities? To address these questions, I first collect all Twitter and Instagram communications in the past decade from the most well-recognized consumer-facing corporate brands in American life. I then merge them with measures of partisan preferences of stakeholders as well as measures of firm’s revealed agendas on issues connected to their speech (described further in the following paragraph). Examining how and when brands mirror the partisan linguistic cues of Democratic and Republican elites I demonstrate, firstly, that most recognized brands in American life are not meaningfully political in their speech. Of brands that do, most invoke liberal or Democratic appeals in their speech, but only after the salient police killing of George Floyd. Prior to 2020, brands’ usage of many other types of partisan cues (e.g. attention to cultural observances and demographic groups) have more often appealed to a Republican world-view. Finally, I show that corporate brands’ political speech on social media is modestly correlated with the revealed preferences of most stakeholders – though no particular stakeholder more than the rest – and largely predictive of the ideological direction of various firm-level priorities.

The methodological innovation in this study comes from mapping speech from a comprehensive set of corporate actors onto the full spectrum of ideological language. Indeed, there are many types of political communication beyond explicit position-taking (e.g. “I support policy X”) including: how stances or issues themselves are framed (12, 13); overall attention paid to certain issues over others (14, 15); lifestyle or cultural cues (16, 17); and social, racial, and geographic makers (18). Figure 1 illustrates some of the ways brands can use speech cues to tacitly appeal to Democrats or Republicans. The hashtag #blacklivesmatter and the American flag emoji are distinctly associated with the national Democrat and Republican brands respectively (empirically confirmed in this study via the social media speech of members of Congress) as well as connected to liberal and conservative political identity (18). My primary measure of brand partisanship systematically measures how closely brands employ discernibly partisan phrases in areas ostensibly unrelated to their core business function (e.g., excluding health insurance companies’ mentions of “health care”). Throughout the article, I refer to these usages as partisan signals.

Employees, managers, board members, and consumers together are functionally a business’s central stakeholders and are often loudest proponents of corporate activism (19–22). In this study, I more specifically identify employees of specific branding-oriented departments – legal, public relations, marketing, and human resources – who are operationally involved in brand messaging and are popularly implicated as internal stewards of ‘woke’ corporate speech. If this claim is true, brands’ partisan signals should more narrow align more with these groups’ preferences over others. Additionally, voters proximal to the retail locations and headquarters of firms may be seen as important stakeholders since they contribute di-
Figure 1: **Examples of Partisan Signals from Corporate Brands on Social Media**

Notes: The top two posts from Coca-Cola and Harley-Davidson are screenshots from Twitter, the bottom post from Chevron is from Instagram.

Directly to the customer base and the workforce; indirectly to corporate tax subsidies; and may offer support or opposition, via local political participation, to the firm’s relocation itself. Finally, Senators and members of Congress that represent the state and districts respectively of brands’ headquarters may be important audiences to please – they can levy influence by securing tax subsidies for firms and also benefit from firms through revolving door appointments, campaign donations, lobbying resources, and local job creation (23). This study is the first to identify which of these stakeholders are actually represented by their brands’ speech.

Although firms make many decisions that are informative of organizational values, I consider three crucial areas of corporate governance with clear implied partisan ideologies: broad areas: climate policy, regulatory compliance, and DEI (diversity, equity, and inclusion). Broadly speaking, these are all activities that Democrats, who hold more socially liberal and pro-regulation attitudes, favor *more* (i.e. attention, compliance, co-operation) of
while Republicans, consistent with anti-regulation, small government, and socially conservative attitudes, favor less (24). To demonstrate ideological consistency, brands’ attention to these issues online should be proportionate to their firms’ attention in offline activities. As such, I directly test this using various revealed measures of firms agendas.

Taken together, these results reject characterizations of corporate political speech as misinformation, hypocrisy, or false advertising. Rather, on the whole, this study argues that corporate speech reflects a largely genuine re-alignment between the business sector in America and liberal, Democratic interests – with the caveat that this is relatively recent, moderate in magnitude, and not uniform across all issues, sectors, and stakeholders.

2 Materials and Methods

2.1 Sample of Corporate Brands

The sample of corporate brands in this paper consists of the 1,186 most recognized consumer brands in the United States according to the quarterly YouGov Audience panel, which is nationally representative on gender, race, age, education. While many other studies of firms focus on the universe of publicly trade firms (25) or Fortune 500 companies (26), this paper’s population of interest is firms with brands that are highly visible in daily American life for two reasons. First, this population is of greater substantive import since they are more likely to have brand social media accounts with significant audiences and are more likely to have communications teams that engage in comparable patterns of political speech within industry. Second, as detailed further below, such brands are more likely to have available measures of stakeholders and firm characteristics (independent variables), reducing issues of missing data in analyses. Overall, this choice of sample is likely to place an upper bound on both the magnitude and directional alignment results when compared to the complete universe of all firms in the United States.

Many different sectors are represented in this sample of brands ranging from Auto Manufacturers to Clothing/Footwear to Food & Drink (the most represented sector in the sample). Importantly, I exclude brands from the media and communications-affiliated sectors (e.g. Fox News, CNN) since sending political signals is endogenous to the core business function of media outlets.

I then link each of the brands from YouGov to their parent firms and their affiliated U.S. Twitter and Instagram accounts, if available. If multiple Twitter or Instagram accounts exist for different locales, I select the account localized for a U.S. audience. The choice of Twitter is motivated by a rich literature establishing the importance of Twitter for producers and
consumers of online political information (see Tucker *et al.* (27) for a review of the field). The choice of Instagram is motivated, conversely, by a relative lack of study on the platform despite its extreme popularity relative to other social platforms and widespread usage by corporate brands.

I manually collect additional characteristics for each brand and firm including U.S. headquarter location, number of employees, and revenue all at the time of writing in 2022 from various sources including Orbis and Wikipedia. Only a small percentage of firms shift headquarters during the period of our study and this is accounted for in any analyses involving headquarter locations. Nearly all of the firms in this sample are publicly traded firms and multinational corporations. Additional analyses that disaggregate firms based on location do so based on whether their main headquarter (if there is one) is based in the United States.

Altogether this leaves us with 880 brands in relevant sectors with active social media accounts on either Twitter or Instagram and any of the aforementioned covariates.

### 2.2 Measurement of Partisan Brand Signals

I collect all Twitter and/or Instagram posts by corporate brands with accounts on either or both platforms between 2014-2021. I chose 2014 as the starting year since (1) activity on both Twitter and Instagram – the number of active brands and the number of daily posts – sharply rose prior to this year and stabilized in early 2014, (2) this period offers a substantively useful comparison of brand activity before and after key polarizing events in U.S. politics such as Donald Trump’s surprise election win in 2016, the police murder of George Floyd, and the January 6th Capitol riot. Altogether my sample consists of 2,243,078 posts.

