Disclosing to Politicians

John Gallemore
University of North Carolina
john_gallemore@kenan-flagler.unc.edu

Jeffrey L. Hoopes
University of North Carolina
hoopes@unc.edu

Irene Tan
Harvard Business School
itan@hbs.edu

Ricky Xu Yao
University of Hong Kong
rickyyao@connect.hku.hk

First version: July 2025
This version: November 2025

Abstract. We examine whether public companies change their disclosures to align with the policy preferences of powerful political actors—which we refer to as "political tailoring." Focusing on the setting of President Donald Trump's first and second terms in office, we study the political tailoring of discussions around tariffs, an issue with both substantial policy salience and cash flow implications. Using earnings conference call transcripts, we employ a large language model to classify the extent to which tariff discussions are politically tailored. We find that firms with incentives to appease those in charge of tariff policy, such as firms who are the most exposed to tariffs, firms that engage in other forms of political catering, such as via PAC contributions and lobbying, and firms with republican CEOs engage in greater political tailoring of these disclosures. We find evidence consistent with this tailoring having payoffs: political tailoring is positively associated with the granting of tariff exemptions during the first Trump administration, but not with the awarding of government contracts. We also find that political tailoring is negatively (positively) associated with disclosure readability (verbosity), suggesting that a potential cost to political tailoring is less informative disclosures. Our findings contribute to literatures on political influence and corporate disclosure by documenting a novel form of non-financial strategic communication with potential implications for transparency and firm value.

Acknowledgements: We appreciate helpful feedback from Grant Bischoff, Rita Gunn, Maximilian Muhn, Robbie Moon, Mohan Venkatachalam (discussant), participants at the 2025 Kellogg Accounting Conference, and workshop participants at the University of North Carolina.
Keywords: corporate disclosures, conference calls, politics, tariffs
JEL Codes: M41, G38

1. Introduction

Public companies communicate with external stakeholders via disclosures, such as financial reports and conference calls, and prior research has extensively examined these disclosures from the perspective of investors and analysts, focusing on transparency, voluntary disclosure incentives, and shareholder value implications (Blankespoor, deHaan, and Marinovic 2020). However, while these disclosures are primarily intended for these capital market participants to help in capital allocation decisions, they are also public documents accessible to employees, customers, regulators, and politicians. Far less is known about whether firms strategically tailor their disclosures to these non-investor audiences. In particular, powerful politicians—especially high-profile officeholders like the U.S. President—can wield enormous influence over regulatory policy, government contracts, and public sentiment toward firms. During periods of heightened political salience, companies with incentives to please politicians may adjust their public communications by being positive about the policies espoused by the current presidential administration. We refer to this strategic language adjustment as "political tailoring" in disclosure. In this study, we examine whether firms tailor their investor disclosures to political actors by emphasizing language that aligns with the politicians' agendas.

Real-world anecdotes illustrate the potential for firms to be targeted by prominent politicians, the negative attention they can receive as a result of how they discuss tariffs, and the case to be made for political tailoring. For example, in April 2025, Amazon found itself in a high-stakes political skirmish over tariffs. The White House publicly accused Amazon of a hostile political act after reports that the company considered informing customers about the added costs of Trump's tariffs on imported products. Amazon swiftly backed off the idea, prompting President Trump to praise founder Jeff Bezos for "doing the right thing" by not drawing attention to tariff impacts (Shepardson, Bensinger, and Shalal 2025). Furthermore, in May 2025, Walmart's CEO Doug McMillon indicated on the firm's quarterly earnings conference call that the firm would be unable to "absorb all the pressure" from the proposed tariffs. Subsequently, President Trump indicated on social media that "Walmart should STOP trying to blame Tariffs as the reason for raising prices" (Holman 2025).

Such incidences are not isolated to Donald Trump. Many companies and industries have drawn the ire of sitting presidents, from pharmaceutical companies under President Clinton (McGinley 1999), to oil companies under President George W. Bush (McKinnon, Fialka, and Ball 2006), to AIG and other firms being criticized by President Obama (Hitt and Weisman 2009), to retail firms increasing their prices in the face of inflation under President Biden (Peterson 2022). These episodes indicate that when firms capture the attention of high-profile politicians via their actions and communications that involve prominent policy issues, they can receive negative attention. Therefore, when deciding how to communicate information to investors, firms may consider the political ramifications, knowing they may inadvertently draw ire from powerful officials, encouraging firms to tread carefully or even sympathetically on that topic in their communications to prevent the negative attention ex ante.

While this political tailoring could happen about any issue in any communication venue, we focus on firm's incentives to politically tailor regarding tariffs during the two Trump presidential administrations, for several reasons. First, tariffs have been a key policy tool in both Trump administrations. Tariffs were a part of his 2016 presidential campaign, and his administration introduced substantial tariffs against China during his first term. Furthermore, his policy platform in the 2024 election prominently included protectionist trade measures, including tariffs on imports, and his administration enacted the most sweeping set of tariffs in the U.S. since the Smoot-Hawley era in the 1930s. These clear stances and policies create a laboratory to observe if firms tailored their tone on tariffs in ways that align with Trump's positions once he was in power. Second, of the multiple issues that were at the core of the Trump 2024 platform (e.g., tariffs, DEI, climate change, etc.), tariffs may have the largest immediate cash flow implications for firms. Third, because tariff discussions tend to use a uniform set of terms, it is relatively straightforward to identify these discussions in conference calls. Finally, tariffs can be unilaterally enacted by the president under authority granted by Congress—most notably through Section 232 of the Trade Expansion Act and Section 301 of the Trade Act—making them a rare policy tool where executive preferences can instantly translate into substantive firm-level financial consequences without having to rely on legislation being passed by Congress.

Furthermore, while there are many other communication venues in which we could explore political tailoring, we focus on earnings conference calls. This setting is ideal for studying political tailoring because earnings conference calls are near-universal (unlike comments to the press, etc.), they are covered by the financial media (unlike other more technical disclosures), and the back-and-forth nature of an earnings conference call involves analysts questioning managers about issues that have material cash flow implications, potentially forcing managers to confront politically sensitive topics they might otherwise prefer to avoid. Firms may well communicate these same messages via other venues, but because they are likely to have a cohesive communication strategy and message, earnings conference calls, which are low-cost to identify for the universe of publicly traded firms, are an excellent venue to exploring political tailoring.

In our empirical approach, we assemble a comprehensive dataset of earnings conference call transcripts for all publicly listed U.S. firms from November 2016 through August 2025. This period covers multiple administrations (Trump's first term, Biden, and the beginning of Trump's second term), allowing us to observe how firm disclosures of tariff issues evolved with shifts in the political landscape. We use a combination of text analysis and generative artificial intelligence to identify the discussions in both sections of the conference call—the prepared remarks and Q&A—related to tariffs. We observe that tariff-related discussions are particularly prevalent during the Trump administrations, reflecting the central role tariffs played in Trump's economic agenda. We then feed tariff discussions from conference calls that occur during the two Trump terms into OpenAI's GPT-based API, asking it to rate the extent to which the discussion was tailored for the politicians who introduced tariff policies on a scale from 1 (indicating no tailoring) to 5 (indicating strong and pervasive tailoring). We implement robust prompt engineering to ensure that the generative AI-based categorization of this nuanced issue is valid, and similar to what we would get if we asked humans to perform this task. Using this approach, we construct firm-level metrics of political tailoring regarding tariff discussions.

We document several facts regarding the extent of political discussion tailoring in our sample. First, we find that political tailoring in tariff discussions is broadly similar across the two Trump terms, although the proportion of calls with a high degree of political tailoring increased by 2.4 percentage points in the second Trump term. Second, we analyze how much of the variation in the firm-level political tailoring scores is explained by various sets of fixed effects (i.e., time, industry, and firm). We find that, while we observe time-series variation in political tailoring across administrations, time fixed effects only account for a small percentage (< 2 percent) of the total variation. Rather, we find that the vast majority of the variation in political tailoring plays out at the firm or industry level.

Third, motivated by the variance decomposition, we next examine whether certain firm-level characteristics are associated with the extent of political tailoring. We find that firms that indicate greater exposure to tariffs (based on the mentions of imports in the Form 10-K filing) are more likely to engage in political tailoring in their disclosures around tariffs. Additionally, we find that politically active firms—measured using their lobbying activities or political donations through corporate political action committee (PAC)—are also more likely to engage in political tailoring. We also reveal that the tailoring around tariff messaging is more likely to happen when the CEO is politically aligned with the Republican party.

We then examine the potential consequences of political tailoring. We find that greater political tailoring is associated with more redundant and less readable tariff discussions. These findings suggest a potential cost to political tailoring—such tailoring could obscure value-relevant information and distract investor attention.

Finally, we examine whether firms' political tailoring of tariff discussions is associated with two potential benefits: receiving tariff exemptions and being awarded government contracts. Following the announcement of tariffs in 2018, the Trump administration introduced a new exemption process overseen by the Office of the U.S. Trade Representative for tariffs enacted under Section 301 of the Trade Act of 1974, and prior research has shown that political connections and lobbying affected exemption outcomes (Chor, Grant, and Li 2025; Fotak, Lee, Megginson, and Salas 2025). Similarly, federal government contracting decisions often allow room for political considerations (Faccio 2006; Goldman, Rocholl, and So 2013). Using firm-level data on government contracts and application-level data on tariff exemptions, we test whether our measures of political tailoring correlate with these outcomes, controlling for traditional political connections such as lobbying, political donations, and CEO political ideology. We find no robust relationship between political tailoring and the awarding of government contracts, but we observe that products from firms exhibiting greater political tailoring were significantly more likely to receive tariff exemptions, even after accounting for other political factors. While these findings do not establish causality, they suggest that public political alignment through disclosure may have been part of a broader firm strategy to mitigate tariff exposure.

Overall, our findings suggest that some companies appear to adapt the language in their investor communications to align with those with political power to affect the firm, which in turn impacts other disclosure characteristics as well as real firm outcomes. These findings hold even after controlling for firms' direct economic exposure to these issues, suggesting the changes in tone are not solely driven by fundamentals but at least partly by strategic motives. Thus, our findings suggest that the content of investor communications can be influenced by current politics, potentially at the expense of candor or completeness. Because disclosure time and attention are limited resources, time spent tailoring to political interests could crowd out discussion of information more relevant to shareholders. For example, a company which praises tariffs might devote less time to discussing core financial metrics or risks. Our results contribute to the understanding of how the political environment can shape corporate information flow and raises caution for investors and regulators: when political stakes are high, corporate disclosure may become a venue for political messaging, which could diminish its transparency and reliability for capital market participants.

Our findings are subject to several caveats. First, our LLM-based approach to measuring strategic political tailoring may capture the construct with noise and/or bias. We therefore conduct several validation exercises, including re-running the scoring procedure multiple times and estimating scores using alternative LLM models. The political tailor scores from multiple runs have high correlation and our results remain consistent across all models and all rounds. However, given the nuanced question we are asking, we concede that even human raters may vary substantially in their ratings. We opt to use an LLM approach as opposed to a bag-of-words approach because the nuanced way in which firms discuss tariffs is likely to be poorly measured by simpler approaches such as "tone" or "sentiment".[1] Second, our analyses cannot speak to the exact channel(s) through which politicians might become aware of firm investor disclosures. To be clear, we do not expect that politicians need to be themselves reading firm disclosures for the incentives for political tailoring to exist—rather, it simply needs to be the case that these disclosures could come to the attention of politicians (e.g., via the media or staff members). Anecdotal evidence suggests that indeed prominent politicians can become aware of conference call discussions (e.g., President Trump's reaction to Walmart's conference call in the spring of 2025). Further, as corporate communication and messaging will likely be consistent across communication channels, the firm itself may communicate similar messages through other venues which are less observable to researchers.

While we examine political tailoring in the context of tariff policy during the two Trump administrations, we believe our findings have implications for other settings. For example, other topics (such as climate change and diversity, equity, and inclusion) have become politically charged in recent years, and we expect that firms may tailor their communications to signal support for these policies depending on the preferences of the current administration.[2] Furthermore, while we focus on the U.S. setting, firms in other countries may face similar incentives to ensure their disclosures do not attract negative attention from prominent politicians.

[1] Executives often discuss tariffs in euphemistic and creative ways, which LLMs excel at identifying, but which a bag-of-words approach would likely fail to identify (i.e., tariffs may create a "bumpy road" for the firm ahead). We provided examples of conference call discussions exhibiting political tailoring in Appendix A.

[2] For example, Murray and Bohannon (2025) indicate that many companies initiated and discussed DEI policies in light of the Biden administration's preferences for such policies, and are reigning these discussions back because of the Trump administration's preferences against such programs.

Our study contributes to two academic literatures. First, we add to the literature examining firms' political activities. Prior research in this area documents that firms engage in a variety of activities, including lobbying and donations via political action committees (PACs) (Blau, Brough, and Thomas 2013; Hill, Kelly, Lockhart, and Van Ness 2013; Lambert 2018; You 2017; Claessens, Feijen, and Laeven 2008). We document a novel way in which firms manage their political exposure: by tailoring the language in their public communication—firms can curry favor not only with their dollars, but also with their disclosures. Second, we contribute to the literature on non-investor consumers of financial disclosures. This has been documented previously in the context of certain government regulators (Bozanic, Hoopes, Thornock, and Williams 2017; Li, Lind, Ramesh, and Shen 2023), employees (deHaan, Li, and Zhou 2023; Bova, Dou, and Hope 2015), and customers and suppliers (Chen, Kim, Wei, and Zhang 2019; Chiu, Kim, and Wang 2019). More recently, research has explored how politicians may seek out information from firms (Ma, Pan, Rouen, and Wellman 2025), and that firms' disclosure strategies may be influenced by political uncertainty (Bird, Karolyi, and Ruchti 2023) and by information obtained via political connections (Christensen, Morris, Walther, and Wellman 2023). We add to this stream of research by documenting how the accessibility of public disclosures by politicians—either directly or indirectly—can shape the disclosures themselves.

