Political Speech from Corporate America:
Sparse, Mostly for Democrats, and Somewhat Representative

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Abstract

How do corporations engage in political speech in the age of social media? Evidence suggests that online corporate brands employ a variety of *partisan signals* which include not only ideological positions but also more subtle, implicit appeals to partisans. Identifying and scaling a broad range of these signals in ≈2 million Twitter and Instagram posts from the 1,000 most popular corporate brands in the United States, I find that most corporate brands' speech mirrors the speech of Democrats, but this is concentrated in a handful of brands and occurs in uneven bursts across time. Moreover, this communication is not as dishonest as popular narratives suggest: the majority of brands' partisan speech well represents the political preferences of key stakeholders (e.g. employees, voters, and consumers) and is at least somewhat informative about corporate governance practices (e.g. political spending, DEI priorities, and climate policy). These results provide a measured counterbalance to popular narratives of 'woke capitalism', suggesting that political speech from corporate America is, at worst, sometimes inconsistent with stakeholders and firm agendas rather than outright hypocritical.

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1 Introduction

The American public increasingly seeks political leadership from companies on issues ranging from abortion access to gun violence to climate change (Goldberg, 2022; Dowling and Sathya, 2022; Malhotra, Monin, and Tomz, 2019). At the same time, the rise of social media as a preeminent source of political information for many voters (King, Schneer, and White, 2017; Pew Research Center, 2021), and the primary marketplace for many young consumers (Faverio and Anderson, 2022) provides a powerful platform for corporate brands to set the agenda on these issues. Companies recognize this value: according to annual tax filings in the past decade, oil industry trade groups' expenditures on advertising and public relations (including social media efforts) totalled more than 10 times their spending on federal lobbying (Quinn and Young, 2015). Yet, how business interests harness communication remain understudied relative to traditional political channels such as legislative lobbying (Hall and Deardorff, 2006; Baumgartner, Berry, et al., 2009; De Figueiredo and Richter, 2014) and campaign finance (Milyo, Primo, and Groseclose, 2000; Ansolabehere, De Figueiredo, and Snyder Jr, 2003; Fowler, Garro, and Spenkuch, 2020) – channels that are often shown to yield poor returns (Ansolabehere, De Figueiredo, and Snyder Jr, 2003; Kang, 2016; You, 2017; Fowler, Garro, and Spenkuch, 2020).

Recently, this gap has become relevant in light of critics who accuse corporate brands of hypocrisy in their public communications – 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' (Douthat, 2018; Dowell and Jackson, 2020). If companies actually do so en masse, this poses a significant barrier to a well-informed public and an accountable capitalism responsive to its stakeholders (Bernays, 1945; Freeman, 1984). More specifically, it suggests that Americans' growing civic trust in corporations may be misplaced. Indeed, recent studies confirm that companies 'green-wash' their environmental externalities (Supran, 2021; Malhotra, Monin, and Tomz, 2019) and 'diversity-wash' their hiring practices (Baker et al., 2022), with the effect of masking harmful climate policies and social inequities in the workforce. Other studies find mixed results in public and elite demands for corporate social responsibility (Hersh, 2023; Hersh and Shah, 2023b). Against the 'woke capitalism' hypothesis, Z. Li and Disalvo (2022) find that in the wake of the 2021 Capitol insurrection, companies with more Democratic-leaning stakeholders were, in fact, more likely to publicly refuse contributing to Republican legislators who objected to the electoral college results. Still, no single study to date provides a complete description of the *supply* of corporate political communication across industries, time, stakeholders, and issues.

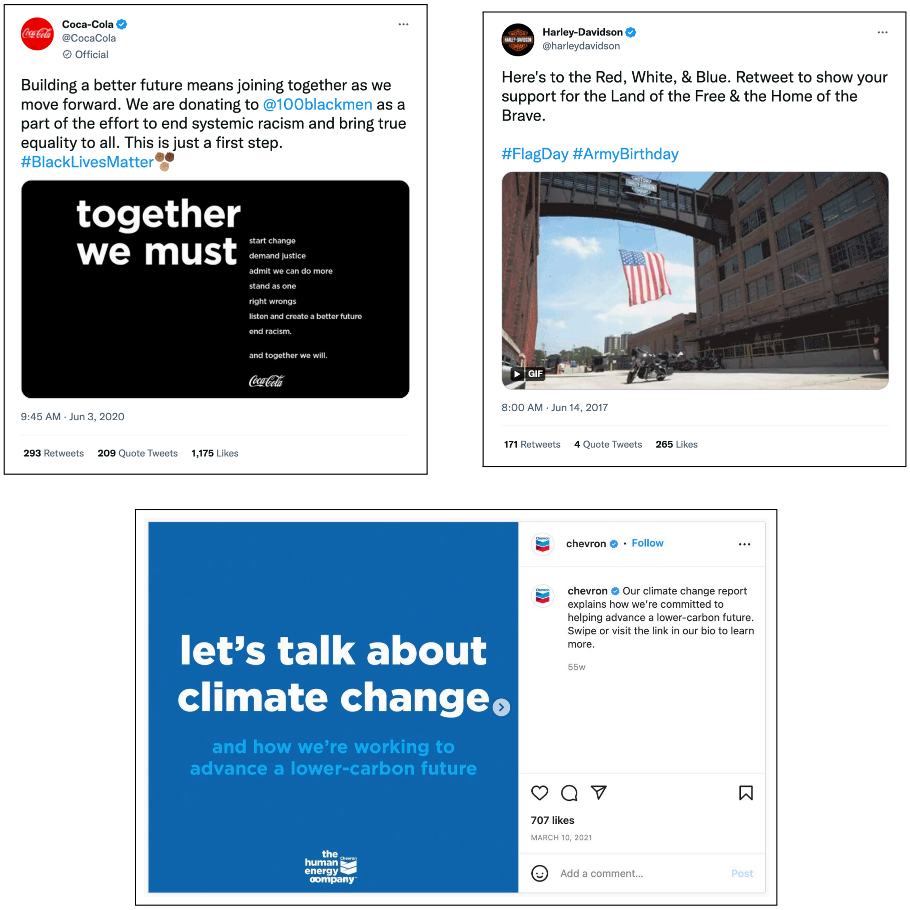
This paper leverages a novel dataset of more than 2 million social media posts from the most well-recognized consumer-facing corporate brands to answer a series of descriptive questions around political speech in corporate America. First, to what extent do major corporations in the United States actually send political signals in their communications with the mass public? Second, where do these signals fall on the partisan spectrum? Do they overwhelmingly appeal to Democrats as critics of 'woke capitalism' contend or does it align more with Republicans as with corporate behavior in other political arenas in the post-*Citizens United* era (Klumpp, Mialon, and Williams, 2016)? Third, is speech representative of the preferences of important stakeholders and informative about firm activities and priorities? Each of these questions speak to specific dimensions of the 'woke capitalism' hypothesis.

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 a partisan sense – in their speech. Of brands that do, most lean towards liberal or Democratic appeals in their speech, but most consistently 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) just as often appealed to a Republican world-view. Finally, I show that corporate brands' political speech on social media is not just empty signaling, but is modestly correlated with the revealed preferences of most stakeholders – though no particular stakeholder more than the rest – and generally predictive of the ideological direction of different firm priorities.

1.1 Partisan Brand Signals

The first methodological innovation in this study comes from mapping speech from a comprehensive set of corporate actors onto the full spectrum of ideological language between the two parties in the United States. 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 (Chong and Druckman, 2007; Tversky and Kahneman, 1981); attention paid to certain issues over others (Gentzkow and Jesse M Shapiro, 2010; Egan, 2013); lifestyle or cultural cues (Bennett, 1998; Hetherington and Weiler, 2018); and references to social, racial, and geographic markers (DellaPosta, 2020). Well before the first social media platform, political scientists understood that partisan identification (Democrat

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.

vs. Republican) and even ideological labels (liberal vs. conservative) strongly draw on emotional associations with 'ideological symbols" of social conflict or divergence (Converse, 1964; Conover and Feldman, 1981).

Figure 1 illustrates some of the ways brands employ such symbols 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 (DellaPosta, 2020). Hence, in this study I operationalize political speech as the usage of *partisan signals*: the systematic usage of phrases strongly associated with either Democratic or Republican identity in areas ostensibly unrelated to brands' core business function (e.g. excluding health insurance companies' mentions of "health care").

The second methodological innovation in this study is the merging of these measures of partisan signals with measures of partisan preferences of stakeholders as well as measures of firm's revealed agendas on issues connected to their speech. These allows us to evaluate theories of preference alignment and agenda alignment which I describe next.

1.2 Brand Signals and Stakeholder Preferences

Partisan brand signals are one of many observable and (potentially) costly signals that employers may send to job-seekers in Spence (1973)'s signaling theory. However, according to the stakeholder theory of management, there is a much wider set of stakeholders that firms must consider in these branding decisions (Freeman, 1984; Aaker, 2012).

First, taken together, employees, managers, board members, and consumers are a business's central stakeholders and often the loudest proponents of corporate activism (Panagopoulos et al., 2020; Grossman and D. Hopkins, 2022; Fos, Kempf, and Tsoutsoura, 2022; Grewal, Serafeim, and Yoon, 2016). Current and future members of these groups are theorized to be the primary audiences for a company's social media presence which serves both an important informational role about company performance, organizational culture, and job function (Carpentier, Van Hoye, and Weijters, 2019) and a signaling function about corporate values (Appels, 2023). In this study, I further identify employees of specific branding-oriented departments – legal, public relations, marketing, and human resources – who are operationally involved in branding and communications decisions (Aaker, 2012). Comparing brands' partisan signals to the preferences of these employees against all employees should reveal whether partisan brand signaling disproportionately aligns with decision-makers' preferences at the expense of others, defying the stakeholder theory.

Additionally, voters proximal to the retail locations and headquarters of firms may be seen as important stakeholders since they contribute 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 states 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 (Bisbee and You, 2023).

Amazon's failed 2019 headquarters relocation to New York City is an example of the possible consequences of public communications mis-aligning with the political preferences of these latter local constituencies (Goodman, 2019). Among the criticisms from local residents and elected officials were Amazon's position on employee unionization and implied position on immigration based on prior work with the the federal U.S. Immigration and Customs Enforcement agency. Public relations experts suggested that Amazon could have avoided the ensuing negative press if Amazon's public communications had either (a) not made "too much noise" altogether or (b) highlighted corporate investments, stances, and activities more responsive to local preferences, while minimizing attention to controversial positions or activities (E. Kim, 2019).

1.3 Brand Signals and Firm Agendas

Although firms make many decisions that are informative of organizational values, I consider three crucial areas of corporate governance that clearly align with current partisan ideologies: climate policy and DEI (diversity, equity, and inclusion). Broadly speaking, Democrats – consistent with socially liberal, pro-regulation attitudes – would prefer companies allocate *more* attention and resources to these areas of corporate governance, while Republicans – consistent with anti-regulation, small government, socially conservative attitudes – prefer companies dedicate *less* attention and resources (Pew Research Center, 2016; Hersh, 2021). This, however, should not be conflated to mean that all else equal and across all contexts and industries Republicans advocate that their companies commit regulatory violations. Research has shown that Republicans tend to be over-represented in more "traditional" oligopolistic industries – e.g. oil and gas, real estate, and utilities including companies like Chevron (Bonica, 2014) – that are less likely to comply with institutional regulations (Jain, Aguilera, and Jamali, 2017), more likely to engage in strategic environmental infractions (Luo, Kaul, and Seo, 2018), and are less likely to engage with LGBTQ advocacy in CSR reporting compared to service sector and high tech companies (Zhou, 2021).

For the clearest demonstration of ideological consistency, if brands mirror Democrats' out-sized attention to climate change and issues of racial and gender inclusion, this should be reflected in progressive track records on climate policy and DEI issues. As such, I directly test this using various revealed measures of firms' agendas.

2 Materials and Methods

Replication materials for this study are available at [REDACTED FOR PEER REVIEW].

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 (Stuckatz, 2022b) or Fortune 500 companies (Bonica, 2016), 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 more relevant to this study 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 Gentzkow, Jesse M. Shapiro, and Stone, 2015.

I then manually link each of the brands from YouGov to their affiliated U.S. Twitter and Instagram accounts, if available and active, with the help of a research assistant. If multiple Twitter or Instagram accounts exist for different locales, I select the account localized for a U.S. audience. Active accounts are those that are verified and have posted at least once a year during this period. 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, Guess, et al. (2018) 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 (M. Li, 2022).

Many brands themselves are firms (e.g. McDonald's). However, for brands that are not (e.g. Snickers), a research assistant manually matched these to the firm owning the intellectual property of the brand (e.g. Mars, Incorporated). Additional characteristics for each brand and firm including U.S. headquarter location, number of U.S. employees, and revenue all at the time of writing in 2022 from various sources including Orbis and Wikipedia. Only a small percentage of firms shifted 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 a total of 879 brands in relevant sectors with active social media accounts on either Twitter ($n = 803$) or Instagram ($n = 523$) and any of the aforementioned covariates. The full sample of these brands along with their matched firms, and Twitter and/or Instagram accounts can be found in Appendix D.

2.2 Measurement of Partisan Brand Signals

I collect all Twitter and/or Instagram posts[1] by corporate brands with active accounts on either or both platforms between 2015–2021. I chose 2015 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 2015 (see Appendix Figure D29) creating a more uniform sample of posts over time and across brands, (2) this period offers a substantively useful comparison of brand Agenda 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 from brands during this period.

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 Jesse M Shapiro (2010) and Slapin and Proksch (2008). 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 χ^2 statistic of the difference in counts of bigram between Democrats and Republicans. This measure of the partisan leaning of the jth bigram is hereby denoted as γ_j. More extreme values correspond to greater partisan leaning; a more negative value of γ_j indicates a greater differential usage by Democrats while a more positive

[1] The complete corpus of Twitter posts for each brand in our period are collected via the Twitter API while the complete corpus of Instagram posts for each brand in our period are collected via an automated scraper written in Python.

value of γ_j 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 $\widetilde{\psi}_i$ with a simple non-parametric weighted count (by occurrence) of the bigrams' partisan lean:

$$\widetilde{\psi}_i = \frac{\sum_{j=1}^{J} w_{ij}\gamma_j}{\sum_{j=1}^{1000} w_{ij}}. \tag{1}$$

Here J denotes the revised size of the reference phrase set after pruning the 1,000 most partisan bigrams of any phrases used less than 5 times[2] by brands in my sample. This avoids the finite-sample bias observed by Gentzkow and Jesse M Shapiro (2010) where infrequently used bigrams unduely influence the measure.

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, a research assistant removed certain industry-specific phrases from the construction of $\widetilde{\psi}_i$, a full list of which can be found in the replication code.

[2]Results are not sensitive to this particular threshold of phrase count.

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 (Laver, Benoit, and Garry, 2003). However, as Lowe (2008) 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 signaling on the two platforms. Thus, in Appendix C.4, I replicate key analyses using alternative measurement strategies. These are: binarizing χ^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 signaling keywords and related corporate governance areas as well as stakeholder characteristics (Appendix C13).

2.3 Measurement of Revealed Stakeholder Preferences

Firm Affiliates' Campaign Donations. Following other studies (Atalay et al., 2020; Stuckatz, 2022a), 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 (Federal Election Commission, 2022). 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. (2020) and Stuckatz (2022a) in matching character strings denoting occupation to the Bureau of Labor Statistics' official occupation (SOC) codes for these categories of firm affiliates (U.S. Bureau of Labor Statistics, 2022). 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.

Brands' Twitter Followings. Although it would be ideal to directly observe the partisan orientation of brands' consumers, such measures are not readily available. Instead, following other studies (Z. Li and Disalvo, 2022; Schoenmueller, Netzer, and Stahl, 2022), I construct a proxy measure of consumer partisan preferences by scaling the recent followers of all available brands. In particular, in 2021 I sampled the most recent 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 (Barberá, 2015) manually supplemented with other known accounts of partisan media outlets, commentators, and interest groups and measured each follower's partisanship 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 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 C20). Sampling recent followers is desirable since it filters out inactive followers or users who began following these brands prior to the period of study. However, depending on when each brand was scraped, this recency feature may result in unrepresentative samples of follower communities. To safeguard against this, as well as against extrapolating from a potentially small ($n = 200$) sample of followers, I match my brands to Schoenmueller, Netzer, and Stahl (2022)'s 2017 and 2021 large-n cross-sections of brand Twitter followerships in supplementary analyses. The followerships across these two time periods are averaged for static analyses and disaggregated for over-time analyses (Appendix Section C.3). Still, the usage of Twitter followers – particularly recent followers – may be problematic: followers may not be consumers of brands' products at all or they might just follow brands due to previous political communications or incidental reasons. With these limitations in mind, I also construct offline measures of brand consumers' partisan preferences, described next.

Partisan Votes in Retail/Business Locations. I create geographic measures of stakeholders' partisan preferences (consumers, employees, and proximal voters), by matching brands' parent firms to ZIP codes of points of interests (POIs) provided by SafeGraph and scraped from Zippia, two commercial providers of consumer business POIs in the United States (SafeGraph, 2022; Zippia, 2022). I refer to these points of interests as retail (sites visited by consumers) and/or business (sites visited by corporate employees) locations. A relative weakness of these datasets is that they are unable to disaggregate *between* retail locations and business locations. This disaggregation, however, is already captured by the previously described campaign donation data. Moreover, this data is able to target a stakeholder not observable from the donation data: proximal voters who may pay attention to, interact with, and potentially hold strong attitudes in support or opposition of these brands and their firms.

I combine both of these datasets together since they have complementary strengths:

SafeGraph offers access to many more individual retail locations but with a slightly lower match rate to the brands' firms in the sample, while Zippia offers a better match rate but only list the top 20 ZIP code retail locations (by number of employees) per firm. 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, an election data vendor (TargetSmart, 2022).[3] Indeed the period of study extends to 2022, however ZIP code level presidential returns on the whole are nearly perfectly correlated in American elections, which reduces concerns about period mismatch. Capturing voters only in the immediate ZIP code around the firms' headquarters and retail locations may elude employees, customers, and residents who reside outside of the ZIP code but may encounter the business. Hence, I additionally match these locations to the average county-level Presidential vote share from 2016 to 2020 and replicate my analyses using these more inclusive measures.

Company Demographics. Additionally, I collect a number of brand-level consumer and employee demographic summaries from the YouGov Audience Panel (exactly covering the brands in my sample) and Zippia corporate surveys respectively (YouGov, 2022). These measures are both highly informative of stakeholders' partisan preferences as well as firms' hiring practices.

Ideology of HQ Representatives in Congress. I next turn to measuring the preferences of elected officials with a significant stake in firms' communications. Specifically, I focus on members of Congress – both the House Rep and the two Senators – who represent the home district or state where brands' corporate headquarters are located. I measure the

[3] I thank Jake Brown and Ryan Enos for providing me this data aggregated from the Census tract to the ZIP code level.

degree of partisanship of these representatives using DW-NOMINATE scores (Lewis et al., 2022) corresponding to the Congressional sessions over the course of the study period, which measure how closely each representative votes on informative bills with their party. The analyses use both DW-NOMINATE scores capturing Senators' revealed preferences (averaged across two Senators elected in the state of the headquarters from 2014-2022) and House Representatives' revealed preferences (averaged across elected representatives in each term from 2014-2022).

2.4 Measurement of Revealed Firm Agendas

Political Activity Records. I gather the most direct measures of firms' political agendas – donations to partisan candidates and groups – from the OpenSecrets database (Center for Responsive Politics, 2022). 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 (I. S. Kim, 2018).

Corporate Governance Evaluations. For corporate governance areas with an implied partisan agenda, I focus on two categories of environmental and social governance (ESG): climate policy and diversity/equity/inclusion (DEI). 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+ projects (Climate Disclosure Project, 2022; Climate

Action 100+, 2022). To assign these scores, analysts closely adhere to an assessment framework that is standardized within and across industries and draw on public disclosures from companies themselves. For measures of each firm's DEI priorities, I rely on three sets of measures. First, I scraped employees' evaluations of their workplace from Glassdoor, a widely used website that aggregates reviews of employers posted by current and past employees (Glassdoor, 2022). Crucially these reviews are disaggregated by characteristics such as race and gender allowing me to compare specific employee groups' workplace evaluations with references to those same groups in online speech. Second, I collected "equality scores" from the Human Rights Campaign (HRC), or analysts' evaluations of corporate policies and benefits specifically for LGBTQ employees (Human Rights Campaign, 2022). An added advantage of this second dataset (available without scraping) is that scores are available across time, enabling over-time analyses (Appendix Section C.3). Finally, I track regulatory violations by my brands' associated firms using the Good Jobs First Violation Tracker, a comprehensive database of federal agency actions and class-action lawsuits against corporations (Good Jobs First, 2022). I focus on three categories of regulatory violations that directly correspond to partisan cues used by brands and that, in theory, firms should engage *less* if their brands' follow Democratic party policy scripts and firm agendas match brand speech: social discrimination both in hiring and workplace contexts ("black community", "pride month"), labor law violations ("mental health", "child care", "health care"), and environmental violations ("climate change").

As Baker et al. (2022) show, availability of company's disclosures of climate practices and DEI priorities may itself coincide with whether they project a congruent, progressive image on social media. A similar selection dynamic may exist for employee evaluations from overwhelmingly Democrat-leaning groups who may evaluate workplaces with congruent values, agendas, and communications more positively. With this concern in mind, I have especially selected the aforementioned ratings over others (e.g. MSCI indices) because of their greater incidence rate with brands in my sample. Relying on multiple ratings, rather than a single index reduces the risk of selection bias spoiling our conclusions. For inferences based on employee evaluations, I weight relevant analyses by numbers of Glassdoor ratings and across all corporate governance data, I test whether missing values in each variable 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, it should be acknowledged 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 more direct measure of a firm's commitment to diverse hiring.

An overview of the various stakeholder and firm datasets used, how they were collected, along with the aforementioned (and other) strengths and weaknesses is provided in Appendix Table 2 and Table 3. Further discussion and descriptions of these data are available in Appendix Section B.

3 Results

Before proceeding to the results, the reader should take note of the following. First, all results shown in this section rely on non-parametric measure of brands' partisan signals described in 1. 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. Unless otherwise noted, labels, lines, and dots are colored red to denote Republican cues or Republican-sounding brands and blue to denote Democrat cues or Democrat-sounding brands.

3.1 Brands Sparingly Send Partisan Signals.

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 (are verified and have posted at least once a year) on Twitter or Instagram during this period. However, the overall supply of cues exhibits a highly skewed distribution; for example, only about 450 active brands use more than 5 partisan bigrams (51% of active 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 when using the entire sample.

3.2 Brands Sound More Like Democrats.

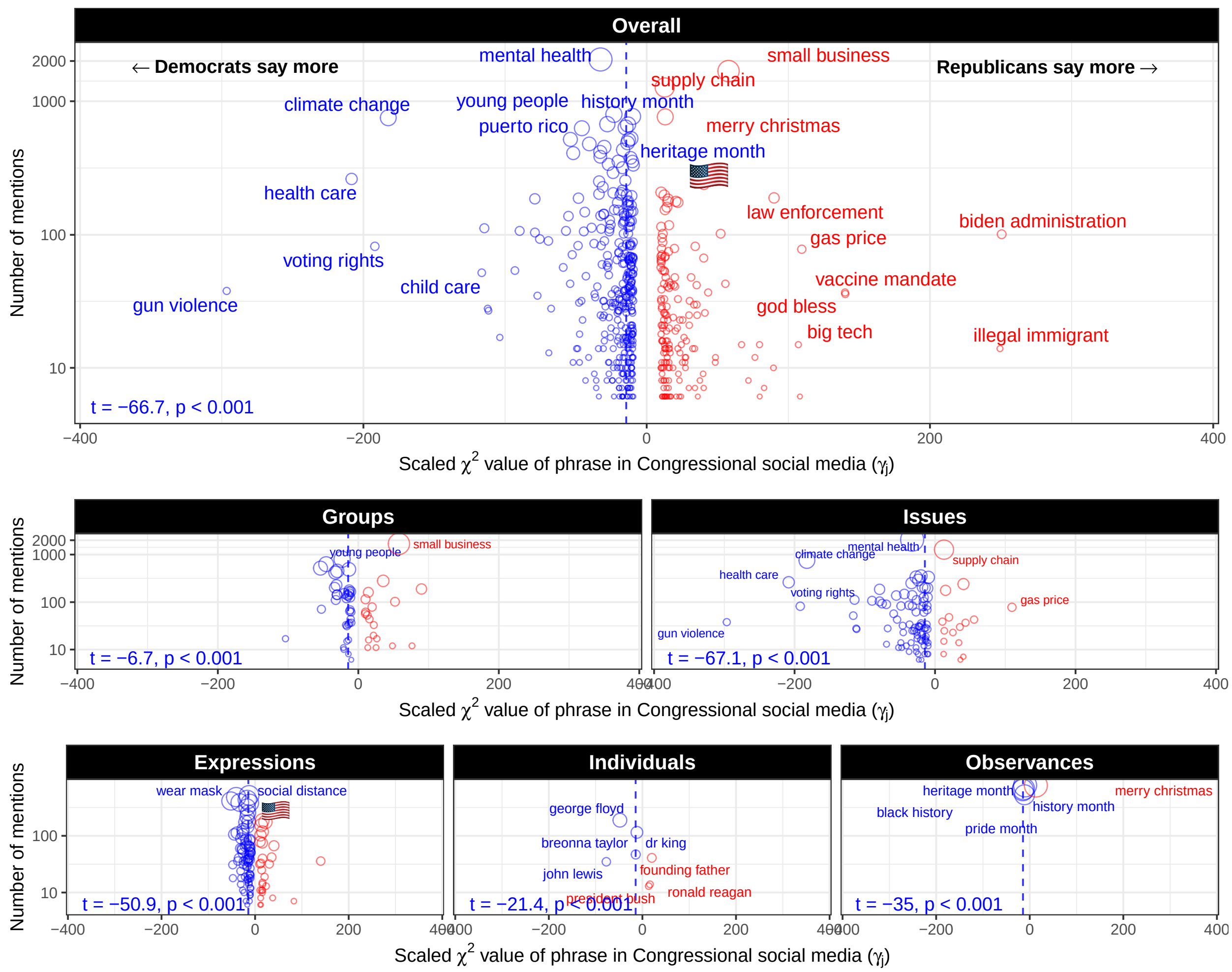
Next, I examine the specific ideological phrases most used by brands and the resulting ideological distribution of corporate brands according to these usages.

Figure 2 shows that, both overall ($t = -66.7, p < 0.001$) and across different categories[4] of rhetorical signals, brands' partisan cues 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.[5] 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. Overall, 73% of all partisan cues in brands' speech over this period is left-leaning.

[4]This classification was identified from the author's close qualitative analysis of the bigrams, applied to the phrases by a research assistant, and the resulting partition was validated by another research assistant. See Appendix Section A.2 for further details.

[5]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.

Figure 2: **Types of Partisan Signals from Corporate Brands**



Notes: The horizontal axis shows the γ_j 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 mean partisan lean γ_j of phrases (weighted by the count of each phrase) used by brands in each category. The results of a t-test of significance for the mean denoted by each dashed line is shown in the lower left of each panel. Bigrams shown here from the set of the 1,000 most polarized bigrams between Democrat and Republican members of Congress as described in Section 2.2. Counts of certain phrases for some brands were excluded if the phrase was judged (by a research assistant) to be related to a core, apolitical brand function (e.g. mentions of 'health care' by health insurance brands). Brands that have a phrase count less than 5 are also excluded from consideration.

The most common type of partisan rhetorical cue is an appeal to social or political *issue* ranging from gun violence to climate change to economic growth. Roughly 27% of all partisan cues on social media fall under this category. This is followed closely by references to sociopolitical groups (22%) and use of political expressions (20%). Brands' usage of *all* categories of cues lean towards the language of Democrats on average ($p < 0.001$ in all cases), though it would be inaccurate to claim they lean far or exclusively to the left. As the top panel in Figure 2 shows, the phrase used by brands that is most associated with Democrats is 'gun violence', however the dashed line in each panel (the average lean in that category) is far to the right of this left-leaning linguistic cue.