Measuring partisan cues from speech requires observations of exemplar partisan speech. As such, I additionally collect all Twitter and Instagram posts from members of the 116th Congress (MCs) during this period, totalling 1,436,732 posts. To measure the usage of partisan cues from corporate brands, I use a methodology similar to Gentzkow and Shapiro (14) and Slapin and Proksch (28). First I compile the 1,000 most partisan bigrams between Democrats and Republicans (i.e. 500 most predictive of each respectively) during my sample according to the $\chi^2$ statistic of the difference in counts of bigram between Democrats and Republicans. More extreme values correspond to greater partisan leaning; for $\chi^2_j$ value corresponding to bigram $j$, a more negative value indicates a greater differential usage by Democrats while a more positive value indicates more disproportionate usage by Republicans. As shown in the Appendix Figure A1, the most Republican leaning phrase used at least once in our sample is “southern border” while the most Democrat-associated phrase in the sample...
is “gun violence”, two undoubtedly significant issues of party politics in this period. Using each observed count $w_{ij}$ of each partisan phrase $j$ by each brand $i$, I then summarise each brand $i$’s partisan signal $\tilde{\psi}_i$ with a simple non-parametric weighted count of partisan bigrams $\tilde{\psi}_i = \frac{\sum_{j=1}^{1000} w_{ij} \gamma_j}{\sum_{j=1}^{1000} w_{ij}}$.

The core assumption behind this measure is that a brand’s partisan signal can be measured by the average of the Democrat and Republican lean of speech commonly used in the political arena. However, in some contexts certain otherwise partisan phrases are arguably only signals of core market functions and not politics. For example, a fashion brand’s attention to “health care” is orthogonal to its product marketing and may signal political support for affordable healthcare policies, while a hospital brand’s mention of “health care” is more likely to be entirely related to its central activity of healthcare provision. To account for this, I remove certain industry-specific phrases from the construction of $\tilde{\psi}_i$, a full list of which can be found in the replication code.

This measurement strategy is desirable since it does not involve any modelling assumptions, closely resembling other non-parametric text-as-data measures that rely on a reference corpus (29). However, as Lowe (30) points out, such measures can often be sensitive to skewed frequencies of select words in either the reference (Congress) or target (brands) corpus. Moreover, this measure pools Twitter and Instagram speech together and fails to detect any substantive differences in brand signalling on the two platforms. Thus, in Appendix C.4, I replicate key analyses using alternative measurement strategies. These are: binarizing $\chi^2$ to classify phrases as either Democrat or Republican-leaning (essentially a dictionary approach), subsetting to phrases that specifically invoke known political groups or issues, disaggregating to Instagram and Twitter posts respectively, and fitting a parametric model that identifies out brand- and phrase-specific baselines in brands’ speech. Additionally, I eschew external measures of phrase partisanship itself and examine the link between specific signalling keywords and related activities and stakeholder characteristics (Appendix C13).

2.3 Stakeholders

Following other studies (31, 32), I draw on individual contributions to political parties, candidates, and groups recorded by the Federal Election Commission (FEC) as a measure of revealed partisan preferences of brands’ firm affiliates. Firm affiliates are considered as an aggregate group as well as disaggregated to rank-and-file employees, executives, board members, as well as employees in specific corporate departments (if they exist in each company). The chosen departments are those typically involved in both decisions of explicit political position-taking as well as the incorporation of more implicit cues into brand messaging. I
follow Atalay et al. (31) and Stuckatz (32) in matching character strings denoting occupation to the Bureau of Labor Statistics’ official occupation (SOC) codes for these categories of firm affiliates. The results in this paper use share of dollars donated to Republicans, but all substantive conclusions remain the same when using share of unique donors instead.

Although it would be ideal to directly observe the partisan orientation of brands’ consumers, such measures are not readily available. Instead, following other studies (33, 34), I construct a proxy measure of consumer partisan preferences by scaling the Twitter followers of all available brands. In particular, in 2021 I sampled the top 200 followers of all available brand Twitter accounts using the Twitter API. For each of these 200 followers, I additionally mapped the partisan composition of their followings based on a list of Congressional Twitter accounts (35) (manually supplemented with other known partisan accounts of media outlets, commentators, and interest groups) and measured each follower’s partianship as the % of Republican accounts followed. I summarised the partisan orientation of a brand’s consumer base as the % of Republican followers. To account for potential noise originating from the unevenness in the number of partisan accounts followed by some brands’ consumers, I replicate key analyses by weighting on the total number of partisan accounts followed by each sample of brands’ followers (Appendix Figure C18). Additionally, as a safeguard against extrapolating from a small sample of followers in a single point in time, I match my brands to Schoenmueller et al. (34)’s 2017 and 2021 cross-sections of brand Twitter followerships; followerships across these two time periods are averaged for static analyses and disaggregated for over-time analyses (Appendix Section C.3).

For geographic measures of stakeholders’ partisan preferences (consumers, employees, and proximal voters), I match brands’ parent firms to point-of-interest zip codes from Safe-graph and Zippia. I refer to these points of interests as “retail” locations or sites of direct consumption of each brand. Moreover, I use two datasets with complementary strengths: Safegraph offers access to many more fine-grained locations but with a slightly lower match rate to my brands, while Zippia offers a better match rate but only a list of the top 20 zip code locations with the most employees. I then match these along with firm headquarter zip codes to average Presidential vote share in the 2012 and 2016 elections made available from TargetSmart. Indeed the period of study extends to 2022, however zip-level presidential returns on the whole are nearly perfectly correlated in American elections, which reduces concerns about period mismatch.

Additionally, I collect a number of brand-level consumer and employee demographic summaries from YouGov and Zippia respectively. These measures are both highly informative of stakeholders’ partisan preferences as well as firms’ hiring practices.
2.4 Activities

I gather my primary measures of firms’ expressly political activity – donations to partisan candidates and groups – from OpenSecrets. The results in this paper use share of dollars donated to Republicans in the aggregate as well as over time (Appendix Section C.3). Supplementary analyses consider an additional measure of political activity – indirect connections to partisan legislators via lobbying – gathered from the LobbyView database (36).

For specific activities with an implied partisan agenda, I focus on three broad areas: climate policy, DEI (diversity, equity, and inclusion), and regulatory violations. Unfortunately, firms’ actions in the first two domains cannot be directly observed, so I rely on proxy measures instead. In particular, I rely on both aggregate climate impact and sustainability grades as well as more specific indicators of priorities and direct actions evaluated by the Climate Disclosure Project (CDP) and the Climate Action 100+ project. These scores are constructed by analysts using an assessment framework standardized within and across industries based on public disclosures by companies themselves. For measures of each firm’s DEI priorities, I rely on employees’ evaluations of their workplace from Glassdoor and LGBTQ “equality scores”, or holistic evaluations of companies’ policies and benefits for LGBTQ employees from the Human Rights Campaign (HRC). Glassdoor evaluations are available for specific social groups – women, racial minorities, and LGBTQ employees – and Human Rights Campaign scores are available across time. Finally, counts of regulatory violations by different companies are available from the Good Jobs First project. I focus on three categories of regulatory violations that are directly related to partisan cues often used by brands: social discrimination both during hiring and in the workplace (“black community”, “pride month”), labor law violations (“mental health”, “child care”, “health care”), and environmental violations (“climate change”).

As Baker et al. (10) show, availability of company’s disclosures of climate practices and priorities may itself be correlated with both the extent and slant of their online brands’ political speech. A similar dynamic may exist for employee evaluations, the number of which may be greater and more positive for left-leaning work environments and consequently correlated with left-leaning brand speech. To address these concerns, I weight relevant analyses by numbers of Glassdoor ratings and test for whether missingness in activity data is correlated with brand signal (Appendix Figure B9). Besides for LGBTQ+ equality scores from the HRC, I do not find these factors to be a threat to inference. On a conceptual level, I note that Glassdoor evaluations capture employee perceptions of a firm’s prioritization of DEI and may be biased; as such, I also use the demographic composition of each firm’s workforce (identified by Zippia) as a a more direct measure of a firm’s commitment to diverse
hiring.