2. Background

2.1. Prior literature on firms' political activities

Prior research documents that firms often seek to shape or respond to political forces through lobbying, campaign contributions, and advertising campaigns because politicians can dramatically affect corporate outcomes (Blau et al. 2013; Hill et al. 2013; Lambert 2018; You 2017; Claessens et al. 2008). For example, in a seminal paper highlighting politician's ability to affect corporate outcomes, Fisman (2001) find that politically aligned firms suffered substantial decreases in stock market valuations upon the untimely death of a powerful Indonesian politician. Cuny, Kim, and Mehta (2024) further document that firms strategically use advertisements in anticipation of political costs, such as regulatory scrutiny or investigations, to influence politicians and their constituents, highlighting advertisement as a channel for firms to actively seek political influence. The broad consensus from this literature is that companies are keenly aware of political forces and will take actions to influence policy or curry favor when needed.

A related stream of research shows that partisan leanings, which refers to the tendency of firms or executives to support a particular political party or ideology, also shape firm behavior. For example, Fos et al (2022) categorizes companies by the partisan leanings of their managers and directors and finds that, for example, executives who are politically misaligned with their employees are more likely to leave the firm. Other research suggests that the phenomenon of polarization, which refers to the widening gap between different political parties, is increasingly affecting corporate decisions, from investment to employment policies (see Kempf and Tsoutsoura (2024) for a review).

There is also growing evidence that firms engage in corporate political activism or take public stands on social/political issues, which can influence investors (Bhagwat, Warren, Beck, and Watson 2020; Brownen-Trinh and Orujov 2023). This research generally focuses on voluntary activism (e.g., CEOs making public statements on policy issues or firms joining political campaigns externally), rather than the content of investor disclosures. This research suggests that firms take these political positions because they either reflect the sentiment of corporate leaders or because they align with customers' preferences, and not necessarily to placate politicians.

2.2. Prior literature on politics and firm disclosure

A recent stream of accounting research connects firms' political activities or leanings to their disclosure choices. For example, Christensen et al. (2023) provide evidence that firms connected to government officials were more likely to issue management forecasts, consistent with using disclosure to influence or respond to policymakers. Cassidy and Kempf (2025) document the rise of partisan corporate speech in recent years, showing that corporate communications (press releases, etc.) have increasingly taken on a partisan tone based on the ideology of the firm's executives, aligning more openly with either conservative or liberal viewpoints. Regarding the consumption of firm disclosures by political actors, Ma et al (2025) find evidence that congressional staffers download firms SEC filings. While this growing literature broadly shows that political factors and incentives influence firms' disclosure behavior (i.e., whether or not to issue a management forecast), this literature has not yet explored whether firms alter the way they discuss key issues to capital market stakeholders in response to the possibility—whether real or perceived—that politicians will access or otherwise become aware of these disclosures.

2.3. Background on tariffs

Tariffs are taxes imposed on imported goods, typically calculated as a percentage of the product's value (ad valorem) or as a fixed amount per unit (specific tariffs). While tariffs were a major source of federal revenue in the 19th century, their importance as a fiscal tool has diminished over time, and they now function primarily as instruments of trade and industrial policy. In recent years, U.S. tariff policy has seen notable shifts. Beginning in 2018, the first Trump administration imposed a series of tariffs on imports from major trading partners, most prominently China, under Section 301 of the Trade Act of 1974. These measures were justified on the grounds of addressing unfair trade practices and protecting domestic intellectual property. Additional tariffs were also levied on steel and aluminum imports under Section 232 of the Trade Expansion Act of 1962, citing national security concerns. These actions marked a departure from several decades of gradual tariff reduction and multilateral trade liberalization pursued through agreements such as NAFTA (now replaced by the USMCA) and the World Trade Organization framework. Many of these tariffs were kept in place by the Biden administration, and President Biden layered on new tariffs, most notably on electric vehicles from China (Wilmot 2024).

In 2025, the second Trump administration threatened an unprecedented suite of tariffs, raising the average U.S. applied tariff rate to historic levels. These measures included a universal 10% tariff on most imports, country-specific "reciprocal" tariffs—some exceeding 40%—and sharply increased duties on steel, aluminum, automobiles, and goods from key trading partners such as China, Canada, Mexico, and the European Union. The administration justified these actions as necessary to address trade imbalances, protect national security, and promote domestic manufacturing, while also threatening or initiating sector-specific tariffs in areas like digital services, pharmaceuticals, and critical minerals. These policies provoked significant retaliation, legal challenges, and market volatility, with major economic institutions projecting negative impacts on U.S. and global growth.

2.4. Why firms might engage in political tailoring of tariff disclosures

Firms' motivations for seeking political favor are obvious. Through regulation, taxation, intellectual property enforcement, procurement decisions, and trade policy, policymakers can directly and massively affect corporate cash flows. As the government grows in scope, firms have even stronger incentives to manage their political exposure. For companies with large regulatory or global footprints, the stakes can be enormous—billions of dollars can hinge on a single policy change. In such an environment, engaging with politicians, shaping public discourse, or signaling alignment with political priorities could become a part of maximizing shareholder value.

Tariffs are a particularly salient example of this dynamic. For firms reliant on imported inputs, components, or finished goods, tariff increases can dramatically reshape their cost structure, pricing strategy, and competitiveness. Thus, through tariff policy, policymakers can have massive impacts on firm valuations. For example, a single Trump administration policy that exempted iPhones from tariffs allegedly added $3 trillion to Apple's firm value (Leswing 2025). Furthermore, unlike many other economic levers, tariff policy in the United States is largely under executive branch control—a result of decades of congressional delegation to the president. This means the White House can in many cases unilaterally impose or remove tariffs on specific goods or countries with limited oversight. Although recent legal challenges have called aspects of this authority into question, the practical reality remains that for many firms, tariff decisions are the result of decisions and preferences from a small set of actors. That makes understanding how firms anticipate and respond to those preferences particularly important. Thus, it is not surprising that firms do not passively accept tariff outcomes—they often attempt to influence them. Some firms seek product-specific exclusions from tariffs, while others push for broader industry-level exemptions. These efforts can also target the timing of tariff implementation, arguing for delays or phase-ins. Firms with operations or customers in key countries may advocate for those countries to receive more favorable treatment in trade negotiations.

Given the firm-specific and discretionary nature of tariff enforcement, firms may also try to present themselves as politically aligned or sympathetic to the political administration making these decisions, reducing the likelihood of adverse treatment or increasing the chance of carveouts. The incentive to appear aligned or avoid the appearance of misalignment can come from the fear that prominent politicians may become aware of the firm's disagreement, leading these politicians then may take actions, such as impacting the firm's regulatory environment or likelihood of obtaining government business. Alternatively, these politicians may publicly criticize these firms, which, in a polarized environment, may cause a loss of reputation with customers or suppliers. We expect that, by framing their activities in ways that resonate with the priorities of those in power, firms may reduce the likelihood of negative scrutiny or position themselves for favorable treatment.

While firms have a variety of mechanisms through which to curry favor with policymakers, we posit that corporate disclosures provides a particularly powerful and visible tool for firms to signal alignment with political actors. Disclosures are public, timely, and widely disseminated, meaning that politicians can become aware of disclosures—either directly from the disclosures themselves, or, more likely, indirectly via third parties such as advisors or the media. Importantly, they are also presumed to be neutral, investor-focused documents, which may make subtle political messaging within them appear more credible or less overtly strategic. This allows firms to send a political signal without appearing overtly sycophantic. Furthermore, disclosures are produced routinely and predictably, especially in the context of earnings conference calls, offering firms recurring opportunities to reinforce alignment with political agendas. Because high-profile politicians are more likely to react to public facing actions than to private ones, firms may find that adapting the tone or emphasis in disclosures offers a relatively low-cost way to avoid scrutiny or attract goodwill, especially on issues that are politically salient. Lastly, since firms likely have coordinated messaging across various channels, the earnings conference call disclosure provides a measurable and observable feature of the firm's general attitude towards the specific political issue. In this way, disclosures may serve not only as a tool for capital market communication, but also as a strategic channel for political positioning.

We focus on disclosures specifically about tariffs in this study precisely because they represent a high-stakes, politically discretionary policy tool that disproportionately affects some firms. They offer a clean setting to observe how companies may tailor disclosures to appeal to politicians or mitigate political risk. Of course, the broader behavior we study—strategic messaging aimed at political audiences—is not limited to tariffs or to the Trump administration. For instance, during the Biden administration, many firms publicly embraced environmental, social, and governance (ESG) issues such as climate change and diversity, equity, and inclusion (DEI)—topics that aligned with prevailing political priorities. Some of these stances have since been scaled back as political tides shifted, indicating these firms may well have embraced them solely for political convenience, not out of a deep-seated belief (Murray 2025). While these issues may not carry the same immediate cash flow implications as tariffs, they reflect the same underlying calculus: firms selectively shaping their public messaging in ways that help manage their political environment.

3. Methodology

3.1. Conference call sample

Our analysis is based on a dataset of quarterly earnings conference call transcripts for U.S. public companies from November 2016 to August 2025. Earnings calls typically occur shortly after firms release their quarterly financial results, and feature management's prepared remarks followed by Q&A with analysts. Earnings conference calls are an ideal setting to examine political tailoring in disclosure for several reasons. First, they occur frequently, providing a consistent and timely window into how firms communicate during changing political climates. Second, these calls are public and often covered by financial media, making them visible to a wide array of audiences, including potentially politicians. As such, they provide a plausible channel through which firms might attempt to signal alignment with or avoid antagonizing political actors. Third, the presence of a live Q&A component means firms cannot fully script the discussion and thus may be compelled to address politically sensitive topics like tariffs when asked directly by analysts. We obtain transcripts of earnings announcements from S&P Global Capital IQ Pro Transcripts, including 93,110 firm-quarters call transcripts. Each call transcript is disaggregated individual components by speakers. A common transcript contains three parts: the prepared remarks, analyst questions, and management responses.

3.2. Identifying tariff-related discussions

For each transcript, we identify tariff-related discussions using a hybrid approach combining keyword screening with a large language model.[3] We first compile a list of keywords that are directly and indirectly associated with tariffs to maximize the capture of relevant content. For components in prepared remarks, we retain the entire component if at least one keyword is present. For one Q&A pair, we keep both the question and the answer if either contains a keyword. Next, we use OpenAI's GPT-4.1 mini API to further extract the portion of the executive discussions related to tariffs. The benefit of using GPT to isolate the discussion relevant for tariffs is that it can better identify the relevant context for a tariff discussion than a keyword approach (e.g., preceding and subsequent comments that are related to tariffs, but do not contain keywords). We provide details on our extraction process (e.g., the specific prompt) in Appendix A1.

We graphically depict the frequency of tariff discussions in our sample in Figure 1, which plots the proportion of earnings conference calls that include a discussion of tariffs over time. The

[3] Given the time and resource intensity of processing all conference call transcripts with GPT, we first apply a keyword-based screening to improve efficiency. To minimize Type I errors (i.e., false negatives), we employ a broad set of keywords. We use the following keywords along with their common variants: tariff, duty, Section 201, Section 232, Section 301, antidump, US trade representative, trade policy.

proportion rises notably during the height of the U.S.–China trade war, peaking around late 2018, when roughly 25% of conference calls included tariff-related content. This share then declines sharply beginning in late 2019 and remains relatively low (<5%) throughout the Biden administration (2021–2024). This decline is notable because the tariffs largely remained intact under President Biden, suggesting that the initial surge in tariff disclosures was likely the result of firms discussing a new policy, which the Biden administration continued. Beginning in late 2024, the proportion of calls with tariff discussions increases dramatically, jumping from under 5% in Q3 2024 to over 75% by Q2 2025. This surge coincides with the election and start of Trump's second term and reflects a renewed salience of tariff policy for firms.

Next, in Figure 2 we present the proportion of earnings conference calls that included tariff-related discussion, broken out by industry and year. Across most industries, mentions of tariffs peaked during the U.S.–China trade tensions of 2018–2019 and then declined substantially during the Biden administration. However, in 2025, there is a sharp resurgence in tariff talk across nearly all sectors, with particularly large proportions in Wholesale Trade (75.5%), Retail Trade (72.6%), Construction (71.6%), and Manufacturing (68.6%). Even traditionally less trade-exposed sectors like Finance and Services—which did not exhibit material tariff disclosures in 2018—show noticeable increases in 2025. This pattern suggests that firms across a wide swath of the economy renewed their attention to tariff policy following Trump's return to office.

3.3. Measuring political disclosure tailoring

To measure political tailoring in firms' tariff discussions during conference calls, we begin by aggregating the extracted tariff discussions from both the prepared remarks and Q&A sections at the call level. We then employ a Role, Task, Format (RTF) prompt to instruct GPT to assign a political tailoring score to each discussion. The prompt provides the LLM with context, specifying that the text is a tariff discussion from an earnings call transcript. The model is instructed to rate the level of political tailoring on a 5-point Likert scale—ranging from 1 (no tailoring) to 5 (strong and pervasive tailoring). The 5-point Likert scale rating is a common approach for capturing nuanced linguistic attributes (e.g., Blankespoor, Hendricks, and Miller 2017). Following the chain-of-thought rationale, which has been shown to improve LLM reasoning (Wei et al. 2023; Li, Castelo, Katona, and Sarvary 2024; de Kok 2025), the prompt also requires the model to provide explanatory quotes and a scoring rationale for each assessment. See Appendix A2 for more details on our scoring method.

We conduct several analyses to verify the robustness and reliability of our political tailoring measurement approach. First, we test whether our findings depend on a particular API run or model realization by generating multiple alternative *Political Tailoring* scores through independent API calls. We obtain two additional sets of scores by re-running the same baseline model (GPT-4.1 mini) and a third set by using a higher-capacity model (GPT-4.1). These alternative measures closely track the baseline scores: the two GPT-4.1 mini runs correlate with the baseline (Pearson correlation of 0.95), and the GPT-4.1-based score also correlates positively with the baseline measure (0.68).[4,5]

In Appendix A3, we provide examples of tariff discussions of different political tailoring scores along with GPT's reasoning. For example, executives from American Axle and Cleveland-Cliffs Inc. strongly endorse the Trump administration's trade agenda, using patriotic framing and portraying tariffs as a necessary path to economic revitalization. Example 4 (INNOVATE Corp.) reflects more cautious language but includes a subtle alignment with the administration's

[4] We use GPT-4.1 mini, the second most advanced model offered by OpenAI during our analysis period, for the full-scale implementation given its substantial cost efficiency.