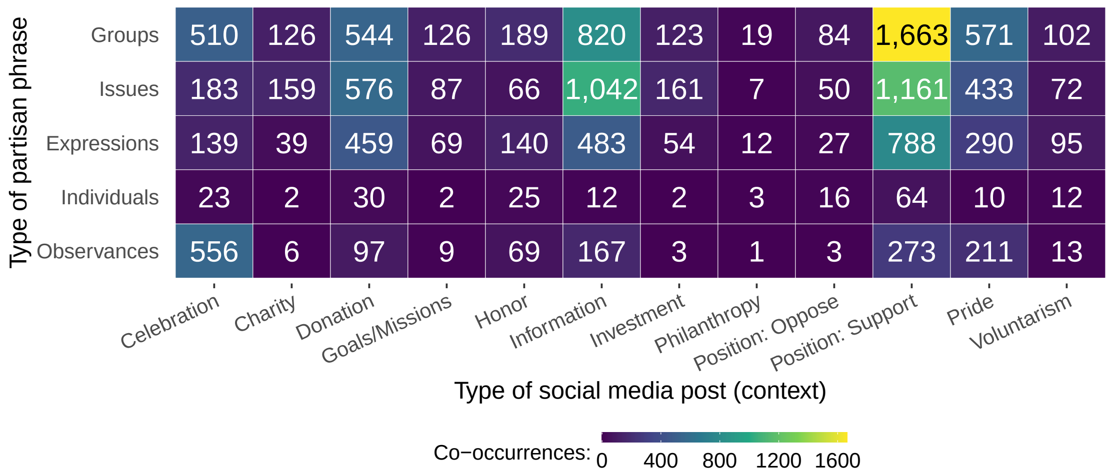
What are the contexts for these cues? Are these partisan cues merely used to spread awareness about particular issues or groups or are they used in explicit instances of position-taking? To shed light on these questions, partisan phrases were categorized into a dictionary by a research assistant. The 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, Lam, and Roberts (2017). The result in Figure 3 shows that, with the exception of mentions of observances, these cues are deployed in the context of *position-taking* – meaning support or opposition of a cause associated with an issue or group – rather than other contexts such as information or credit-claiming around charity.[6] 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[7]: "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 which center on small business

[6] A potential issue is that categories of phrases are uneven (e.g. there are many more posts about political issues than there are posts about observances). See Appendix Figure A5 for the same conclusion normalized over the total number of mentions in each category (row).

[7] See `twitter.com/tiffanyandco/status/861913660951732226`.

owners, current and past armed service members, and law enforcement.

Figure 3: **Contexts for Partisan Brand Signals**



Notes: See replication code for a full list of phrases.

3.3 Brands Only Recently Sound More Like Democrats.

Figure 4 decomposes brands' partisan signals over time, which increasingly lean Democrat between the years of 2017 and mid-2020. As the smoothed trend line in the top panel shows, the average χ^2 statistic (i.e. association with Republican elites' speech) of brand phrases doubles in the Democrats' 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.

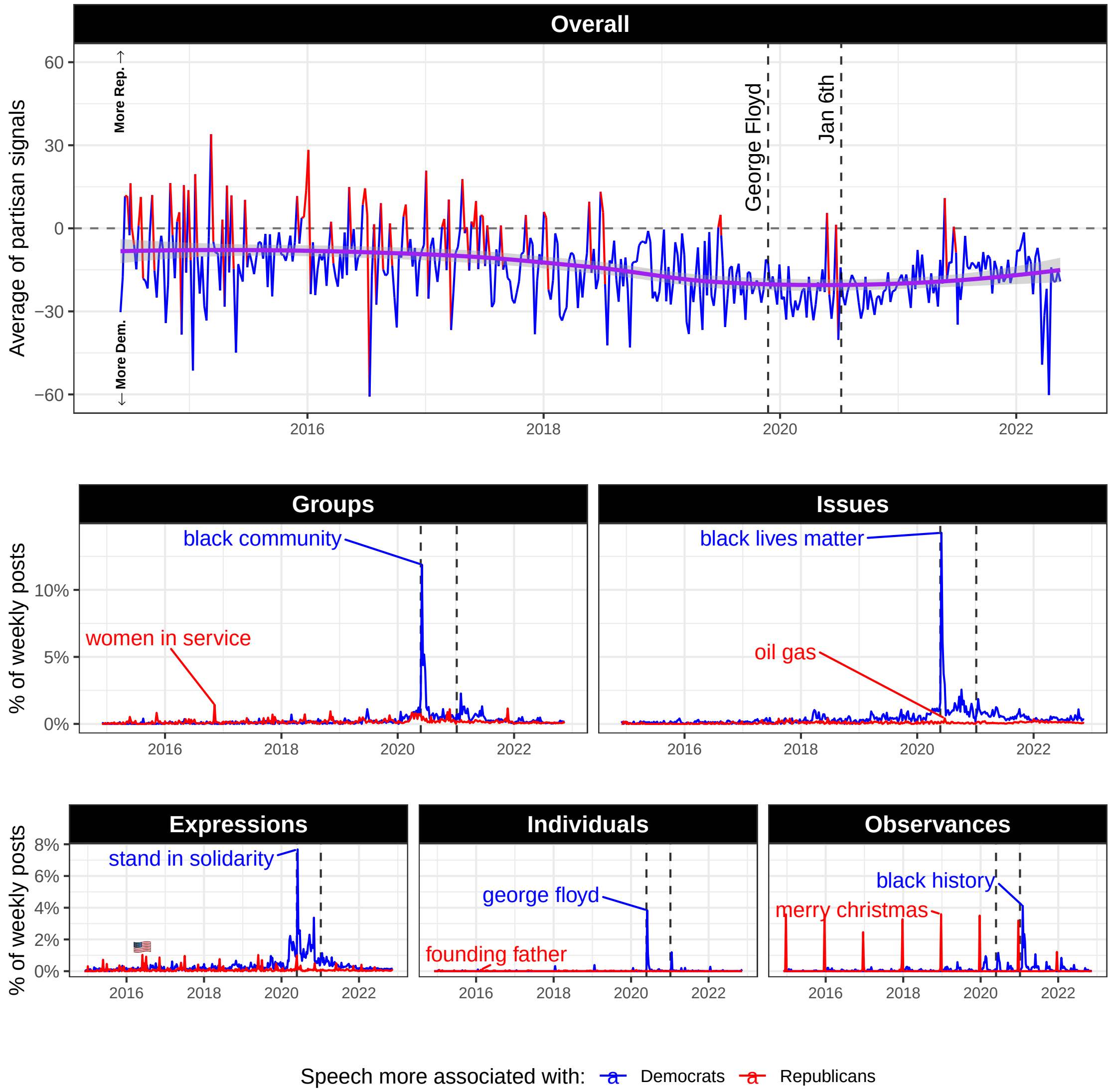
Notably, the burst of corporate attention to Black Lives Matter, racial issues, and the black community mirrors broader patterns of public racial attitudes following George Floyd's murder (Reny and Newman, 2021). In contrast, there does not appear to be any other event-driven shift in either broad partisan 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 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 (Z. Li and Disalvo, 2022), the January 6th insurrection did not seem to nudge brand attention towards Democrat-branded issues.

3.4 Brand Send Partisan Signals That Represent Their Stakeholders' Preferences and Firms' Agendas.

Figure 5 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.[8] The majority of brands that are out of step across these stakeholders, are in

[8]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.

Figure 4: **Partisan Signals from Corporate Brands Over Time**

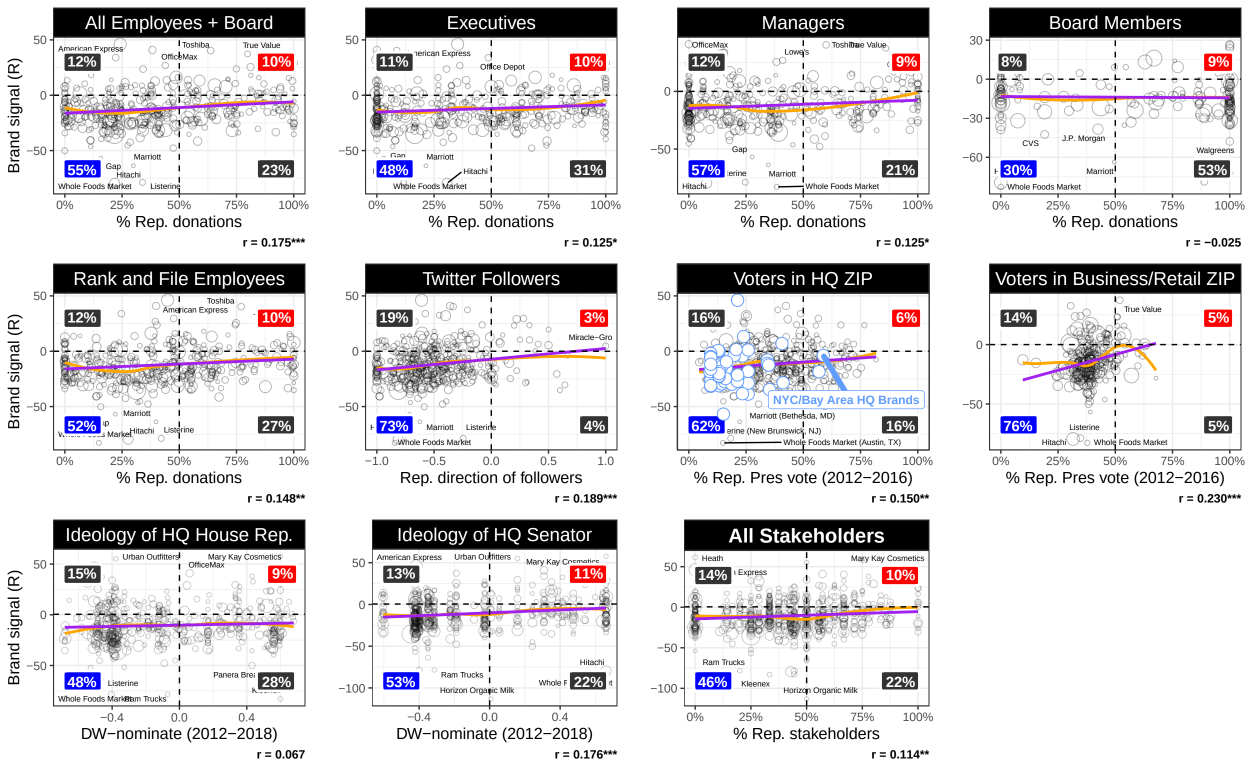


Notes: The vertical axis in the top panel denotes the average χ^2 statistic of differential usage by Republicans (i.e. the average γ_j of partisan phrases used) each week in our sample. The purple line in the top panel is a lowess spline fitted to these weekly averages.

the lower right quadrant or, in other words, out of step because they speak too often like Democrats relative to the preferences of that stakeholder group.

Figure 6 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.

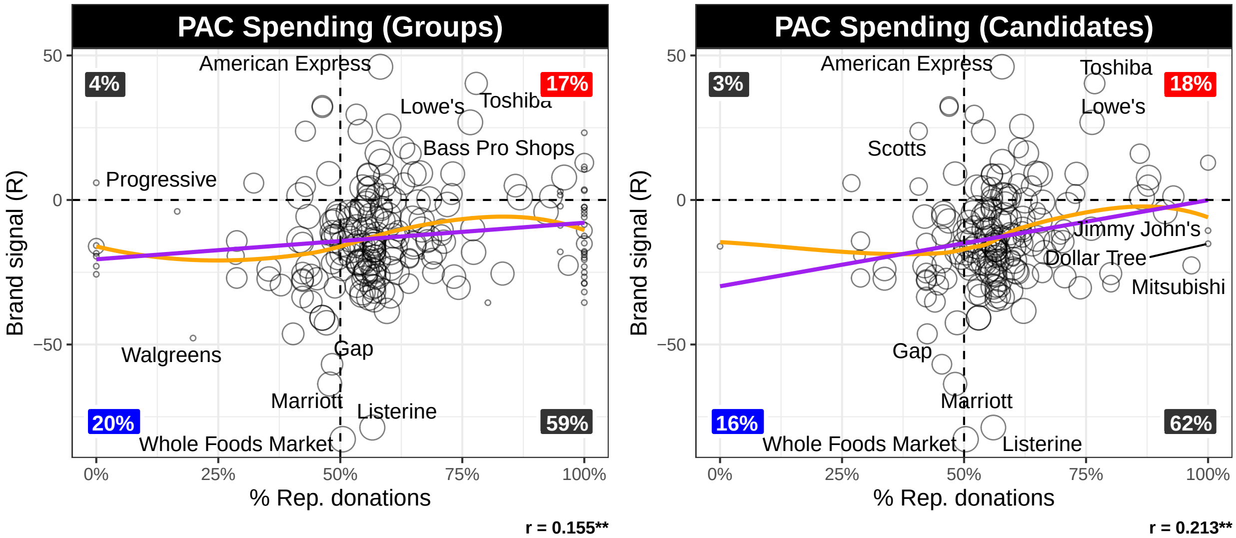
Figure 5: **Alignment Between Brand Signals and Partisan Stakeholder Preferences**



Notes: Percentage of brands in each quadrant are shown in the corner of each plot. The purple lines denote linear OLS regression lines of best fit, while the orange lines denote LOESS regression lines of best fit. Shown below each plot is the Pearson correlation (r) between each stakeholder measure (horizontal axis) and their corresponding brand signals (vertical axis). Statistical significance is determined using a robust t-test or equivalently the HC0-corrected standard errors of univariate regression between stakeholder measure and brand signal. For the ZIP code-level geographic measures, the alignments are replicated using county-level geographic measures in Appendix Figure C17.

Notably, unlike with stakeholder preferences, most brands are *off-quadrant* with their firm activities. In fact, a slight majority of brands (54-62%) are Republican-leaning in these 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 generally leans Republican, more Democrat-like speech predicts less Republican spending on the margins.

Figure 6: **Alignment Between Brand Signals and Firm Political Activities**

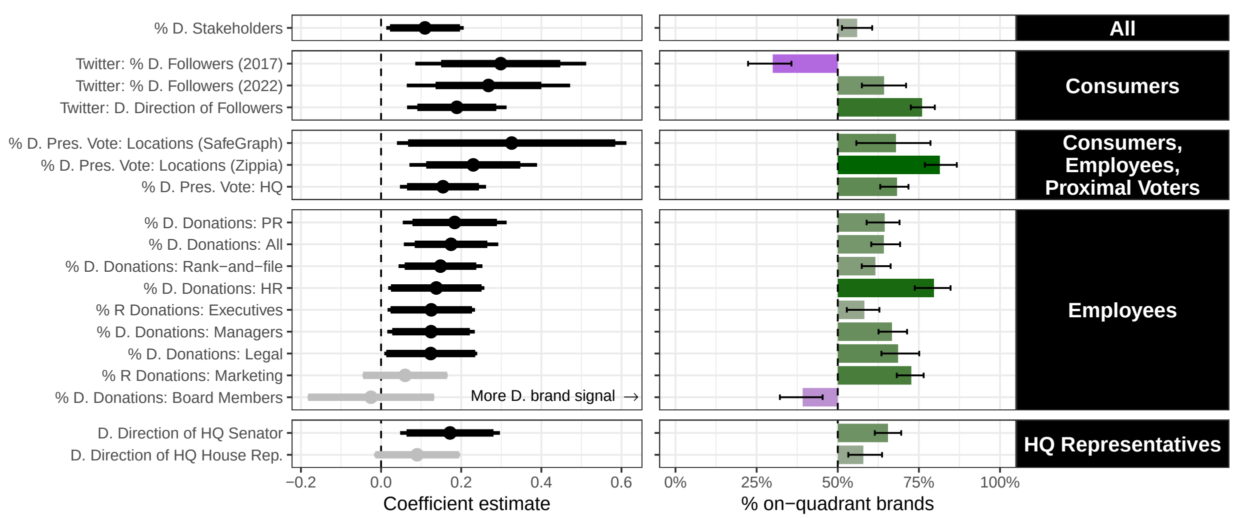


Notes: Dots for each brand are sized according to the total logged dollar contributions towards groups and candidates respectively during the study period. The purple lines denote linear OLS regression lines of best fit, while the orange lines denote LOESS regression lines of best fit.

Finally, Figures 7–8 present a more comprehensive set of coefficient and quadrant alignment estimates for stakeholder preferences and firm agendas adjusting for multiple testing. Relatively speaking, Figure 7 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 5 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 are 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 C21–C22). 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.

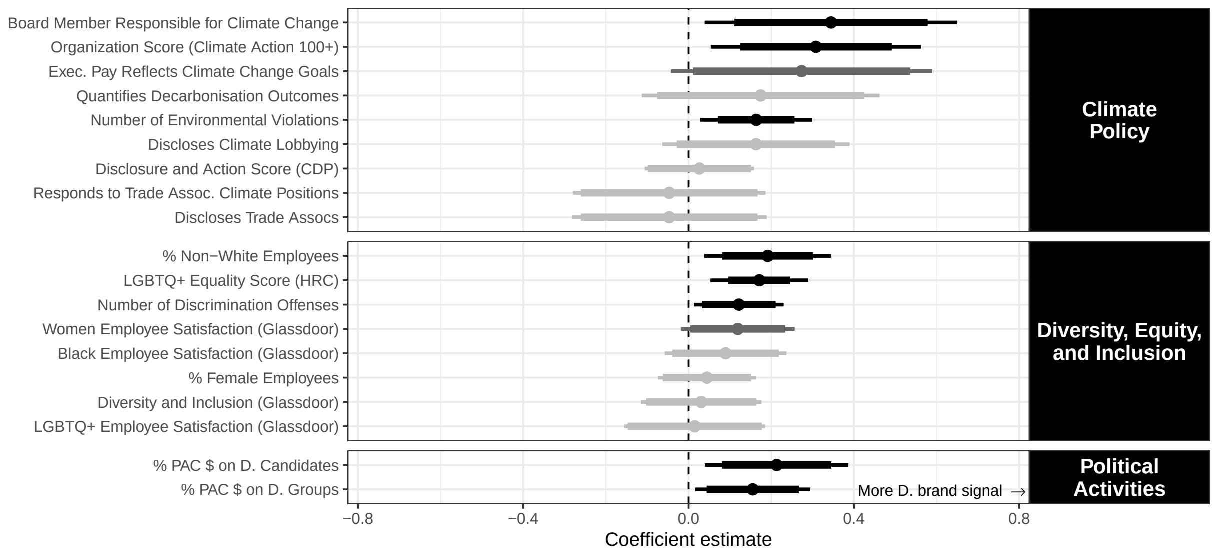
Figure 8 reveals that in addition to political spending, relevant corporate agendas are at least somewhat informative about brands' online political cues. More positive workplace perceptions by LGBTQ+ employees, better LGBTQ+ equality scores all predict more liberal, Democratic signals, though with relatively small effect sizes. An intriguing exception to this is that firms with more workplace and employment discrimination offenses and environmental regulatory violations tend to have more Democrat-leaning brands. This pattern suggests that firms may yet engage in 'woke washing' specifically in the regulatory arena (Luo, Kaul, and Seo, 2018; Supran, 2021), developing a progressive public reputation and political track record while committing regulatory infractions in related issue areas.

Figure 7: **Stakeholder Preferences Moderately Predict (*left*) and Align with (*right*) 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 inervals 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.

Figure 8: **Firm Agendas Weakly to Moderately Predict Partisan Brand Signals**



Notes: Coefficients are standardized estimates from univariate regressions of brand signal on each firm characteristic. Wider lines corresponding to 95% confidence inervals and the thinner lines corresponding to 95% confidence intervals adjusted for multiple hypothesis testing using the BH-q procedure. Regulatory compliance predictors are log-transformed.

3.5 Other Results

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

It is difficult to learn much about the temporal dynamics of brand signals since (i) the data for measuring brand signals, stakeholder preferences, and corporate practices are differentially missing or unavailable altogether across time and (ii) the present methods for detecting alignment cannot be interpreted causally. Still, the limited time-varying analyses suggest that both signal-stakeholder and signal-agenda correlations are weaker or non-existent prior to 2018 (Appendix C.3). We also cannot determine, without stricter assumptions, whether firms' communications are responsive to the previously established preferences of stakeholders (lagging alignment) or whether stakeholders select into affiliating with firms' with congruent political brands. Still, performing a regression of lagging, leading, and contemporaneous measures of time-varying brand signals with stakeholder preferences with fixed effects for year, Figure C16 does not provide any suggestive evidence that either may be case. Rather, the analyses imply (but cannot conclude) that the brand-stakeholder alignments we have identified may happen in relatively short timespans with little anticipation or selection/

More definitively, supplementary analyses show that brand-stakeholder and brand-agenda alignments 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. In summary, partisan signal alignments vary in magnitude across alternative measures of the outcome, different geographic measures of stakeholder preferences, and different regression specifications (Appendix Figures C17–C20), but the main substantive conclusion holds. Conditional on firm size, industry, and origin, knowledge of how a company 'speaks' on social media often (but not always) provides marginal information about their political priorities, conduct on ESG-related issues, and their stakeholders' politics.

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 predictors of a Democrat-leaning brand signal (Appendix Figure C11). Larger firms with more online followers and tweets in their history are also more likely to send Democrat-leaning signals (Appendix Figure C12), though these are generally weaker correlations than those shown in Figure 7.

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 (I. S. Kim, 2018). Theoretically, lobbyists have stronger incentives to subsidize partisan allies rather than persuade opponents (Hall and Deardorff, 2006), 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 C28 that larger, popular brands with more Democrat stakeholders also tend to produce more partisan cues overall. Thus, Republican 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 up on sociopolitical issues is certainly not a new phenomenon (Friedman, 1970). 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 (Sides and D. J. Hopkins, 2015); (ii) a public that places greater trust in corporations than in traditional political institutions (Pew Research Center, 2022); (iii) a “diploma divide” or an emerging re-alignment between highly-educated, affluent, white-collar professionals and the Democratic Party (Brint, Curran, and Mahutga, 2022; Grossman and D. Hopkins, 2022; Zacher, 2023; Hersh and Shah, 2023a); (iv) and a democratization of mass communication and public relations vis-à-vis social media (Tucker, Theocharis, et al., 2017).

Within this environment, this paper finds that most recognized corporate brands in America do not meaningfully use partisan linguistic cues on social media. Simply put, the polarization observed in American society does not obviously extend to online brand communications. However, if the claim is that corporate speech tends to favor the world-view of Democrats, it is a correct one: more often than not, corporate partisan cues mirror the language of progressive elites. To complicate the ‘woke’ accusation, however, this language does not obviously misrepresent the partisan direction of corporate workforces, ESG commitments, DEI evaluations, or electoral activities. Companies are also not egregiously out-of-step with their stakeholders, as the vast majority of firms either do not signal at all or are aligned (on-quadrant) with the different audiences evaluated here. *Knowing nothing* *else, a company's social media presence is likely to be somewhat informative about how they – both as a firm and as a group of interconnected stakeholders – engage in politics.* That being said, the alignment of Democrat-aligned speech with Democrat-aligned corporate values is not consistent across time, firm type, or industry: *conditional on these contextual factors, the alignment between partisan speech and partisan values widely fluctuates.* Taken together, these results contribute to growing literatures on social media, public relations, and corporate social responsibility (Yuan Wang, Cheng, and Sun, 2021; Yang Wang et al., 2022; Lee, 2021; Liaukonyt, A. Tuchman, and Zhu, 2022; M. Li, 2022; DesJardine, Grewal, and Viswanathan, 2023; Burbano, 2021), some of which uses similar computational approaches (Zhou, 2021).

Temporally, most of the Democrat-aligned speech that can be observed in our sample occurred largely after (and likely because of) George Floyd's murder. The results suggest 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 (Kingdon and Stano, 1984; Baumgartner and Jones, 2010; Birkland, 1998; Wasow, 2020) 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 (M. T. Boykoff and J. M. Boykoff, 2004; Hoffman, 2015). While these unprecedented activating events tend to 'push' corporations towards the progressive political language of Democrats, Figure 4 shows certain recurring cultural observances like Christmas, Veteran's Day, and Independence Day tend to 'pull' corporations towards the more traditionalist language used by Republicans.

Two industries with unusual degrees of stakeholder alignment are the technology and clothing/retail sectors (see Figure C26 in Appendix C.8). On closer examination, this is unsurprising given the concentration of highly educated and Democrat-leaning workers and female consumers in the tech and clothing/retail sectors respectively (Bonica, 2014; YouGov, 2022). As Appendix Figures C10–C11 show, these characteristics are amongst the strongest predictors of a Democrat-leaning brand signal. Sectors that offer the consumption of "hedonic goods," rather than "utilitarian goods" (Batra and Ahtola, 1991; Mano and Oliver, 1993) may also be intrinsically better able to connect characteristics of their products to the ideologically or culturally liberal symbols and values used by Democratic elites Conover and Feldman (1981). Finally, most U.S. firm headquarters in these sectors are based in urban areas (mostly commonly New York City and the Bay area, as Figure 5 shows) with more liberal voters and political representation. This adds an important dimension to the "diploma divide": younger, left-leaning employees in culturally cosompolitan sectors (Jackman and Vavreck, 2011) 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 A4) and (2) exhibits the strongest congruity between brands' online signals and firms' campaign finance (see Appendix Figure C26), this paper provides substantive evidence for the "liberal bubble" characterization of Silicon Valley (Manjoo, 2017; Malhotra, Monin, and Tomz, 2019).

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 inconclusive whether employees, elected officials, voters, and managers *select* into association with politically like-minded firms (and if they do, whether they do so on the basis of firms' online speech), *influence* the speech of their firms, or are *influenced* by the speech of their employers. I offer limited suggestive evidence in supplementary analyses (Appendix C.3) that are skeptical of any such temporal dynamics and imply corporate brand alignments may occur over limited windows, however some studies provide compelling evidence to the contrary. Adrjan et al. (2023) demonstrate, for example, that companies dialoguing about abortion care in the aftermath of the 2022 *Dobbs v. Jackson* Supreme Court ruling – a significant activating event around the issue of abortion care – had a causal impact on employee recruitment and satisfaction. 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 could be considered as well: investors, as Baker et al. (2022) notes, are a crucial audience for firms' ESG communications. 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 (B. T. Shapiro, Hitsch, and A. E. Tuchman, 2021) and political consumerism more broadly (Liaukonyt, A. Tuchman, and Zhu, 2022).

Lastly, it remains to be seen how these trends generalize beyond the platforms, time period, and particular measures of partisan cues I have selected. In the present study, I find little difference in the distribution (Figure A6) and alignments (Figure C18–Figure C19) 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.4 suggests that the extent of partisan brand signals on social media may be an upper bound on different communication channels. Finally, there may be other methods of measuring partisan signals including different public communications such as 10-K reports (Andreou, Harris, and Philip, 2020), different reference corpora or scaling methods. 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.

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Political Speech from Corporate America:
Sparse, Mostly for Democrats, and Somewhat Representative

Online Appendix

Contents

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 χ^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: $\widetilde{\psi}_k = \frac{\sum_{j=1}^{1000} w_{kj}\gamma_j}{\sum_{j=1}^{1000} w_{ij}}$ where w_{kj} is the number of times the jth most partisan phrase is used in post k. I randomly sampled 100 posts (whether or not they contain any partisan language) 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 κ between the research assistant and the binarized direction according to my measure is 0.84. Roughly 7% of posts were perceived as being political in either direction, yet did not contain any phrases from the set of 1,000 bigrams, suggesting that my measure adequately captures nearly all of the partisan language used by brands in this sample.

Figure A3 shows the equivalent of Figure 4 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 A5 normalizes the results in Figure 3 as percentages and supports the main finding that the most common context for most categories of speech is *position-taking* rather than information, affective appeals, or calls for/credit-claiming around charity.

Figure A4 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 (Broockman, Ferenstein, and Malhotra, 2019). 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 Epstein, 2014; Nather, 2019. Though not on this figure, brands from Vogel (2007)'s case analysis such as Nike and Ben & Jerry's also arise as amongst the most left-leaning brands in my sample.

A.2 Categorization of Phrases

The 1,000 most partisan bigrams used throughout this study was classified into five categories based on the author's substantive knowledge and close qualitative analysis of the bigrams:

- *Groups*: clear references to demographic, socioeconomic, political, and identity groups in American society that are made more often to either Democrats or Republicans (e.g. 'black community', 'the troops', 'working people').

- *Issues*: references to sociopolitical issues and related concepts referred to disproportionately by (and perceived to be 'owned' by) either Democrats or Republicans (e.g. 'criminal justice', 'economic growth', 'gun violence').

- *Individuals*: references to prominent individuals of sociopolitical importance in the United States referred to disproportionately by either Democrats or Republicans (e.g. 'Ronald Reagan', 'George Floyd', 'Martin Luther King').

- *Observances*: cultural observances or holidays of sociopolitical significance in the United States referred to disproportionately by either Democrats or Republicans (e.g. 'Veteran's Day', 'Black Pride Month', 'Christmas')

- *Expressions*: common political expressions, slogans, or phrases used by Democrats or Republicans that span across issues or are issue non-specific (e.g. 'serve the nation', 'face discrimination', 'stand for freedom', 'climate change').