3 Results

The purpose of these results is descriptive and correlational, rather than causal, inference. As such, I report summary statistics on the distributions of partisan brand signal in the population of interest (recognized brands) and evaluate whether the aforementioned firm characteristics (independent variables) are informative or predictive of brand signals (dependent variables). For the latter, I use a mix of Pearson correlations and coefficient confidence intervals from univariate regressions. All confidence intervals are shown according to a global $\alpha = 0.05$ and additionally with family-wise Benjamini-Hochberg adjustments to account for multiple testing. Robustness checks on these inferences – including checks on influential observations, accounting for additional uncertainty in both independent and dependent variables, and equivalence tests to test for meaningfully large effects – are conducted in the appendix. Finally, I note that I use ‘liberal’ and ‘Democrat’ interchangeably as well as ‘conservative’ and ‘Republican’ interchangeably.

3.1 Partisan Brand Signals are Sparse.

I begin by enumerating the brands that use any political signals as defined by the reference corpus of detectably partisan Congressional bigrams on Twitter and Instagram. I count that of the original sample of 1,000 household name brands, 645 brands use any of the 1,000 most partisan bigrams on social media during our entire study period. Equivalently, this is 64% of all brands or 73% of brands that are actually active on Twitter or Instagram during this period. However, the overall supply of cues exhibits a highly skewed distribution; for example, only about 450 brands use more than 5 partisan bigrams (51% of social media brands) and 295 (33%) use more than 15. Thus, we can initially conclude that the majority of corporate brands are not sending any strong partisan cues of any kind, subtle or obvious. In fact, of the corporate brands on social media, roughly equal numbers are affiliated with a political action committee ($n = 634$) as are sending partisan cues on social media ($n = 645$).

The remaining findings in this section are derived from the subsample of brands that use at least 5 partisan bigrams during our study period, though results are similar, but slightly weaker when using the entire sample.
3.2 Partisan Brand Signals Sound More Like Democrats.

Next, I examine the specific ideological phrases most used by brands and the resulting ideological distribution of corporate brands according to these usages.

In Figure 2, the horizontal axis shows the $\chi^2$ value, or degree of Republican association, for each phrase while both the vertical axis and the size of each dot convey how frequently the phrase is used by brands in the sample. The dashed line in each panel denotes the weighted average partisan lean of signals used by brands in each category. Overall, Figure 2 shows that both overall and across different categories of rhetorical signals, brands’ language choices lean slightly towards the left. Phrases strongly associated with Democrats appear much more frequently in brands’ speech (in particular climate change and gun violence) than do any phrases strongly associated with Republicans.\(^1\) Appendix Figure A6 shows that distributions of brands’ partisan slant measured according to a variety of alternative methods, including a parametric model meant to parse out a-political usages of certain Congressional phrases, are all consistently left-leaning.

Based my classification of partisan cues, the most common type of rhetorical cue is an appeal to social or political groups ranging from the LBTQ community to African Americans to small business owners. Roughly 37% of all partisan cues used on social media fall under this category. This is followed closely by mentions of issues (30%) and expressions (19%). Brands’ usage of these cues observably lean to the left of center, though they are far from the most extreme scenario, i.e. each dashed line positioned where gun violence is located suggesting an exclusive usage of the most left-leaning linguistic cue.

What are the contexts for these cues? Are these partisan cues merely used to spread awareness about particular issues or groups or are they used in explicit instances of position-taking? Appendix Figure A4 shows that, more often than any other context, these cues are deployed in the context of position-taking, or support or opposition of a cause associated with an issue or group. For instance, many brands’ mentions of climate change are situated in statements of support for the Paris Accord following President Trump’s announced withdrawal in 2017; the luxury jewelry brand, Tiffany & Co., wrote on Twitter:\(^2\) “Tiffany strongly supports keeping the U.S. in the #ParisAgreement. #ClimateChange #ActOnClimate #TiffanyCSR #ParisAgreement.” Democratic cues out-number Republican cues in nearly all contexts, however a non-trivial share (40%) of support statements involve Republican cues.

\(^1\)Noticeably, some phrases like biden administration arguably are used by corporate brands in a different context than members of the oppositional party during the Biden administration, removing these phrases from corpus does not significantly change any of these findings.

\(^2\)See twitter.com/tiffanyandco/status/861913660951732226.
which center on small business owners, current and past armed service members, and law enforcement.

### 3.3 Partisan Brand Signals are Only Recently Liberal.

Figure 3 decomposes brands’ partisan signals over time, which are increasingly liberal between the years of 2017 and mid-2020. As the smoothed trend line in the top panel shows, the average $\chi^2$ statistic (i.e. association with Republican elites’ speech) of brand phrases doubles in the Democratic direction between the start of our sample and after George Floyd’s death in May 2020. Within the 2018-2020 period, however, the trend does not significantly
increase in a liberal direction. When examining specific categories of language by partisanship there is a clearly observable spike of Democratic rhetorical appeals related to George Floyd’s murder, including mentions of black lives matter (nearly 15% of all posts during the week of Floyd’s death) and subsequent attention to black history month in 2021.

Notably, the burst of corporate attention to Black Lives Matter, racial issues, and the black community mirrors broader patterns of public racial attitudes following George Floyd’s murder (37). In contrast, there does not appear to be any other event-driven shift in either broad partisan attention or specific issue focus in our data. A much smaller swell of Democratic appeals occurred after the January 6th insurrection at best indirectly related to the event itself including a greater volume of references to Martin Luther King. The contrast in attention to these two “activating events” is striking: while direct mentions of George Floyd took up 4% of all posts the week of his death and occur roughly 200 times in our corpus, there are only 5 posts referencing the January 6th insurrection (i.e. “insurrection”, “riot”) the week it occurred and roughly 50 references thereafter. Although it successfully mobilized corporate financial resources (33), the January 6th insurrection did not seem to nudge brand attention towards Democrat-branded issues.

3.4 Partisan Brand Signals are Moderately Representative of Stakeholder Preferences and Firm Agendas.

Figure 4 next shows how each brand’s aggregate signal in our sample maps onto stakeholders’ revealed partisan preferences during the same period. Across the board, left-leaning brands’ speech largely aligns with and are moderately predictive of the preferences of key potential audiences: employees, consumers, and elected officials. Notable exceptions are corporate board members, who lean more to the right than any other cohort, and the members of Congress representing firms’ headquarters, who are highly polarized in their ideological preferences.\(^3\) The majority of brands that are out of step across these stakeholders, are in the lower right quadrant or, in other words, out of step because they are speak too liberally relative to members of that stakeholder group.