[5] In Table OA-2 of the Online Appendix, we show that our main findings remain consistent across these alternative API-generated measures.

optimistic projections, which GPT interprets as moderate political tailoring. In contrast, Example 5 (Corteva) features neutral, technical language focused on supply chain logistics, cost of goods sold and internal simulations, resulting in a minimal tailoring score. Together, these examples demonstrate that GPT can effectively differentiate between highly politicized rhetoric, subtle alignment, and apolitical discourse that simpler methods traditionally used before the advent of LLMs would likely not be able to capture.[6]

3.4. Other data sources

We obtain financial accounting data from Compustat. We source firm-level lobbying activities data from Kim (2018).[7] To compute corporate political donations, we obtain campaign finance data including donations from corporate-sponsored political action committees (PACs) and individuals from OpenSecrets.[8] For government contract award information, we match federal procurement data from Cox, Müller, Pastén, Schoenle, and Weber (2024) to our sample based on company names. We identify whether the federal government is a firm's major customer using the Compustat Segment files. We measure CEO political ideology using the individual Campaign Finance Scores (CFScore) from Stanford University's Database on Ideology, Money in Politics, and Elections (DIME) database (Bonica 2024), linked to firm executives in BoardEx via the crosswalk provided by Steel (2025). We obtain data on tariff exemption application and grant status from Fotak et al. 2025.

[6] These examples also show how alternative methodologies, such a "bag-of-words" approach using predefined corpora of text, are likely to miss important context that indicates tailoring. For example, in Example 1, the executive describes the challenges in the face of tariffs as a "bumpy road" and uses a phrase "level the playing field", which carry no inherent positive or negative sentiment, but, in the case of "level the playing field", does indicate a positive attitude toward tariff policy.
[7] The data is derived from mandatory federal filings and widely used in recent studies (e.g., Kalmenovitz 2023; Bonsall, Holzman, and Miller 2024; Kalmenovitz, Lowry, and Volkova 2025).
[8] We utilize the linkage file provided by Dane Christensen (Christensen, Jin, Sridharan, and Wellman 2022; Christensen, Morris, Walther, and Wellman 2023) to link corporate-sponsored PACs to Compustat firms.

To construct alternative measures of firms' exposure to tariffs, we incorporate two additional data sources. First, we obtain firms' mentions of offshore sourcing in their 10-Ks from the Hoberg–Moon Offshoring Repository (Hoberg and Moon 2017 and Hoberg and Moon 2019).[9] Second, we use shipment-level data for U.S. maritime import from S&P Panjiva.[10]

3.5. Sample selection

Table 1 describes our sample selection process. Since the vast majority of tariff discussions occur during the two Trump administrations, we focus on those two time periods for our remaining analyses. We begin with all 47,444 quarterly earnings conference call transcripts from S&P Global Capital IQ Pro Transcripts during the two Trump administrations (defined by presidential election dates). We focus on transcripts with tariff discussions, based on the approach detailed in Section 3.2. After merging call transcripts with quarterly financial information from Compustat, we further exclude observations with insufficient data to compute regression variables. Our final sample includes 7,843 firm-quarter observations across 2,109 unique firms.

4. Main analyses

4.1. Political tailoring over time and in the cross-section

We begin our analyses by describing the characteristics of our political tailoring measure and documenting several stylized facts. First, we examine how political tailoring of tariff discussions varies across the two Trump administrations. Figure 3 presents the distribution of political tailoring scores for each administration. We find that about half of the firms receive score of two or below, indicating minimal tailoring. However, around 15 percent of the sample exhibits tailoring scores of four or five, suggesting high level of political tailoring. These findings suggest

[9] Available at: https://faculty.marshall.usc.edu/Gerard-Hoberg/HobergMoonDataSite/index.html. The most recent year available in the Hoberg–Moon Offshoring Repository is 2017.
[10] Our access to S&P Panjiva covers data through 2020.

that while most firms do not appear to tailor their tariff discussions, a non-trivial portion of firms appear to engage in substantial tailoring. Furthermore, political tailoring in tariff discussions is broadly similar across the two Trump terms, although the proportion of calls with high degree of political tailoring (scores of four or five) increased by 11.7% in the second Trump term relative to the first Trump term.

Next, we present a variance decomposition of the political tailoring score in Table 2. Results in Panel A indicate that firm-level factors drive most of the variation (over 70% with two-digit SIC), declining with more granular industry definitions but remaining above 48%. Panel B confirms this firm-level dominance holds across two presidential terms, peaking during the second Trump administration. Overall, firm-level factors explain the majority of variation in political tailoring.

Finally, we examine the variation across industries in political tailoring in Figure 4. We find that the manufacturing sector consistently shows one of the highest levels of political tailoring, reaching the maximum annual average score of 2.8 in 2018. The wholesale trade and retail trade sectors also frequently record high average scores throughout the sample period. While the existence of strong political tailoring varies across industries, it tends to peak during the second Trump administration.

4.2. Determinants of political tailoring

We next examine which firm characteristics are associated with the extent of political tailoring in tariff discussions by estimating the following regression via OLS:

$$\begin{aligned}
Political\ Tailoring_{ijt} &= \beta_1 Import\ 10K_{it} + \beta_2 Lobby_{it} + \beta_3 PAC\ Donation_{it} \\
&+ \beta_4 CEO\ Political\ Ideology_{it} + \beta_5 Government\ Contractor_{it} + \beta_6 Size_{it} \\
&+ \beta_7 BTM_{it} + \beta_8 Sales\ Growth_{it} + \beta_9 Leverage_{it} \\
&+ \beta_{10} Institutional\ Ownership_{it} + \beta_{11} ROA_{it} + \beta_{12} Sentiment_{it} + \gamma_j + \delta_t \\
&+ \varepsilon_{ijt}\ ,
\end{aligned}$$

The dependent variable is *Political Tailoring*, the firm-year-quarter-level score of political tailoring in tariff-related discussions, as defined in section 3.3. We include several sets of independent variables that capture firm-level incentives to engage in political tailoring, all of which are defined in Appendix B. First, we include *Import 10K*, which is the ratio of import-related words to the total number of words in the firm's most recent Form 10-K filing. We expect this variable to be positively associated with tailoring, as firms that heavily discuss imports are more likely to be exposed to tariff policy thus have stronger incentives to align with the administration's views on trade.

Second, we include variables to capture the firm's political engagement. *Lobby* is the sum of trade related lobby expenditures during the past four years, scaled by total assets. *PAC Donation* is the sum of political donations through a corporate PAC in the most recent two election cycles, scaled by total assets.[11] Lobbying activities and PAC donation suggest firms' political activism. We expect politically active firms will be more likely to tailor their tariff disclosures. Additionally, we include the executive's political donation orientation, *CEO Political Ideology*, which is the CEO's individual-level CFScore from Stanford's DIME database (Bonica 2024). The CFScore places individuals on a continuous liberal–conservative scale based on the ideological pattern of their campaign contributions, with lower (higher) values indicating a more liberal (conservative) orientation.[12] Including both firm and executive political activism measures provides a comprehensive view of what drives political tailoring.

Third, we include a vector of additional firm-level controls. We include *Government Contractor*, an indicator that equals one if the firm discloses the U.S. Federal government as a

---

[11] We also construct two additional variables that separately capture donations to Democratic and Republican recipients: *Donation to Democratic* and *Donation to Republican*.

[12] We also construct binary versions of this measure: *Republican CEO* and *Democratic CEO*, which equal one if the CEO is political aligned with the Republican and Democratic Party based on their CFScore, respectively.

major customer.[13] The idea behind this variable is to capture the incentives for political tailoring that arise from a firm's established direct financial ties to the federal government. We further include *Size, Leverage, BTM, Sales Growth, ROA,* and *Institutional Ownership*, to account for differences in business scale, financial structure, performance, and investor base that may independently influence disclosure behavior. Finally, we include two textural characteristics of tariff discussions to ensure that our political tailoring measure does not simply capture for the length or sentiment of tariff discussions. *Length* is defined as the ratio of the extracted tariff discussion length to the total transcript length. This measure intuitively captures a firm's exposure to tariff issues and serves as a control to ensure that our political tailoring score is not driven merely by the length of the discussion. To isolate political tailoring from general sentiment, we control for the sentiment of the tariff discussions using the sentiment wordlist from the Loughran-McDonald (LM) dictionary (Loughran and McDonald 2011). We add industry and year-quarter fixed effects to control for time-invariant industry characteristics and aggregate time trends. We cluster standard errors at the firm level.

Table 3 provides summary statistics for the full sample of 7,843 firm-quarter observations used in the regression analysis. We winsorize all continuous firm-level variables at 1% and 99% levels. Our key outcome variable, *Political Tailoring*, has a mean (median) of 2.47 (2) on a 1–5 scale. Regarding the other variables, we document that 74% of firms mention imports in their 10-Ks (*Import 10K>0*). Political exposure variables show that 10% of firms engage in trade related lobbying (*Lobby>0*) and 27% donated through a PAC (*PAC Donation>0*) in the past two election cycles.

[13] Statement of Financial Accounting Standards (SFAS) 14 and the Securities and Exchange Commission's Regulation S-K mandate the disclosure of major customers in segment reporting, which is available from the Compustat Segment files.

The determinants regression results are presented in Table 4, column 1.[14] Firms more exposed to tariffs, as proxied by import disclosures in 10-K filings, exhibit significantly greater political tailoring, consistent with these firms engaging in political tailoring to either avoid negative attention from prominent politicians or to curry favor with them in hopes of individual tariff carveouts and exemptions, similar to those granted to Apple (Leswing 2025). Regarding the political engagement variables, we find that both *PAC Donation* and *Lobby* are significantly positively associated with political tailoring, suggesting that politically active firms are more likely to tailor the language surrounding tariff discussions to match the policy preferences of the administration. The positive and significant coefficient for *CEO Political Ideology* suggests greater political tailoring among CEOs politically aligned with the Republican party. Interestingly, we find that firms for which the federal government is a major customer are less likely to engage in political tailoring (negative coefficient on *Government Contractor*), potentially because these firms' incentives to curry favor with prominent politicians is mitigated in the aftermath of established contracts with the government.

In column 2 of Table 4, we further decompose corporate political contributions and CEO ideology into partisan components (e.g., Republican vs. Democratic). We document a positive and significant coefficient on *Donation to Republican*, whereas the coefficient on *Donation to Democratic* is statistically insignificant, Similarly, *Republican CEO* is positively and significantly associated with political tailoring, while *Democratic CEO* is not. These findings collectively highlight the role of partisan alignment in shaping firms' strategic communication choices, indicating that firms and executives aligned with the conservative political agenda are more likely to employ tailored tariff-related language in their conference calls.

[14] To facilitate the interpretation of regression coefficients, we standardize all continuous independent variables to have a mean of zero and a standard deviation of one.

Beyond firms' exposure to tariffs and their political engagement, several firm characteristics also help explain cross-sectional variation in political tailoring. Larger firms (*Size*) exhibit more tailoring, consistent with their heightened visibility and the greater political and economic stakes they face in tariff policy. We also find a positive and significant coefficient on *Leverage* and a negative and significant coefficient on *ROA*, suggesting that firms with greater leverage and lower profitability may face stronger incentives to communicate strategically about tariffs. Furthermore, the coefficient on *Sentiment* is positive and statistically significant across both specifications, suggesting that more favorable tone in tariff discussions correlates with higher measured political tailoring. More importantly, the coefficients on other determinants remain robust after controlling for sentiment (*Sentiment*) and length (*Length*) of the tariff discussions, indicating that political tailoring does not merely reflect the overall positivity or negativity or sentiment of executives' language. Instead, political tailoring captures a distinct, nuanced dimension of strategic communication that goes beyond general linguistic tone.

4.3. Political discussion tailoring, disclosure verbosity and readability

Next, we examine a potential negative consequence of political tailoring—its impact on the efficiency and readability of tariff discussions. First, we construct a measure that captures the efficiency of the firm's tariff discussions, which we label *Verbosity*. Specifically, we leverage LLM to summarize the value-relevant information from the tariff discussions.[15] We define *Verbosity* as one minus the ratio of the word count of the LLM summary to the total word count of the original discussion. Intuitively, if the summary can express all value-relevant information in far fewer words, then the original discussion contained more extraneous or repetitive content. We assume the summary produced LLM following the instructions in our prompt (as shown in

[15] We use OpenAI's GPT-4.1 mini API for this exercise. See Appendix A for further details.

Appendix C) captures all value-relevant information from the original tariff discussion; thus, a higher *Verbosity* value means the speaker communicated the core information in a more redundant way in the original discussion. Second, we use *Fog Index* to measure the readability of the tariff discussion (Loughran and Mcdonald 2014; Bonsall, Leone, Miller, and Rennekamp 2017; Lo, Ramos, and Rogo 2017). We hypothesize that more politically tailored tariff discussions are likely to less value-relevant information (i.e., higher *Verbosity*) and less readable (i.e., higher *Fog Index*) as executives may use more words and more complex language when tailoring discussions to indicate alignment with prominent politicians.

Table 5 presents the results of these analyses. In column 1, we find a positive and significant coefficient on *Verbosity*. The coefficient of 0.058 on *Political Tailoring* indicates that moving up by one point on the 1–5 tailoring scale is associated with a 5.8-percentage-point increase in *Verbosity*. Given that the sample mean of Verbosity (0.55), this effect represents roughly a 10% increase relative to the mean, which is economically meaningful. This result implies that more politically tailored tariff discussions contain a noticeably larger share of excess or non–value-relevant language.