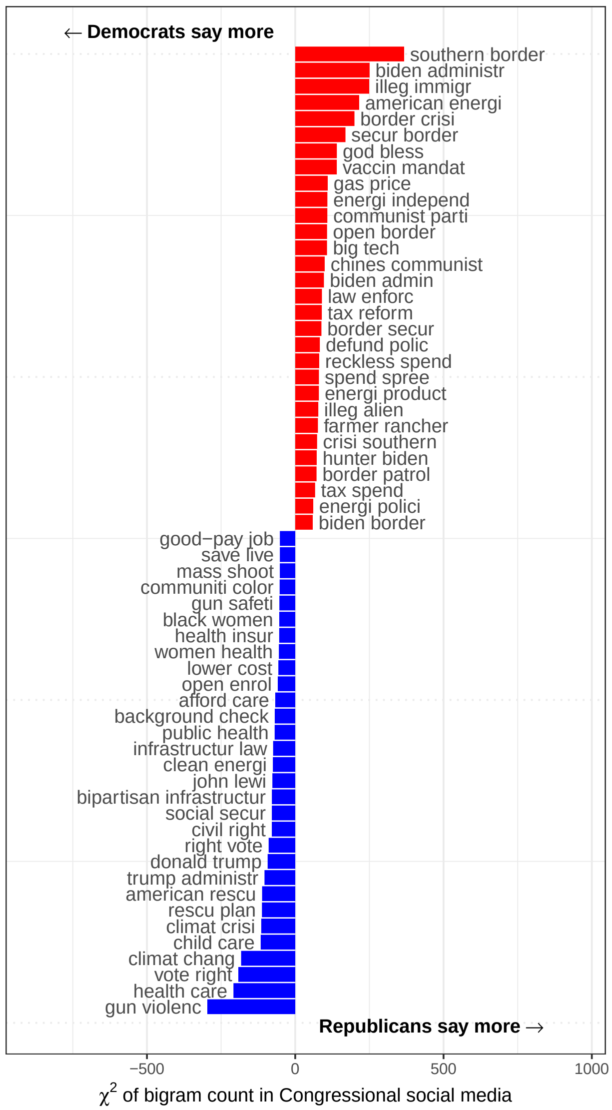
A category pertaining to places as well as historical events was identified, but deemed irrelevant or misleading as a category of study due to its sparsity and the relative lack of agreement over phrase classification.

This scheme along with some description of each category was given to a research assistant who then applied to partition the phrases into their respective categories, and the resulting partition was validated by another research assistant. A total of 405 bigrams were classified without disagreement into these categories. Table 1 shows the number of unique phrases and total bigram mentions of phrases in each category. These categories are not evenly balanced: note that the *issues* category has both the most classified unique bigrams and the most mentions, however note also that expressions is the largest category of bigrams yet receives only the third-most mentions in the corpus.

Table 1: **Categories of Partisan Bigrams**

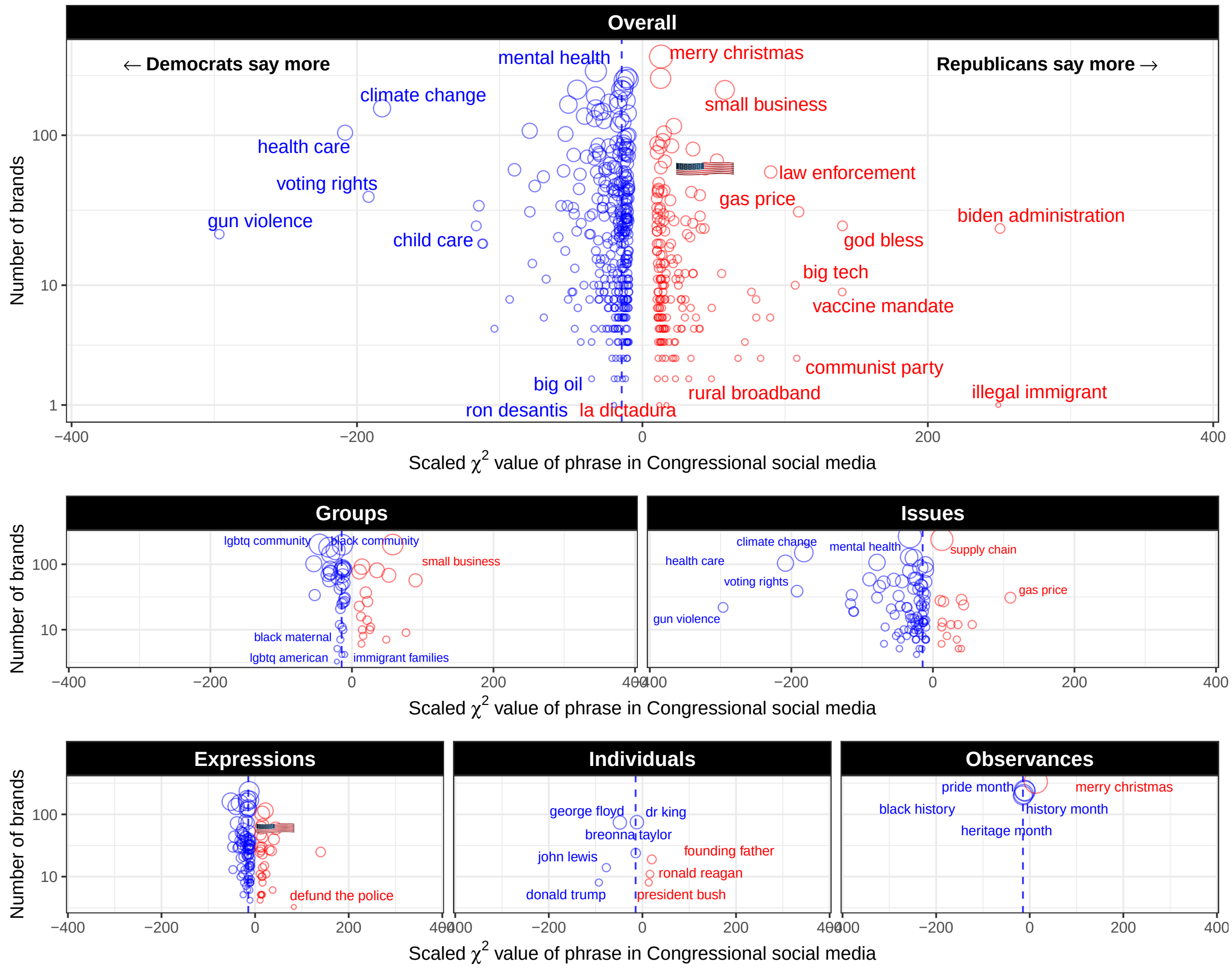
Category	**Number of Bigrams**	**Total Bigram Mentions**
Issues	139	10,691
Groups	90	8,998
Expressions	159	8,292
Observances	9	3,364
Individuals	8	453

Figure A1: **Partisan Bigrams on Instagram and Twitter from Members of Congress (2014-2022)**



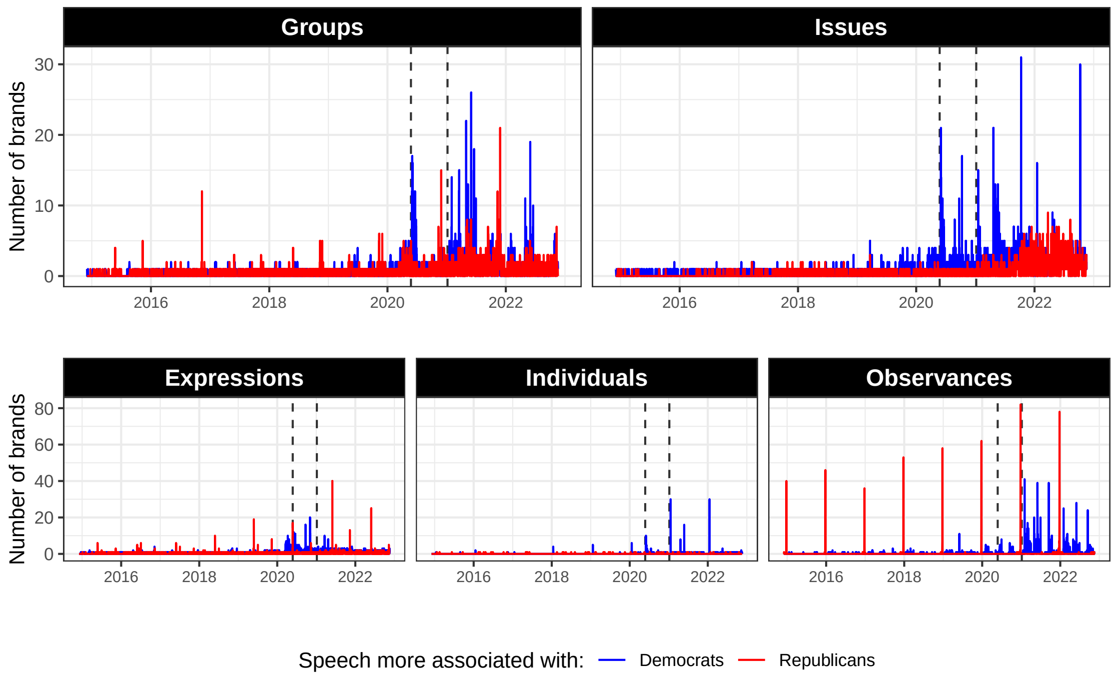
Notes: Shown are top 25 most partisan stemmed bigrams for incumbent members of the 116th Congress on Twitter and Instagram through the period of study (2015-2020). The measure on the horizontal axis is the simple χ^2 measure of differential counts between the two parties.

Figure A2: **Types of Partisan Signals from Corporate Brands (By Number of Brands)**



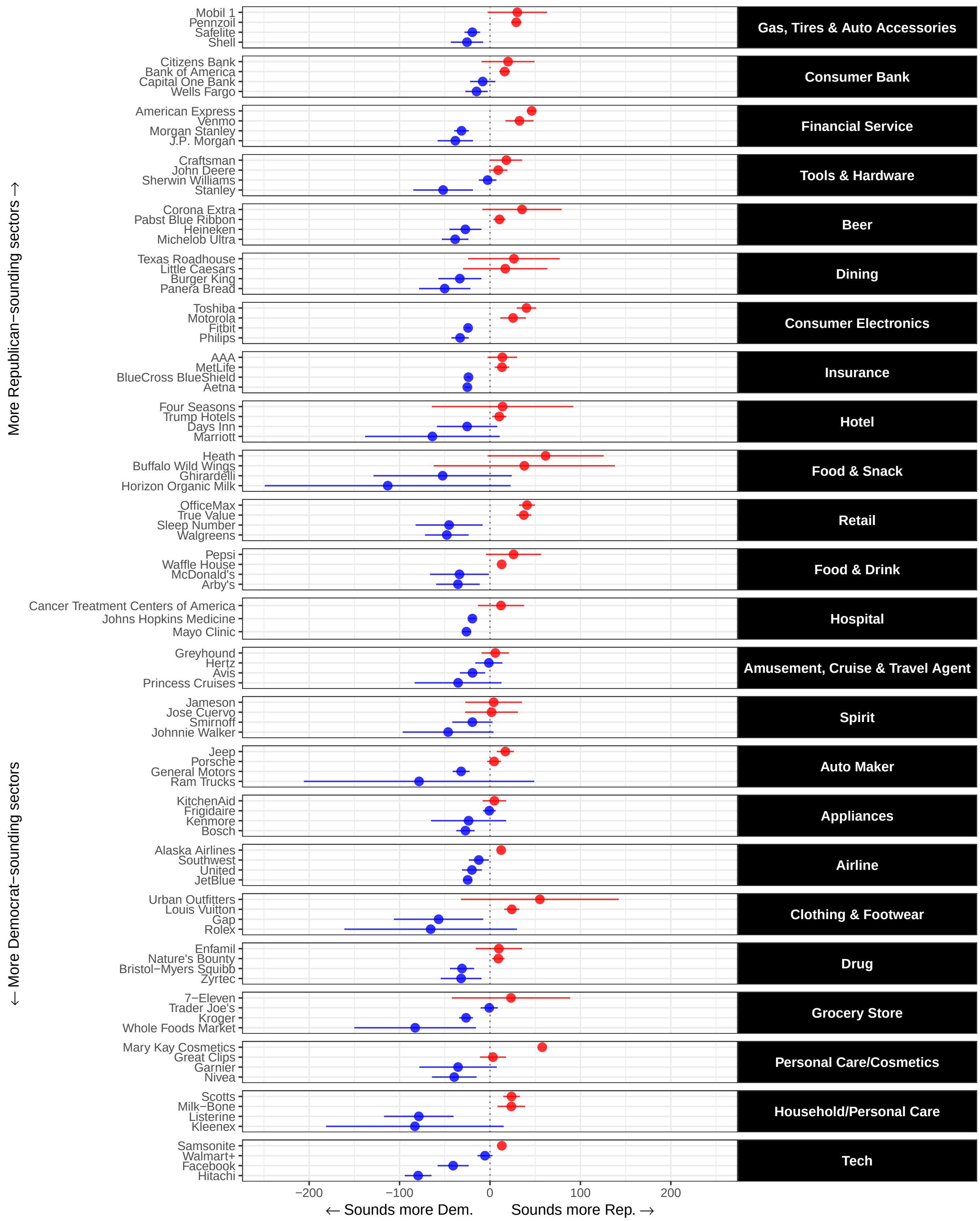
Notes: The horizontal axis denotes the χ^2 statistic of differential Republican usage value of each bigram. Panels are ordered from most left-leaning in the usage of cues within that category to most right-leaning. Some labels of phrase bigrams are omitted for visual clarity.

Figure A3: **Partisan Signals from Corporate Brands Over Time (By Number of Brands)**



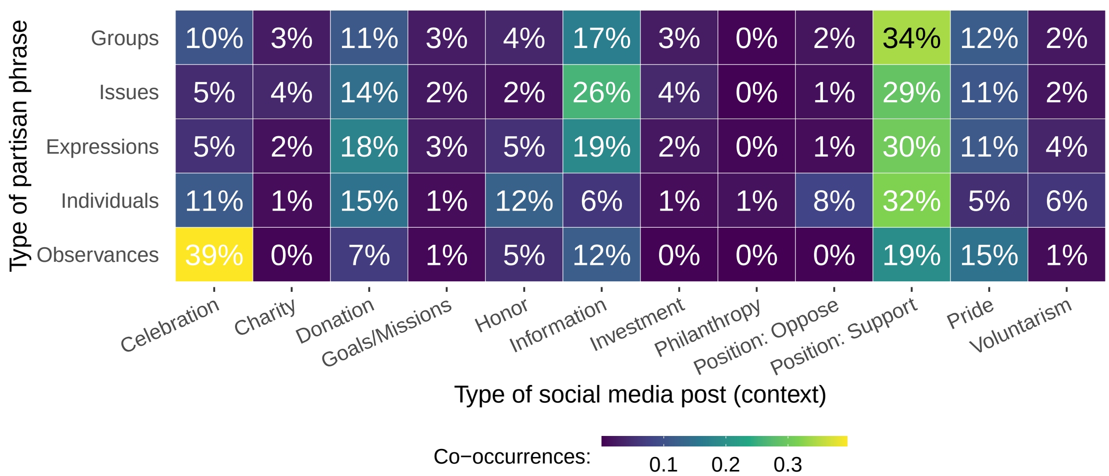
Notes: As in Figure 4, the two dashed lines denote in time (i) George Floyd's murder and (ii) the January 6th 2021 U.S. Capitol insurrection.

Figure A4: **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 χ^2 of partisan language used on the horizontal axis (with 95% confidence intervals). Note that some sectors do not have four or more partisan-signaling brands on social media in my sample.

Figure A5: **Contexts for Partisan Brand Signals (Row-Wise Percentage)**



Notes: Each row sums up to 100%. See Figure 3 for methodological details and results with raw counts.

A.3 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 χ^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 Instagram 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, β_i, and the degree of its *slant*, ψ_i, in a Democrat or Republican direction. To accomplish this, I fit the following model:

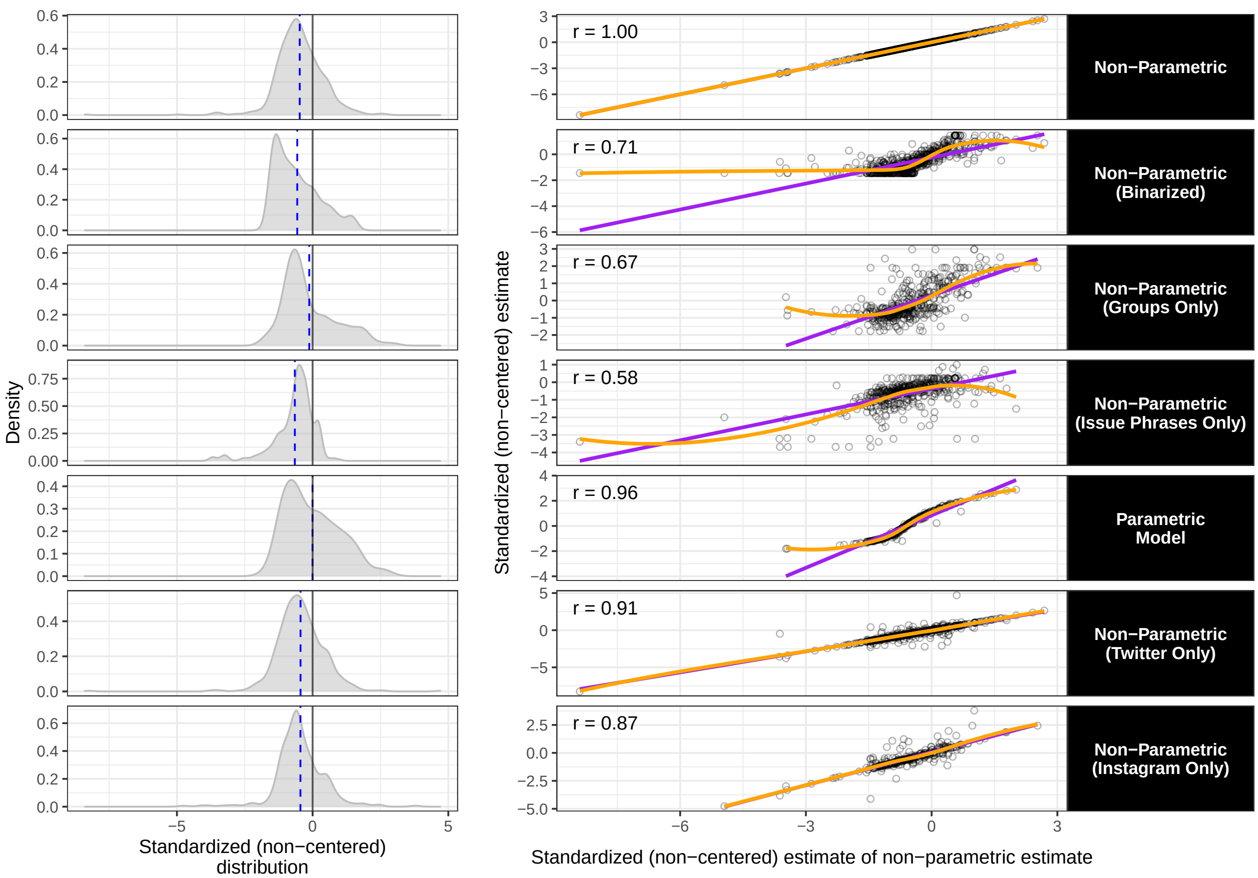
$$\begin{aligned} w_{ij} &\sim \text{Pois}\big(\lambda_{ij}\big), \\ \lambda_{ij} &= \exp\big(\alpha_j + \beta_i + \psi_i \gamma_j\big). \end{aligned} \tag{2}$$

The quantities of interest estimated from this model are β_i and ψ_i. The fixed effect β_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 ψ_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, Lo, and Olmsted (2016). 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 C20.

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.4 Other Brand 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 conveniece sample of 2,000 TV advertisement transcripts linked to ≈400 brands in my sample (K. Hartman, 2020). 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 signaling on other channels.

B Additional Variable Description

This section provides additional description of the stakeholder preference and firm agenda variables used to make the main descriptive inferences in the study (related to Figures 5–8).

An overview of the various stakeholder and firm datasets used, which particular stakeholders and agendas they aim to cover, along with their respective strengths and weaknesses is provided in Table 2 and Table 3.

In both tables, I describe four dimensions that comprehensively describe the data collection procedure for each dataset:

1. *Open Access*. Whether any of the data was downloaded for free.

2. *Scraped*. Whether any of the data was computationally scraped (if so, this would be done in Python).

3. *Bought*. Whether any of the data was bought (either one shot or over a recurring subscription).

4. *Coded*. Whether any of the data was manually coded (e.g. HQ locations) or heavily filtered/matched via an automated coding process (e.g. SOC occupation codes).

In Table 2, I evaluate each of the stakeholder preference datasets on six criteria:

1. *Is the data **disaggregated** across stakeholders?* For example, the FEC data is able to provide disaggregated partisanship measures for each category of firm affiliates while geographic vote shares are not.

2. *Does the data provide a **large-n measure** for each brand?* Here, large-n refers to the sample size used to measure an individual brand which is distinct from the size of the stakeholder dataset. For example, the SafeGraph point-of-interest dataset identifies nearly every business/retail location for each brand of interest, but is missing from more than 60% of brands in the sample; in contrast, the Zippia point-of-interest dataset only uses 20 business/retail locations to capture the partisan geography for each brand (thus small-n) but is missing in closer to 40% of brands.

3. *Does the data **under cover** the target population?* Here, coverage refers to the survey sampling definition: how much of the target stakeholder population is included at the sampling stage. For instance, my collection of Twitter followers (via the Twitter API) under covers the population of brands' followers since I only collect the 20 most recent followers at the time of sampling and I am excluding possible offline consumers who do not have Twitter accounts. The usage of ZIP-level vote also potentially excludes the population of dispersed voters and consumers beyond the ZIP code who live near a business location.

4. *Does the data **over cover** the target population?* In contrast to the previous criterion, whether the data may over-include non-relevant actors, thus covering the preferences of non-stakeholders. For example, county-level voteshare may include voters who are not aware of the brands' business/retail locations in their county. Similarly, the Twitter followership data may include online users who incidentally follow the brand.

5. *Is the resulting measure* ***missing in*** $\geq$ ***40% of brands?*** Here, the denominator is the 879 brands deemed to be active brands. See Section B.2 for further discussion and evaluation of this.

In Table 3, I evaluate each of the firm agenda datasets on three criteria:

1. *Is the data based on* ***subjective perceptions****?* This may introduce selection bias into each individual firm's revealed agenda measure (e.g. selecting for evaluations that are strongly negative or positive rather than representative). For example, Glassdoor ratings rely on subjective employee evaluations while the climate policy indicators are largely based on quantitative ratings.

2. *Does the data rely on* ***voluntary firm disclosure****?* This may introduce selection bias into the composition of firms represented in the revealed agenda measure (e.g. firms may opt out when their rating is projected to be negative). I show that this may be the case with the Climate Action 100+ and the HRC scores in Figure **??** which is, itself, a substantive finding (see discussion in Section B.2).

3. *Is the resulting measure* ***missing in*** $\geq$ ***40% of brands?*** Here, again, the denominator is the 879 brands deemed to be active brands. See Section B.2 for further discussion and evaluation of this.

Table 2: **Summary of Stakeholder Preference Data**

Brand-Level Data	**Source(s)** (*** indicates usage in main text**)	*Collection* Open Access	Scraped	Bought	Coded	*Stakeholders* Employees (rank and file)	Managers	Executives	Board	Consumers	Proximal Voters	HQ House Rep	HQ Senator	*Strength/Weakness* Disaggregated?	Large-n Measure?	Under Covers?	Over Covers?	Missing in ≥40% of Brands?
Political Donors	SOC (occupation codes) + FEC*	✓			✓	✓	✓	✓	✓					Y	Y	N	N	N
Twitter Followers	Twitter API*		✓							✓				NA	N	Y	N	N
	Schoenmueller et al. (2022)	✓								✓				NA	Y	N	N	Y
Pres. Vote near Headquarters	TargetSmart (ZIP-level)*	✓			✓	✓	✓	✓			✓			N	NA	Y	N	N
	MEDSL (county-level)	✓			✓	✓	✓	✓			✓			N	NA	N	Y	N
Pres. Vote near Business Locations	SafeGraph only			✓		✓	✓	✓		✓	✓			N	Y	N	N	Y
	Zippia only		✓			✓	✓	✓		✓	✓			N	N	Y	N	Y
	SafeGraph + Zippia*	✓	✓			✓	✓	✓		✓	✓			N	Y	N	N	N
Consumers' Demographics	YouGov			✓						✓				NA	Y	N	N	N
HQ Representatives' Ideology	DW-NOMINATE*	✓										✓	✓	Y	Y	N	N	N

Notes: NA values are given where either only one stakeholder is being measured leaving no possibility for disaggregation across stakeholders or where the sample used in measurement represents the entire target population (e.g. vote returns) obivating the distinction between small- and large- samples. Here, MEDSL is short for MIT Election Data and Science Lab (2020).

Table 3: **Summary of Firm Agenda Data**

Firm-Level Data	**Source(s)** (* indicates usage in main text)	*Collection*: **Open Access**	**Scraped**	**Bought**	**Coded**	*Agendas*: **Climate Policy**	**Political Activity**	**Workplace DEI**	*Strength/Weakness*: **Subjective Perception?**	**Voluntary Firm Disclosure?**	**Missing in ≥40% of Brands?**
Climate Policy Indicators	Climate Disclosure Project (CDP)*	✓				✓			N	Y	Y
	Climate Action 100+*	✓				✓			N	Y	Y
PAC Spending:											
$$ to Dem/Rep Candidates	OpenSecrets*	✓					✓		N	N	N
$$ to Dem/Rep Groups	OpenSecrets*	✓					✓		N	N	N
Lobbying Dem/Rep MCs	LobbyView	✓					✓		N	Y	Y
Regulatory Compliance:											
Employment/Workplace Discrimination	Good Jobs First*			✓				✓	N	N	N
Environmental Violations	Good Jobs First*			✓		✓			N	N	N
Employee Satisfaction	Glassdoor		✓					✓	Y	N	Y
LGBTQ Workplace Equity Scores	Human Rights Campaign (HRC)*	✓						✓	Y	N	Y
Employee Demographics	Zippia		✓					✓	N	N	N

Notes: Values of certain variables may be missing for brands either due to unavailability, voluntary non-disclosure (e.g. CDP scores, HRC scores), or non-applicability (e.g. some firms may not employ lobbyists or have affiliated PACs).

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, Netzer, and Stahl (2022). 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, Netzer, and Stahl (2022)'s measures only include influential followers from each brand that exclusively follow either the Republican party or Democratic party national Twitter acconuts. (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 8 due to their skew; similar results follow when using a Negative Binomial or Poisson regression.