Figure 5 similarly compares each brand’s online signal to measures of firm-level partisan activities: contributions to political action committees (PACs) affiliated with partisan interest groups, and contributions to PACs associated with partisan candidates for office. Notably, unlike with stakeholder preferences, most brands are off-quadrant with their firm activities. In fact, a slight majority of brands (54-62%) are conservative or Republican-leaning in these

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\(^3\)Although ideological preferences as measured by DW-nominate scores are not conceptually identical to MCs’ partisan preferences, due to the high degree of partisan sorting in roll call votes in the modern Congress, we may treat them as measures of MCs’ in-party vs. out-party preference.
partisan activities despite presenting mostly liberal or Democrat-leaning messages online. Marriott, for example, mentions climate change while maintaining a nearly even partisan portfolio of groups and candidates in its disclosed PAC spending. However, there still exist detectable, moderately sized correlations with between expenditures and brand signal. Thus, even if corporate political spending is generally shifted to right, more liberal speech predicts less conservative spending on the margins.

Finally, Figures 6–7 present a more comprehensive set of coefficient and quadrant alignment estimates for stakeholder preferences and firm agendas adjusting for multiple testing.
Relatively speaking, Figure 6 reveals that brands’ speech is most representative of their local geographic constituents: voters living proximal to firm headquarters and retail locations which includes both potential consumers and employees. In the case of headquarter geography, Figure 4 shows this is driven in bulk by the firms that are based in New York City or the California Bay Area. Notably, these and other estimated coefficients relatively small in magnitude according to widely accepted definitions. In the appendix, formal equivalence tests reveal that these effects mostly reject a null hypothesis of conventionally accepted “large effect sizes” (Appendix Figures C19–C20). Nevertheless, the quadrant-based measures with bootstrapped standard errors tell us that only a slim minority of brands send partisan signals contrary to each stakeholder. Altogether, as visualized in the upper right panel, 57% of brands are on-quadrant with the net Republican lean of all of their stakeholders.

Figure 7 reveals that in addition to political spending, relevant firm activities and agendas are at least somewhat informative about their brands’ online political cues. More positive workplace perceptions by LGBTQ+ employees, better LGBTQ+ equality scores, and fewer...
environmental regulatory infractions all predict more liberal, Democratic signals, though with relatively small effect sizes.

### 3.5 Other Results

Further questions remain about how these correlations may vary over time, across firms, as well as between different measurement strategies. Moreover, many other characteristics about a brand may more strongly predict its online political image.

In the Appendix, I show that both signal-stakeholder and signal-activity correlations are weaker or non-existent prior to 2018 (Appendix C.3), are somewhat unevenly distributed across industries, are stronger in American-based firms relative to foreign-based firms, and generally stronger in largest half of firms in my sample relative to the smallest (Appendix C.8). The technology, household goods, and retail/clothing (including luxury fashion) sectors in particular demonstrate noticeably higher degrees of alignment between stakeholders and brand signals than others; existing literature offers compelling reasons for this and is discussed further in the concluding section. Though these results vary in magnitude across alternative measures of the outcome and different regression specifications (Appendix Figures C16–C18), substantive conclusions largely remain unchanged.

Compared to stakeholder preferences or the firm agenda variables shown here, few other consumer-side factors reliably predict brand signal (Appendix Figure C10). The demographics of employees, however, are highly informative of brand speech: greater educational attainment and more diverse ethnic composition of the workforce are arguably the strongest...
Figure 6: Stakeholder Preferences Moderately Predict and Align with Partisan Brand Signals

Notes: Coefficients (left panels) are standardized estimates from univariate regressions of brand signal on each stakeholder preference measure. Wider lines corresponding to 95% confidence intervals and the thinner lines corresponding to 95% confidence intervals adjusted for multiple hypothesis testing using the BH-q procedure. Error bars around on-quadrant (i.e. stakeholder and brand in the same partisan direction) brands (right panels) correspond to 95% confidence intervals of each percentage estimated via a non-parametric bootstrap. The % of Republican stakeholders (top-most estimates in both panels) for each brand is computed by counting the percentage of net Republican-leaning stakeholders across all stakeholder measures available.

Predictors of a liberal brand signal (Appendix Figure C11). Larger firms with more online followers and tweets in their history are also more likely to send liberal signals (Appendix Figure C12), though these are generally weaker correlations than those shown in Figure 6.

One major corporate political activity not examined in the main text is legislative lobbying. Although firms’ positions on federal legislation in areas ranging from reproductive rights to immigration have markedly ideological implications, no reliable measure is available whether firms lobby for or against these bills, unlike with PAC spending. Instead, the closest measure is the partisan composition of the bill sponsors’ for each bill that my brands’ parent firms lobby on (36). Theoretically, lobbyists have stronger incentives to subsidize partisan allies rather than persuade opponents (38), thus the partisan composition of legislators associated with a firm’s lobbying portfolio might be ideologically informative of its legislative agenda. Appendix Figure C12 suggests a link between this firm-level composition and associate brands’ online speech likely does not exist.

Finally, although the relative partisan slant of brand speech is of primary importance in this study, the absolute amount of partisan speech itself is consequential: more cues result in greater exposure by the very stakeholders examined in this study. I show in Appendix Figure C26 that larger, popular brands with more liberal stakeholders also tend to produce more partisan cues overall. Thus, conservative stakeholders of corporate America are less
likely to hear congruous speech than their liberal colleagues, and less speech altogether at that.

4 Discussion

Corporations speaking out on sociopolitical issues is certainly not a new phenomenon (39). Contemporary business-society relations in the United States is noteworthy, however, for an unprecedented confluence of four factors: (i) a historically wide gap between Democrats and Republicans, voters and elites alike, on issues ranging from gender identity to climate change (40); (ii) a public that places greater trust in corporations than in traditional political institutions (41); (iii) a “diploma divide” or an emerging re-alignment between highly-educated, affluent, white-collar professionals and the Democratic Party (20, 42, 43); (iv) and a democratization of mass communication and public relations vis-à-vis social media (44).

Within this environment, this paper finds that most recognized corporate brands in America do not meaningfully use partisan linguistic cues online. Simply put, the polarization observed in American society does not obviously extend to the business world. Most partisan cues that can be observed occur in large part after George Floyd’s murder are discernibly left-leaning, concentrated in a smaller number of brands, and are at least somewhat informative of stakeholder interests and firm priorities. Mismatches in brand signals, when
they occur, are asymmetric: they are sometimes too liberal relative to their stakeholder’s political preferences and mostly too liberal relative to their firms’ political spending. But, on the whole, these results do not suggest that companies are outright lying about the partisan direction of their workforce, climate, DEI, or electoral agendas, since none of these indicators are significantly predictive of the opposite partisan brand signal. The example of Chevron posed in Figure 1, which scores amongst the lowest in the climate indicators shown in Figure 7, is an outlier. Companies are also not egregiously out-of-step with their stakeholders, as the vast majority of firms are either non-aligned or aligned (on-quadrant) with the different audiences evaluated here. This paper clarifies the role that social media plays in businesses’ public relations: a tool that is used sparingly for political speech that is usually relatively credible and particularly attuned to the interests of the employee base and the retail geography. Rather than woke capitalism, firm communications are approaching the ideals of responsive stakeholder capitalism, even if the degree and consistency of this responsiveness could be improved.

The results also speak to the long-studied power of activating events, particularly concerning civil rights and race relations, in shifting not just American public opinion, but elite and interest group agendas \((45–48)\) in a progressive direction. The relative lack of media coverage on urgent and discrete climate-related events may be one reason that corporate attention to climate change is stable rather than increasing \((49, 50)\). While unprecedented activating events are associated with liberal speech, Figure 3 shows that the converse is true for recurring cultural observances: Christmas, Veteran’s Day, and Independence Day tend to coincide with more conservative appeals.