In column 2, we find *Political Tailoring* is positively correlated with *Fog Index*, suggesting that tariff discussions are framed with greater linguistic complexity when the level of political tailoring is higher. The coefficient of 0.393 on *Political Tailoring* corresponds to a 2.8% increase in linguistic complexity relative to the sample mean (13.97) for each one-unit rise in *Political Tailoring*. Because the Fog Index increases with longer sentences and a higher density of complex words, this magnitude reflects a meaningful decline in communication clarity. In total, Table 5 indicates a potential trade-off to political tailoring—the conference call discussions may be less efficient at communicating information to capital markets.

4.4. Specific favorable outcomes associated with tailoring

4.4.1. Tariff exemption grants

In our final set of analyses, we examine whether political tailoring is associated with two specific beneficial outcomes: the granting of tariff exemptions and government contracts. During the first Trump administration, the tariff actions under Section 301 were unprecedented in scale and scope, covering hundreds of billions of dollars of imports from China and creating substantial exposure for U.S. firms reliant on Chinese inputs. To mitigate unintended harm to domestic producers, the administration established a formal exclusion mechanism through which firms could seek relief from these duties. Unlike earlier tariff exemption programs overseen by Congress or the Department of Commerce, this process, managed solely by the Office of the U.S. Trade Representative (USTR), was largely insulated from legislative oversight (USTR 2018).

Firms submitted an exclusion petition for each individual product imported into the United States, and the USTR evaluated and ruled on each petition separately. This design required applicants to provide detailed descriptions and justifications for every product for which relief was sought. Firms could apply for exemptions on the grounds that tariffs would cause significant harm to American interests, that suitable substitutes were unavailable outside China, or that the products were not strategically significant to China's industrial policy goals. Recent empirical work (Chor et al. 2025; Fotak et al. 2025) documents that political connections, such as campaign contributions to the ruling party and lobbying expenditures, played a statistically and economically significant role in determining which exemption requests were granted, revealing that this supposedly arm's-length process was subject to political influence. We provide further background details on Section 301 tariffs and the corresponding tariff exemption process in Appendix D.

We measure the grant of exemption for tariffs using *Tariff Exemption,* an indicator variable equal to one if the tariff exemption was granted for a particular tariff exemption application during the first Trump term. We then regress this outcome on our political tailoring measure: *Political Tailoring*. In constructing this measure, we use conference calls occurring on or after the election day of Trump's first term (November 8, 2016) and prior to the decision of granting tariff exemption.[16] We include industry, product, and tariff list (which are the four tariff types employed during the first Trump administration) fixed effects, and cluster standard errors at the firm and product level (Chor et al. 2025).

We present the results in Table 6. Column 1 presents a baseline specification for the determinants of whether a tariff exemption is granted. Consistent with prior literature, we document that several political engagement variables also influence exemption outcomes. The positive coefficient on *Lobby* suggests that firms engaging more actively in lobbying on trade issues enjoy a higher likelihood of securing tariff exemptions, consistent with trade lobbying meaningfully shaping tariff exemption outcomes (Chor et al. 2025). We also find a strong partisan asymmetry in political contributions: *Donation to Republican* is positively and significantly associated with receiving an exemption, while *Donation to Democratic* is negatively associated with exemption success. These results are consistent with recent evidence that partisan alignment with the executive branch explains the outcomes of tariff exemption requests (Fotak et al. 2025).

In column 2, we add the political tailoring measure as an additional independent variable. The positive and significant coefficient on *Political Tailoring* suggests that applications for tariff exemptions are more likely to be granted for firms exhibiting greater political tailoring in their

[16] For the tariff exemption tests, if a firm has no conference call with tariff discussions prior to a tariff exemption decision during the first Trump term, we assign political tailoring measures a value indicating "no tailoring." In untabulated tests, our results remain robust when restricting the sample to firms with at least one tariff-related conference call before each exemption decision.

tariff discussions preceding the exemption decision. This relation holds even after accounting for conventional political connections such as lobbying, PAC contributions, and political alignment.

It is important to note that these results do not necessarily indicate that political tailoring of tariff discussions in conference calls causally impacted the tariff exemption process. Indeed, it could be the case that these firms were also engaging in other approaches—such as tailoring of other public and private communications. However, these findings indicate that firms that engaged in political tailoring in conference calls were more successful in obtaining tariff exemptions, suggesting that such tailoring was potentially part of the firm's overall strategy for mitigating the impact of tariffs. In short, our results suggest that firms may have obtained benefits from strategically shaping their public narrative to align with the policy priorities of key political actors.

4.4.2. Government contracts

We next examine whether political tailoring of tariff discussions is associated with the awarding of federal government contracts and the granting of tariff exemptions during the first Trump term. When firms signal publicly their alignment with the administration's agenda via public disclosures (such as conference calls), this information can influence those making decisions about these decisions. This could occur either because those making the decisions are themselves aware of the tariff discussions, or because the firm discussions were communicated to the decision-makers via third parties (e.g., the traditional media, etc.), or simply because the discussions are representative of a general alignment with the administration, which is generally rewarded. The awarding of federal government contracts often involves discretionary decision-making by political appointees or agencies sensitive to political priorities. While many procurement processes are competitive, firms perceived as aligned with the administration may have an advantage in tie-breaker scenarios or in meeting opaque eligibility criteria (Faccio 2006; Goldman et al. 2013; Child, Massoud, Schabus, and Zhou 2021).

We measure future government contract award using *Future Gov Contract,* which is defined as the total value of new federal government contracts scaled by total assets awarded over the four quarters following the earnings call. We again regress two outcomes on *Tailoring* and *Strong Tailoring*. We include industry and year-quarter fixed effects, and cluster standard errors at the firm level. We present the results in Table 7. We find no evidence that political tailoring in tariff discussions is associated with subsequent federal contract awards, suggesting that political tailoring does not appear to shape the awarding of government procurement contracts

5. Robustness Tests

We conduct several robustness tests to ensure the reliability of our results.[17] First, we examine whether results in the disclosure quality, tariff exemption, and contract award analyses are sensitive to the distribution of the political tailoring score. To do so, we replace the continuous tailoring measure with an indicator for "strong tailoring," which isolates firms with the highest tailoring scores (four or five). The results suggest that the documented associations are not driven by low or moderate levels of tailoring and that the main patterns persist when focusing only on pronounced tailoring behavior.

Second, we evaluate the robustness of the political tailoring measure to alternative GPT runs, including repeated API calls and an alternative LLM model. These tests mitigate concerns that our measure may depend on stochastic variation in a particular LLM implementation. We show that our findings remain consistent across independent API runs and LLM models versions.

[17] We report all robustness analyses in the Online Appendix.

We then assess the sensitivity of the results on the determinants of political tailoring to alternative measures of tariff exposure. In addition to our main proxy, we incorporate two distinct measures: a disclosure-based indicator of China sourcing from firms' 10-K filings and a shipment-based measure constructed using S&P Panjiva's transaction-level data on U.S. maritime import from China. The results remain stable across all specifications, suggesting that our conclusions are not driven by the baseline tariff-exposure measure. [18] Finally, we re-estimate all main specifications using industry and year fixed effects instead of industry and year-quarter fixed effects. The resulting estimates are quantitatively similar, indicating that the finer year-quarter fixed-effect structure is not driving our findings.[19]

6. Conclusion

In this study, we examine whether and how publicly listed U.S. firms tailor their investor disclosures to align with the policy positions of sitting politicians, focusing specifically on tariff discussions during conference calls. Leveraging text analysis and large language models to quantify the extent of political tailoring in investor disclosures, we find evidence that some firms tailored their discussions of tariffs, a political salient issue during our sample period. Furthermore, we find that political tailoring intensified following President Trump's re-election in 2024, with a concurrent rise in those showing high levels of tailoring. In the cross-section, we find that the extent of political tailoring is positively associated with the firm's economic exposure to tariffs, the firm's general political engagement (as measured by lobbying or political donations), and the

[18] Our main analyses rely on a 10-K-based measure of import exposure that is constructed from standardized SEC filings and updated through the most recent year. In contrast, the alternative measures used in this panel either rely on non-standardized sources (e.g., earnings-call text) or cover older periods: the Hoberg–Moon Offshoring Repository is available only through 2017 and S&P Panjiva data is available through 2020. Further, shipment-level data from S&P Panjiva generally do not report dollar values and are subject to extensive redactions by importers, which reduce the completeness and accuracy of shipment-level information (Flaaen et al. 2023).

[19] Our preferred specifications use year-quarter fixed effects to absorb common shocks from rapidly evolving policy developments related to tariffs that affect all firms simultaneously.

political ideology of its CEO. Regarding consequences of political tailoring, we document that political tailoring is associated with less readable and more redundant discussion, suggesting that altering investor disclosures for political reasons may potentially impact the informativeness of disclosures. However, we document that political tailoring is positively associated with the granting of tariff exemptions during the first Trump administration, consistent with such tailoring providing some economic benefits.

Our findings contribute to the literature on corporate political behavior by documenting a novel form of engagement: the tailoring of disclosures towards politicians. Prior work has shown firms donate to campaigns, lobby regulators, and even CEOs personally campaign on issues. Our findings suggest that even routine financial communications can be politicized when managers see benefit in sending a signal of alignment to those in power. From a shareholder's perspective, this behavior might be rational—aligning with government priorities could secure contracts or favorable treatment—but it introduces a tension with the goal of transparency. If management adjusts the language used in a conference call to appease politicians rather than to inform investors, investors may receive a distorted picture of the firm's true outlook. In extreme cases, important risks might be downplayed or not discussed at all because they are politically sensitive. This underscores a potential agency problem in disclosure: managers might sacrifice some informational quality to serve their own strategic interests with external parties.

For policymakers and regulators, our results suggest that the content of public firm communications can be a barometer of political currents—and possibly a casualty of them. Securities regulators may need to be mindful that when political pressure is high, mandatory disclosures (like 10-K risk factors or earnings calls) might omit or sugarcoat certain information. One practical implication is to ensure that critical information (e.g., exposure to tariffs) is still being disclosed somewhere in case it is being tailored in earnings calls. Investors, on their part, may want to read between the lines, especially for firms known to be politically connected: a sudden silence on a topic like tariffs or carbon regulation might not mean the risk disappeared, but rather that the firm chose not to highlight it.

AI Disclosure

We used generative artificial intelligence (AI) tools to help in drafting the original text of this paper, as well as part of its methodology. To create some content, we give ChatGPT specific instructions of what we want a portion of text to say, spelling out the arguments we want to make, and instructing it to put those arguments cohesively together for an academic accounting publication, which we then heavily edited and refined. For our analysis, we use the OpenAI ChatGPT API to (i) identify tariff-related discussions in quarterly earnings conference calls, and (ii) classify the extent to which these discussions indicate political tailoring (as described in the paper). The authors reviewed and validated the output on a sample of observations to assess accuracy and refine prompts. The authors take full responsibility for the contents of this paper.

References

Bhagwat, Y., N. L. Warren, J. T. Beck, and G. F. WatsonIV. 2020. Corporate Sociopolitical Activism and Firm Value. *Journal of Marketing* 84 (5): 1–21.

Bird, A., S. A. Karolyi, and T. G. Ruchti. 2023. How Do Firms Respond to Political Uncertainty? Evidence from U.S. Gubernatorial Elections. *Journal of Accounting Research* 61 (4): 1025–1061.

Blankespoor, E., E. deHaan, and I. Marinovic. 2020. Disclosure processing costs, investors' information choice, and equity market outcomes: A review. *Journal of Accounting and Economics* 70 (2): 101344.

Blankespoor, E., B. E. Hendricks, and G. S. Miller. 2017. Perceptions and Price: Evidence from CEO Presentations at IPO Roadshows. *Journal of Accounting Research* 55 (2): 275–327.

Blau, B. M., T. J. Brough, and D. W. Thomas. 2013. Corporate lobbying, political connections, and the bailout of banks. *Journal of Banking & Finance* 37 (8): 3007–3017.

Bonica, A. 2024. Database on Ideology, Money in Politics, and Elections: Public version 4.0 [Computer file]. *Stanford, CA: Stanford University Libraries*. https://data.stanford.edu/dime.

Bonsall, S. B., IV, E. R. Holzman, and B. P. Miller. 2024. Wearing out the Watchdog: The Impact of SEC Case Backlog on the Formal Investigation Process. *The Accounting Review* 99 (1): 81–104.

Bonsall, S. B., A. J. Leone, B. P. Miller, and K. Rennekamp. 2017. A plain English measure of financial reporting readability. *Journal of Accounting and Economics* 63 (2): 329–357.

Bova, F., Y. Dou, and O.-K. Hope. 2015. Employee Ownership and Firm Disclosure. *Contemporary Accounting Research* 32 (2): 639–673.

Bozanic, Z., J. L. Hoopes, J. R. Thornock, and B. Williams. 2017. IRS Attention. *Journal of Accounting Research* 55 (1): 79–114.

Brownen-Trinh, R., and A. Orujov. 2023. Corporate socio-political activism and retail investors: Evidence from the Black Lives Matter campaign. *Journal of Corporate Finance* 80 (C).

Cassidy, W. M., and E. Kempf. 2025. Partisan Corporate Speech. Working Paper. Working Paper Series. National Bureau of Economic Research.

Chen, C., J.-B. Kim, M. Wei, and H. Zhang. 2019. Linguistic Information Quality in Customers' Forward-Looking Disclosures and Suppliers' Investment Decisions. *Contemporary Accounting Research* 36 (3): 1751–1783.

Child, T. B., N. Massoud, M. Schabus, and Y. Zhou. 2021. Surprise election for Trump connections. *Journal of Financial Economics* 140 (2): 676–697.

Chiu, T.-T., J.-B. Kim, and Z. Wang. 2019. Customers' Risk Factor Disclosures and Suppliers' Investment Efficiency. *Contemporary Accounting Research* 36 (2): 773–804.

Chor, D., M. Grant, and B. Li. 2025. Exclusions for Sale? Tariff Exclusions in the US-China Trade War. *Working Paper*.