Figure B7: **Distribution of Stakeholder Preference Variables**

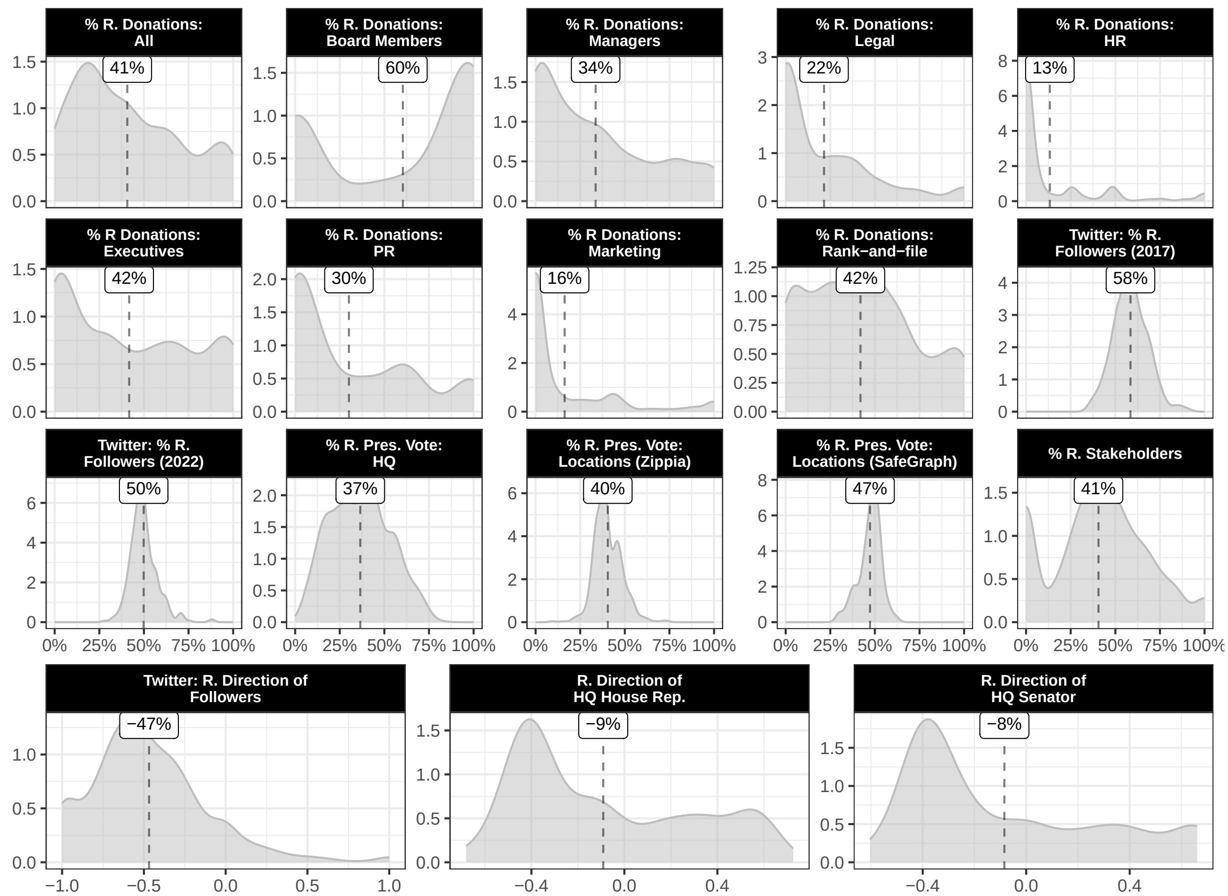
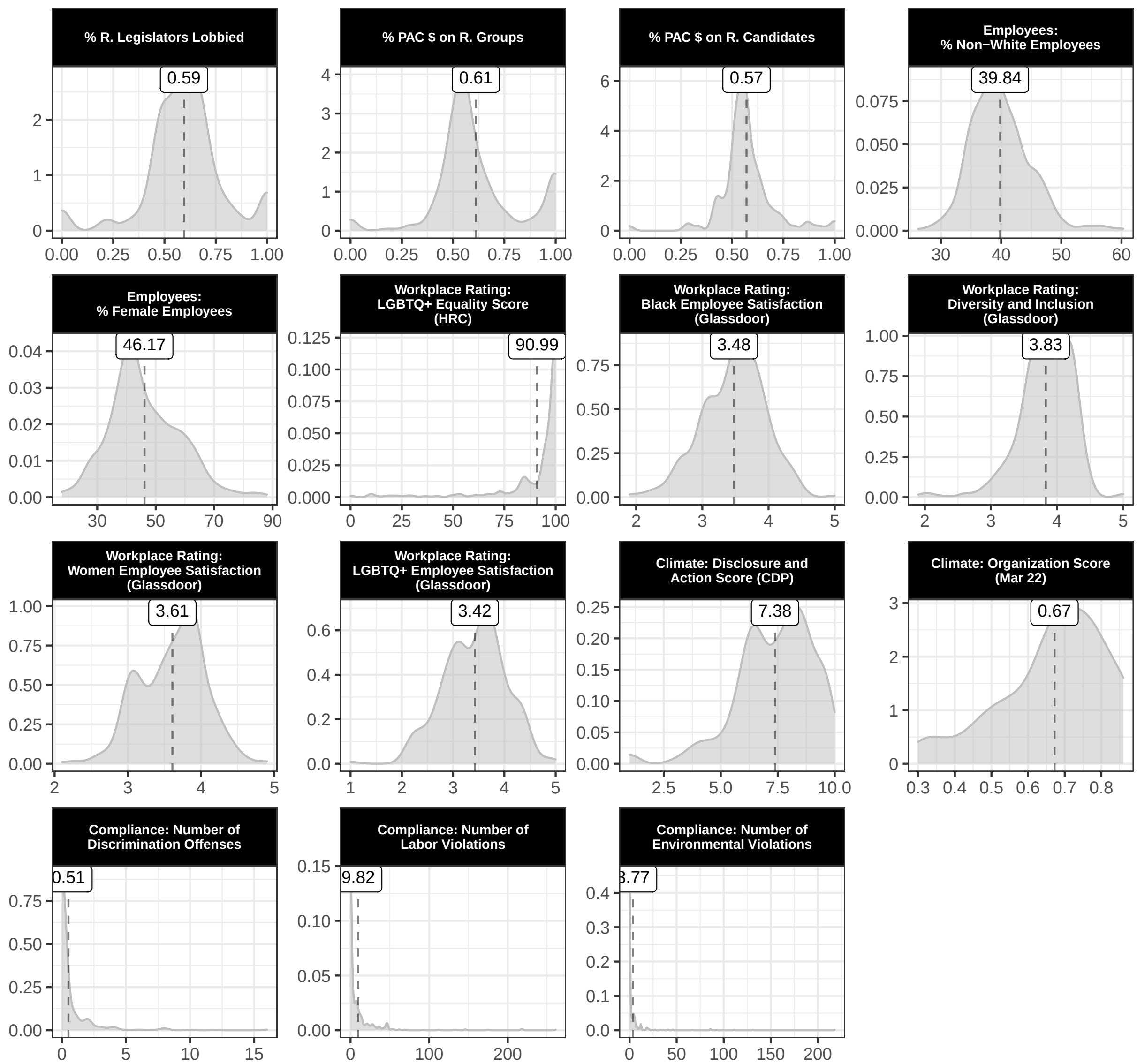


Figure B8: **Distribution of Corporate Agenda Variables**



B.2 Missing Data

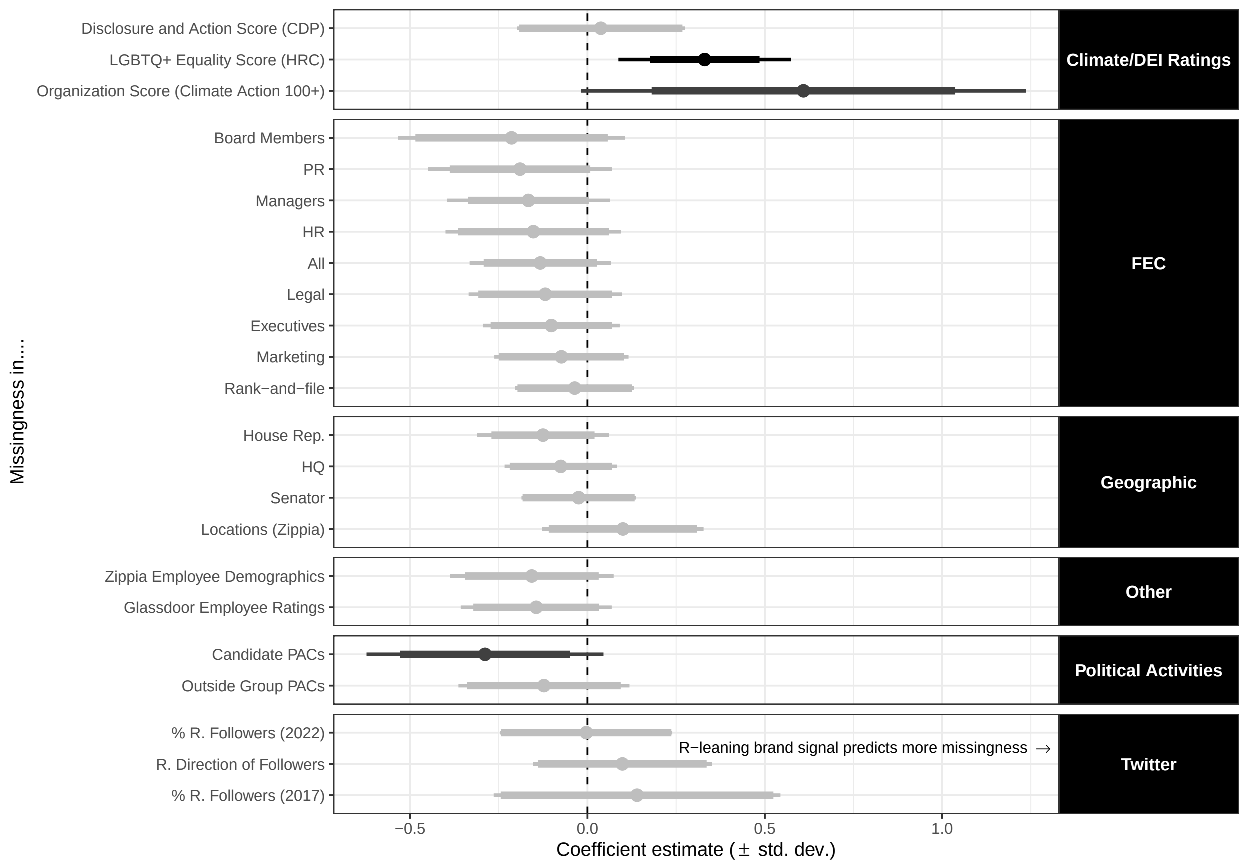
Some brand covariates of interest in this paper are missing due to lack of *availability* from the provider (Zippia workforce characteristics, Glassdoor employee reviews) and/or imperfect *matching* from my end (FEC data, variables involving headquarter or business/retail locations). Other covariates 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 praent 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 missing data for any of these reasons is correlated with my main measure of interest, brand signal, I regress a missing value indicator 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 these missing values. 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 8 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 an indicator of missing values of each firm covariate (vertical axis) on brand partisan signal. Estimates are sorted and grouped by category (black panels).

C Additional Results

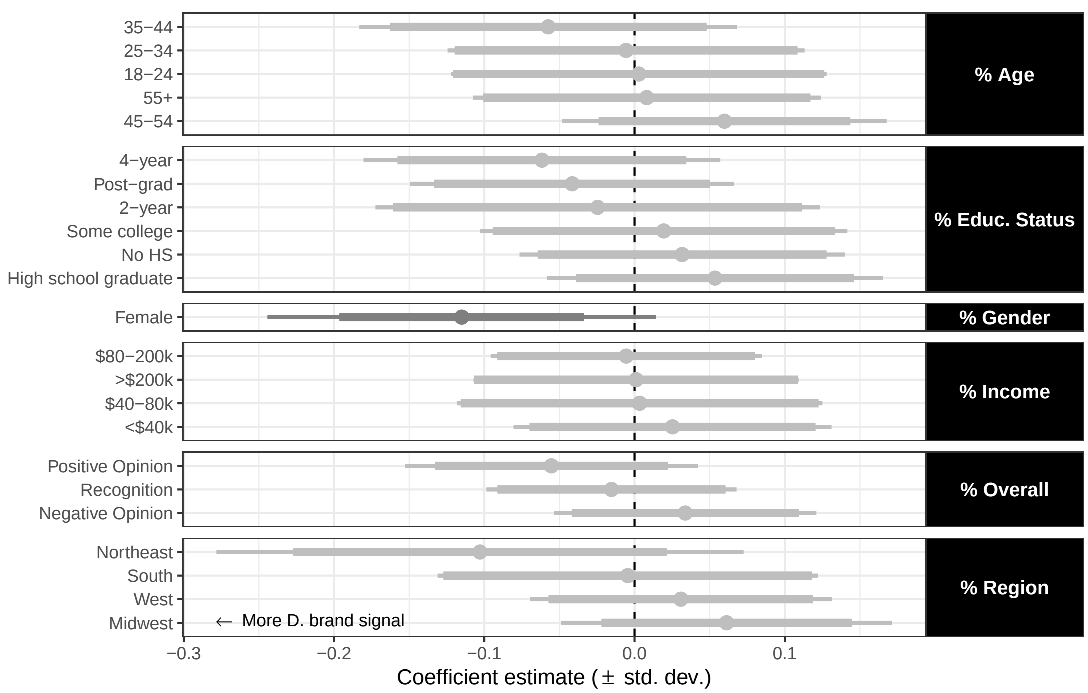
This section provides additional regression analyses bolstering the main regression analyses in the paper.

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.

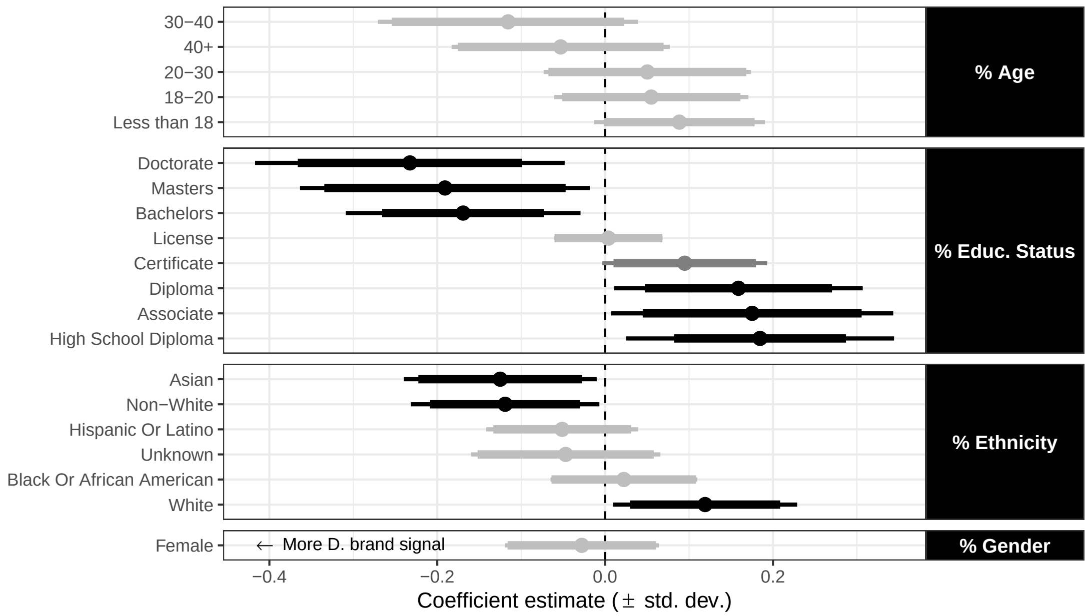
Figure C10 shows that besides a weak link to gender composition, there is no detectable relationship between the consumer characteristics of brands in my sample and online partisan speech. On the other hand, Figure C11 shows that there are stronger (albeit still not "large" according to conventional 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**



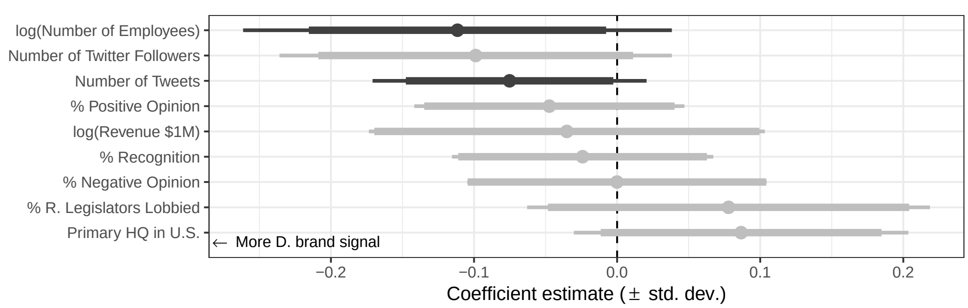
Notes: Coefficients estimated from univariate regressions of brand signal on consumer demographic cross-tabs measured via YouGov audience panel surveys for each brand in our sample.

Figure C11: **Employee Demographics Moderately Predict Partisan Brand Signals**



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**



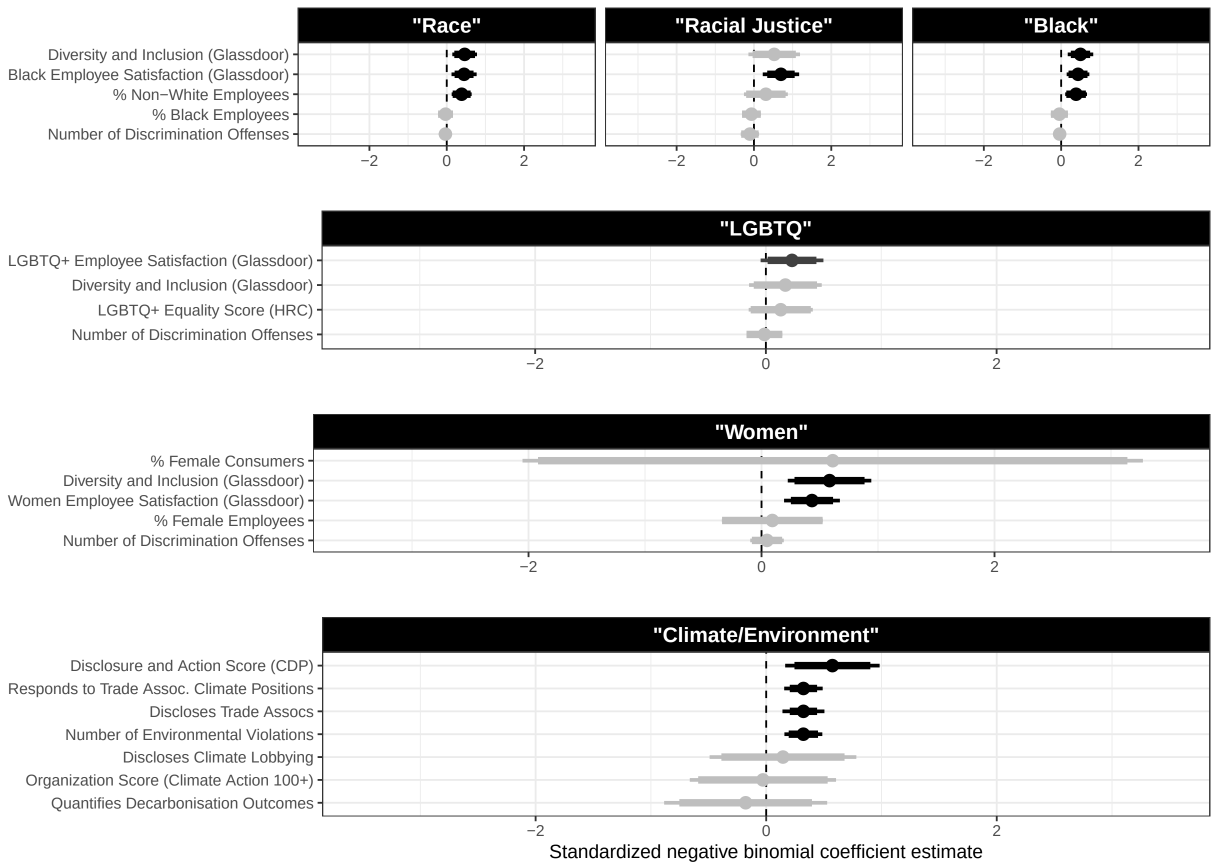
Notes: Coefficients estimated from univariate regressions of brand signal on brand (and brand parent firm) characteristics collected from a number of sources including Wikipedia, Glassdoor, and Zippia.

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 indiciators 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.

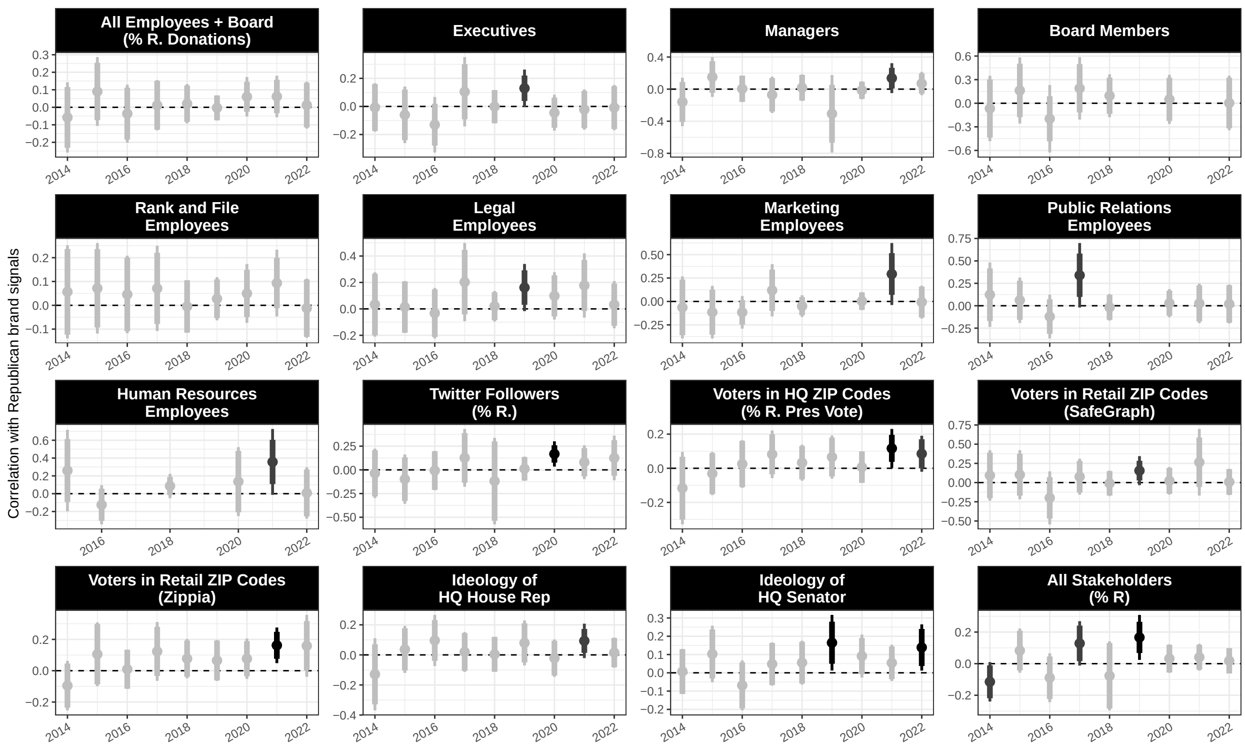
C.3 Temporal Patterns

I exploit several variables with over-time variation to show how the correlations between brand signals and stakeholder preferences/corporate governance agendas changes (if at all) over the period of study and whether the main results are local to a particular moment in time. I caution the reader from over-interpreting these results in either direction, since there is evidence of differential missing-ness of certain measures over time. *Hence, the results in this section are merely suggestive, not conclusive.*

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.

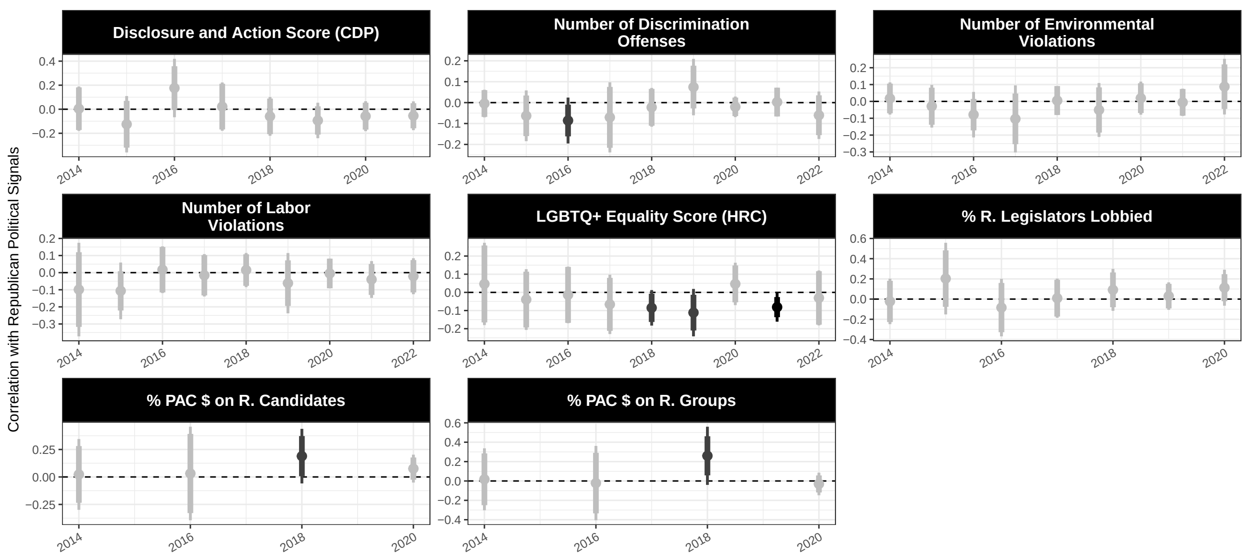
Figure C14 replicates the univariate regression coefficients from the main text using time-varying measures of brand signal and stakeholder preferences with leading, lagging, and contemporaneous brand signals. In theory, this would suggest whether brand signals *precede* or *follow* stakeholder preferences. Noting the limitations of this exercise given the missing-ness of over-time measures, there does not initially appear to be any evidence of either phenomenon. Instead, brand alignment with firm affiliates appears to occur contemporaneously within a particular year with little anticipation on firms' parts or selection on stakeholders' parts.

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



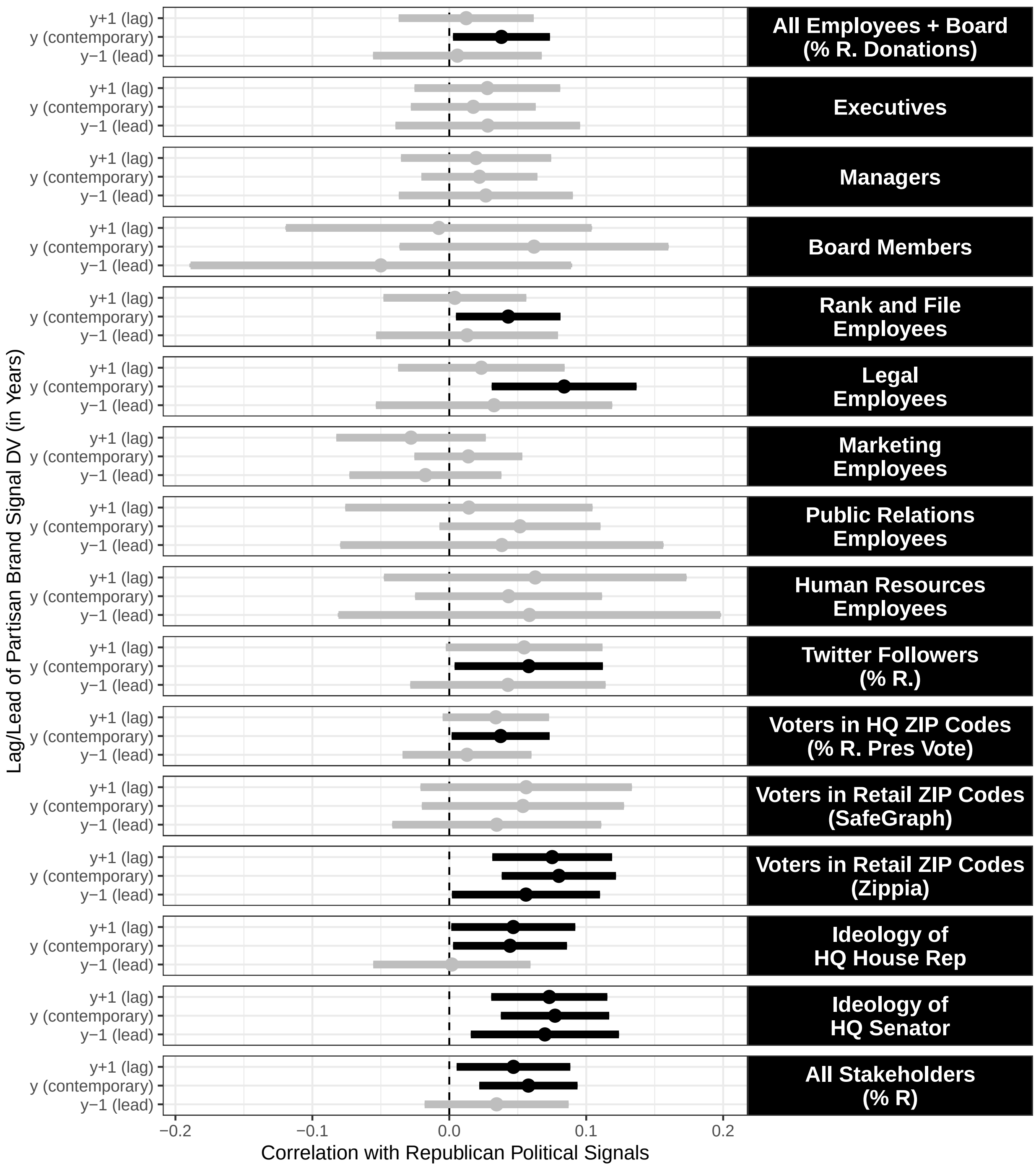
Notes: Coefficients estimated from univariate regressions of brand signal (measured using only brand posts and Congressional language in the given year) on stakeholder preferences measured in that given year. Estimates for certain stakeholders (e.g Human Resources employees in 2019) are missing due to 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.