Two industries with unusual degrees of stakeholder alignment are the technology and clothing/retail sectors (see Figure C24 in Appendix C.8). On closer examination, this is unsurprising given the concentration of highly educated workers and female consumers in the tech and clothing/retail sectors respectively. As Appendix Figures C10–C11 show, these characteristics are amongst the strongest predictors of a Democrat-leaning brand signal. Moreover, most U.S. firm headquarters in these sectors are based in urban areas (most commonly, as Figure 4 shows, New York City and the Bay area) with more liberal voters and representatives. This adds an important dimension to the “diploma divide”: younger, left-leaning employees in culturally cosmopolitan sectors \((51)\) such as tech and fashion are slightly more likely, on average, to find their employer’s speech favorable to their own as well as their managers’, elected officials’, fellow voters’. Taken with the findings that the tech industry is (1) the most left-leaning sector on average (see Appendix Figure A5) and (2) exhibits the strongest congruity between between brands’ online signals and firms’ campaign finance (see Appendix Figure C24), this paper provides substantive evidence for the “liberal
“bubble” characterization of Silicon Valley (3, 52).

Noting the descriptive nature of this paper, future research would do well to clarify the causal direction of brand messaging alignments (or lack thereof), uncover their underlying mechanisms, as well as estimate their effects on key outcomes. For example, a question remains of the extent that activating events themselves prompt brands to online speech relative to mediating factors such as the activity of competing brands, professional networks of crisis management teams, or bottom-up demands from stakeholders. Similarly, it is unclear whether employees, elected officials, voters, and managers exert influence on, are influenced by the speech of their employers, or operate in a feedback loop of influence. Macro-level dynamic causal inferences may help adjudicate these theories, as would qualitatively studying the micro-level decision-making at individual companies. Other stakeholders not studied in this paper due to data constraints (e.g. journalists, investors) could be considered as well. Finally, studying the returns of this messaging on short-term outcomes such as earned media attention, brand favorability, and stock valuation as well as longer-term outcomes such as employee satisfaction, market performance, and political subsidies would contribute to a rich literature on brand media effects (53) and political consumerism more broadly (54).

Finally, it remains to be seen how these trends generalize beyond the platforms and time period studied. In the present study, I find little difference in the distribution (Figure A6) and alignments (Figure C16–Figure C17) of speech on Twitter vs. Instagram (the latter believed to have a younger consumer base). Comparisons to televised brand advertisements are constrained by a lack of data, however an investigation in Appendix A.3 suggests that the extent of partisan brand signals on social media may be an upper bound on different communication channels. Limitations notwithstanding, this paper contributes an important and up-to-date benchmark of political polarization in corporate America, supporting the emergence of an alignment between big business and liberal Democrats.

References

Political Speech from Corporations is Sparse, Only Recently Liberal, and Moderately Representative: Evidence from Social Media

Online Appendix

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A Partisan Signal Measure

This section provides additional details, context, and robustness checks on the central measure of brands’ partisan signal used in the main text.

A.1 Additional Details & Checks

Figure A1 confirms that the most partisan bigrams discovered by a simple $\chi^2$ analysis are substantively meaningful. Figure A2 shows that the specific keywords and general left lean shown in Figure 2 is invariant to the type of count (number of brands rather than total usages).

I performed an additional check on the validity of scaling brands via the Congressional reference corpus, as follows. I first summarised the weighted partisan lean of each post $k$:

$$\tilde{\psi}_k = \frac{\sum_{j=1}^{1000} w_{kj} \gamma_j}{\sum_{j=1}^{1000} w_{ij}}$$

where $w_{kj}$ is the number of times the $j$th most partisan phrase is used in post $k$. I randomly sampled 100 posts and asked a research assistant to classify each of them as politically left-leaning, right-leaning, or neither. The intercoder reliability as measured by Cohen’s $\kappa$ between the research assistant and the binarized direction according to my measure is 0.84.

Figure A3 shows the equivalent of Figure 3 using number of brands instead of % of posts on the horizontal axis; we again see a discernible spike following the events of George Floyd, however this plot reveals it came from a relatively small (<10%) number of brands.

Figure A4 reveals that (i) groups and issues receive the most attention across categories of phrases and (ii) the most common context for such speech is position-taking rather than information, affective appeals, or calls for/credit-claiming around charity.

Figure A5 highlights both the most partisan sectors as well as four most partisan brands within-sector (sectors labelled according to YouGov’s brand classification). The most right-leaning sector is the GAS, TIRE & ACCESSORIES sector which is generally consistent with the partisan agenda revealed from climate policy indicators but also confirms that Chevron’s self-presentation in Figure 1 is unusual. The most left-leaning sector is the TECH sector which is consistent with prior literature (55). Specific brands that surface from as liberal and conservative brands such as Whole Foods, Trump Hotels, Trader Joe’s, and Bank of America align with prior brand evaluations, while other brands such as General Motors and Capitol One are more left-leaning than expected (56, 57). Though not on this figure, brands from Vogel (58)’s case analysis such as Nike and Ben & Jerry’s also arise as amongst the most left-leaning brands in my sample.
Figure A1: Partisan Bigrams on Instagram and Twitter from Members of Congress (2014-2022)

Notes: Shown are top 25 most partisan stemmed bigrams for incumbent members of the 116th Congress on Twitter and Instagram through the period of study (2014-2020). The measure on the horizontal axis is the simple $\chi^2$ measure of differential counts between the two parties.
Figure A2: Types of Partisan Signals from Corporate Brands (By Number of Brands)

Notes: The horizontal axis denotes the $\chi^2$ statistic of differential Republican usage value of each bigram. Panels are ordered from most left-leaning in the usage of cues within that category to most right-leaning. Some labels of phrase bigrams are omitted for visual clarity.
Figure A3: Partisan Signals from Corporate Brands Over Time (By Number of Brands)

![Graphs showing partisan signals over time for different groups and issues.]

**Notes:** As in Figure 3, the two dashed lines denote in time (i) George Floyd’s murder and (ii) the January 6th 2021 U.S. Capitol insurrection.

Figure A4: Contexts for Partisan Brand Signals

![Table showing the co-occurrences of partisan phrases in different contexts.]

**Notes:** Partisan phrases (vertical axis) are categorized into a dictionary by hand. The dictionary for context keywords (horizontal axis) was inductively discovered by first carefully analyzing the social media corpus and then iteratively including and excluding keyword strings using the computer-assisted methodology introduced by King et al. (59). See replication code for a full list of phrases.
Figure A5: Scaled Corporate Brands Across Sector

Notes: Panels in the left column show the top 2 most left-leaning and right-leaning brands in each sector according to bootstrapped estimates of the weighted average $\chi^2$ of partisan language used on the horizontal axis (with 95% confidence intervals). Note that some sectors do not have four or more partisan-signalling brands on social media in my sample.
A.2 Other Measures

Figure A6 presents six additional measures of partisan brand signal according to their distributions as well as correlations with the main measure. The six measures are: (i) binarizing $\chi^2$ to classify phrases as either Democrat or Republican-leaning (essentially a dictionary approach), (ii) subsetting to phrases that specifically invoke known political groups, (iii) subsetting to issues, (iv) a parametric model that identifies out brand- and phrase-specific baselines in brands’ speech, (v) disaggregating to Twitter posts only and (vi) disaggregating to Twitter posts only. Figure A6 shows that one of the central findings of the paper – the slight left lean of brands – holds across all of these measures and that no particular measure deviates significantly from the main measure.