Christensen, D. M., H. Jin, S. A. Sridharan, and L. A. Wellman. 2022. Hedging on the Hill: Does Political Hedging Reduce Firm Risk? *Management Science* 68 (6): 4356–4379.

Christensen, D. M., A. Morris, B. R. Walther, and L. A. Wellman. 2023. Political information flow and management guidance. *Review of Accounting Studies* 28 (3): 1466–1499.

Claessens, S., E. Feijen, and L. Laeven. 2008. Political connections and preferential access to finance: The role of campaign contributions. *Journal of Financial Economics* 88 (3): 554–580.

Cox, L., G. J. Müller, E. Pastén, R. Schoenle, and M. Weber. 2024. Big *G*. *Journal of Political Economy* 132 (10): 3260–3297.

Cuny, C., J. Kim, and M. N. Mehta. 2024. Political Costs and Strategic Corporate Communication. Working Paper.

deHaan, E., N. Li, and F. S. Zhou. 2023. Financial Reporting and Employee Job Search. *Journal of Accounting Research* 61 (2): 571–617.

Faccio, M. 2006. Politically Connected Firms. *American Economic Review* 96 (1): 369–386.

Fisman, R. 2001. Estimating the Value of Political Connections. *American Economic Review* 91 (4): 1095–1102.

Flaaen, A., F. Haberkorn, L. Lewis, A. Monken, J. Pierce, R. Rhodes, and M. Yi. 2023. Bill of lading data in international trade research with an application to the COVID-19 pandemic. *Review of International Economics* 31 (3): 1146–1172.

Fos, V., E. Kempf, and M. Tsoutsoura. 2022. The Political Polarization of Corporate America. Working Paper. Working Paper Series. National Bureau of Economic Research.

Fotak, V., H. S. (Grace) Lee, W. L. Megginson, and J. M. Salas. 2025. The Political Economy of Tariff Exemption Grants. *Journal of Financial and Quantitative Analysis*: 1–40.

GAO. 2021. *U.S.-China Trade: USTR Should Fully Document Internal Procedures for Making Tariff Exclusion and Extension Decisions*. United States Government Accountability Office.

Goldman, E., J. Rocholl, and J. So. 2013. Politically Connected Boards of Directors and The Allocation of Procurement Contracts. *Review of Finance* 17 (5): 1617–1648.

Hill, M. D., G. W. Kelly, G. B. Lockhart, and R. A. Van Ness. 2013. Determinants and Effects of Corporate Lobbying. *Financial Management* 42 (4): 931–957.

Hitt, G., and J. Weisman. 2009. Political Backlash Against AIG Threatens to Hurt Other Firms. *Wall Street Journal*, March 19, sec. US.

Hoberg, G., and S. K. Moon. 2017. Offshore activities and financial vs operational hedging. *Journal of Financial Economics* 125 (2): 217–244.

Hoberg, G., and S. K. Moon. 2019. The Offshoring Return Premium. *Management Science* 65 (6): 2876–2899.

Holman, J. 2025. C.E.O.s Hold Their Tongues to Avoid Attracting Trump's Anger. *The New York Times*, May 21, sec. Business.

Kalmenovitz, J. 2023. Regulatory Intensity and Firm-Specific Exposure. *The Review of Financial Studies* 36 (8): 3311–3347.

Kalmenovitz, J., M. Lowry, and E. Volkova. 2025. Regulatory Fragmentation. *The Journal of Finance* 80 (2): 1081–1126.

Kempf, E., and M. Tsoutsoura. 2024. Political Polarization and Finance. SSRN Scholarly Paper. Rochester, NY: Social Science Research Network.

Kim, I. S. 2018. LobbyView: Firm-level Lobbying & Congressional Bills Database.

de Kok, T. 2025. ChatGPT for Textual Analysis? How to Use Generative LLMs in Accounting Research. *Management Science*.

Lambert, T. 2018. Lobbying on Regulatory Enforcement Actions: Evidence from U.S. Commercial and Savings Banks. *Management Science* 65 (6): 2545–2572.

Leswing, K. 2025. Apple regains $3 trillion market cap after Trump exempts tariffs on iPhones. *CNBC*, April 14, sec. Technology.

Li, E. X., G. Lind, K. Ramesh, and M. Shen. 2023. Externalities of Accounting Disclosures: Evidence from the Federal Reserve. *The Accounting Review* 98 (5): 401–427.

Li, P., N. Castelo, Z. Katona, and M. Sarvary. 2024. Frontiers: Determining the Validity of Large Language Models for Automated Perceptual Analysis. *Marketing Science* 43 (2): 254–266.

Lo, K., F. Ramos, and R. Rogo. 2017. Earnings management and annual report readability. *Journal of Accounting and Economics* 63 (1): 1–25.

Loughran, T., and B. Mcdonald. 2011. When Is a Liability Not a Liability? Textual Analysis, Dictionaries, and 10-Ks. *The Journal of Finance* 66 (1): 35–65.

Loughran, T., and B. Mcdonald. 2014. Measuring Readability in Financial Disclosures. *The Journal of Finance* 69 (4): 1643–1671.

Ma, M., J. Pan, E. Rouen, and L. Wellman. 2025. Legislators' Demand for Firms' Financial Statements: Evidence from U.S. Congressional Redistricting Events. *Working Paper*.

McGinley, L. 1999. Clinton Orders Study of Drug Costs, Attacks Drug Firms Over "Flo" Ads. *Wall Street Journal*, October 26, sec. Front Section.

McKinnon, J. D., J. Fialka, and J. Ball. 2006. Bush Takes Steps to Expand Oil Supplies. *Wall Street Journal*, April 26, sec. News.

Murray, C. 2025. All The Major Companies And Orgs Dumping Their DEI Programs (Full List). *Forbes*. https://www.forbes.com/sites/conormurray/2025/04/11/ibm-reportedly-walks-back-diversity-policies-citing-inherent-tensions-here-are-all-the-companies-rolling-back-dei-programs/.

Peterson, K. 2022. Biden's Inflation Blame Game. *WSJ*. https://www.wsj.com/podcasts/opinion-potomac-watch/biden-inflation-blame-game/21cb0d8e-b69e-49c1-8762-a95d9db53d61.

Shepardson, D., G. Bensinger, and A. Shalal. 2025. Amazon in White House crosshairs over report of displaying tariff costs | Reuters. *Reuters*, April 29.

Steel, R. S. 2025. The Political Transformation of Corporate America, 2001–2022. *American Political Science Review*: 1–17.

USTR. 2018. Procedures To Consider Requests for Exclusion of Particular Products From the Determination of Action Pursuant to Section 301: China's Acts, Policies, and Practices Related to Technology Transfer, Intellectual Property, and Innovation.

Wei, J., X. Wang, D. Schuurmans, M. Bosma, B. Ichter, F. Xia, E. Chi, Q. Le, and D. Zhou. 2023. Chain-of-Thought Prompting Elicits Reasoning in Large Language Models. arXiv.

Wilmot, S. 2024. U.S. Tariffs Close Off the Easiest Route to Affordable EVs. *WSJ*. https://www.wsj.com/business/autos/u-s-tariffs-close-off-the-easiest-route-to-affordable-evs-a9deeb2b.

You, H. Y. 2017. Ex Post Lobbying. *The Journal of Politics* 79 (4): 1162–1176.

Appendix A. Measuring Political Tailoring

This appendix details our methodology for leveraging the OpenAI API to process and analyze earnings call transcripts, including the prompts utilized for each task.

For all tasks, we use the OpenAI API with the GPT-4.1 mini model (collectively referred to herein as "GPT"). Each API call is executed in a stateless session, meaning that GPT does not retain memory of previous prompts or outputs across calls. We set the temperature parameter to zero to minimize randomness in output. This setting is important in our context, as it increases the consistency and replicability of results across identical prompts and inputs.

A1. Extracting Tariff-Related Discussions

We use GPT to extract tariff-relevant content from each passage identified from an initial keyword screen. For prepared remarks, we input the speaker-level components and instruct the mode to extract only the paragraphs that involve tariff discussions. For the Q&A section, we input one pair of Q&A each time and instruct the model to identify tariff discussion from the answer if the Q&A is related to tariff. Below is the Role Task Format (RTF) prompt we provide to GPT for prepared remarks extraction:

Role:
You are an analyst trained in political economy, international trade policy, and corporate communications, specializing in analyzing corporate communications related to U.S. trade and customs policy.

Task:
Your task is to identify and extract a firm executive's discussions related to U.S. customs tariff policy from a section of the firm's quarterly earnings conference call. For this task, these discussions refer to a firm executive's remarks describing the firm's interpretation, positioning, impacts, or actions related to U.S. customs tariff policy — whether existing, proposed, or anticipated. In this context, "tariffs" refer exclusively to customs duties imposed on cross-border trade in goods and do not include non-customs tariffs such as pipeline, utility, or transportation fees.

Instructions:
1. *Read the entire provided transcript carefully.*
2. *Determine whether the executive's remarks contain any discussion related to U.S. customs tariff policy. Do not limit your judgment to sentences that explicitly use the word "tariff(s)." Focus instead on complete, contextual discussions about U.S. customs tariff policy or related U.S. trade policy measures.*
3. *Extract and combine all relevant discussions.*
    - *If discussions related to U.S. customs tariff policy are present in the executive's remarks, extract complete, coherent passages (full paragraphs or multi-sentence segments) that capture the discussion and any nearby context needed for clarity.*
    - *If the transcript contains multiple tariff-related discussions located in different sections, extract all of them.*
    - *Combine these passages into a single, chronologically ordered excerpt that captures the full discussion of U.S. customs tariff policy.*
    - *Use "[…]" to indicate where unrelated text has been omitted.*
    - *Do not paraphrase, summarize, or infer meaning beyond what is explicitly stated. The extracted text must be verbatim from the transcript.*
4. *If no substantive discussion related to U.S. customs tariff policy appears, return an empty string.*

5. *For the extracted discussions, include a short (1–3 sentence) explanation describing why they qualify as discussions related to U.S. customs tariff policy.*

A2. Rating Political Tailoring

After identifying tariff-related discussions, we aggregate the extracted tariff discussions from prepared remarks and Q&A sections to construct call-level tariff discussions. We then use GPT to assign a tailoring score to each tariff discussion. We instruct GPT to use a 5-point scale, which allows us to capture nuanced differences in the tone, language, and strategic positioning of executives when discussing tariffs. We also provide the date of the call and the sitting president in the prompt.

Below is the RTF prompt we provide to GPT to generate the tailoring scores:

Role:
You are an analyst trained in political economy, corporate communications, and U.S. presidential politics, with a focus on identifying how firms adjust communications to align with presidential priorities and reduce political risk.

***Task**:*
You will evaluate whether executives' tariff-related discussions in a firm's quarterly earnings conference call appear to be politically tailored.

For this task, political tailoring means deliberately adjusting conference call disclosures so they would be more likely to create a favorable impression with the sitting U.S. President if the content of these disclosures were relayed directly to him. This includes emphasizing topics aligned with presidential priorities, framing firm outcomes as consistent with or enabled by administration policies, and signaling support through language or commitments that resonate with the President's stated goals.

The call took place on {date} when the sitting U.S. President was Donald Trump.

***Instructions**:*
1. *Evaluate the extent to which the firm's discussions are politically tailored so they would be more likely to create a favorable impression with the sitting U.S. President if their contents were relayed directly to him.*
2. *Assign a score from 1–5 using the following scale:*
    - *1 — No political tailoring: Discussions are frank or technical, with no framing toward presidential favorability.*
    - *2 — Minimal political tailoring: Isolated tailoring with little emphasis or strategic intent.*
    - *3 — Moderate political tailoring: Several deliberate but not dominant favorable framings.*
    - *4 — Substantial political tailoring: Frequent and clearly deliberate favorable framings, though not universal.*
    - *5 — Strong and pervasive tailoring: Favorability framing is a consistent, strategic communication pattern.*
3. *If political tailoring is present (score ≥ 2), extract the most representative 1–3 passages that illustrate it. If absent (score = 1), return an empty list.*
4. *For each passage, briefly (1–3 sentences) explain why it exhibits political tailoring.*

A3. Examples of Tariff Discussions and Political Tailoring Scores

Example 1: American Axle & Manufacturing Holdings, Inc., May 2, 2025 | **Score = 5**

Quote:

"Listen, Trump is doing exactly what he said he was going to do when he was campaigning as he wants to build a strong manufacturing base in the U.S. He wants to support and strengthen the U.S. auto industry. He wants to bring jobs back to America and strengthen our economy. We're going through a bumpy road right now. We all just seem to be patient and work our way through this whole thing together and not overreact. At the same time, when we get to the other side, I think America will be much stronger. At the same time, he's driving a lot of investment by foreign companies into the U.S. instead of a lot of money going offshore, it's going to stay in the U.S. and it's going to create those jobs for Americans here.

I mean part of the concern, it was kind of raised by Joe earlier, is labor availability. There's a lot of open jobs today. That's why I think automation, robotics and other things are going to have to come into play in order to be able to support the amount of jobs that potentially can be created with the policies that are put into place. But make no mistake, I mean, Trump is just attacking the tariff and balance that existed for decades. And he's just trying to level the playing field to give the U.S. auto industry and other industries for that matter, a competitive playing filed or a level playing field to do business on. And if we didn't, then there is a risk of some of those businesses being at risk longer term."

GPT's explanation:

This passage explicitly praises President Trump's trade and manufacturing policies, aligning the firm's narrative with his stated goals of job creation, reshoring, and economic strengthening. It signals strong support and frames the firm's strategy as consistent with the administration's priorities.

Example 2: Cleveland-Cliffs Inc., February 25, 2025 | **Score = 5**

Quote:

"With the Trump administration in office, action is being taken and we are starting to see positive signs ahead of us. We at Cleveland-Cliffs appreciate the recently announced 25% tariffs on steel importers from all countries. These tariffs are critical to addressing the problem, and we thank the Trump administration to have the courage to implement these tariffs."