Figure C16: **Lagging vs. Leading Correlations of Partisan Brand Signal and Stakeholder Preferences**



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 all available years from 2015 to 2022, controlling for year.

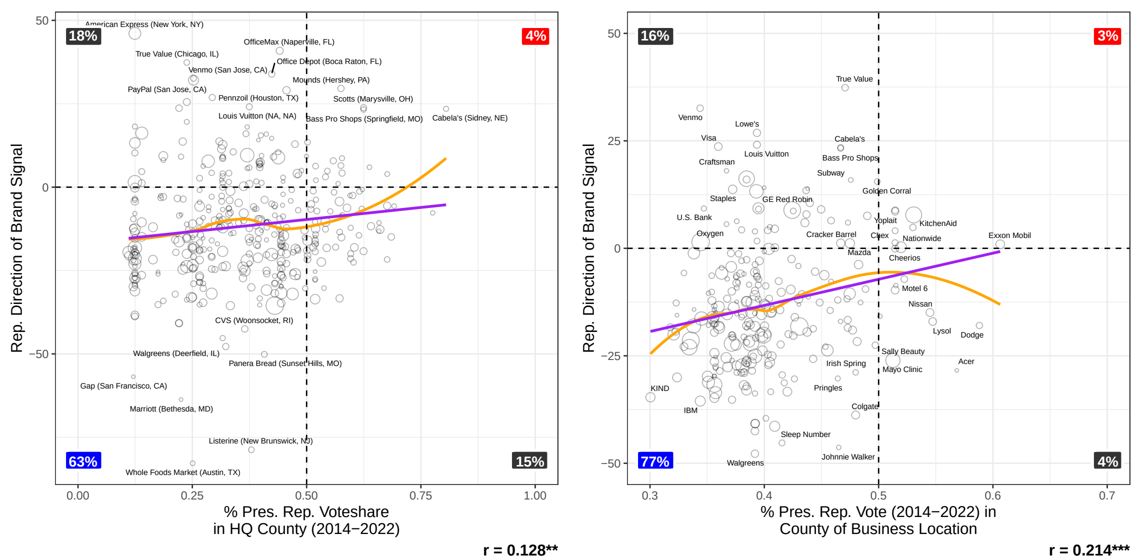
C.4 Results with Alternative Measures

Figure C17 computes alignment between brand signals and partisan stakeholder preferences for geographic measures of the latter using *county level* rather than *ZIP code level* measures (as is used in the main text). As is the case in the main text, for business/retail data, the SafeGraph and Zippia datasets of business/retail locations are pooled together. Similar positive and statistically significant alignment patterns arise, ameliorating the concern that many employees and customers of business locations may reside outside the ZIP code of said locations (I thank the anonymous reviewer for raising this).

Figure C18 and Figure C19 replicate select analyses from the main text (for brevity) using the alternative measures of brand signal described in Appendix A.3. Substantive conclusions from the paper largely do not change across these measures.

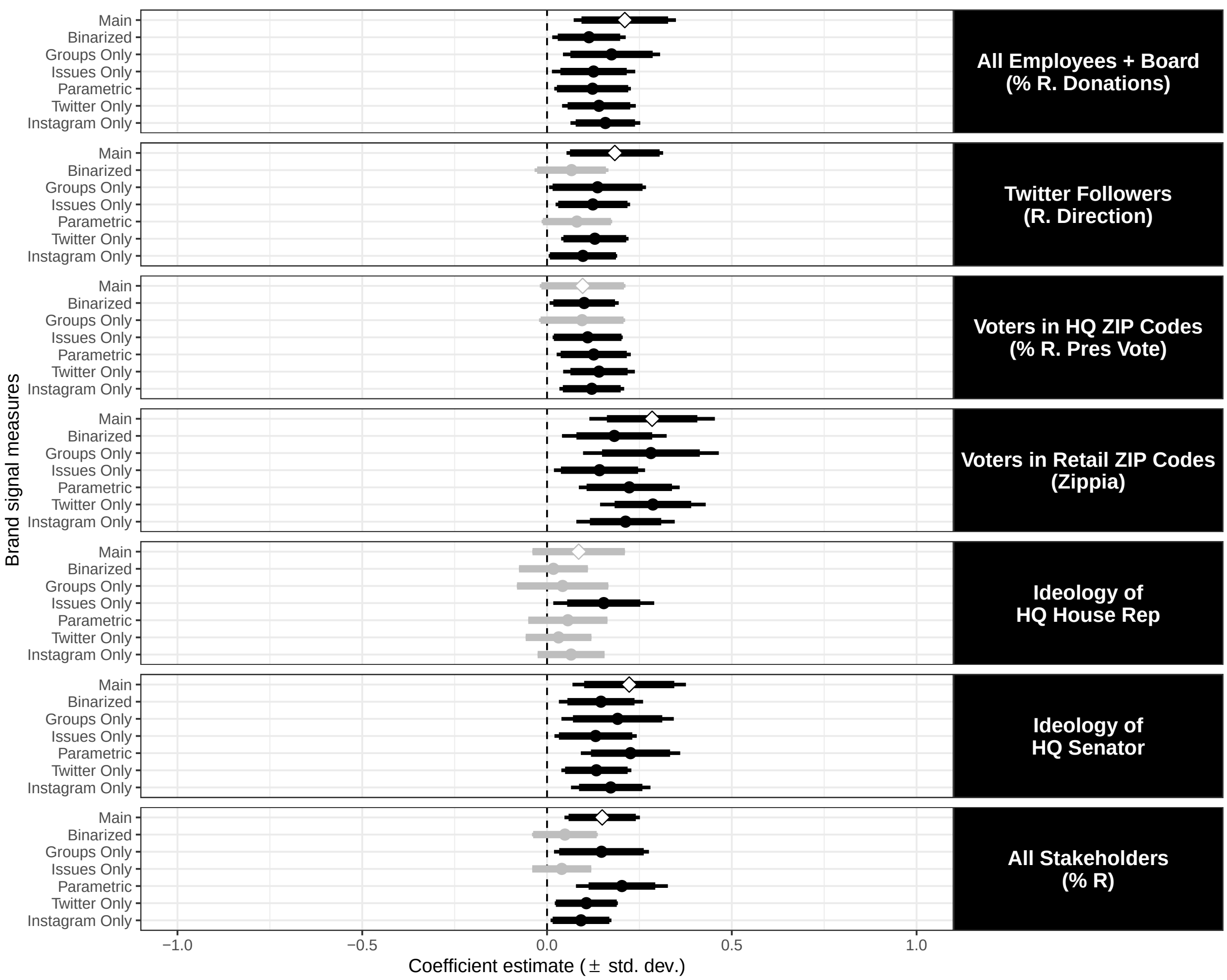
Figure C17: **Alignment Between Brand Signals and Select Partisan Stakeholder Preferences (County-Level Geographic Measures)**

(a) *Voters in HQ County* (b) *Voters in Business/Retail County*



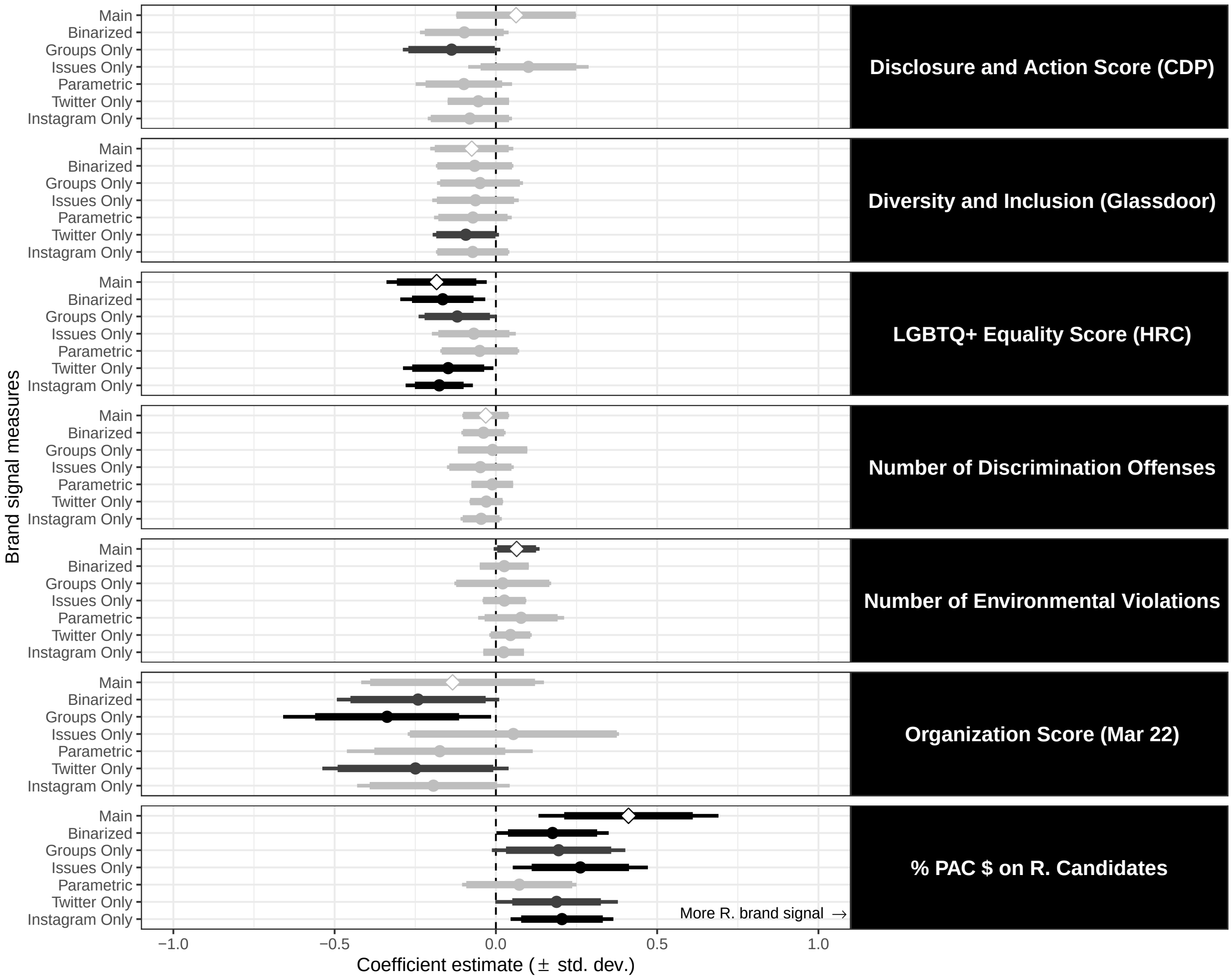
Notes: Percentage of brands in each quadrant are shown in the corner of each plot. The purple lines denote linear OLS regression lines of best fit, while the orange lines denote LOESS regression lines of best fit. Shown below each plot is the Pearson correlation (r) between each stakeholder measure (horizontal axis) and their corresponding brand signals (vertical axis). Statistical significance is determined using a robust t-test or equivalently the HC0-corrected standard errors of univariate regression between stakeholder measure and brand signal.

Figure C18: **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 C19: **Correlations Between Different Measures of Partisan Brand Signal and Firm Activities**



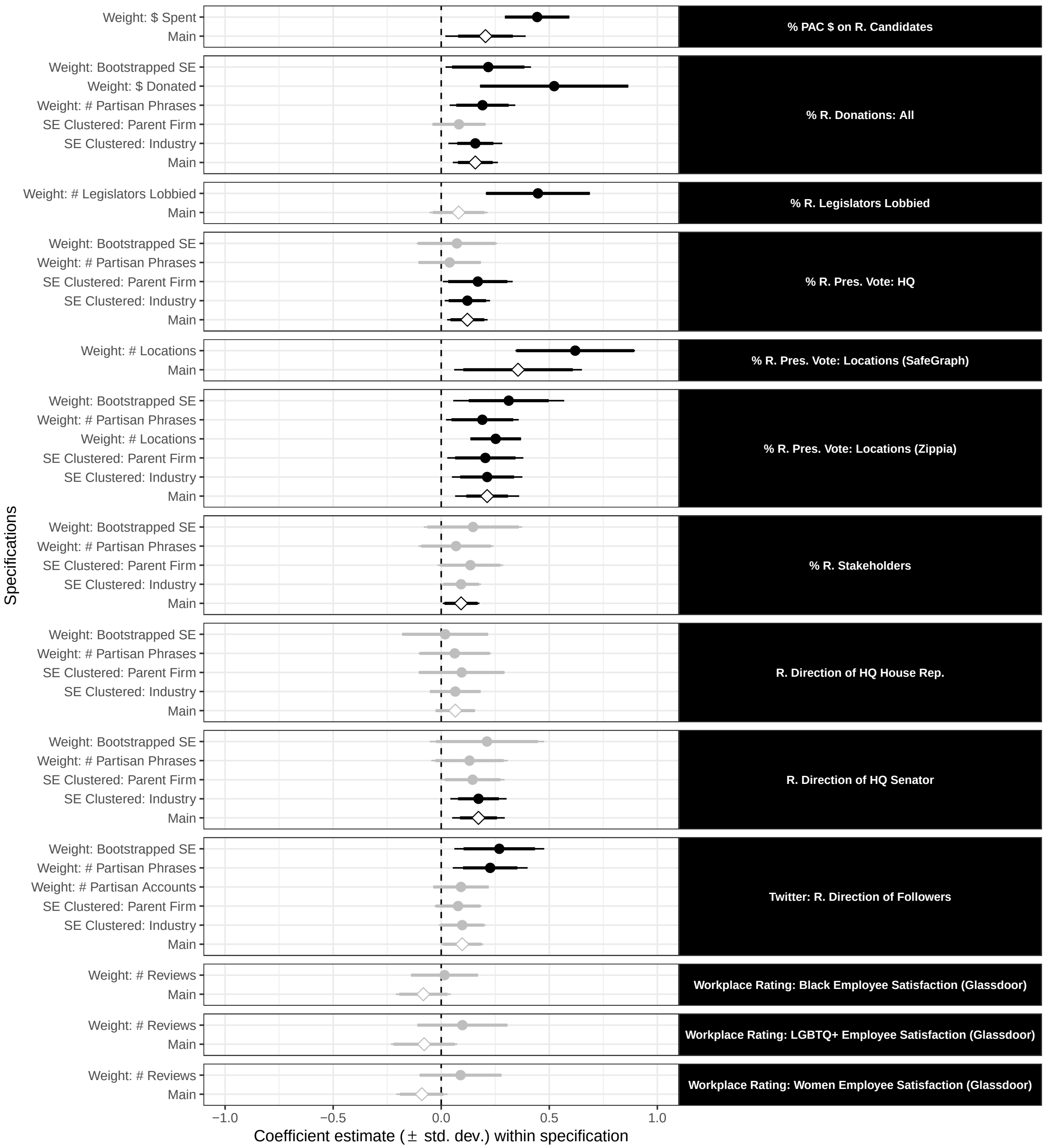
Notes: Coefficients estimated from univariate regressions of brand signal (measured in the ways labelled on the vertical axis) on firm characteristics labelled by the black panels (for brevity, only a subset of characteristics used in the main text are shown). Confidence intervals for coefficients involving 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 C20 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 7–8). These including weighting by the precision of point estimates of each preditor (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 C20: **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

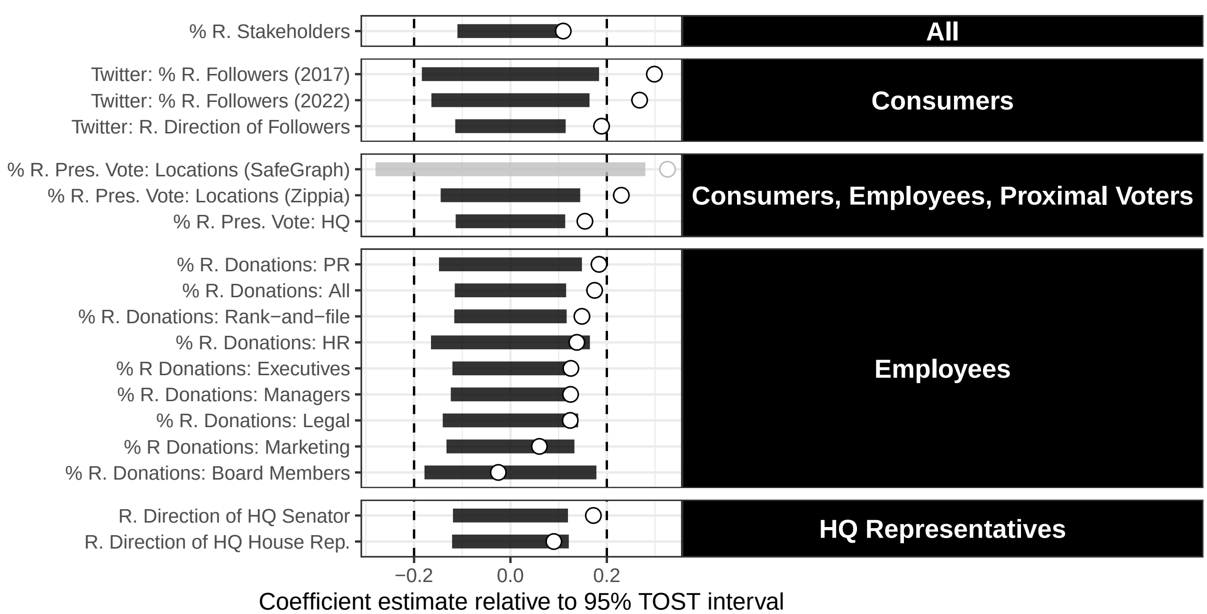
Even statistically significant coefficient results may be rejected on the basis of small effect sizes; moreover the absence of statistically significant results do not necessarily imply minimal or zero relationships in reality. Thus, I turn to equivalence tests to seek evidence that the effect sizes shown in the main text are negligible (Rainey, 2014; Lakens, 2017; E. Hartman and Hidalgo, 2018).

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 Cohen, 2013, 0.20 standard deviations. E. Hartman and Hidalgo (2018) recommend a more conservative threshold of 0.36 standard deviations.

Figures C21–C22 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.

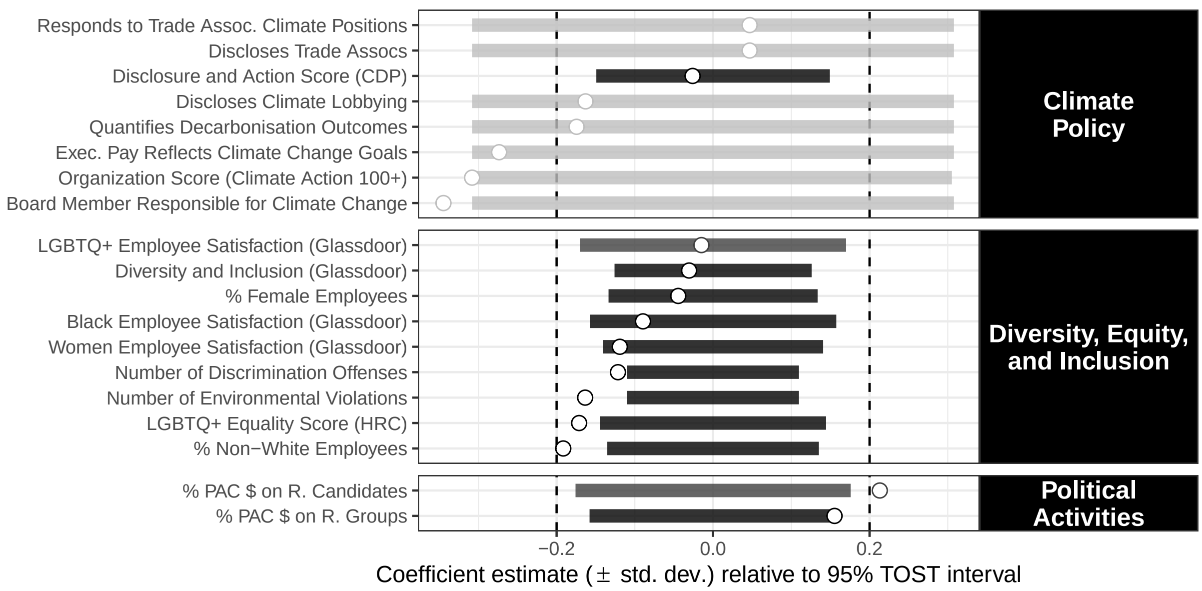
Note that in many cases, eequivalence tests detect minimal relationships in finite samples of a larger population due to a lack of statistical power. That is not an applicable reason in this study since I observe the entire population of interest (highly recognizable brands in the United States).

Figure C21: **Equivalence Tests for Stakeholder Preference Regressions**



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 Cohen, 2013. In comparison, points denote the original estimates.

Figure C22: **Equivalence Tests for Firm Activity Regressions**



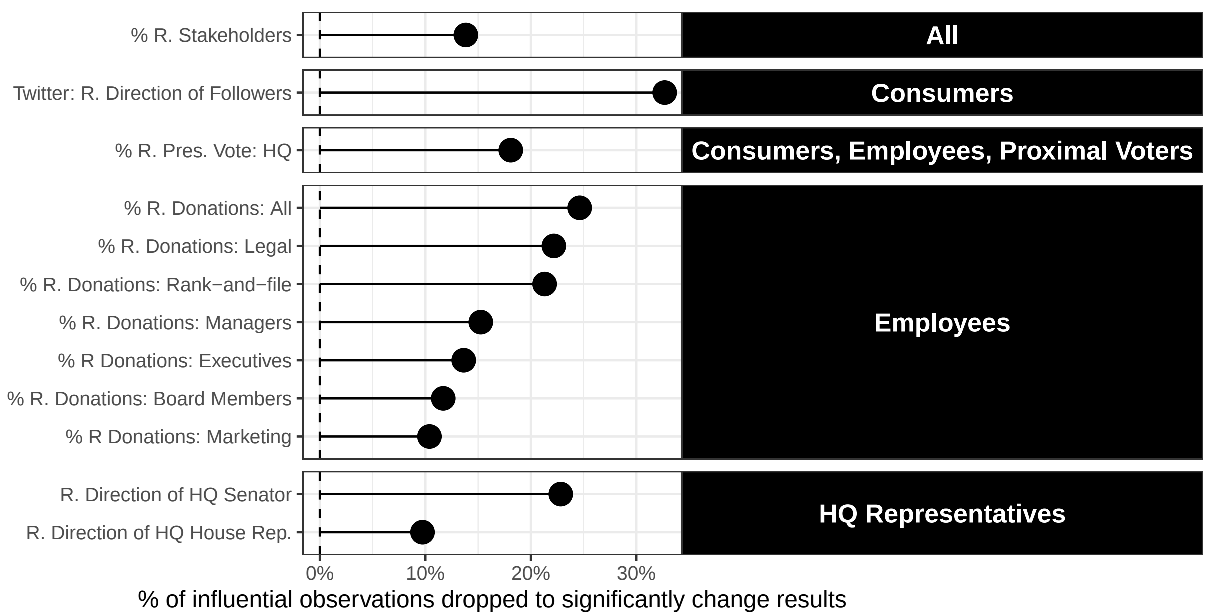
Notes: Bands show the 95% two-sided TOST intervals for the regressions of brand signals on each of the (standardized) measures of firm activities shown on the vertical axis. Bands are colored black if they are able to reject the null hypothesis of at least a 0.20 standardized difference – a common benchmark for a minimal effect size Cohen, 2013. 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 signaling seen in Figures 5–6 raise the concern that a few influential observations are entirely "responsible" for the minimal alignments/correlations we do observe.

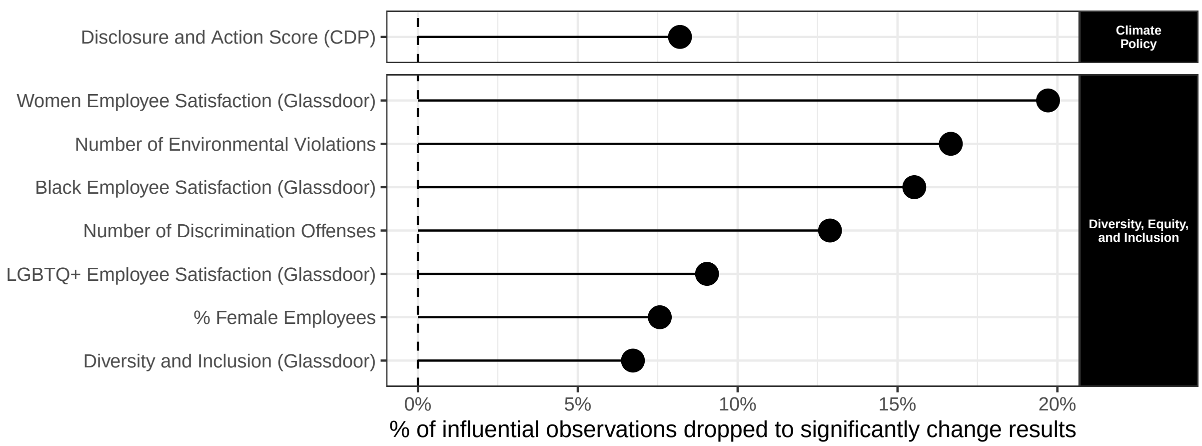
Figures C23–C24 show the results of a procedure (Broderick, Giordano, and Meager, 2020) used to identify the most pivotal observations (if they exist) in a regression model, the removal of which would reverse the sign of the estimated coefficients significantly. In summary, the correlations estimated in Figures 7–8 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 (Broderick, Giordano, and Meager, 2020).

Figure C23: **Estimated Influential Observations for Stakeholder Preference Regressions**



Notes: Percentages denoted by each black dot are estimated via the estimator proposed by Broderick, Giordano, and Meager (2020). Shown are only the independent variables from Figure 7 for which an influential set could be estimated.

Figure C24: **Estimated Influential Observations for Firm Characteristic Regressions**



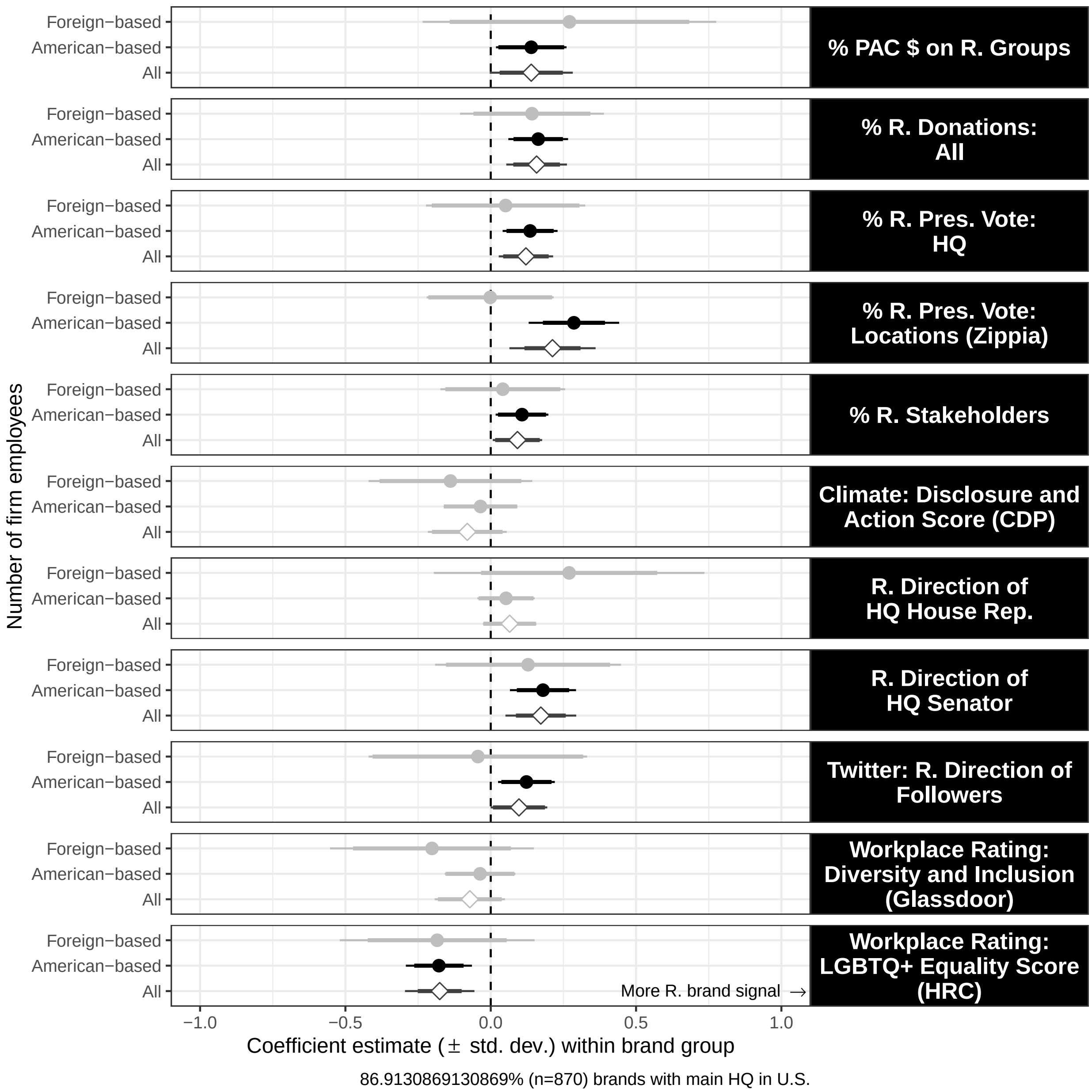
Notes: Percentages denoted by each black dot are estimated via the estimator proposed by Broderick, Giordano, and Meager (2020). Shown are only the independent variables from Figure 8 for which an influential set could be estimated.