Estimates from the parametric model are as follows. Suppose that $w_{ij}$ is the usage of each of the 1000 most partisan phrases indexed by $j$ by each brand $i$. The goal of the model is to separately measure both its baseline intensity of partisan language, $\beta_i$, and the degree of its slant, $\psi_i$, in a Democrat or Republican direction. To accomplish this, I fit the following model:

$$w_{ij} \sim \text{Pois}(\lambda_{ij}),$$
$$\lambda_{ij} = \exp(\alpha_j + \beta_i + \psi_i \gamma_j).$$

(1)

The quantities of interest estimated from this model are $\beta_i$ and $\psi_i$. The fixed effect $\beta_i$ can be interpreted as a brand-level intercept of partisan expression which captures its baseline proclivity for attention to sociopolitical issues associated with either party, while the $\psi_i$ parameter captures how strongly a brand’s mentions of a particular phrase can be explained by its partisan leaning, the main quantity of interest in this study. The model itself is fitted using an Expectation-Maximization algorithm. I note that $w_{ij}$ could plausibly follow other distributions such as the Negative Binomial distribution which would account for features such as overdispersion. Results from such an assumption are largely similar to that of a Poisson distribution and are omitted for brevity.

To estimate standard errors from the parametric model, I perform a parametric bootstrap for a thousand iterations on each brand, following Imai et al. (60). In addition to obtaining estimates in the entire sample, in order to make valid within-year and within-sector comparisons between brands, I repeat this procedure on each individual sector and each individual year. Additionally, I exclude all brands that use less than 15 of the 500 most partisan bigrams in my period. The standard errors from this model are used for additional robustness checks in Figure C18.

Additionally, the key correlational analyses from the paper are replicated using all of these measures in Section C.4.
Figure A6: Comparison of Different Partisan Brand Signal Measures

Notes: Estimates are non-centered in order to assess whether each measure demonstrates a similar degree of left-ward shift as the original non-parametric measure (with the exception of estimates from the parametric model which are transformed during estimation).
A.3 Other Media

This article focuses on brands’ partisan signal on social media; measuring the same on other media is out of scope due to data limitations. Nevertheless, as a preliminary effort to inform the reader, I conduct a small-\(n\) study of partisan signals in a crowd-sourced convenience sample of 2,000 TV advertisement transcripts linked to \(\approx 400\) brands in my sample (61). The air dates for the ads in this sample are no later than 2020 and date back as early as 2008 (timestamps are not available).

I find that a mere two ads in this entire sample mention any partisan phrases and no particularly informative ad phrases predict either Democratic or Republican leanings online. The reader is cautioned from extrapolating too much from these results; still, given the available data and resources, a reasonable prior (to be confirmed in future studies) is that brands’ partisan signals on social media may be an upper bound for their partisan signalling on other channels.
B Additional Covariate Description

This section provides additional description of the stakeholder and activity variables used to make the main descriptive inferences in the study (related to Figures 4–7).

B.1 Distributions

Figure B7 provides baseline distributions of the stakeholder preference covariates for brands in this study. Two insights in particular are worth highlighting. First, the most Republican-leaning stakeholders (relative to the maximum value for each scale) are board members (60% on average across companies) and Twitter followers (59% on average across brands) in 2017; the most Democrat-leaning stakeholders are the human resources and marketing departments and significantly more so (13% and 16% of donations respectively). Second, there are more Democrat-leaning stakeholders on average than there are Republican-leaning stakeholders: 59% of donations go to Democrats across all employees and board members (upper left-most subplot) and 59% of all stakeholders across companies are Republicans (lower right-most subplot).

Note that my measure of Twitter followers (middle right-most subplot in Figure B7) differs from the 2017 and 2022 measures from Schoenmueller et al. (34). This is because (i) different brands are represented by each of the measures due to imperfect matching, (ii) my measure uses random snapshots of followers from 2021, (iii) Schoenmueller et al. (34)’s measures only include influential followers from each brand that exclusively follow either the Republican party or Democratic party national Twitter accounts. (ii) may explain the greater similarity to the 2022 measure and (iii) suggests that my measure may better represent ideologically extreme (left-leaning in particular) users by capturing their full portfolio of partisan followings, thus shifting the distribution further to the left.

Figure B8 similarly provides baseline distributions of the firm activity covariates. In contrast with stakeholder distributions, we see a more conservative lean in firms’ political activities in the lobbying (59% of all bills lobbied by a brands’ parent firm are sponsored by Republicans) and campaign finance arenas (57-61% of organizational PAC donations go to Republicans). Similarly, on average, firms are majority non-white and male in the composition of their workforce despite their online attention to diversity. On the other hand, firms’ ratings – on LGBTQ equity (HRC) and on climate policy (CDP and Climate Action 100+) – are more positive than not. This may imply a sincerely strong liberal direction in their DEI and climate activities or a selection mechanism: since these ratings rely on voluntary firm disclosures, firms with worse underlying performances in those areas may not disclose the necessary information to even receive ratings. A bigger concern for my study is that this selection may additionally be correlated with the direction of firms’ online political branding. I evaluate the latter in the next section (B.2). Figure B8 also informs the choice of logging the regulatory violations in Figure 7 due to their skew; similar results follow when using a Negative Binomial or Poisson regression.
Figure B7: Distribution of Stakeholder Preference Variables

- % R. Donations: All
  - 0.41
- % R. Donations: Board Members
  - 0.6
- % R. Donations: Managers
  - 0.34
- % R. Donations: Legal
  - 0.22
- % R. Donations: HR
  - 0.13

- Twitter: % R. Followers (2017)
  - 0.59
- Twitter: % R. Followers (2022)
  - 0.5
- % R. Pres. Vote: HQ
  - 0.37
- % R. Pres. Vote: Locations (Zippia)
  - 0.4
- % R. Pres. Vote: Locations (SafeGraph)
  - 0.47

  - -0.09
- R. Direction of HQ Senator
  - -0.08
- % R. Stakeholders
  - 0.41
Figure B8: Distribution of Firm Activity Variables
B.2 Missingness

Some brand covariates of interest in this paper are missing due to lack of availability from the provider (Zippia workforce characteristics, Glassdoor employee reviews) and/or imperfect matching from my end (FEC data, variables involving headquarter or retail locations). Other covariates are missing for some brands due to selection: the covariate itself is not observed. In the case of political activities, this may be because a brand’s parent firm does not have access to a PAC. In the case of ratings, this may be because a brand’s parent firm is not reviewed on Glassdoor or did not disclose the necessary information to even receive ratings (from HRC, CDP, or Climate Action 100+).

To test whether the degree of missingness for any of these reasons is correlated with my main measure of interest, brand signal, I regress missingness in each of the above variables on partisan signal at the brand level.

Figure B9 summarises the three important takeaways from this exercise which are as follows. First is a validity takeaway: results in the main paper concerning covariates that are missing due to lack of availability or imperfect matching are unlikely to be skewed due to this missingness. That is, no covariate in this category is over-matched, under-scraped, or otherwise provided unevenly by its source for liberal or conservative brands specifically. Second is a substantive takeaway about ratings: indeed, more liberal-presenting brands are more likely to receive climate policy evaluations and LGBTQ+ DEI evaluations to begin with. Third is a related substantive takeaway about political activities: brands that use more Republican speech are more likely to have a PAC that contributes to any candidate or group.