GPT's explanation:

"This passage explicitly praises the Trump administration's tariff policies, framing them as courageous and essential, directly aligning the firm's positive outlook with the President's actions, which is a clear example of strategic political tailoring."

Example 3: Ford Motor Company, May 5, 2025 | **Score = 4**

Quote1:

"On tariffs, Ford supports the administration's goal to strengthen the U.S. economy by growing American manufacturing. And we also support a level playing field globally for domestic and foreign OEMs. We also appreciate the ongoing cooperation we've had with the administration. "

GPT's explanation:

"This passage explicitly aligns Ford with President Trump's stated priorities of strengthening American manufacturing and fair trade, signaling clear support for the administration's tariff policies and cooperation, which is a direct political tailoring to create a favorable impression."

Quote2:
“As America's largest auto manufacturer, our engagement with Washington is helping U.S. policymakers better understand how their proposed policy changes would impact our industry and, of course, our communities. Last year, we assembled over 300,000 more vehicles in the U.S. than our closest competitor. That includes 100% of all our full-size trucks.”

GPT’s explanation:
“Here, Ford emphasizes its leadership in U.S. manufacturing and active engagement with the administration, framing its large domestic footprint as a competitive advantage that supports the President’s agenda of boosting American jobs and manufacturing.”

Example 4: INNOVATE Corp., May 6, 2025 | **Score = 3**

Quote:
“We continue to monitor the ongoing tariff situation. At this point, DBM has not seen material impact to its business. Given policy is constantly evolving, there is uncertainty about the full impact of tariffs on the cost of materials and project delays. DBM continues to actively monitor its project backlog and new project pipeline to mitigate any impacts. Longer term, tariff economics could potentially spur additional economic investments in the United States. Of note, President Trump expects $6 trillion to $7 trillion in investments to come into the United States after the tariffs take effect.”

GPT’s explanation:
“This statement frames tariffs positively by suggesting they could lead to increased domestic investment, aligning with President Trump's priority of boosting U.S. economic growth and reshoring manufacturing.”

“Directly referencing President Trump's expectations signals alignment with his policy goals and shows the firm is attentive to and supportive of the administration's economic agenda.”

Example 5: STRATA Skin Sciences, Inc., August 13, 2025 | **Score = 2**

Quote1:
“On the first quarter call, in May, we highlighted the potential impact of the tariffs on our international business. While we were able to completely -- to complete some sales in China during the 90-day tariff pause, the uncertainty about the future they have caused has created a temporary drag on our international business.”

GPT’s explanation:
“This passage acknowledges the tariffs and their impact but also highlights the firm's ability to complete sales during the tariff pause, which subtly aligns with the Trump administration's tariff policies by recognizing the temporary relief provided and framing the disruption as temporary.”

Quote2:
“That said, we believe it is important to caution investors about the potential impact of tariffs on our international business. While it is no meaningful impact on our business in the first quarter, we saw some weakening in China in the second quarter.”

GPT’s explanation:

"By carefully balancing caution with reassurance, the firm demonstrates awareness of the tariffs' effects without outright criticism, which can be seen as a politically cautious approach to avoid antagonizing the administration while still informing investors."

Example 6: Corteva, Inc., February 6, 2025 | **Score = 1**

Tariff Discussion:
"The situation is changing almost daily. And so we have, I'd say, a task team that's working and running models and simulations on what could happen with the different scenarios. Let me start by just saying a couple of things upfront. So our two -- this is really a CP issue for us, right, because it's a global supply chain. Corn is a little different. It's essentially grown and sold in the same region. So this for us is a CP issue. And our two biggest franchise businesses, Enlist and spinosyns, they are manufactured exclusively in the United States. So that sets up Corteva to be basically a net exporter as a company.

Now to give you a view on CP, and we'll just use China as an example, it's about 2% of our COGS come from China. And about 80% of that 2%, we have multi-sourced. So the simulation, the models that we've run and who knows exactly what will eventually happen. But the scenarios that we've run, we think that most of these situations are very manageable. But you are right to call out, we have put none of this in our guide because we just don't have enough confidence on what it may or may not be. So the scenarios that are being discussed right now, we think, are completely manageable."

Appendix B. Variable Definitions

Variable	Definition
Political Tailoring Variables	
Political Tailoring	Political tailoring score at the earnings call level. A 5-point scale measure generated by GPT that assesses the extent of political tailoring in the tariff-related discussions. The score for each call ranges from 1 to 5, where 1 indicates no signs of political tailoring and 5 indicates clear and strong and pervasive political tailoring.
Strong Tailoring	An indicator equal to one if the political tailoring score is above three, and zero otherwise.
Other Outcome Variables	
Future Gov Contract	The total dollar value of new federal government contracts awarded to the firm in the four quarters following the conference call, scaled by total assets.
Tariff Exemption	An indicator variable that equals one if a tariff exemption application during the first Trump administration is granted, zero otherwise.
Independent Variables	
Import 10K	The number of import-related keywords in the 10-K for the fiscal year preceding the conference call, scaled by the total number of words in the 10-K. The import-related keywords are “import”, “imports”, “importing”, “importation”, and “imported”.
Lobby	The sum of trade related lobby expenditures during the past four years, scaled by total assets.
PAC Donation	The sum of total political donations through a corporate political committee (PAC) for the previous two election cycles, scaled by total assets.
Donation to Republican	The sum of corporate PAC donations made to Republican candidates and committees over the previous two election cycles, scaled by total assets.
Donation to Democratic	The sum of PAC donations made to Democratic candidates and committees over the previous two election cycles, scaled by total assets.
CEO Political Ideology	A continuous measure of the CEO’s political ideology based on the individual CFScore from Bonica (2024), where higher values indicate a more conservative ideological orientation and lower values indicate a more liberal orientation.
Republican CEO	An indicator that equals one if the CEO’s political ideology is conservative, defined as having a CFScore greater than zero (Bonica 2024), zero otherwise.
Democratic CEO	An indicator that equals one if the CEO’s political ideology is liberal, defined as having a CFScore less than zero (Bonica 2024), zero otherwise.
Institutional Ownership	The percentage of stock held by institutional investors.
Size	The natural logarithm of total assets.
ROA	Income before extraordinary items divided by total assets.
BTM	Book value of equity divided by market value of equity.
Leverage	Total debts divided by total assets.
Sales Growth	Change in sales over the same quarter in the previous year, divided by sales in the same quarter in the previous year.
Sentiment	Textual sentiment of the tariff-related discussion, measured as the number of positive words less negative words, scaled by the total number of words, where positive and negative words are based on the sentiment word lists provided by Loughran and McDonald (2011).
Length	The number of words of the tariff-related discussion relative to total words of the conference call transcript.
Fog Index	A readability index calculated as 0.4 times the sum of the average sentence length and the percentage of words with three or more syllables, excluding proper nouns and common suffixes.
Verbosity	The difference in word count between the original tariff-related discussions and the GPT-generated summary, scaled by the original word count, as detailed in Appendix B.

Appendix C. Measuring Verbosity

This appendix illustrate how we measure the verbosity of the tariff discussions. We use the following prompt to summarize the tariff discussions extracted from conference call transcript:

Role:
You are a financial analyst specializing in interpreting corporate disclosures and earnings communications to assess their implications for firm valuation.

Task:
Your task is to summarize the following discussion of tariffs by an executive in a firm's quarterly earnings conference call with security analysts. The summary should represent information relevant for assessing the company's stock price.

Instructions:
Focus only on company-specific information that is relevant to investors' assessment of the company's stock price. Exclude tangential remarks or general commentary. The summary should be concise but comprehensive in capturing all substantive or actionable points.

Verbosity is then defined as:

$$Redundancy = 1 - \frac{Number\ of\ words\ in\ GPT\ summry}{Number\ of\ words\ in\ tariff\ discussions}$$

The spirit of this measure mirrors the compression process from information theory, the encoding of information using fewer bits than the original representation. We assume the summary produced by our prompt captures all value-relevant information from the original tariff discussion; thus, a higher *Verbosity* score means the speaker communicated the core information in a less redundant way in the original discussion. Conversely, a lower Verbosity score indicates a more verbose original discussion.

Appendix D. Background of Tariff Exemption for Section 301 Tariffs

Section 301 Tariffs

The first-term Trump administration launched major trade measures in 2018 using various statutory authorities, including the safeguard provisions under Section 201 and national-security tariffs under Section 232. The most economically sweeping action, however, relied on Section 301 of the Trade Act of 1974, which empowers the United States Trade Representative (USTR) to impose retaliatory duties when a foreign government maintains practices that are "unjustifiable, unreasonable, or discriminatory" and burden U.S. commerce. In March 2018, following a year-long investigation into China's practices, particularly in technology transfer, intellectual property and innovation, the USTR determined that China had engaged in acts warranting a Section 301 remedy.

During the period from mid-2018 through 2019, the USTR implemented four rounds of tariffs on Chinese imports, denoted as Lists 1, 2, 3 and 4, with each covering certain products. These rounds successively expanded product coverage and increased duty rates. For instance, List 1 covered around $34 billion of Chinese imports, List 2 about $16 billion, while Lists 3 and 4 broadened to hundreds of billions of dollars in trade value.[20]

Table D1: Lists Section 301 Tariffs

Tariff List	Tariff Announcement	Tariff Effective Date	Value of Import
1	April 6, 2018	July 6, 2018	$34 billion
2	June 20, 2018	August 23, 2018	$16 billion
3	July 10, 2018	September 24, 2018	$200 billion
4	May 17, 2019	September 1, 2019	$300 billion

Source: USTR and Chor et al. (2025).

Relative to earlier programs under Section 232 or Section 201, the Section 301 initiative stands out because it is targeted on a single country (China) with broad product coverage. Unlike other tariff tools that rely on legislated process, Section 301 grants the USTR relatively broad discretion, making the policy design less subject to legislative or regulatory oversight. The combination of scale, scope, and discretion make the policy historically unprecedented in recent U.S. trade enforcement (GAO 2021).

Tariff Exemption Process for Section 301 Tariffs

Recognizing that blanket tariffs could impose disproportionate harm on U.S. firms dependent on Chinese inputs, the USTR established an official process for firms to request exclusions from the Section 301 duties. In its oversight review, the Government Accountability Office (GAO) notes that the exclusion program was initiated in response to concerns from industry and Congress about the burden on U.S. manufacturers.

Under the exclusion procedure, the USTR first published the finalized list of tariffed products and then opened an application window (typically 90 days) during which firms could file exclusion requests for specific imported products. Each request was posted publicly, followed by a period for comments and rebuttals. The USTR conducted a multi-stage interagency review involving economic, legal, and technical assessment. If an exclusion was approved, it generally applied retroactively to the date the tariff became effective, allowing firms to obtain refunds of duties paid while their applications were under review.
To guide the review process, the USTR evaluated applications using several substantive criteria that applicants were required to address (GAO 2021; Chor et al. 2025), including:

[20] See https://ustr.gov/issue-areas/enforcement/section-301-investigations/tariff-actions.

1. Availability of the product outside China, including whether suppliers in the United States or other countries could feasibly provide substitutes.
2. Economic harm to the applicant or broader U.S. interests if the tariff remained in place.
3. Strategic considerations, including whether the product was tied to Chinese industrial policy initiatives.
4. Consistency with the objectives of the Section 301 action, ensuring the exclusion would not undermine the rationale for the tariffs.
5. Product specificity, requiring applicants to describe the product in detail sufficient for U.S. Customs and Border Protection to administer the exclusion.

Figure 1: Proportion of Conference Calls with Tariff Discussion

This figure presents the quarterly proportion of earnings conference calls that include any tariff discussion from November 2016 to August 2025. We identify tariff-related discussions using a hybrid keyword screening and large language model approach, as detailed in Section 3.2.

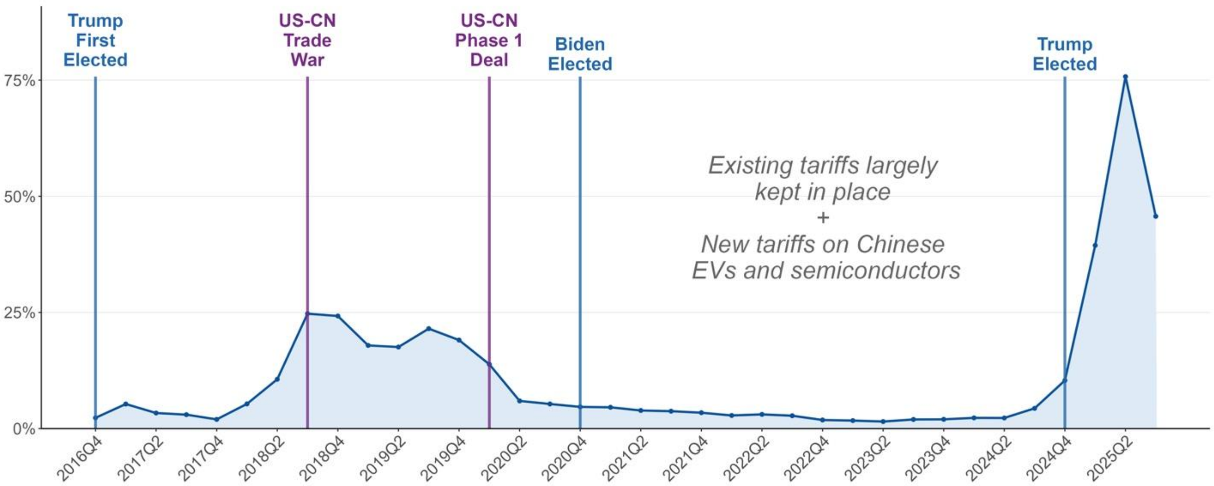

Figure 2: Proportion of Conference Calls with Tariff Discussion by Industry

This figure presents the annual proportion of earnings conference calls that include tariff discussions, segmented by industry, from November 2016 to August 2025. The color intensity of each cell corresponds to the percentage of calls with tariff discussions within that specific industry and year. Industries are ordered by their average proportion of tariff discussions in 2025.