C.8 Heterogeneity

Figures C25–C26 show how a subset of key results in the main regressions (Figures 5–6) 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.

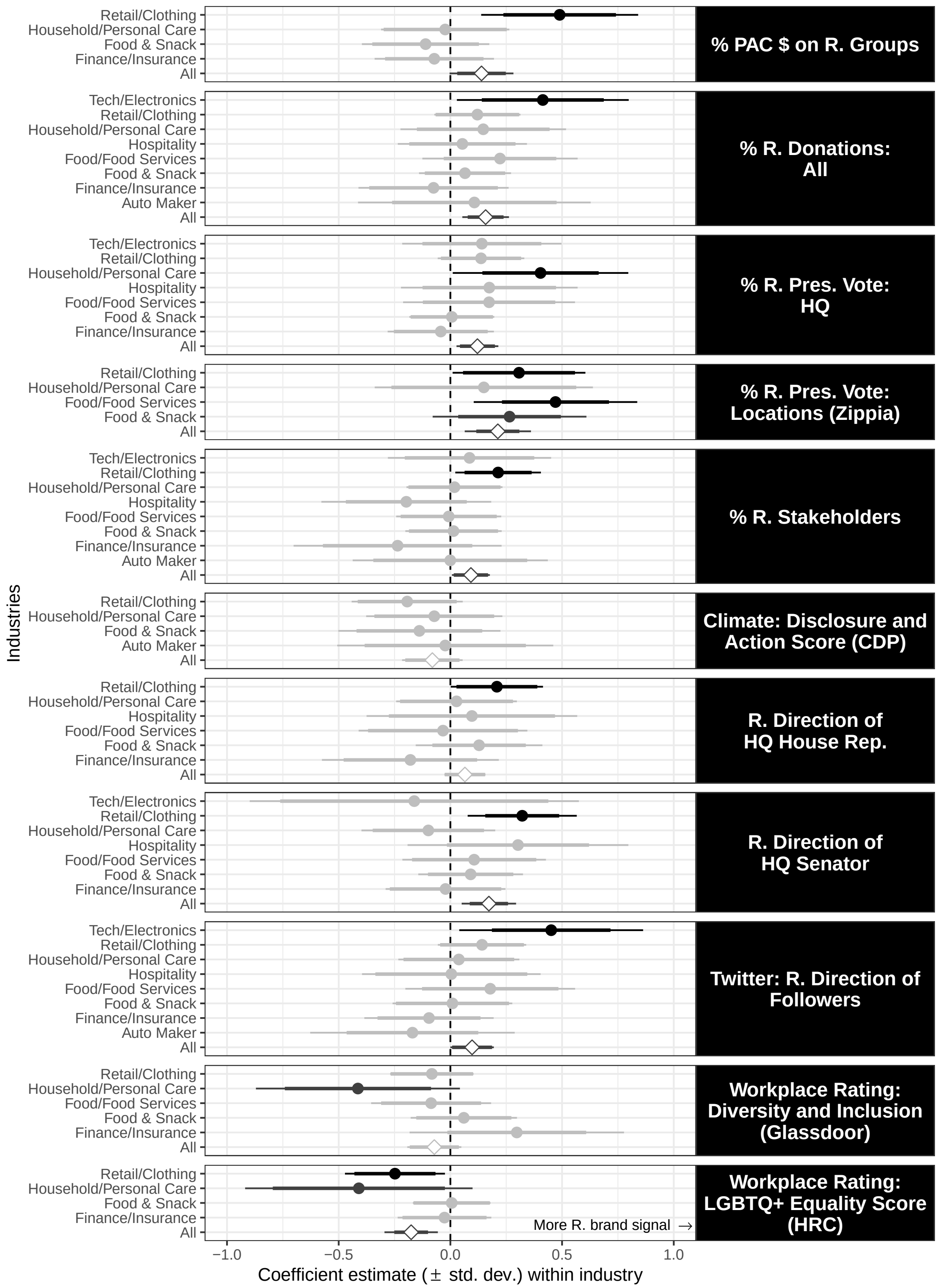
An interesting exception is that that smaller firms's brand speech is more aligned with the ideology of their headquarters' elected representatives. The reason for this is that smaller firms are Republican-leaning in their partisan appeals (Figure C12) and also more likely to be located in rural, Republican-leaning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

Figure C25: **Heterogeneity in Stakeholder and Agenda Correlations by Firm Head-quarter**



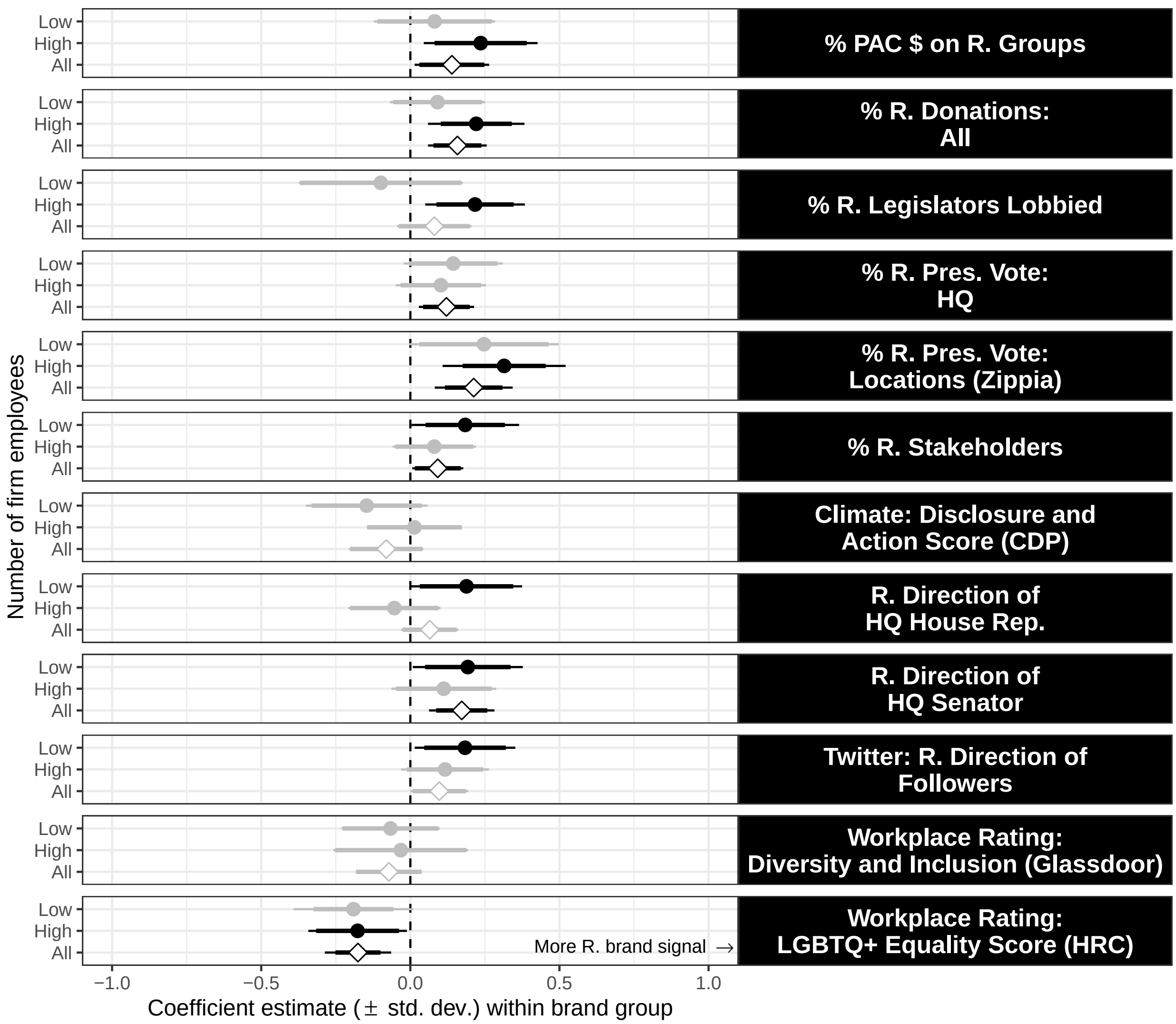
Notes: Foreign-based firms are those with no "main" headquarters in the United States; note that this differs from the definition of a *multinational corporation* because the parent firms of nearly all brands in our sample are multinational. Coefficients are estimated from univariate regressions of brand 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.

Figure C26: **Heterogeneity in Stakeholder and Agenda Correlations by Firm Industry**



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 ommitted 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 C27: **Heterogeneity in Stakeholder and Agenda Correlations by Firm Size**



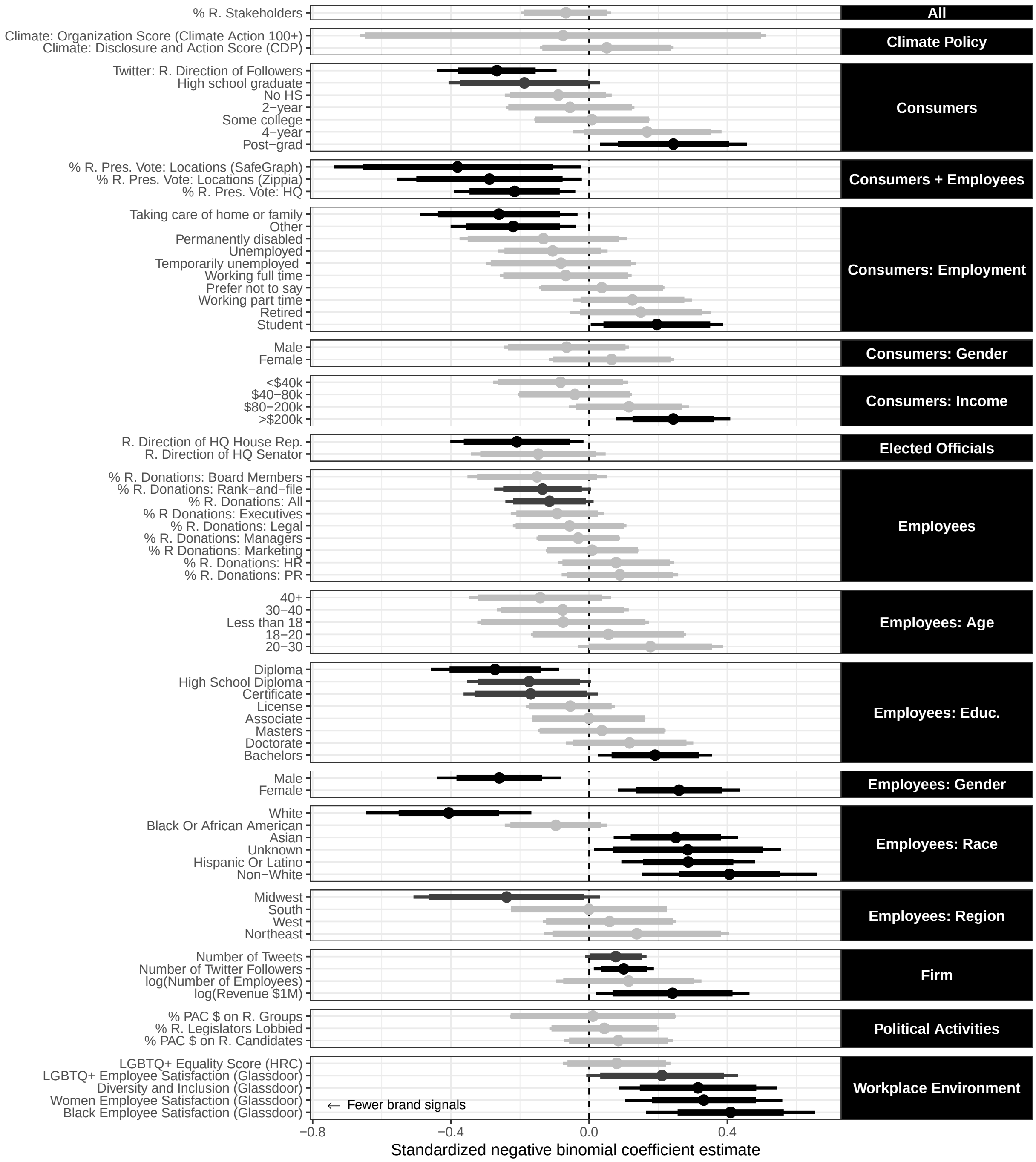
Notes: Employee bins are constructed using the median of the log count of employees across all brands as the cut-off. Coefficients are estimated from univariate regressions of brand signal (main measure) on each of the covariates shown in the right black panels for the subset of brands denoted on the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

C.9 Predictors of the Number of Partisan Signals

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 C28 reveals that larger more popular brands with more progressive, Democrat-leaning 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 C28: **Correlations Between Number of Partisan Phrases and Brand Covariates**

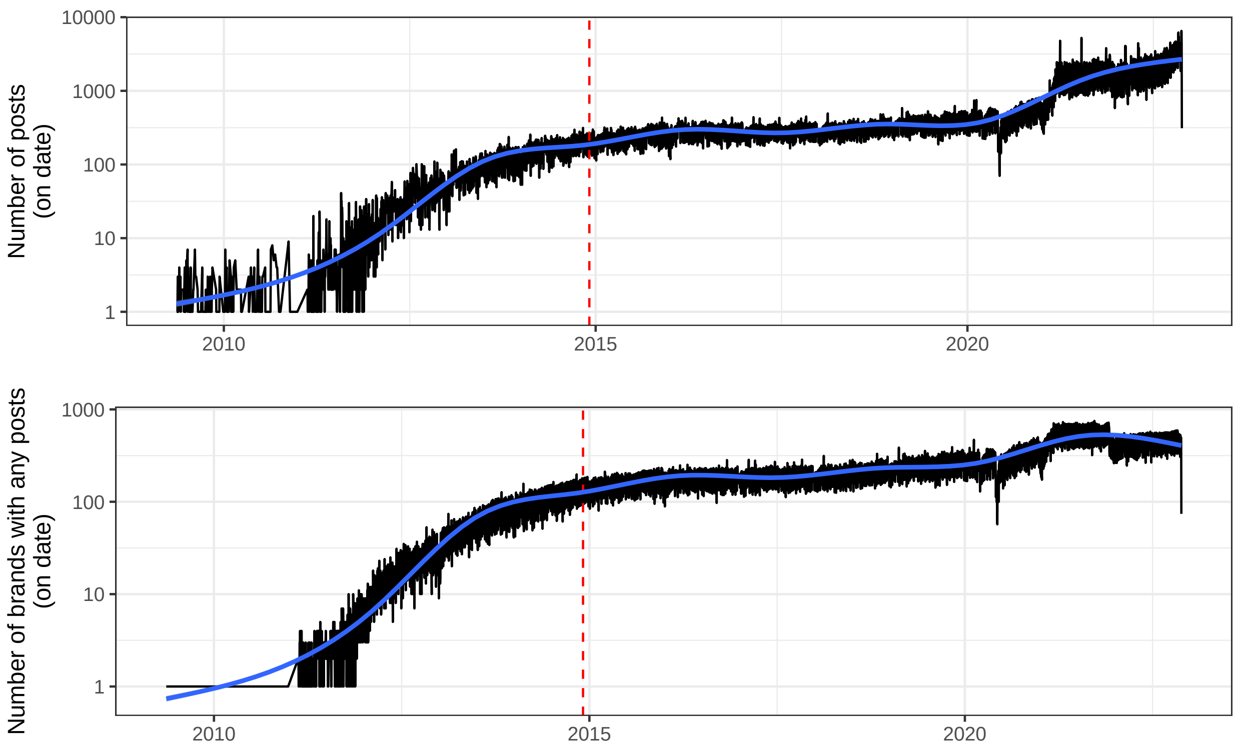


Notes: Coefficients are estimated from Negative Binomial regressions of the number of partisan phrases used by each brand on firm covariates (vertical axis). Estimates are sorted and grouped by category (black panels).

D Brand Sample

Figure D29 shows the number of posts and postings brands each day across our collected social media dataset in relation to the start period of our study.

Figure D29: **Number of Posts from Brands in Sample Over Time**



Notes: The dotted red line refers to the start of the study period (2015). The blue lines of LOESS lines of best fit.

The following 21 pages list the 879 corporate brands with active social media accounts that are the primary sample of analysis in this study.

Table 4: **List of Brands with Active Social Media Accounts**

	Brand	Firm	% Recognition	Twitter	IG
1	Pepsi	PepsiCo	99%	@pepsi	@pepsi
2	Facebook	Facebook	99%	@Facebook	@facebook
3	PayPal	PayPal	99%	@PayPal	
4	Target	Target	99%	@Target	
5	7-Eleven	Seven-Eleven Japan	99%	@7eleven	
6	Jeep	Stellantis	99%	@Jeep	
7	M&M's	Mars, Incorporated	99%	@mmschocolate	
8	Chevrolet	General Motors	99%	@chevrolet	
9	Wendy's	The Wendy's Company	99%	@Wendys	
10	Nike	Nike	99%	@Nike	@nike
11	Applebee's	Dine Brands Global	99%	@Applebees	
12	Clorox	Procter & Gamble	99%	@Clorox	
13	Heinz Ketchup	Heinz	99%	@heinz_ca	
14	Coca-Cola	The Coca-Cola Company	98%	@CocaCola	@cocacola
15	Apple iPhone	Apple Inc.	98%	@Apple	
16	Chick-fil-A	Chick-fil-A	98%	@ChickfilA	@chickfila
17	Ritz	Ritz	98%	@Ritzcrackers	
18	Band-Aid	Johnson & Johnson	98%	@Ba_15021515983	
19	Best Buy	Best Buy	98%	@BestBuy	@bestbuy
20	Lowe's	Lowe's	98%	@LowesMedia	
21	McDonald's	McDonald's	98%	@McDonaldsUK	
22	Oreo Cookies	Mondelez International	98%	@Oreo	@oreo
23	Taco Bell	Yum!	98%	@tacobell	@tacobell
24	Cheetos	PepsiCo	98%	@CheetosCanada	
25	Oreo	Mondelez International	98%	@Oreo	
26	Snickers	Mars, Incorporated	98%	@SNICKERS	
27	Cheerios	General Mills	98%	@cheerios	
28	Bounty	Procter & Gamble	98%	@Bounty	
29	Burger King	Restaurant Brands International	98%	@BurgerKing	@burgerking
30	Domino's	Domino's	98%	@dominos	
31	Johnson & Johnson	Johnson & Johnson	98%	@JNJCares	@jnj
32	Gap	Gap	98%	@Gap	
33	Adidas	Adidas	98%	@adidas	
34	Samsung	Samsung	98%	@SamsungMobile	
35	Lay's	PepsiCo	98%	@LAYS	
36	Walmart	Walmart	98%	@Walmart	@walmart
37	Hershey's	The Hershey Company	98%	@Hersheys	
38	Nickelodeon	Nickelodeon Networks	98%	@Nickelodeon	

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List of Brands with Active Social Media Accounts *(continued from last page)*

	Brand	Firm	% Recognition	Twitter	IG
39	Denny's	Denny's	98%	@DennysDiner	@dennysdiner
40	Ford	Ford	98%	@Ford	
41	Doritos	PepsiCo	98%	@Doritos	
42	Old Navy	Gap Inc.	98%	@oldnavymx	@oldnavy
43	Windex	S. C. Johnson & Son	98%	@Windex	
44	Chips Ahoy!	Mondelez International	98%	@ChipsAhoy	
45	Subway	Subway	98%	@SUBWAY	
46	Tostitos	PepsiCo	98%	@Tostitos	
47	iPad	Apple Inc.	98%	@cxrdellini	
48	Crest	Procter & Gamble	98%	@Crest	
49	Bank of America	Bank of America	98%	@BankofAmerica	@bankofamerica
50	Pizza Hut	Yum! Brands	98%	@pizzahut	@pizzahut
51	Kmart	Transformco	98%	@Kmart	
52	Victoria's Secret	Victoria's Secret	98%	@VictoriasSecret	@victoriassecret
53	Baskin-Robbins	Inspire Brands	98%	@BaskinRobbins	
54	Eggo	Kellogg's	98%	@eggo	
55	Kellogg's	Kellogg's	98%	@KelloggsUS	
56	Dunkin'	Inspire Brands	98%	@dunkindonuts	
57	Frito-Lay	PepsiCo	98%	@Fritolay	
58	Kleenex	Kleenex	97%	@Kleenex	
59	Google	Alphabet Inc.	97%	@Google	
60	Arby's	Inspire Brands	97%	@Arbys	
61	Papa John's	Papa John's	97%	@PapaJohnsTrophy	@papajohns
62	Febreze	Procter & Gamble	97%	@Febreze_Fresh	@febreze
63	Frosted Flakes	Kellogg's	97%	@frosted_flakes	@kelloggsfrostedflakes
64	Charmin	Procter & Gamble	97%	@Charmin	
65	Calvin Klein	Calvin Klein	97%	@YoYo	@calvinklein
66	Home Depot	Home Depot	97%	@HomeDepot	@homedepot
67	State Farm	State Farm	97%	@StateFarmCenter	@statefarm
68	Rice Krispies Treats	Kellogg's	97%	@AdamSchifter	@kelloggsricekrispies
69	MasterCard	MasterCard	97%	@Mastercard	
70	Apple	Apple Inc.	97%	@Apple	
71	Dell	Dell Technologies	97%	@Dell	
72	Mercedes-Benz	Mercedes-Benz	97%	@MercedesBenzUSA	
73	Playstation	Sony	97%	@PlayStation	
74	Head & Shoulders	Procter & Gamble	97%	@Headshoulders	@headandshoulders
75	BMW	BMW	97%	@BMW	
76	Lay's Chips	PepsiCo	97%	@lay_chips	@lays
77	Pringles	Kellogg's	97%	@Pringles	
78	Vaseline	Unilever	97%	@VaselineBrand	
79	Tide	Procter & Gamble	97%	@tide	
80	Dawn	Procter & Gamble	97%	@DawnRichard	

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List of Brands with Active Social Media Accounts *(continued from last page)*

	Brand	Firm	% Recognition	Twitter	IG
81	Special K	Kellogg's	97%	@RadioSpecialK	@specialk
82	Macy's	Macy's	97%	@Macys	
83	Nesquik	Nestlé	97%	@Nesquik	
84	Sony	Sony	97%	@Sony	
85	Skittles	Skittles	97%	@Skittles	
86	Honda	Honda	97%	@Honda	
87	Olive Garden	Darden Restaurants	97%	@olivegarden	@olivegarden
88	Amazon	Amazon	97%	@amazon	
89	Kit Kat	Nestlé	97%	@KitKat_US	
90	Reese's Peanut Butter Cup	The Hershey Company	97%	@etaerealbwi	
91	HP	HP	97%	@HP	
92	Pillsbury	Pillsbury	97%	@Pillsbury	
93	Colgate	Colgate-Palmolive	97%	@Colgate	
94	CVS	CVS	97%	@cvspharmacy	
95	Visa	Visa	97%	@Visa	
96	Office Depot	Office Depot	97%	@officedepot	@officedepot
97	Kohl's	Kohl's	97%	@Kohls	
98	Microsoft	Microsoft	97%	@Microsoft	
99	Dove	Unilever	97%	@DoveCameron	
100	Fritos	PepsiCo	97%	@OfficialFritos	
101	Jif	The J.M. Smucker Company	97%	@Jif	
102	Sears	Sears Holdings	97%	@Sears	
103	Chase	JPMorgan Chase	97%	@Chase	
104	Cheez-It	Kellogg's	97%	@cheezit	
105	Nestlé Crunch	Nestlé Crunch	97%	@crunchbar	
106	Toys "R" Us	Toys "R" Us	97%		@toysrus
107	Shell	Shell plc	97%	@Shell	
108	Wells Fargo	Wells Fargo	97%	@WFInvesting	@wellsfargo
109	Kia	Kia	97%	@Kia	
110	Walgreens	Walgreens Boots Alliance	97%	@WBA_Global	
111	Swiffer	Procter & Gamble	97%	@Swiffer	
112	Kraft Foods	Kraft Heinz	97%	@KraftBrand	@kraft_brand
113	Honey Nut Cheerios	Honey Nut Cheerios	97%	@HoneyNutBuzz	
114	Hershey's Kisses	The Hershey Company	97%	@tsokolaaateee	
115	Red Lobster	Darden Restaurants	97%	@redlobster	@redlobster
116	Twizzlers	The Hershey Company	97%	@TWIZZLERS	
117	Cadillac	General Motors	97%	@CadillacArabia	
118	Old Spice	Procter & Gamble	97%	@oldspicecologne	@oldspice
119	AutoZone	AutoZone	97%	@autozone	
120	Petco	Petco	97%	@Petco	
121	Reese's	The Hershey Company	97%	@reeses	
122	Campbell's	Campbell's	97%	@Campbells	

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List of Brands with Active Social Media Accounts *(continued from last page)*

	Brand	Firm	% Recognition	Twitter	IG
123	Ace Hardware	Ace Hardware	97%	@AceHardware	@acehardware
124	Dairy Queen	Berkshire Hathaway	97%	@DairyQueen	@dairyqueen
125	Chuck E. Cheese's	Atari	97%	@ChuckECheese	@chuckecheese
126	Hanes	Hanesbrands	97%	@Hanes	
127	Little Caesars	Little Caesars	97%	@littlecaesars	@littlecaesars
128	Lucky Charms	General Mills	97%	@LuckyCharms	@luckycharms
129	Tabasco	Tabasco	96%	@TABASCO	@tabasco
130	Chili's	Brinker International	96%	@Chilis	
131	Nissan	Nissan	96%	@NissanUSA	
132	J. C. Penney	J. C. Penney	96%		@jcpenney
133	Gillette	Procter & Gamble	96%	@Gillette	
134	Holiday Inn	IHG Hotels & Resorts	96%	@HolidayInn	@holidayinn
135	LG	LG	96%	@LGUS	
136	Lifesavers	Mars, Incorporated	96%	@LifeSavers	
137	Quaker	Quaker	96%	@Quaker	
138	Starburst	Mars, Incorporated	96%	@Starburst	
139	Twix	Mars Incorporated	96%	@twix	
140	Benadryl	Johnson & Johnson	96%	@Benadryl	
141	Heinz	Kraft Heinz	96%	@heinz_ca	
142	Chex Mix	General Mills	96%	@ChexMix	@chexcereal
143	Volkswagen	Volkswagen Group	96%	@VWGroup	
144	Sam's Club	Walmart Inc.	96%	@SamsClub	@samsclubrasil
145	CNN	CNN Global	96%	@cnnbrk	
146	Ziploc	S. C. Johnson & Son	96%	@Ziploc	
147	Kellogg's Rice Krispies Treats	Kellogg's Rice Krispies Treats	96%	@KelloggsUS	@kelloggsricekrispies
148	Motorola	Motorola	96%	@MotoSolutions	
149	Lexus	Toyota	96%	@Lexus	@lexususa
150	T.J. Maxx	TJX Companies	96%	@tjmaxx	@tjmaxx
151	Hot Wheels	Mattel	96%	@Hot_Wheels	
152	GEICO	Berkshire Hathaway	96%	@GEICO	
153	American Express	American Express	96%	@AmericanExpress	@americanexpress
154	Bud Light	Bud Light	96%	@budlight	@budlight
155	Energizer	Energizer	96%	@Energizer	
156	Krispy Kreme	Krispy Kreme	96%	@krispykremeUK	@krispykreme
157	Kraft Mac & Cheese	Kraft Heinz	96%	@kraftmacncheese	@kraft_macandcheese
158	Budweiser	AnheuserBusch	96%	@budweiserusa	
159	Toyota	Toyota Group	96%	@Toyota	
160	Fruit of the Loom	Berkshire Hathaway	96%	@FruitOfTheLoom	@fruitoftheloom
161	Betty Crocker	General Mills	96%	@BettyCrocker	@bettycrocker
162	Buick	General Motors	96%	@Buick	
163	Hidden Valley Ranch	Hidden Valley Ranch	96%	@HVRanch	
164	Reebok	Authentic Brands Group	96%	@Reebok	