In other words, firms in my sample that do not receive HRC ratings or fund political action committees are different than those that do. The magnitude of these imbalances based on the standardized coefficients (0.25–0.5 standard deviations of the outcome) suggests that the significant correlations shown in the main Figure 7 for LGBTQ+ equality scores and political activities may be even weaker or altogether null when considering all brands in the sample.
Figure B9: Correlation Between Brand Missing Covariate and Brand Signal

Notes: Coefficients are estimated from univariate regressions of missingness of each firm covariate (vertical axis) on brand partisan signal. Estimates are sorted and grouped by category (black panels).
C Additional Regression Results

This section provides additional regression analyses bolstering the main regression analyses in the paper.

C.1 Other Predictors of Signal Direction

Even though many of the activity and stakeholder variables in the main text exhibit weak or null correlations with brand speech, other empirically and conceptually related variables that are available may be more informative of brand signal.

Figure C10 shows that besides a weak link to gender composition, there is no detectable relationship between the consumer characteristics of brands in my sample and online partisan speech. On the other hand, Figure C11 shows that there are stronger (albeit still not “large” according to conventional definitions) correlations between partisan brand signal and employee characteristics, in particular the educational composition of the workforce, in the expected direction. Taken together with Figure C12, I find that brands belonging to larger, more educated, and more racially diverse firms are more likely to send liberal or Democratic appeals on social media.

Figure C10: Consumer Demographics (At Most) Weakly Predict Partisan Brand Signals

Notes: Coefficients estimated from univariate regressions of brand signal on consumer demographic cross-tabs measured via YouGov audience panel surveys for each brand in our sample.
Figure C11: **Employee Demographics Moderately Predict Partisan Brand Signals**

![Diagram showing employee demographics impact on brand signal]

**Notes:** Coefficients estimated from univariate regressions of brand signal on employee characteristics measured using Zippia profiles matched to each available brand in our sample.

Figure C12: **Brand and Firm Characteristics (At Most) Weakly Predict Partisan Brand Signals**

![Diagram showing brand and firm characteristics impact on brand signal]

**Notes:** Coefficients estimated from univariate regressions of brand signal on brand (and brand parent firm) characteristics collected from a number of sources including Wikipedia, Glassdoor, and Zippia.
C.2 Keyword Outcomes

The broad measure of partisan brand signal used in this paper may elide more issue-specific connections between firm activities and firm speech. For example, although firms with strong DEI initiatives may not brand themselves as liberal “on average” on social media, they may still mention issues of race and racial diversity.

The keyword regression results from Figure C13 at least partially corroborates this story, specifically on racial issues but also for select indicators of firms’ attention to LGBTQ and gender inclusion as well as climate. The magnitude of the coefficients are not unsubstantial when transformed to linear scale: a standard deviation increase in a brand’s black employee satisfaction predicts, on average, $\approx$ twice as many keywords about racial justice. However, the usage of these specific liberal keywords is skewed across brands and thus low overall: “racial justice”, for example, is said $\approx$ 600 times in our sample but only by 20% of brands overall resulting in an average count of less than 1. Additionally, the number of regulatory offenses intriguingly appears to positively correlate with attention to keywords in that area. This provides some limited counter-evidence of false advertising, i.e. that brands are not only exaggerating but sending the opposite partisan signals of their implied agenda.
Figure C13: Relevant Firm Activities (At Most) Moderately Predict Usage of Specific Democrat Signal Keywords

Notes: Coefficients estimated from a Negative Binomial regression – to account for the over-dispersion of zero usages – of keyword counts of specific categories of partisan phrases on relevant firm activities. Coefficients are shown on the original log scale. Substantive conclusions are the same as using a linear regression model with a logged outcome. Regulatory offense counts are logged whenever used. Keywords are taken directly from the list of Congressional phrases (the top 25 of which are shown in Figure A1) and supplemented with synonyms and closely related phrases. See replication code for a list of the exact phrases.
C.3 Predictors Over Time

I exploit several variables with over-time variation to show how the correlations between brand signals and preferences/activities changes (if at all) over the period of study and whether the main results are local to a particular moment in time.

Taken together, Figures C14–C15 suggest that most correlations shown in the main paper only became significant (if at all) after 2019. I note that these results do not elucidate whether brands’ online speech caused a shift in stakeholder preferences (or stakeholders themselves) and their activities or the other way around.

Figure C14: Correlations Between Partisan Brand Signal and Stakeholder Preferences Over Time

Notes: Coefficients estimated from univariate regressions of brand signal (measured using only brand posts and Congressional language in the given year) on stakeholder preferences measured in that given year. Estimates for certain stakeholders (e.g. Human Resources employees in 2019) are missing due to fewer matches in particular years. Results involving the presidential vote use the most recently available presidential vote-share available for each year, though noting that presidential vote-share across years at the ZIP code level are highly correlated. For Twitter followers, followership is only available in 2017 and 2022, so brand-year observations are matched to the closest year of Twitter followership.
Figure C15: Correlations Between Partisan Brand Signal and Firm Activities Over Time

Notes: Coefficients estimated from univariate regressions of brand signal (measured using only brand posts and Congressional language in the given year) on firm activities in that given year. Certain activities (e.g. PAC donations) are only available for election years.
C.4 Results with Alternative Measures

Figure C16 replicates select analyses from the main text (for brevity) using the alternative measures of brand signal described in Appendix A.2. Substantive conclusions from the paper largely do not change across these measures.

Figure C16: Correlations Between Different Measures of Partisan Brand Signal and Stakeholder Preferences

Notes: Coefficients estimated from univariate regressions of brand signal (measured in the ways labelled on the vertical axis) on stakeholder preferences labelled by the black panels (for brevity, only a subset of preferences used in the main text are shown). Confidence intervals for coefficients involving the main measure used in the text (♦) are re-adjusted using BH-q procedure relative to the other results shown here, though the substantive conclusion remains with the confidence intervals shown in the main text.
Figure C17: Correlations Between Different Measures of Partisan Brand Signal and Firm Activities

Notes: Coefficients estimated from univariate regressions of brand signal (measured in the ways labelled on the vertical axis) on firm characteristics labelled by the black panels (for brevity, only a subset of characteristics used in the main text are shown). Confidence intervals for coefficients involving the main measure used in the text (♦) are re-adjusted using BH-q procedure relative to the other results shown here, though the substantive conclusion remains with the confidence intervals shown in the main text.
C.5 Results with Alternative Specifications

Figure C18 replicates select analyses from the main text (for brevity) using alternative regression specifications that incorporate additional measurement error in both the predictors and outcomes in the main regressions (Figures 6–7). These including weighting by the precision of point estimates of each predictor (e.g. total number of PAC dollars spent, number of locations matched in Safegraph data, number of partisan Twitter accounts used to infer follower partisanship), clustering regressions by parent firm (many brands belong to the same conglomerates such as Procter & Gamble) or industry, and weighting by the bootstrapped standard errors of partisan brand signal itself.