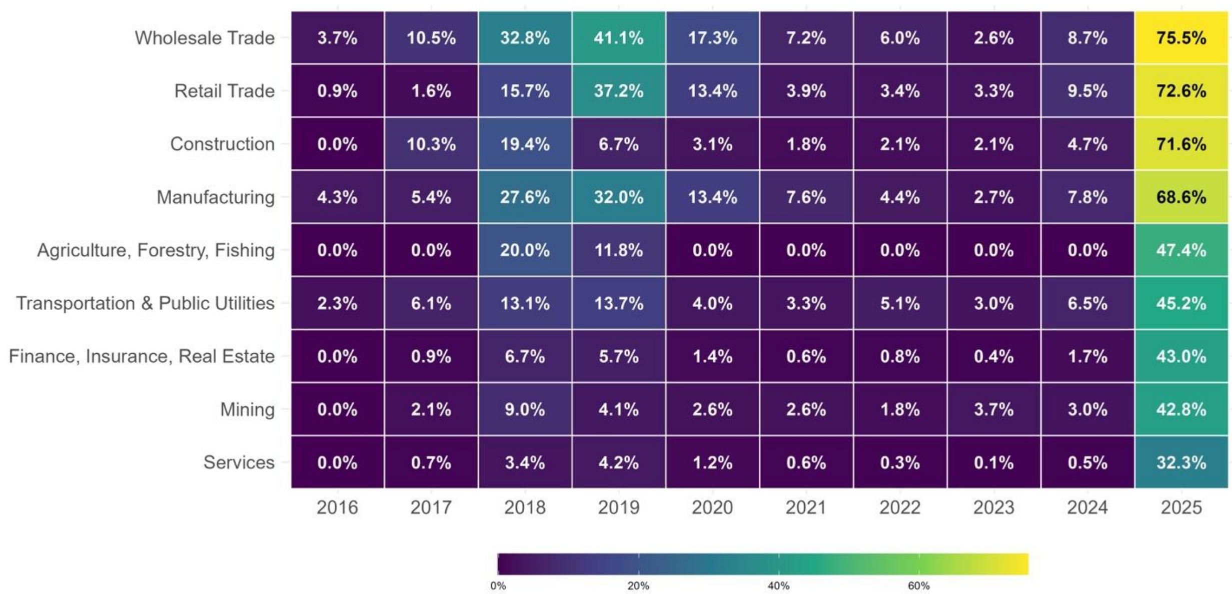

Figure 3: Distribution of Political Tailoring by Administration

This figure presents the distribution of political tailoring scores (*Political Tailoring*) across the two Trump administrations based on election dates. Each bar represents the proportion of firm-quarter observations falling within each political tailoring score (1 to 5) for a given administration. A score of 1 indicates no political tailoring, while 5 indicates strong and pervasive political tailoring.

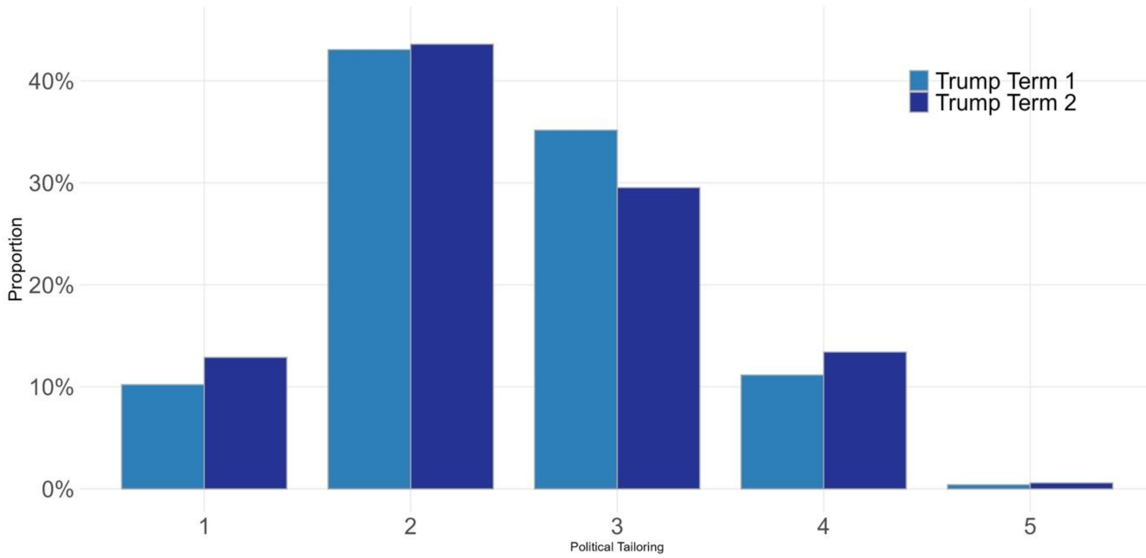

Figure 4: Political Tailoring by Industry

This figure presents the average political tailoring score by year and industry. Each cell displays the average tailoring score (ranging from 1, no tailoring, to 5, strong and pervasive tailoring) among all firm-quarter observations for the corresponding industry and year.

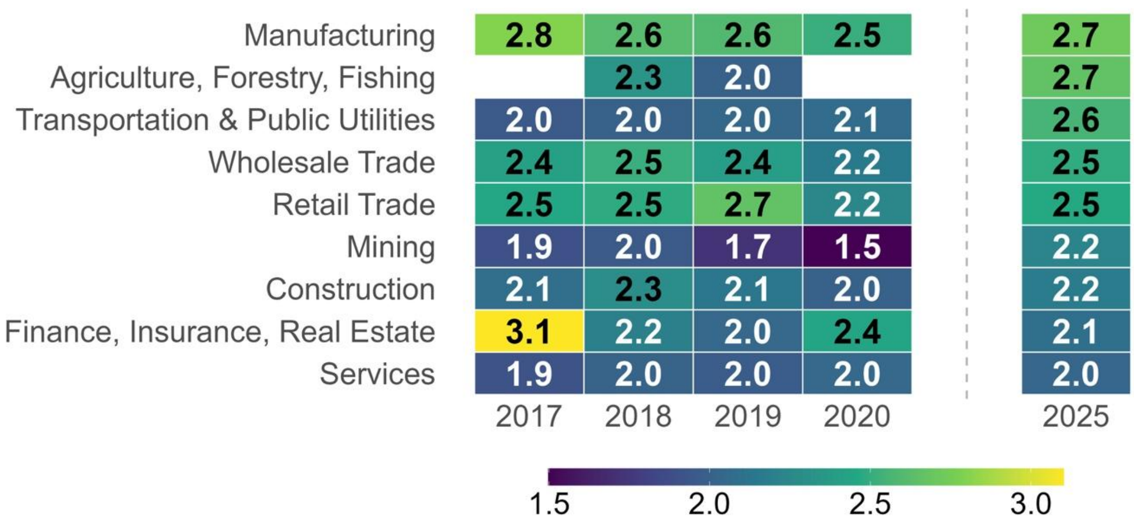

Table 1: Sample Selection

This table details our sample selection process.

		Firm-quarters	Firms
Quarterly earnings conference call transcripts spanning both Trump administrations (defined by presidential election dates)		47,444	4,086
Less:	Calls without any tariff discussions	39,387	1,903
Less:	Firm-quarters with insufficient data to compute regression variables	210	74
Final sample		7,843	2,109

Table 2: Variance Decomposition of Political Tailoring

This table presents the variance decomposition of *Political Tailoring*. Panel A reports the proportion of variance explained by Time Fixed Effects, Industry Fixed Effects, and Industry × Time Fixed Effects, as well as the implied firm-level variance, at different levels of industry aggregation (2-digit, 3-digit, and 4-digit SIC codes). Panel B provides a variance decomposition for sample periods that correspond to different presidential administrations at the 2-digit SIC level.

Panel A: By Level of Industry Aggregation

Industry Level	2-digit SIC	3-digit SIC	4-digit SIC
Time FE	1.49%	1.49%	1.49%
Industry FE	15.80%	21.32%	23.55%
Industry × time FE	9.68%	21.84%	27.27%
Implied Firm-level	73.03%	55.34%	47.69%
Number of Industries	67	226	341

Panel B: By Presidency at 2-digit SIC Level

2-digit SIC	Trump Term 1	Trump Term 2
Time FE	0.86%	2.16%
Industry FE	15.82%	19.14%
Industry × time FE	11.42%	4.25%
Implied Firm-level	71.89%	74.46%
Number of Industries	60	67

Table 3: Summary Statistics

This table presents descriptive statistics for our sample. All variables are defined in Appendix B. We winsorize all continuous firm-level variables at 1% and 99% levels.

	N	Mean	SD	P25	P50	P75
Political Tailoring	7843	2.47	0.87	2.00	2.00	3.00
Import 10K>0	7843	0.74	0.44	0.00	1.00	1.00
Import 10K	7843	0.00	0.00	0.00	0.00	0.01
Tariff Discussion	7843	0.06	0.06	0.02	0.04	0.07
China Sourcing	7843	0.22	0.51	0.00	0.00	0.00
China Shipment	7843	2.80	2.67	0.00	2.30	5.18
Lobby>0	7843	0.10	0.30	0.00	0.00	0.00
Lobby (non-zero ’000$)	766	2603.94	5252.59	150.00	500.00	3120.00
PAC Donation>0	7843	0.27	0.44	0.00	0.00	1.00
PAC Donation (non-zero ’000 $)	2084	498.22	913.87	42.25	181.35	498.75
Donation to Republican (non-zero ’000 $)	2037	318.42	561.37	27.57	124.00	335.70
Donation to Democratic (non-zero ’000 $)	1922	202.75	382.93	15.00	63.19	197.01
CEO Political Ideology	7843	0.29	0.67	0.00	0.00	0.97
Republican CEO	7843	0.47	0.50	0.00	0.00	1.00
Democratic CEO	7843	0.21	0.41	0.00	0.00	0.00
Government Contractor	7843	0.05	0.21	0.00	0.00	0.00
Sentiment	7843	0.00	0.02	-0.00	0.00	0.01
Length	7843	0.06	0.06	0.02	0.04	0.07
Verbosity	7843	0.55	0.25	0.43	0.60	0.73
Fog Index	7843	13.97	3.60	11.45	13.39	15.82
Size	7843	8.00	1.83	6.79	8.00	9.22
BTM	7843	0.55	0.50	0.22	0.44	0.77
Sales Growth	7843	0.07	0.21	-0.03	0.04	0.13
Leverage	7843	0.32	0.21	0.16	0.31	0.44
Institutional Ownership	7843	0.76	0.25	0.67	0.84	0.94
ROA	7843	0.01	0.03	0.00	0.01	0.02

Table 4: Determinants of Political Tailoring

This table presents the regressions results on the determinants of political tailoring in tariff-related discussions in earnings calls. The dependent variable in both columns is *Political Tailoring*. Both columns include explanatory variables related to firms' import exposure (*Import 10K*), political engagement (*Lobby, PAC Donation,* and *CEO Political Ideology*), financial ties to the federal government (*Government Contractor*), firm characteristics (*Institutional Ownership, Size, ROA, BTM, Leverage,* and *Sales Growth*), and the length (*Length*) and sentiment of tariff discussions. Column (2) replaces (i) *PAC Donation* with *Donation to Republican* and *Donation to Democratic* and (ii) *CEO Political Ideology* with *Republican CEO* and *Democratic CEO*. All columns include industry and year-quarter fixed effects. We winsorize all firm-level continuous variables at 1% and 99% levels. To facilitate the interpretation of regression coefficients, we standardize all continuous independent variables to have a mean of zero and a standard deviation of one. Standard errors are clustered at the firm-level. *, **, and *** represent significance levels of 10%, 5%, and 1% using two-tailed tests, respectively. All variables are defined in Appendix D.

	(1)	(2)
Dependent Variable	*Political Tailoring*	*Political Tailoring*
Import 10K	0.027**	0.027**
	(2.198)	(2.187)
Lobby	0.032**	0.032**
	(2.574)	(2.502)
PAC Donation	0.037***	
	(3.266)	
Donation to Republican		0.034**
		(1.979)
Donation to Democratic		0.001
		(0.040)
CEO Political Ideology	0.017	
	(1.542)	
Republican CEO		0.057**
		(2.297)
Democratic CEO		0.015
		(0.519)
Government Contractor	-0.109**	-0.110**
	(-2.231)	(-2.245)
Size	0.073***	0.071***
	(5.019)	(4.881)
BTM	0.019	0.019
	(1.583)	(1.511)
Sales Growth	0.011	0.011
	(1.177)	(1.193)
Leverage	0.034***	0.035***
	(2.759)	(2.760)
Institutional Ownership	-0.015	-0.016
	(-1.263)	(-1.353)
ROA	-0.024**	-0.023**
	(-2.107)	(-2.010)
Sentiment	0.112***	0.112***
	(13.785)	(13.790)
Length	0.385***	0.384***
	(32.758)	(32.679)
Observations	7,843	7,843
R^2 Adj.	0.345	0.346
Industry FE	Yes	Yes
Year-Quarter FE	Yes	Yes

Table 5: Political Tailoring and Disclosure Quality

This table presents the regression results on the relationship between political tailoring in firms' tariff-related discussions during earnings conference calls (*Political Tailoring*) and the disclosure quality of these discussions, measured using two textual measures of tariff discussions: *Verbosity* (column 1) and *Fog Index* (column 2). All specifications include industry and year-quarter fixed effects. We winsorize all firm-level continuous variables at the 1% and 99% levels. To facilitate interpretation, all continuous independent variables are standardized to have a mean of zero and a standard deviation of one. Standard errors are clustered at the firm level. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. All variable definitions are provided in Appendix B.