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List of Brands with Active Social Media Accounts *(continued from last page)*

	Brand	Firm	% Recognition	Twitter	IG
165	Bounce	Bounce	96%	@BounceFresh	
166	Outback Steakhouse	Bloomin' Brands	96%	@OutbackBrasil	@outback
167	Capital One Bank	Capital One Bank	96%	@COBATX	@capitalone
168	Bed Bath and Beyond	Bed Bath and Beyond	96%	@BedNeeds	@bedbathandbeyond
169	Staples	Staples	96%	@StaplesCanada	@staples
170	Google Chromebook	Alphabet Inc.	96%	@Google	
171	Cool Ranch Doritos	PepsiCo	96%	@crustable63	
172	Costco	Costco	96%	@JoshCostco15	@costco
173	Dollar Tree	Dollar Tree	96%	@Katie3278	@dollartree
174	Mac	Mac	96%	@tobymac	
175	Dial	Henkel	96%	@Dial	
176	Chrysler	Stellantis	96%	@Chrysler	@chrysler
177	Walmart+	Walmart	96%	@Walmart	@walmart
178	Universal Studios	Universal Parks & Resorts	96%	@UniStudios	@unistudios
179	Hooters	Hooters	96%		@hooters
180	Duracell	Berkshire Hathaway	96%	@Duracell	@duracell
181	Mr. Clean	Procter & Gamble	96%	@RealMrClean	
182	Tums	Haleon	96%	@TUMSOfficial	@tumsofficial
183	Goldfish	Campbell Soup Company	96%	@GoldFishLive	@goldfishsmiles
184	Oscar Mayer	Kraft Heinz	96%	@oscarmayer	
185	Subaru	Subaru Corporation	96%	@SubaruCustCare	@subaru_usa
186	Jack Daniel's	BrownForman Corporation	96%	@JackDanielsSA	@JackDaniels_US
187	The Cheesecake Factory	The Cheesecake Factory	96%	@Cheesecake	@cheesecakefactory
188	Lysol	Reckitt	96%	@Lysol	@lysol
189	Dayquil	Procter & Gamble	96%	@Palaverd	@nyquildayquil
190	Bath & Body Works	Bath & Body Works	96%	@bathbodyworks	
191	Advil	Advil	96%	@AdvilRelief	@advil
192	Hallmark	Hallmark	96%	@Hallmark	@hallmark
193	Ben & Jerry's	Unilever	96%	@benandjerrys	@benandjerrys
194	Dodge	Stellantis	96%	@Dodge	@dodgeofficial
195	Barbie	Barbie	96%	@Barbie	@barbie
196	Nyquil	Procter & Gamble	96%	@NyQuilDayQuil	@nyquildayquil
197	Popeyes Chicken & Biscuits	Restaurant Brands International	96%	@PopeyesChicken	@popeyeslouisianakitchen
198	Almond Joy	The Hershey Company	96%	@balonsor	
199	Land O'Lakes	Land O'Lakes	95%	@LandOLakesKtchn	@landolakesktchn
200	Gain	Gain	95%	@GAINalliance	
201	Fisher Price	Mattel	95%	@FisherPrice	@fisherprice
202	Baby Ruth	Ferrero SpA	95%	@ruth_switfeesh	@babyruthbar
203	IKEA	IKEA	95%	@IKEAITALIA	@ikeausa
204	Petsmart	Petsmart	95%	@PetSmart	@petsmart
205	TGI Friday's	TGI Friday's	95%	@jrharrington13	@tgifridays
206	Jolly Rancher	The Hershey Company	95%	@Jolly_Rancher	@jollyrancher

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List of Brands with Active Social Media Accounts *(continued from last page)*

	Brand	Firm	% Recognition	Twitter	IG
207	Porsche	Volkswagen AG	95%	@Porsche	@porsche
208	Butterfinger	Ferrero SpA	95%	@Butterfinger	
209	Kindle	Amazon	95%	@AmazonKindle	
210	Coffee-Mate	Coffee-Mate	95%	@CoffeeMateTR	@coffeemate
211	Reese's Pieces	The Hershey Company	95%	@_sblue7	
212	Tyson	Tyson	95%	@tysonchandler	@tyson_foods
213	Marshalls	Melville Corporation	95%	@marshalls	@marshalls
214	Skechers	Skechers	95%	@SKECHERSUSA	@skechers
215	Nestlé Toll House	Nestlé	95%	@NestleTollHouse	
216	Pampers	Procter & Gamble	95%	@Pampers	@pampersus
217	Allstate	Sears	95%	@Allstate	@your_agent
218	BlueCross BlueShield	BlueCross BlueShield	95%	@BCBST	@bcbsassociation
219	Sonic	Independent	95%	@sonic_hedgehog	@sonicdrivein
220	Tootsie Pop	Tootsie Pop	95%	@farahsolovely	@tootsieroll
221	Barnes & Noble	Barnes & Noble	95%	@BNBuzz	@barnesandnoble
222	OxiClean	Church & Dwight	95%		@oxicleanofficial
223	Glade	S. C. Johnson & Son	95%	@Glade	@glade
224	Chex	General Mills	95%	@ChexCereal	@chexcereal
225	French's Mustard	McCormick & Company	95%		@frenchs
226	RadioShack	General Wireless IP Holdings LLC	95%	@RadioShack	@radioshack
227	Foot Locker	Foot Locker	95%	@footlocker	@footlocker
228	Bisquick	General Mills	95%	@Bisquick	
229	Whole Foods Market	Amazon	95%	@WholeFoods	@wholefoods
230	Capital One	Capital One	95%	@CapitalOne	@capitalone
231	Yoplait	General Mills	95%	@Yoplait	@yoplaitusa
232	Downy	Procter & Gamble	95%	@Downy	@downy
233	Mitsubishi	Mitsubishi	95%	@mitsucars	
234	Honey Bunches of Oats	Post Holdings	95%	@shuhrelleean	@hboats
235	Milky Way bar	Mars, Incorporated	95%		@milkywaybar
236	Miller Lite	Miller Lite	95%	@MillerLite	@millerlite
237	Buffalo Wild Wings	Independent	95%	@BWWings	@bwwings
238	Walt Disney Parks and Resorts	The Walt Disney Company	95%	@DisneyParks	
239	Big Lots	Big Lots	95%	@mr_crowly28	@biglots
240	Dick's	Dick's	95%	@DICKS	@dickssportinggoods
241	GE	GE	95%	@GELighting	@generalelectric
242	Lamborghini	Audi AG	95%	@Lamborghini	@lamborghini
243	Purell	Gojo Industries	95%		@purellbrand
244	Cracker Barrel	Cracker Barrel	95%	@CrackerBarrel	@crackerbarrel
245	Smirnoff	Smirnoff	95%	@SmirnoffUS	@smirnoffvodka
246	Amazon Alexa	Amazon	94%	@alexarb24	@alexa99
247	Listerine	Johnson & Johnson	94%	@ListerineGlobal	@listerine
248	Planters	Hormel Foods	94%	@NUTmobile_Tour	

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List of Brands with Active Social Media Accounts *(continued from last page)*

	Brand	Firm	% Recognition	Twitter	IG
249	Ruffles	PepsiCo	94%	@RUFFLES	@ruffles
250	Six Flags	Six Flags	94%	@SixFlags	@sixflags
251	Olay	Procter & Gamble	94%	@OlaySkin	@olay
252	Xbox	Microsoft	94%	@Xbox	@xbox
253	Converse	Nike	94%	@Converse	@converse
254	Motel 6	G6 Hospitality	94%	@motel6	@motel6
255	Panera Bread	JAB Holding Company	94%	@askpanera	@panerabread
256	Orville Redenbacher's Popcorn	Conagra Brands	94%	@OrvillePopcorn	@orvillepopcorn
257	Goodyear	Goodyear	94%	@goodyear	@goodyear
258	Hyundai	Hyundai Motor Group	94%	@hyundaisaudi	@hyundaiusa
259	OfficeMax	Kmart	94%	@OfficeMax	@officedepot
260	Breyers	Unilever	94%	@Breyers	@breyers
261	Panda Express	Panda Restaurant Group	94%	@PandaExpress	@officialpandaexpress
262	AAA	AAA	94%	@AAAnews	@aaa_national
263	Dove (chocolate)	Mars, Incorporated	94%	@DoveChocolate	@dovechocolate
264	Discover	Dean Witter Reynolds	94%	@Discover	@discover
265	Citibank	Citigroup	94%	@Citibank	@citibank
266	PUMA	PUMA	94%	@PUMA	@puma
267	Trader Joe's	Trader Joe's	94%		@traderjoes
268	Neutrogena	Johnson & Johnson	94%	@Neutrogena	@neutrogena
269	Payless	Payless	94%	@PaylessInsider	@payless
270	Quiznos	REGO Restaurant Group	94%	@Quiznos	@quiznos
271	Aleve	Aleve	94%	@aleve	@aleve_us
272	Corona Light	Corona Light	94%	@anahaedra	@coronausa
273	Mazda	Mazda	94%	@MazdaUSA	@mazdausa
274	Claritin	Claritin	94%	@Claritin	@claritinusa
275	Marriott	Marriott	94%	@Marriott	
276	General Mills	General Mills	94%	@GeneralMills	@generalmills
277	Delta Air Lines	Delta Air Lines	94%	@Delta_Pilots	@delta
278	Wheat Thins	Mondelez International	94%	@WheatThins	
279	Hefty	Reynolds Consumer Products, Inc	94%	@Hefty	
280	Progresso	General Mills	94%	@Fundicao	@progresso
281	Orville Redenbacher's	Conagra Brands	94%	@OrvillePopcorn	
282	Elmer's	Newell Brands	94%	@Elmers	
283	Rolex	Rolex	94%	@ROLEX	@rolex
284	Whirlpool	Whirlpool	94%	@Whirlpool_CA	
285	Volvo	Volvo	94%	@volvocars	
286	Panasonic	Panasonic	94%	@panasonic	@panasonic
287	The LEGO Store	The LEGO Store	94%	@theLEGOStore	@lego
288	Long John Silver's	Independent	94%	@longjohnsilvers	@longjohnsilvers
289	Black & Decker	Stanley Black & Decker	94%	@BLACKANDDECKER	@blackanddecker_us
290	Tostitos Scoops	PepsiCo	94%		@tostitos

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List of Brands with Active Social Media Accounts *(continued from last page)*

	Brand	Firm	% Recognition	Twitter	IG
291	Tesla	Tesla	94%	@Tesla	
292	Nature Valley	General Mills	94%	@NatureValley	@nature_valley
293	McCormick	McCormick	94%	@McCormickCorp	
294	Hertz	Hertz	94%	@Hertz	@hertz
295	General Motors	General Motors	94%	@GM	@generalmotors
296	Western Union	Western Union	93%	@WesternUnion	@westernunion
297	Coors	Molson Coors	93%	@CoorsLight	
298	Cinnabon	AFC Enterprises	93%	@Cinnabon	
299	Corona	Corona	93%	@corona	@coronabeerwine
300	Golden Corral	Golden Corral	93%	@goldencorral	@goldencorral
301	Alka-Seltzer	Bayer	93%	@alkaseltzer	
302	Cinnamon Toast Crunch	General Mills	93%	@CTCSquares	@cinnamontoastcrunch
303	Red Robin	Red Robin	93%	@redrobinburgers	@redrobinburgers
304	Nabisco	Kraft Foods Inc.	93%	@Astros_Jenn	@nabiscosnacks
305	Ragú	Mizkan	93%	@ragusauce	
306	Dollar General Corp.	Dollar General Corp.	93%	@DollarGeneral	@dollargeneral
307	Dove Chocolate Candy Bar	Mars, Incorporated	93%		@dovechocolate
308	Hampton Inn	Hilton Worldwide	93%		@hamptonbyhilton
309	Progressive	Progressive	93%	@progressive	@progressive
310	Rite Aid	Rite Aid	93%	@riteaid	@riteaid
311	GMC	General Motors	93%	@GMC	@gmc
312	Secret	Secret	93%	@SecretWorldLgds	
313	John Deere	John Deere	93%	@JohnDeere	@johndeere
314	Tommy Hilfiger	PVH Corp.	93%	@TommyHilfiger	@tommyhilfiger
315	Heinz Mustard	Kraft Heinz	93%	@mustard_heinz	
316	Pfizer	Pfizer	93%	@pfizer	@pfizerinc
317	Disney Store	Disney Consumer Products	93%		@shopdisney
318	Land O Lakes (butter)	Land O Lakes (butter)	93%		@landolakesktchn
319	Holiday Inn Express	IHG Hotels & Resorts	93%	@HIExpress	@holidayinnexpress
320	Smucker's	Smucker's	93%	@smuckers	
321	Hard Rock Cafe	Hard Rock Cafe	93%	@HardRock	@hardrockcafe
322	Aflac	Aflac	93%	@aflac	@aflacduck
323	Suave	Unilever	93%	@SuaveBeauty	@suave
324	Huggies	Kimberly Clark	93%	@Huggies	@huggies
325	Days Inn	Days Inn	93%		@daysinn
326	Sherwin Williams	Sherwin Williams	93%		@sherwinwilliams
327	Jimmy Dean	Jimmy Dean	93%	@JimmyDean	
328	Irish Spring	Colgate-Palmolive	93%	@IrishSpring	@irishspring
329	Ralph Lauren	Ralph Lauren	93%	@RalphLauren	@poloralphlauren
330	Air Wick	Reckitt	93%	@airwickus	@airwickus
331	Dr. Scholl's shoes	Dr. Scholl's	93%		@drschollsshoes
332	Gucci	Kering	93%	@gucci	@gucci

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List of Brands with Active Social Media Accounts *(continued from last page)*

	Brand	Firm	% Recognition	Twitter	IG
333	Triscuit	Mondelez International	93%	@SoundRemedy	
334	Jiffy Lube	Shell US	93%	@jiffylube	@jiffylubeintl
335	Velveeta	Kraft Heinz	93%	@EatLiquidGold	@velveeta
336	Liberty Mutual	Liberty Mutual	93%	@LibertyMutual	
337	Viagra	Viagra	93%	@ViagraBoys	@viagra_official_
338	Häagen-Dazs	Häagen-Dazs	93%	@HaagenDazs_US	
339	Ferrari	Ferrari N.V.	93%	@Ferrari	@ferrari
340	SweetTarts	SweetTarts	93%		@sweetartscandy
341	Tampax	Procter & Gamble	93%	@Tampax	@tampax
342	Kroger	Kroger	93%	@kroger	
343	Audi	Volkswagen Group	93%	@AudiOfficial	@audi
344	Trump Hotels	Trump Hotels	93%	@TrumpHotels	@trumphotels
345	Family Dollar	Dollar Tree	93%	@myfamilydollar	@familydollar
346	Junior Mints	Junior Mints	93%	@JuniorMints	
347	Exxon Mobil	Exxon Mobil	93%		@exxonmobil
348	Toshiba	Toshiba	93%	@ToshibaUSA	@toshibausa
349	Enterprise	Enterprise	92%	@Enterprise	@enterprise
350	Purina	Purina	92%	@Purina	@purina
351	Polo Ralph Lauren	Polo Ralph Lauren	92%		@poloralphlauren
352	Maruchan Ramen Noodle Soup	Toyo Suisan	92%		@maruchan_inc
353	RAM	Stellantis	92%	@RGVzoomin	
354	Under Armour	Under Armour	92%	@UnderArmour	@underarmour
355	Mattel	Mattel	92%	@Mattel	@mattel
356	Best Western	BWH Hotel Group	92%	@BestWestern	
357	Children's Tylenol	Children's Tylenol	92%	@jmarlauskas	
358	Dots	Dots	92%	@dots	
359	Acura	Honda	92%	@Acura	@acura
360	DiGiorno	Nestlé	92%	@DiGiorno	@digiorno
361	Heineken	Heineken	92%	@Heineken	@theheinekencompany
362	Hardee's	Imasco	92%	@hardees_ksa	
363	Keurig	Keurig Dr Pepper	92%	@Keurig	@keurig
364	Whoppers	The Hershey Company	92%	@Whoppers	
365	Miller	Molson Coors	92%	@DavidMillerSA12	
366	Coors Light	Molson Coors	92%	@CoorsLight	@coorslight
367	Pontiac	Oakland Motor Car	92%	@ECAlertQC19	
368	Land Rover	Jaguar Land Rover	92%	@LandRover	@landrover
369	Sour Patch Kids	Mondelez International	92%		@sourpatchkids
370	Maybelline	L'Oréal	92%	@Maybelline	@maybelline
371	Jack in the Box	Jack in the Box	92%	@JackBox	@jackinthebox
372	American Eagle Outfitters	American Eagle Outfitters	92%		@americaneagle
373	Lee	Kontoor Brands	92%	@leehsienloong	@leejeans
374	Revlon	Revlon	92%	@revlon	

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List of Brands with Active Social Media Accounts *(continued from last page)*

	Brand	Firm	% Recognition	Twitter	IG
375	Avon	Avon	92%	@AvonInsider	@avoninsider
376	Old El Paso	General Mills	92%	@oldelpaso	@oldelpaso
377	Chevron	Standard Oil Co.	92%	@Chevron	@chevron
378	Sunchips	PepsiCo	92%	@SunChips	@sunchips
379	AMC	AMC	92%	@AMCTheatres	
380	Pine-Sol	The Clorox Company	92%	@pinesolcleaners	
381	Crocs	Crocs	92%	@Crocs	@crocs
382	Pantene	Procter & Gamble	92%	@Pantene	@pantene
383	Snickers Almond Bar	Mars, Incorporated	92%		@snickers
384	Philips	Philips	92%	@Philips	@philips
385	Fiat	Stellantis Italy	92%	@fiat	@fiat
386	Cottonelle	Cottonelle	92%	@cottonelle	@cottonelle
387	Hilton	Hilton	91%	@HiltonGardenInn	@hilton
388	Werther's Original	Werther's Original	91%	@nottopochico	
389	Firestone	Bridgestone	91%	@FirestoneTires	@firestonetires
390	WD-40	WD-40	91%		@wd40brand
391	Super 8 Motels	Wyndham Hotels & Resorts	91%		@super8
392	Yamaha	Yamaha	91%	@YamahaMusicUSA	@yamahamotorusa
393	Farmers Insurance	Zurich Insurance Group	91%	@WeAreFarmers	@wearefarmers
394	Roku	Roku	91%	@Roku	
395	Wrangler	Kontoor Brands	91%	@Wrangler	@wrangler
396	Chipotle Mexican Grill	Chipotle Mexican Grill	91%	@chipotle_green	@chipotle
397	CoverGirl	Coty	91%	@COVERGIRL	
398	Stouffers	Nestlé	91%	@stouffers	
399	Icy Hot	Icy Hot	91%	@icyhot	@icyhot
400	OFF!	S. C. Johnson & Son	91%	@OFFofficial	
401	Nordstrom	Nordstrom	91%	@Nordstrom	@nordstrom
402	Planet Fitness	Planet Fitness	91%	@PlanetFitness	@planetfitness
403	Splenda	Heartland Food Products Group	91%	@Splenda	@splenda
404	Lincoln	Ford Motor Company	91%	@LCTheater	@lincoln
405	MSNBC	MSNBC	91%	@MSNBC	@msnbc
406	Prego	Campbell Soup Company	91%	@meagon_kinder	@prego
407	Jaguar	Jaguar	91%	@Jaguar	
408	Courtyard by Marriott	Marriott International	91%		@courtyardhotels
409	Tempur-Pedic	Tempur Sealy International	91%	@TempurPedic	@tempurpedic
410	New Balance	New Balance	91%	@newbalance	@newbalance
411	White Castle	White Castle	91%	@WhiteCastle	@whitecastle
412	Infiniti	Nissan	91%	@InfinitiMSport	@infiniti
413	Sargento String Cheese	Sargento String Cheese	91%		@sargentocheese
414	Robitussin	Robitussin	91%	@Robitussin	@robitussinbrand
415	Theraflu	Theraflu	91%	@Theraflu	
416	Tiffany & Co.	LVMH	91%	@TiffanyAndCo	@tiffanyandco

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List of Brands with Active Social Media Accounts *(continued from last page)*

	Brand	Firm	% Recognition	Twitter	IG
417	Trojan	Church & Dwight	91%	@trojanrecords	@trojanbrandcondoms
418	Mobil 1	Mobil 1	91%	@Mobil1	
419	Men's Wearhouse	Men's Wearhouse	91%	@menswearhouse	@MensWearhouse
420	Waffle House	Waffle House	91%	@WaffleHouse	@wafflehouseofficial
421	GNC	Harbin Pharmaceutical Group	91%	@GNCLiveWell	@gnc
422	Banana Republic	Gap Inc.	90%	@BananaRepublic	@bananarepublic
423	Totino's Pizza Rolls	General Mills	90%	@buucciarati	@totinos
424	Fitbit	Google LLC	90%	@fitbit	@fitbit
425	Palmolive	Colgate-Palmolive	90%	@CP_News	@palmoliveph
426	Bass Pro Shops	Bass Pro Shops	90%	@BassProShops	@bassproshops
427	Fiber One	Fiber One	90%	@FiberOne	@fiberone
428	PayDay	PayDay	90%	@payday	@everyonelovespayday
429	Red Baron	Red Baron	90%	@redbaronpizza	
430	Bacardi	Bacardi	90%	@BacardiCanada	
431	Sour Skittles	Sour Skittles	90%	@boiledbongwater	
432	Ram Trucks	Stellantis	90%	@RamTrucksCanada	@ramtrucks
433	L'Oreal Paris	L'Oreal Paris	90%	@LorealParisID	
434	Bayer Aspirin	Bayer Aspirin	90%	@bayeraspirin	
435	Mounds	The Hershey Company	90%	@MoundsView_PD	
436	Miracle-Gro	Scotts Miracle-Gro Company	90%	@MiracleGro	@miraclegro
437	Greyhound	Flixbus	90%	@GreyhoundBus	
438	Abercrombie & Fitch	Abercrombie & Fitch	90%	@Abercrombie	@abercrombie
439	Wayfair	Wayfair	90%	@Wayfair	@wayfair
440	Bentley	Audi	90%	@BentleyMotors	
441	Valvoline	Valvoline	90%	@Valvoline	@valvoline
442	Nick Jr.	Nick Jr.	90%	@nickjr	@nickjr
443	Bissell	Bissell	90%	@BISSELLclean	
444	Woolite	Reckitt	90%	@Woolite	
445	Flamin' Hot Cheetos	PepsiCo	90%	@28andgrumpy	
446	Milk-Bone	The J.M. Smucker Company	90%	@MilkBone	
447	Nick at Nite	Nick at Nite	90%	@nickatnitetv	@nickelodeondeutsch
448	Centrum	Centrum	90%		@centrumusa
449	KitchenAid	Whirlpool Corporation	90%	@KitchenAidUSA	@kitchenaidusa
450	Craftsman	Stanley Black & Decker	90%	@craftsman	
451	Ghirardelli	Lindt & Sprüngli	90%	@LoveGhirardelli	@ghirardelli
452	IBM	IBM	90%	@IBM	@ibm
453	Sealy	Tempur Sealy International	90%	@Sealy	@sealy
454	Cheese Nips	Cheese Nips	90%	@halseys_boob	
455	Dockers	Levi Strauss & Co.	90%	@Dockers	@dockerskhakis
456	Amazon Fire TV	Amazon	90%		@amazonfiretv
457	Ruby Tuesday	Ruby Tuesday	90%	@rubytuesday	@rubytuesday
458	Amazon Echo	Amazon	90%	@Lekstacey	

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List of Brands with Active Social Media Accounts *(continued from last page)*

	Brand	Firm	% Recognition	Twitter	IG
459	Champion	Hanesbrands	89%	@championshockey	@champion
460	Michelin	Michelin	89%	@Michelin	@michelin
461	Pier 1 Imports	Pier 1 Imports	89%		@pier1
462	Gold Bond	Gold Bond	89%		@goldbond
463	J.P. Morgan	J.P. Morgan	89%	@jpmorgan	@jpmorgan
464	Quality Inn	Quality Inn	89%	@QI_Leamington	
465	Texas Roadhouse	Texas Roadhouse	89%	@texasroadhouse	
466	AXE	Unilever	89%	@AXE	@axe
467	Zyrtec	Zyrtec	89%	@Zyrtec	@zyrtecallergy
468	Boston Market	Boston Market	89%	@bostonmarket	@bostonmarket
469	BP	BP	89%	@bp_UK	@bp_plc
470	LongHorn Steakhouse	Darden Restaurants	89%	@LongHornSteaks	@longhornsteaks
471	Burt's Bees	Clorox	89%	@BurtsBees	@burtsbees
472	Zales	Signet Jewelers	89%	@ZalesJewelers	
473	CarMax	Circuit City	89%	@CarMax	@carmax
474	Build-A-Bear Workshop	Build-A-Bear Workshop	89%		@buildabear
475	Mike's Hard Lemonade	Mike's Hard Lemonade	89%	@mhl	@mikeshardbrasil
476	Clearasil	Reckitt	89%	@ClearasilUK	@clearasil
477	Mucinex	Mucinex	89%	@Mucinex	@mucinex_us
478	Kettle Brand Chips	Campbell Soup Company	89%	@kettlebrand	@kettlebrand
479	Kenmore	Kenmore	89%	@kenmore	
480	Pennzoil	Pennzoil	89%	@Pennzoil	@pennzoil
481	Pabst Blue Ribbon	Pabst Blue Ribbon	89%	@PabstBlueRibbon	@pabstblueribbon
482	Atari	Atari SA	89%	@atari	@atari
483	Royal Caribbean Cruises	Royal Caribbean Group	89%		@royalcaribbean_aunz
484	Yankee Candle	Newell Brands	89%	@TheYankeeCandle	@yankeecandle
485	Jimmy John's	Inspire Brands	89%	@jimmyjohns	@jimmyjohns
486	Guinness	Guinness	88%	@GuinnessIreland	@beerguiness
487	A&W Restaurants	A&W Restaurants	88%		@awrestaurants
488	Corona Extra	Corona Extra	88%	@hnh262990	
489	Jenny Craig	Jenny Craig	88%	@JennyCraig	@jennycraigofficial
490	StarKist	Dongwon Group	88%	@StarKistCharlie	
491	Louis Vuitton	LVMH	88%	@LouisVuitton	
492	Bloomingdale's	Macy's	88%	@Bloomingdales	
493	Pep Boys	Icahn Enterprises	88%	@pepboysauto	@pepboysauto
494	Miller High Life	Molson Coors	88%	@millerhighlife	@millerhighlife
495	Michelob Ultra	Michelob Ultra	88%	@MichelobULTRA	@michelobultra
496	Procter & Gamble	Procter & Gamble	88%	@ProcterGamble	@proctergamble
497	Pedialyte	Pedialyte	88%	@pedialyte	@pedialyte
498	Hormel	Hormel	88%	@HormelFoods	
499	Jim Beam	Jim Beam	88%	@JimBeam	@jimbeamofficial
500	Smirnoff Ice	Smirnoff Ice	88%	@s_squidney	@smirnoff

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List of Brands with Active Social Media Accounts *(continued from last page)*