In general, when boosting observations with added precision, the magnitude of correlation increases, sometimes substantially (see correlations with voters in retail locations from the SafeGraph data). No substantive conclusion appears to consistently change or at all reverse.
Figure C18: Correlations Across Weighting and Standard Error Specifications

Notes: Coefficients estimated from univariate regressions of brand signal on selected firm covariates (black panels on right) according to different specifications (vertical axis) of standard errors and weights to account for additional uncertainty in either the dependent variable or the independent variable. The dependent variable for each specification is the main measure of brand signal used in the text (average usage of differentially Republican keywords) with the exception of bootstrapped standard errors which uses bootstrapped estimates of brand signal from the parametric model. Weights for bootstrapped standard errors are inverted (brands with larger standard errors are given less weight).
C.6 Equivalence Tests

Even statistically significant coefficient results may be rejected on the basis of small effect sizes; moreover the absence of statistically significant results do not necessarily imply minimal or zero relationships in reality. Thus, I turn to equivalence tests to seek evidence that the effect sizes shown in the main text are negligible (62–64).

Equivalence tests are operationalized using a Two One-Sided Test (TOST) procedure testing the null hypothesis of a minimal standardized difference in the outcome explained by the predictor of interest. Here I use the most permissive definition of a large effect commonly used in the literature (65), 0.20 standard deviations. Hartman and Hidalgo (64) recommend a more conservative threshold of 0.36 standard deviations.

Figures C19–C20 show that few variables, with the exception of some climate policy indicators, meaningfully explain variation in brands’ partisan signals according to this minimal bar at a 95% confidence level. Those that though fail to do so at the higher threshold of 0.36 that is typically recommended.

Note that in many cases, equivalence tests detect minimal relationships in finite samples of a larger population due to a lack of statistical power. That is not an applicable reason in this study since I observe the entire population of interest (highly recognizable brands in the United States).

Figure C19: Equivalence Tests for Stakeholder Preference Regressions

<table>
<thead>
<tr>
<th>% R. Stakeholders</th>
<th>All</th>
<th>Consumers</th>
<th>Consumers + Employees</th>
<th>Elected Officials</th>
<th>Employees</th>
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<td>Twitter: % R. Followers (2017)</td>
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<td>Twitter: % R. Followers (2022)</td>
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<td>Twitter: R. Direction of Followers</td>
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<td>% R. Pres. Vote: Locations (SafeGraph)</td>
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<td>% R. Pres. Vote: HQ</td>
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<td>R. Direction of HQ Senator</td>
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<td>% R. Donations: PR</td>
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<td>% R. Donations: Rank–and–file</td>
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<td>% R. Donations: Executives</td>
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<td>% R. Donations: Managers</td>
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<td>% R. Donations: Legal</td>
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<td>% R. Donations: Marketing</td>
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<tr>
<td>% R. Donations: Board Members</td>
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Notes: Bands show the 95% two-sided TOST intervals for the regressions of brand signals on each of the (standardized) measures of stakeholder preferences shown on the vertical axis. Bands are colored black if they are able to reject the null hypothesis of at least a 0.20 standardized difference – a common benchmark for a minimal effect size (65). In comparison, points denote the original estimates.
Figure C20: Equivalence Tests for Firm Activity Regressions

Notes: Bands show the 95% two-sided TOST intervals for the regressions of brand signals on each of the (standardized) measures of firm activities shown on the vertical axis. Bands are colored black if they are able to reject the null hypothesis of at least a 0.20 standardized difference – a common benchmark for a minimal effect size (65). In comparison, points denote the original estimates.
**C.7 Robustness to Influential Observations**

The power distribution of speech and influence broadly observed on social media and the apparent outliers amongst our brands in their partisan signalling seen in Figures 4–5 raise the concern that a few influential observations are entirely “responsible” for the minimal alignments/correlations we do observe.

Figures C21–C22 show the results of a procedure (66) used to identify the most pivotal observations (if they exist) in a regression model, the removal of which would reverse the sign of the estimated coefficients significantly. In summary, the correlations estimated in Figures 6–7 are robust up to the removal of roughly 50 and 200 brands (5-20%). Compared to even gold-standard randomized control trials, this is a far higher level of robustness (66).

**Figure C21: Estimated Influential Observations for Stakeholder Preference Regressions**

*Notes:* Percentages denoted by each black dot are estimated via the estimator proposed by Broderick et al. (66). Shown are only the independent variables from Figure 6 for which an influential set could be estimated.
Figure C22: Estimated Influential Observations for Firm Characteristic Regressions

Notes: Percentages denoted by each black dot are estimated via the estimator proposed by Broderick et al. (66). Shown are only the independent variables from Figure 7 for which an influential set could be estimated.
C.8 Heterogeneities

Figures C23–C24 show how a subset of key results in the main regressions (Figures 4–5) vary for different subsets of brands based on headquarter location, size, and industry. I find that the relationships between firm activities/stakeholder preferences and brand cues are concentrated in (i) brands based in the U.S., (ii) in the retail, household goods, and technology sectors, and (iii) with larger parent firms rather than smaller.

An interesting exception is that smaller firms’s brand speech is more aligned with the ideology of their headquarters’ elected representatives. The reason for this is that smaller firms are Republican-leaning in their partisan appeals (Figure C12) and also more likely to be located in rural, Republican-leaning geographies rather than urban knowledge economy hubs.
Figure C23: Heterogeneities in Stakeholder and Activity Correlations by Firm Headquarter

Notes: Foreign-based firms are those with no “main” headquarters in the United States; note that this differs from the definition of a multinational corporation because the parent firms of nearly all brands in our sample are multinational. Coefficients are estimated from univariate regressions of brand signal (main measure) on each of the covariates shown in the right black panels for the subset of brands denoted on the vertical axis. Estimates for all brands (♦) correspond to estimates in the main text.
Notes: Industry labels are pooled categories of consumer brands as categorized by YouGov. Coefficients are estimated from univariate regressions of brand signal (main measure) on each of the covariates shown in the right black panels for the subset of brands denoted on the vertical axis. Estimates for all brands (∙) correspond to estimates in the main text. Some industries are omitted from certain panels due to a lack of comprehensive measures for that particular covariate across firms in that industry (e.g. climate policy for tech brands).
Figure C25: Heterogeneities in Stakeholder and Activity Correlations by Firm Size

Notes: Employee bins are constructed using the median of the log count of employees across all brands as the cut-off. Coefficients are estimated from univariate regressions of brand signal (main measure) on each of the covariates shown in the right black panels for the subset of brands denoted on the vertical axis. Estimates for all brands (♦) correspond to estimates in the main text.
C.9 Predictors of Signal Magnitude

The primary outcome of interest in this paper is the partisan slant of media produced by brands, in a relative sense. However, the absolute amount of partisan speech itself is important: more cues results in more impressions and greater exposure by the very stakeholders examined in this study. What predicts this extensive margin of brand partisan speech?

Figure C26 reveals that larger more popular brands with more liberal stakeholders also tend to produce more partisan cues overall. Thus, not only is the average leaning of corporate brands left-leaning, but so is the total amount.
Figure C26: Correlations Between Number of Partisan Phrases and Brand Covariates

Notes: Coefficients are estimated from Negative Binomial regressions of the number of partisan phrases used by each brand on firm covariates (vertical axis). Estimates are sorted and grouped by category (black panels).