	Brand	Firm	% Recognition	Twitter	IG
501	L. L. Bean	L. L. Bean	88%		@llbean
502	Preparation-H	Preparation-H	88%		@preparationh
503	Frigidaire	Electrolux	88%	@Frigidaire	@frigidaire
504	Mars Bar	Mars Bar	88%	@marsfootball	
505	Gap Kids	Gap Kids	88%		@gapkids
506	Mayo Clinic	Mayo Clinic	88%	@MayoClinic	@mayoclinic
507	Samuel Adams	Boston Beer Company	88%	@SamuelAdamsBeer	
508	Chicken of the Sea	Chicken of the Sea	88%	@COSMermaid	@chickenoftheseaofficial
509	Speed Stick	Colgate-Palmolive	88%	@SpeedStick	@speedstick
510	Nerds	Ferrero SpA	88%	@PegboardNerds	
511	Excedrin	Excedrin	88%	@Excedrin	
512	Carl's Jr.	CKE Restaurants	88%	@NZCarlsJr	@carlsjr
513	Crown Royal	Crown Royal	88%	@CrownRoyal	@crownroyal
514	Nationwide	Nationwide	88%	@Nationwide	@nationwide
515	Nivea	Nivea	88%	@ELeagueAus	@nivea
516	Carnival Cruise Line	Carnival Corporation & plc	88%	@CarnivalCruise	@carnival
517	Dave & Buster's	Dave & Buster's	88%		@daveandbusters
518	Busch	AB InBev	88%	@AnheuserBusch	
519	Motrin	Motrin	88%		@motrin
520	Great Value	Great Value	87%	@Jadecrusade	
521	Sleep Number	Sleep Number	87%	@sleepnumber	@sleepnumber
522	Allegra	Allegra	87%	@AllegraAcosta	
523	Ore-Ida	Kraft Heinz	87%	@OreIdaPotatoes	
524	American Express Travel	American Express Travel	87%		@AmericanExpress
525	Nutrisystem	Kainos Capital	87%	@Nutrisystem	@nutrisystem
526	Nature Made	Otsuka Pharmaceutical	87%		@naturemadevitamins
527	Coleman	Newell Brands	87%	@Astro_Cady	@colemanusa
528	Party City	Party City Holdings Inc.	87%	@Jadedkisses	@PartyCity
529	Dyson	Dyson	87%	@Dyson	@dyson
530	Chanel	Chanel	87%	@CHANEL	
531	Five Guys	Five Guys	87%	@FiveGuysUK	
532	One-A-Day	One-A-Day	87%		@oneaday_us
533	Rogaine	Rogaine	87%	@mdl_2346	
534	Meow Mix	The J.M. Smucker Company	87%	@meowmix	@meowmix
535	Zantac	Zantac	87%	@zantac360	
536	Advance Auto Parts	Advance Auto Parts	87%	@AdvanceAuto	@advanceautoparts
537	O'Reilly Auto Parts	O'Reilly Auto Parts	87%	@oreillyauto	@oreillyautoparts
538	Cold Stone Creamery	Kahala Brands	87%	@ColdStone	@coldstone
539	Omaha Steaks	Omaha Steaks	87%	@OmahaSteaks	@omahasteaks
540	Captain Morgan	Captain Morgan	87%	@CaptainMorganGB	
541	United	United Airlines Holdings	87%	@united	@united
542	Purina Cat Chow	Nestlé S.A.	87%	@PurinaCatChow	@purina

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List of Brands with Active Social Media Accounts *(continued from last page)*

	Brand	Firm	% Recognition	Twitter	IG
543	Toaster Strudel	General Mills	86%	@ToasterStrudel	
544	Aldi	Aldi	86%	@AldiUK	
545	Visine	Johnson & Johnson	86%	@Visine	
546	Coppertone	Coppertone	86%	@givernynormandy	@coppertoneusa
547	Rolaids	Sanofi	86%	@RolaidsCanadaFR	
548	Sargento	Sargento	86%	@SargentoCheese	
549	Ferrero Rocher	Ferrero SpA	86%	@Lil_Ibuprofen	
550	Aveeno	Johnson & Johnson	86%	@caval_artax	@aveenous
551	Miller Genunine Draft	Molson Coors	86%		@mgdbeer
552	RayBan	RayBan	86%	@Hugo_Raybann	
553	Country Crock	Upfield	86%	@country_crock	@countrycrock
554	Equifax	Equifax	86%	@Equifax	
555	Sensodyne	Sensodyne	86%	@SensodyneIndia	
556	Softsoap	Colgate-Palmolive	86%	@_soft_soap	
557	Estée Lauder	Estée Lauder	86%	@EsteeLauder	
558	Jergens	Jergens	86%		@jergensus
559	Dove men+care	Dove men+care	86%	@DoveMenCare	@dove
560	Go-gurt	Go-gurt	86%	@privatepat116	
561	Laffy Taffy	Laffy Taffy	86%	@LaffyTaffy	@laffytaffy
562	Hyatt	Hyatt	86%	@Hyatt	@hyatt
563	Kay	Kay	86%	@heykayadams	
564	Kibbles 'n Bits	The J.M. Smucker Company	86%	@KibblesNBits	@kibblesnbits
565	RCA	GE	86%	@RCARecords	
566	Mary Kay Cosmetics	Mary Kay Cosmetics	85%	@marykaycanada	@marykayus
567	Snyder's Pretzels	Snyder's-Lance	85%		@snyders_hanover
568	Maytag	Whirlpool Corporation	85%	@MaytagCare	@maytag
569	Forever 21	Authentic Brands Group Brookfield Properties Simon Property Group	85%	@Forever21	@forever21
570	Trivago	Trivago	85%	@trivago	@trivago
571	Sheraton	Marriott International	85%	@sheratonhotels	
572	White Castle Frozen Sliders	White Castle Frozen Sliders	85%		@whitecastle
573	Urban Outfitters	Urban Outfitters	85%	@UrbanOutfitters	@urbanoutfitters
574	Seagram's	Seagram's	85%	@SeagramsEscapes	
575	Lactaid	Lactaid	85%	@Lactaid	@lactaid
576	Armor All	Energizer Holdings	85%	@Armor_All	@armorallusa
577	Prada	Prada	85%	@Prada	@prada
578	Bertolli	Bertolli	85%	@Bertolli	
579	Heath bar	Heath bar	85%	@funinspace	
580	Pottery Barn	Williams-Sonoma	85%	@potterybarn	@potterybarn
581	True Value	True Value	85%	@TrueValue	@truevalue
582	Proactiv	Guthy-Renker	85%	@Proactiv	@proactiv
583	The North Face	VF Corporation	85%	@thenorthface	@thenorthface

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List of Brands with Active Social Media Accounts *(continued from last page)*

	Brand	Firm	% Recognition	Twitter	IG
584	Hot Tamales	Hot Tamales	85%	@HOTTAMALESBrand	@hottamalescandy
585	La Quinta Inns & Suites	Wyndham Hotels & Resorts	85%		@laquintahotels
586	Scotts	Scotts	85%	@scottsmenswear	
587	Honeywell	Honeywell	85%	@Honeywell_Home	@honeywell
588	Columbia	Columbia	85%	@Columbia	
589	Merrill Lynch	Bank of America	85%	@MerrillLynch	
590	Ritz-Carlton	Marriott International	85%	@RitzCarlton	@ritzcarlton
591	Soft Scrub	Soft Scrub	85%		@softscrub
592	Embassy Suites	Hilton Worldwide	85%	@EmbassySuites	@embassysuites
593	Southwest	Southwest	85%	@SouthwestAir	
594	Ramada	Wyndham Hotels and Resorts	84%		@ramadabywyndham
595	UnitedHealthcare	UnitedHealthcare	84%	@UHC	@unitedhealthcare
596	Baileys	Baileys	84%	@BaileysOfficial	
597	Wilson Sporting Goods	Amer Sports	84%		@wilsonballglove
598	Timberland	VF Corporation	84%	@Timberland	
599	Herbal Essences	Herbal Essences	84%	@herbalessences	@herbalessences
600	Clear Eyes	Clear Eyes	84%		@cleareyes
601	Humana	Humana	84%	@Humana	@humana
602	Brach's	Ferrero SpA	84%	@Brach_market	
603	Armani	Armani	84%	@armani	
604	Eddie Bauer	Eddie Bauer	84%	@eddiebauer	@eddiebauer
605	Shout	Shout	84%	@ShoutFactory	
606	Hubba Bubba	Hubba Bubba	84%	@JulumMama	
607	Schick	Schick	84%	@SchickHydro	
608	Charles Schwab	Charles Schwab	84%	@CharlesSchwab	
609	Tidy Cats	Tidy Cats	84%	@TidyCats	@tidycats
610	Hilton Garden Inn	Hilton Worldwide	84%	@HiltonGardenInn	@hiltongardeninn
611	Rolo	The Hershey Company	84%	@rolotomassiband	
612	St. Ives	St. Ives	84%	@StIvesSkin	@stivesskin
613	Dollar Shave Club	Unilever	84%	@DollarShaveClub	@dollarshaveclub
614	MetLife	MetLife	84%	@MetLife	
615	Miller Genuine Draft	Molson Coors	84%	@Miller_SLV	@mgdbeer
616	Sharp	Sharp	84%	@SHARP_JP	
617	Budget	Budget	84%	@Budget	
618	Serta	Serta Simmons Bedding	84%	@SertaMattresses	
619	TRESemmé	Unilever	84%	@TRESemme	
620	Fujifilm	Fujifilm	83%	@FujifilmX_US	
621	P.F. Chang's	P.F. Chang's	83%	@PFChangs	@pfchangs
622	Dolby	Dolby	83%	@Dolby	
623	DeWalt	Stanley Black & Decker	83%	@DEWALTtough	
624	Kohler	Kohler	83%	@Kohler	@kohler
625	Flonase	Flonase	83%	@flonase	@flonase

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List of Brands with Active Social Media Accounts *(continued from last page)*

	Brand	Firm	% Recognition	Twitter	IG
626	Quicken Loans	Quicken Loans	83%	@QuickenLoans	@quickenloans
627	Famous Footwear	Caleres	83%	@FamousFootwear	@famousfootwear
628	Acer	Acer Group	83%	@Acer	@acer
629	Metamucil	Metamucil	83%	@Metamucil	@metamucil
630	Banana Boat	Banana Boat	83%	@bananaboat	@bananaboatbrand
631	Hyatt Regency	Hyatt Regency	83%	@hyattregency	@hyattregency
632	BFGoodrich	Michelin	83%	@BFGoodrichTires	
633	Dior	Dior	83%	@Dior	@dior
634	Marie Callender's	Marie Callender's Inc.	83%	@_MarieCallender	@mariecallendersrestaurants
635	Life Lock	NortonLifeLock	83%		@lifelock
636	Oxygen	NBCUniversal Cable Entertainment	83%	@oxygen	@oxygen
637	Johnsonville Sausage	Johnsonville Sausage	83%	@Johnsonvillesa2	@johnsonville
638	USAA	USAA	83%	@USAA	@usaa
639	Nautica	Authentic Brands Group	83%	@nautica	@nautica
640	JetBlue	JetBlue	83%	@JetBlue	@jetblue
641	Sephora	LVMH	83%	@Sephora	@sephora
642	Red Roof Inn	WRRH Investments LP	83%		@redroofinn
643	Castrol	Burmah Oil	83%	@Castrol	@castrolusa
644	Clinique	Estée Lauder Companies	83%	@Clinique	
645	Supercuts	Regis Corporation	82%	@Supercuts	@supercuts
646	Amazon Fresh	Amazon	82%	@AmazonFresh	@amazonfresh
647	Nordic Track	Nordic Track	82%		@nordictrack
648	In-N-Out Burger	In-N-Out Burger	82%		@innout
649	Pasta Roni	PepsiCo	82%	@RiceARoniUS	
650	Ross	Ross	82%	@realrossnoble	
651	Chobani	Chobani	82%	@Chobani	@chobani
652	Safeway	Independent	82%	@Safeway	@safeway
653	Cetaphil	Galderma Laboratories	82%	@2tender4tinder	@cetaphilus
654	Wonderful Pistachios	Wonderful Pistachios	82%	@WonderfulNuts	
655	Jose Cuervo	Jose Cuervo	82%	@JoseCuervo	
656	Bridgestone	Bridgestone	82%	@Bridgestone	@bridgestone
657	Winn-Dixie	Southeastern Grocers	82%	@WinnDixie	
658	Blue Moon	Blue Moon	82%	@BlueMoonBrewCo	@bluemoonbrewco
659	Mike and Ike	Mike and Ike	82%	@mikeandike	@mikeandikecandy
660	Nissin Cup Noodles	Nissin Cup Noodles	82%	@chadieeeee	@originalcupnoodles
661	Sudafed	Sudafed	82%	@KyKyHam	
662	Aetna	CVS Health	82%	@Aetna	@aetna
663	Southern Comfort	Southern Comfort	82%	@southerncomfort	@southerncomfort
664	Wyndham Hotels & Resorts	Wyndham Hotels & Resorts	81%	@WyndhamHotels	@wyndhamhotels
665	Neiman Marcus	Neiman Marcus	81%	@neimanmarcus	@neimanmarcus
666	Coach	Tapestry	81%	@Coach	@coach
667	Airborne	Reckitt	81%	@173rdAbnBde	

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List of Brands with Active Social Media Accounts *(continued from last page)*

	Brand	Firm	% Recognition	Twitter	IG
668	Beggin' Strips	Nestlé	81%	@Beggin	@beggin
669	Ivory	Ivory	81%	@Ivory	
670	Emergen-C	Emergen-C	81%	@emergenc	
671	U.S. Bank	U.S. Bank	81%	@usbankstadium	@usbank
672	Heath	Heath	81%	@HeathBell21	
673	JVC	Matsushita Electric	81%	@JVC_UK	
674	Church's Chicken	Church's Chicken	81%	@ChurchsChicken	@churchschicken
675	Aéropostale	Aéropostale	81%	@Aeropostale	
676	Frank's RedHot Sauce	McCormick & Company	81%		@FranksRedHot
677	Maserati	Stellantis	81%	@Maserati_HQ	@maserati
678	Reynolds	Reynolds	81%	@DanReynolds	
679	Right Guard	Henkel	81%	@RightGuardUS	@rightguardus
680	SanDisk	Western Digital	81%	@SanDisk	@sandisk
681	Pepcid	Pepcid	81%	@PepcidSalix	@pepcid
682	PediaSure	PediaSure	81%	@riio_pediasure	@pediasure
683	Cabela's	Bass Pro Shops	81%	@Cabelas	
684	J.Crew	J.Crew	81%	@jcrew	
685	New York Life	New York Life	81%	@NewYorkLife	@newyorklife
686	Orange Julius	Dairy Queen	81%	@IncredibolBol	
687	Reese's Puffs	Reese's Puffs	81%	@reesespuffs	@reesespuffs
688	Samsonite	Samsonite	81%	@MySamsonite	
689	Swedish Fish	Swedish Fish	81%	@SwedishFish	@swedishfish
690	Michael Kors	Michael Kors	80%	@MichaelKors	@michaelkors
691	Vizio	Vizio	80%	@VIZIO	@vizio
692	Vans	VF Outdoor	80%	@VANS_66	@vans
693	Jersey Mike's Subs	Jersey Mike's Subs	80%	@jerseymikes	@jerseymikes
694	Johns Hopkins Medicine	Johns Hopkins University	80%	@HopkinsMedicine	@HopkinsMedicine
695	Avis	Avis	80%	@Avis	@avis
696	Mattress Firm	Steinhoff International	80%	@MattressFirm	@mattressfirm
697	Kahlúa	Keurig Dr Pepper	80%	@Kahlua	
698	Cisco	Cisco	80%	@Cisco	@cisco
699	Bosch	Bosch	80%	@BoschAmazon	@boschglobal
700	LendingTree	LendingTree	80%	@LendingTree	
701	CiCi's Pizza	CiCi Enterprises Inc.	80%		@officialcicis
702	Dillard's	Dillard's	80%	@Dillards	
703	Hennessy	Hennessy	80%	@Hennessy	
704	King's Hawaiian	King's Hawaiian	80%	@KingsHawaiian	@kingshawaiian
705	Joe's Crab Shack	Joe's Crab Shack	80%	@Noberlober	@officialjoescrabshack
706	Fructis	Fructis	80%	@GarnierFructis	
707	Four Seasons	Four Seasons	80%	@therealfstl1992	@fourseasons
708	Versace	Capri Holdings	80%	@Versace	@versace
709	Bob Evans	Bob Evans	79%	@BobEvansFarms	@bobevansfarms

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List of Brands with Active Social Media Accounts *(continued from last page)*

	Brand	Firm	% Recognition	Twitter	IG
710	Crate & Barrel	Crate & Barrel	79%		@crateandbarrel
711	Kotex	Kimberly-Clark Corporation	79%	@kotex	
712	Boston Baked Beans	Boston Baked Beans	79%	@BeansBoston	
713	Cancer Treatment Centers of America	Cancer Treatment Centers of America	79%		@cancercenter
714	Home Goods	TJX Companies	79%	@lacat2010	@homegoods
715	Hush Puppies	Wolverine World Wide	79%		@hushpuppiesshoes
716	Sunoco	Sunoco	79%	@SunocoRacing	@gosunoco
717	Nordstrom Rack	Nordstrom	79%	@nordstromrack	@nordstromrack
718	Ashley	Ashley	79%	@iSmashFizzle	
719	Steak 'n Shake	Biglari Holdings	79%	@SteaknShake	@steaknshake
720	Clairol	Clairol	79%	@ClairolColor	
721	Radisson	Radisson Hotel Group	79%	@RadissonHotels	@radisson
722	Turtle Wax	Turtle Wax	79%	@TurtleWax	@turtlewax
723	Norwegian Cruise Lines	Norwegian Cruise Line Holdings	79%		@norwegiancruiseline
724	Zenith	LVMH	79%	@zenith	
725	Ulta Beauty	Ulta Beauty	79%	@ultabeauty	@ultabeauty
726	Kashi	Kellogg's	79%	@dkashikar	@kashi
727	AAMCO	American Driveline Systems	79%	@dboyreal100	
728	Hawaiian Tropic	Edgewell Personal Care	79%	@gayy4lana	@hawaiiantropic
729	Hitachi	Hitachi	79%	@HitachiGlobal	@hitachi
730	Johnnie Walker	Johnnie Walker	79%	@JohnnieWalkerUS	@johnniewalkerus
731	Stella Artois	Stella Artois	78%	@StellaArtois	@StellaArtois
732	Stanley	Stanley Black & Decker	78%	@StanleyDonwood	
733	Schwinn	Pon Holdings	78%		@schwinnbikes
734	Clif	Mondelez International	78%	@ClifBar	
735	Liz Claiborne	Liz Claiborne	78%	@LizClaiborne5	
736	Yves Saint Laurent	Kering	78%	@tellemyves	@ysl
737	H&M	H&M	78%	@hm	@hm
738	American Greetings	American Greetings	78%	@amgreetings	@amgreetings
739	Beats by Dr. Dre	Apple Inc.	78%		@beatsbydre
740	Bud Light Platinum	Bud Light Platinum	78%	@BLPlatinum	@budlight
741	Ortega	Ortega	78%	@BrianTcity	
742	Perdue	FPP Family Investments	78%	@PerdueChicken	
743	KIND	Mars, Incorporated	78%	@KINDSnacks	@kindsnacks
744	Aston Martin	Aston Martin	78%	@astonmartin	
745	Rold Gold	PepsiCo	78%	@RoldGold	
746	Venmo	PayPal	78%	@Venmo	@venmo
747	Nexium	Nexium	78%	@Nexium24HR_US	@nexium24hr_us
748	Oakley	EssilorLuxottica	78%	@oakley	
749	Firehouse Subs	Restaurant Brands International	78%	@FirehouseSubs	@firehousesubs
750	STP	Energizer Holdings	78%	@OriginalSTP	@originalstp
751	UGG	Deckers Brands	78%	@UGG	@ugg

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List of Brands with Active Social Media Accounts *(continued from last page)*

	Brand	Firm	% Recognition	Twitter	IG
752	Benjamin Moore	Berkshire Hathaway	78%	@Benjamin_Moore	@benjaminmoore
753	Cigna	Cigna	78%	@Cigna	
754	Knorr	Unilever	77%	@Knorr	@knorr
755	Delta Faucet	Masco	77%	@deltafaucet	@deltafaucet
756	DoubleTree	Hilton Worldwide	77%	@DoubleTree	
757	Milwaukee	Techtronic Industries	77%	@Bucks	
758	Goldman Sachs	Goldman Sachs	77%	@GoldmanSachs	@goldmansachs
759	Lancôme	L'Oréal	77%	@LancomeUSA	
760	Modelo	InBev	77%	@isaaanki	@modelousa
761	TV Land	MTV Entertainment Group	77%	@tvland	@tvland
762	Lubriderm	Lubriderm	77%	@Lubriderm_Mx	
763	Residence Inn	Marriott International	77%	@ResidenceInn	@residenceinn
764	Fidelity	Fidelity	77%	@Fidelity	
765	British Airways	International Airlines Group	77%	@British_Airways	
766	The Vitamin Shoppe	Franchise Group	77%	@VitaminShoppe	@vitaminshoppe
767	Grand Hyatt	Grand Hyatt	77%	@grandhyattbali	@grandhyatt
768	Saab	Saab	77%	@Saab	
769	Natural Light	Natural Light	77%	@naturallight	@naturallightbeer
770	Snyder's	Snyder's-Lance	77%	@Snyders_Hanover	
771	Gulf	Gulf	77%	@gulf_news	
772	Barbasol	Perio, Inc.	77%	@BarbasolShave	
773	Blue Buffalo	Blue Buffalo	77%	@bluebuffalo	@bluebuffalo
774	Malibu Rum	Malibu Rum	77%	@MalibuRum	@maliburumus
775	Westinghouse	Westinghouse	77%		@westinghouse_home
776	Vera Wang	Vera Wang	76%	@VeraWang	
777	Princess Cruises	Carnival Corporation & plc	76%	@PrincessCruises	@princesscruises
778	Claire's	Claire's	76%	@claires	
779	Saks	Saks	76%	@saks	@saks
780	Paul Mitchell	Paul Mitchell	76%	@PaulMitchellUS	@paulmitchellde
781	Hollister	Hollister	76%	@HollisterCo	
782	Whataburger	Whataburger	76%	@Whataburger	
783	Jägermeister	Jägermeister	76%	@JagermeisterUSA	
784	Sally Beauty	Sally Beauty	76%	@SallyBeauty	@sallybeautymx
785	ACT	ACT	76%	@ACT	
786	TD Ameritrade	TD Ameritrade Holding Co.	76%	@TDAmeritrade	@tdameritrade
787	Safelite	Belron	76%	@safelite	
788	John Hancock	Manulife Financial	76%	@JohnHancockJobs	@johnhancock
789	Fuddruckers	Black Titan Franchise Systems	76%	@retnuhsdrawkcab	@fuddruckers
790	Wild Turkey	Campari Group	76%	@WildTurkey	
791	Invisalign	Invisalign	76%	@Invisalign	
792	Cartier	Richemont	76%	@Cartier	
793	Alamo	Enterprise Holdings	75%	@Alamo	

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List of Brands with Active Social Media Accounts *(continued from last page)*

	Brand	Firm	% Recognition	Twitter	IG
794	Jamba Juice	Focus Brands	75%	@Only1Jama	@jambajuice
795	Enfamil	Enfamil	75%	@Enfamil	
796	Waldorf Astoria Hotels & Resorts	Waldorf Astoria Hotels & Resorts	75%		@waldorfastoria
797	Chromecast	Google	75%	@Chromecast	
798	Publix	Publix	75%	@Publix	
799	Alaska Airlines	Alaska Air Group	75%	@AlaskaAir	@alaskaair
800	Great Clips	Great Clips	75%	@GreatClips	@greatclips
801	Cape Cod	Campbell Soup Company	75%	@CapeCodChips	
802	Entenmann's	Bimbo Bakeries USA	75%	@Entenmanns	
803	DKNY	LVMH	75%	@dkny	
804	DieHard	DieHard	75%	@DieHardBattery	
805	Zoloft	Zoloft	75%	@poppersslut	
806	ZzzQuil	ZzzQuil	75%	@ZzzQuil	
807	MINI	MINI	75%	@mini_twjp	
808	Hyatt Place	Hyatt Place	75%	@HyattPlacePune	@hyattplace
809	Logitech	Logitech	74%	@Logitech	
810	Lands' End	Sears	74%	@AskLandsEnd	@landsend
811	Imodium	Imodium	74%	@IMODIUM	
812	Dos Equis	Dos Equis	74%	@DosEquis	
813	Sabra Hummus	Strauss	74%		@sabra
814	Behr	Masco	74%	@BehrPaint	
815	Garmin	Garmin	74%	@Garmin	
816	Intuit	Intuit	74%	@Intuit	
817	JW Marriott	Marriott International	74%		@jwmarriotthotels
818	Investigation Discovery	Warner Bros. Discovery Networks	74%	@IDLatinoamerica	@investigationdiscovery
819	Fossil	Fossil	74%	@Fossil	
820	Garnier	L'Oréal	74%	@garnierUSA	
821	Skinny Cow	Skinny Cow	74%	@SkinnyCowUS	@skinnycowus
822	Duluth Trading Co.	Duluth Trading Co.	74%	@DuluthTradingCo	@duluthtradingcompany
823	Dannon	Dannon	74%	@Dannon	
824	Zatarain's	Zatarain's	74%	@Zatarains	
825	Cape Cod Chips	Campbell Soup Company	74%	@CapeCodChips	@capecodchips
826	Caramello	Caramello	74%	@Mmapu_L	
827	Esurance	Folksamerica Holding Co.	73%	@esurance	
828	K-Y	K-Y	73%	@KYBrand	
829	Swanson	Swanson	73%	@wendysueswanson	
830	Frontier Airlines	Indigo Partners	73%	@FlyFrontier	@flyfrontier
831	Nature's Bounty	Nature's Bounty	73%	@NaturesBounty	@naturesbounty
832	Jos. A. Bank	Tailored Brands	73%		@josabank
833	Lennox	Lennox	73%	@LennoxAir	
834	Moderna	Moderna	73%	@moderna_tx	
835	Morgan Stanley	Morgan Stanley	73%	@MorganStanley	@morgan.stanley

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List of Brands with Active Social Media Accounts *(continued from last page)*

	Brand	Firm	% Recognition	Twitter	IG
836	Peloton	Peloton	73%	@onepeloton	
837	XM	Sirius XM Holdings	73%	@SIRIUSXM	
838	Jared	Signet Jewelers	73%	@ThatsJared	
839	Ann Taylor	Ascena Retail Group	73%	@AnnTaylor	@anntaylor
840	Red Wing Shoes	Red Wing Shoes	73%		@redwingheritage
841	The Hartford	The Hartford	73%	@TheHartford	
842	Dolce & Gabbana	Dolce & Gabbana	73%	@dolcegabbana	@dolcegabbana
843	DSW Shoes	DSW Shoes	73%		@designer_brands
844	Eucerin	Eucerin	73%	@EucerinUS	
845	Absolut	Absolut	73%	@absolutvodka	
846	Skyy	Skyy	73%	@ryanskyy	
847	Brooks Brothers	SPARC Group LLC	72%	@BrooksBrothers	
848	K-Swiss	Xtep	72%	@tournageddon	
849	Gobstopper	Gobstopper	72%	@GabbyAnderson15	
850	Kirkland Signature	Kirkland Signature	72%	@ashadystory	
851	Big Boy	Big Boy	72%	@BigBoy	@bigboysverige
852	Champs	Foot Locker	72%	@champssports	
853	Air Canada	Air Canada	72%	@AirCanada	
854	Rust-Oleum	Rust-Oleum	72%	@RustOleum	
855	Country Inns & Suites	Country Inns & Suites	72%		@countryinn
856	DAVID Seeds	DAVID Seeds	72%	@Davidseeds	@davidseeds
857	Keystone Light	Keystone Light	72%	@KeystoneLightUS	@keystonelightofficial
858	AstraZeneca	AstraZeneca	72%	@AstraZeneca	
859	California Pizza Kitchen	California Pizza Kitchen	72%	@GrittysGooch69	@cpk
860	Jameson	Jameson	72%	@jameson_us	
861	American Girl	American Girl	72%	@American_Girl	@americangirlbrand
862	Bumble Bee Foods	Bumble Bee Foods	72%		@bumblebeefoods
863	Citizens Bank	Citizens Bank	72%		@citizensbank
864	YETI	YETI	72%	@YETICoolers	@yeti
865	Sizzler	Sizzler	72%	@Sizzler_USA	
866	Del Taco	Jack in the Box	72%	@DelTaco	@deltaco
867	Nathans Famous	Nathans Famous	72%		@originalnathans
868	Van Heusen	Van Heusen	72%	@VanHeusen	
869	Auntie Anne's	Focus Brands	72%	@AuntieAnnes	@auntieannespretzels
870	Albertsons	Albertsons	72%	@Albertsons	
871	Ambien	Ambien	72%	@andrizzzyyy	
872	Horizon Organic Milk	Dean Foods	72%		@horizonorganic
873	Seiko	Seiko Group	72%	@locsei	
874	Danimals	Danimals	72%	@dgaunax3	
875	Tony Roma's	Tony Roma's	71%		@tonyromasspain
876	Bristol-Myers Squibb	Bristol-Myers Squibb	71%		@bristolmyerssquibb
877	Sbarro	Sbarro	71%	@Sbarro	

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List of Brands with Active Social Media Accounts *(continued from last page)*

	Brand	Firm	% Recognition	Twitter	IG
878	Kenwood	JVCKenwood	71%	@Kenwood_UK	
879	Saks Off 5th	Saks	71%	@SaksOFF5TH	@saksoff5th