	(1)	(1)
Dependent Variable	*Verbosity*	*Fog Index*
Political Tailoring	0.058***	0.393***
	(17.976)	(5.985)
Import 10K	-0.003	0.073
	(-1.229)	(1.339)
Lobby	-0.001	-0.043
	(-0.609)	(-0.749)
Donation to Republican	-0.000	-0.135
	(-0.018)	(-1.409)
Donation to Democratic	0.003	0.199**
	(0.596)	(2.378)
Republican CEO	-0.002	-0.387***
	(-0.395)	(-3.304)
Democratic CEO	-0.006	-0.236*
	(-0.810)	(-1.713)
Government Contractor	-0.014	-0.055
	(-0.924)	(-0.225)
Size	0.031***	-0.464***
	(9.185)	(-5.933)
BTM	-0.010***	0.271***
	(-3.911)	(5.208)
Sales Growth	0.001	-0.055
	(0.313)	(-1.186)
Leverage	-0.006**	0.102*
	(-1.989)	(1.862)
Institutional Ownership	0.009***	-0.026
	(3.025)	(-0.466)
ROA	-0.007**	-0.021
	(-2.565)	(-0.327)
Sentiment	0.000	-0.087
	(0.052)	(-1.608)
Length	0.130***	-0.604***
	(39.206)	(-11.334)
Observations	7,843	7,843
R^2 Adj.	0.464	0.138
Industry FE	Yes	Yes
Year-Quarter FE	Yes	Yes

Table 6: Political Tailoring and the Grant of Tariff Exemption

This table presents the regression results on the relationship between political tailoring in firms' tariff-related discussions during earnings conference calls (*Political Tailoring*) and the grant of tariff exemption. The regression is at tariff exemption application level based on applications related to Section 301 tariffs during the first Trump administration. The dependent variable, *Tariff Exemption*, is an indicator equal to one if the application for tariff exemption is granted. All specifications include product code, industry, and tariff list fixed effects. Standard errors are two-way clustered at the firm and product level. We winsorize all firm-level continuous variables at the 1% and 99% levels. To facilitate interpretation, all continuous independent variables are standardized to have a mean of zero and a standard deviation of one. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Variable definitions are provided in Appendix D.

	(1)	(2)
Dependent Variable	Tariff Exemption	Tariff Exemption
Political Tailoring		0.048***
		(2.911)
Import 10K	-0.020	-0.021
	(-1.208)	(-1.276)
Lobby	0.046*	0.036*
	(1.931)	(1.675)
Donation to Republican	0.163***	0.172***
	(3.578)	(4.054)
Donation to Democratic	-0.137***	-0.144***
	(-4.008)	(-4.474)
Republican CEO	0.039	0.002
	(0.663)	(0.030)
Democratic CEO	-0.042	-0.054
	(-0.682)	(-0.847)
Government Contractor	0.115	0.132
	(0.566)	(0.643)
Size	0.002	0.013
	(0.081)	(0.419)
BTM	-0.027	-0.031
	(-1.367)	(-1.589)
Sales Growth	0.012	0.033
	(0.535)	(1.240)
Leverage	-0.039	-0.043
	(-1.390)	(-1.573)
Institutional Ownership	0.005	-0.002
	(0.267)	(-0.095)
ROA	-0.012	-0.016
	(-0.589)	(-0.771)
Observations	3,459	3,459
R^2 Adj.	0.347	0.355
Product FE	Yes	Yes
Industry FE	Yes	Yes
Tariff List FE	Yes	Yes

Table 7: Political Tailoring and the Award of Federal Government Contract

This table presents the regression results on the relationship between political tailoring in firms' tariff-related discussions during earnings conference calls (*Political Tailoring*) and the award of future federal government contracts. The dependent variable is *Future Gov Contract*, defined as the total dollar value of new federal government contracts awarded to the firm in the four quarters following the conference call, scaled by total assets. All specifications include firm-level controls, industry fixed effects, and year-quarter fixed effects. We winsorize all firm-level continuous variables at the 1% and 99% levels. To facilitate interpretation, all continuous independent variables are standardized to have a mean of zero and a standard deviation of one. Standard errors are clustered at the firm level. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. All variable definitions are provided in Appendix B.

	(1)	(2)
	Future Gov Contract	*Future Gov Contract*
Political Tailoring		-0.000
		(-0.086)
Import 10K	0.000	0.000
	(0.516)	(0.526)
Lobby	0.000	0.000
	(0.420)	(0.427)
Donation to Republican	-0.001	-0.001
	(-1.600)	(-1.594)
Donation to Democratic	0.001**	0.001**
	(2.394)	(2.398)
Republican CEO	-0.000	-0.000
	(-0.182)	(-0.180)
Democratic CEO	-0.000	-0.000
	(-0.320)	(-0.319)
Government Contractor	0.004***	0.004***
	(3.502)	(3.499)
Size	-0.000	-0.000
	(-0.392)	(-0.391)
BTM	0.000	0.000
	(0.129)	(0.130)
Sales Growth	-0.000*	-0.000*
	(-1.958)	(-1.953)
Leverage	-0.000*	-0.000*
	(-1.829)	(-1.808)
Institutional Ownership	-0.000	-0.000
	(-0.720)	(-0.721)
ROA	0.000	0.000
	(0.092)	(0.092)
Observations	3,627	3,627
R^2 Adj.	0.219	0.219
Industry FE	Yes	Yes
Year-Quarter FE	Yes	Yes

Online Appendix to

Disclosing to Politicians

John Gallemore, Jeffrey L. Hoopes, Irene Tan, and Ricky Xu Yao

November 2025

Table OA-1: Alternative Construction of Political Tailoring in Consequence Tests

This table presents regression results examining the relationship between political tailoring and disclosure quality (Panel A), tariff exemption outcomes (Panel B), and future federal contracting outcomes (Panel C), using alternative constructions of the political tailoring measure. The dependent variables in Panel A are two textual measures of tariff discussions: *Verbosity* (column 1) and *Fog Index* (column 2). The dependent variable in Panel B is *Tariff Exemption*, an indicator equal to one if the application for tariff exemption is granted, and zero otherwise. The dependent variable in Panel C is *Future Gov Contract*, the total value of new federal government contracts scaled by total assets awarded over the four quarters following the earnings call. *Strong Tailoring* is an indicator variable equal to one if the tailoring score equals four or five, and zero otherwise. All specifications include industry and year-quarter fixed effects. We winsorize all firm-level continuous variables at the 1% and 99% levels. To facilitate interpretation, all continuous independent variables are standardized to have a mean of zero and a standard deviation of one. Standard errors are clustered at the firm level. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. All variable definitions are provided in Appendix B.

Panel A: Political Tailoring and Disclosure Quality

	(1)	(1)
Dependent Variable	*Verbosity*	*Fog Index*
Strong Tailoring	0.031***	0.612***
	(4.885)	(5.136)
Observations	7,843	7,843
R^2 Adj.	0.440	0.135
Controls	Yes	Yes
Industry FE	Yes	Yes
Year-Quarter FE	Yes	Yes

Panel B: Political Tailoring and the Grant of Tariff Exemption

	(1)
Dependent Variable	*Tariff Exemption*
Strong Tailoring	0.152***
	(3.431)
Observations	3,459
R^2 Adj.	0.361
Controls	Yes
Product FE	Yes
Industry FE	Yes
Tariff List FE	Yes

Panel C: Political Tailoring and the Award of Federal Government Contract

	(1)
Dependent Variable	*Future Gov Contract*
Strong Tailoring	-0.000
	(-1.380)
Observations	3,627
R^2 Adj.	0.219
Controls	Yes
Industry FE	Yes
Year-Quarter FE	Yes

Table OA-2: Alternative GPT Runs

This table presents the regression results using alternative *Political Tailoring* measures constructed through separate, independent API calls on OpenAI. In all panels, *Political Tailoring* in columns 1-3 correspond to a second API using GPT-4.1 mini (column 1), a third API run using GPT-4.1 mini (column 2), and a fourth API run using GPT-4.1 (column 3). All specifications include industry and year-quarter fixed effects. We winsorize all firm-level continuous variables at the 1% and 99% levels. To facilitate interpretation, all continuous independent variables are standardized to have a mean of zero and a standard deviation of one. Standard errors are clustered at the firm level. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. All variable definitions are provided in Appendix B.

Panel A: Determinants of Political Tailoring

	(1)	(2)	(3)
Dependent Variable		*Political Tailoring*	
GPT Model	GPT 4.1 mini	GPT 4.1 mini	GPT 4.1
Import 10K	0.028**	0.027**	0.026*
	(2.367)	(2.246)	(1.857)
Lobby	0.027**	0.032**	0.042**
	(2.176)	(2.540)	(2.247)
Donation to Republican	0.041**	0.043**	0.042*
	(2.264)	(2.459)	(1.719)
Donation to Democratic	-0.005	-0.004	-0.013
	(-0.270)	(-0.194)	(-0.552)
Republican CEO	0.047*	0.041*	0.048*
	(1.934)	(1.665)	(1.668)
Democratic CEO	0.020	0.004	0.024
	(0.694)	(0.141)	(0.694)
Government Contractor	-0.127**	-0.101**	-0.021
	(-2.465)	(-2.046)	(-0.369)
Size	0.065***	0.066***	0.068***
	(4.454)	(4.654)	(4.184)
BTM	0.022*	0.018	0.021
	(1.757)	(1.491)	(1.429)
Sales Growth	0.010	0.010	0.014
	(1.058)	(1.088)	(1.325)
Leverage	0.036***	0.033***	0.032**
	(2.827)	(2.628)	(2.135)
Sentiment	0.112***	0.108***	0.108***
	(13.871)	(13.108)	(12.710)
Length	0.381***	0.383***	0.216***
	(32.602)	(32.857)	(14.644)
Observations	7843	7843	7843
R^2 Adj.	0.343	0.346	0.239
Industry FE	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes

Table OA-2: Alternative GPT Runs (Continued)

Panel B: Political Tailoring and Disclosure Verbosity

	(1)	(2)	(3)
Dependent Variable		*Verbosity*	
Model	GPT 4.1 mini	GPT 4.1 mini	GPT 4.1
Political Tailoring	0.057***	0.057***	0.038***
	(18.010)	(17.642)	(14.437)
Observations	7843	7843	7843
R^2 Adj.	0.463	0.463	0.451
Controls	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes

Panel C: Political Tailoring and Disclosure Readability

	(1)	(2)	(3)
Dependent Variable		*Fog Index*	
Model	GPT 4.1 mini	GPT 4.1 mini	GPT 4.1
Political Tailoring	0.384***	0.407***	0.106**
	(5.865)	(6.103)	(1.982)
Observations	7843	7843	7843
R^2 Adj.	0.138	0.138	0.133
Controls	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes

Panel D: Political Tailoring and Grants of Tariff Exemptions

	(1)	(2)	(2)
Dependent Variable		*Tariff Exemption*	
Model	GPT 4.1 mini	GPT 4.1 mini	GPT 4.1
Political Tailoring	0.041**	0.032**	0.103***
	(2.349)	(2.041)	(5.238)
Observations	3,459	3,459	3,459
R^2 Adj.	0.353	0.351	0.371
Controls	Yes	Yes	Yes
Product FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Tariff List FE	Yes	Yes	Yes

Panel E: Political Tailoring and Awarding of Federal Government Contracts

	(1)	(2)	(3)
Dependent Variable		*Future Gov Contract*	
Model	GPT 4.1 mini	GPT 4.1 mini	GPT 4.1
Political Tailoring	0.000	0.000	-0.000
	(0.180)	(0.192)	(-0.428)
Observations	3,627	3,627	3, 627
R^2 Adj.	0.219	0.219	0.219
Controls	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes

Table OA-3: Alternative Tariff Exposure Measures

This table presents the regression results on the determinants of political tailoring in tariff-related discussions in earnings calls, using alternative measures of tariff exposure. Each column uses a different proxy for firms' exposure to tariffs (*Tariff Exposure*). Column (1) uses *China Sourcing,* measured as the number of mentions in 2017 10-K filings of sourcing specifically from China based on the Hoberg-Moon Offshoring Repository. Column (2) employs *China Shipment*, an import-shipment–based measures constructed using 2017 transaction-level data from S&P Panjiva, defined as the maritime import shipments from China scaled by total assets. All specifications include industry and year-quarter fixed effects. We winsorize all firm-level continuous variables at the 1% and 99% levels. To facilitate interpretation, all continuous independent variables are standardized to have a mean of zero and a standard deviation of one. Standard errors are clustered at the firm level. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. All variable definitions are provided in Appendix B.

	(1)	(2)
Dependent Variable	*Political Tailoring*	*Political Tailoring*
Tariff Exposure Measure	*China Sourcing*	*China Shipment*
Tariff Exposure	0.033**	0.030**
	(2.535)	(2.318)
Lobby	0.037***	0.032**
	(2.797)	(2.474)
Donation to Republican	0.029*	0.032*
	(1.661)	(1.871)
Donation to Democratic	0.004	0.002
	(0.224)	(0.097)
Republican CEO	0.071***	0.057**
	(2.754)	(2.328)
Democratic CEO	0.026	0.018
	(0.826)	(0.598)
Government Contractor	-0.112**	-0.109**
	(-2.164)	(-2.212)
Size	0.088***	0.074***
	(5.746)	(5.092)
BTM	0.025*	0.017
	(1.894)	(1.442)
Sales Growth	0.001	0.012
	(0.098)	(1.298)
Leverage	0.033**	0.033***
	(2.383)	(2.619)
Institutional Ownership	-0.017	-0.016
	(-1.430)	(-1.381)
ROA	-0.016	-0.025**
	(-1.333)	(-2.193)
Sentiment	0.113***	0.112***
	(13.283)	(13.717)
Length	0.384***	0.384***
	(31.291)	(32.847)
Observations	6997	7843
R^2 Adj.	0.347	0.346
Industry FE	Yes	Yes
Year-Quarter FE	Yes	Yes

Table OA-4: Alternative Fixed Effects

This table presents the regression results on the determinants of political tailoring in tariff-related discussions in earnings calls (Panel A) and the relationship between political tailoring and disclosure quality (Panel B), using alternative fixed effect structures. The dependent variable in Panel A is the political tailoring score of the firm's tariff-related discussions (*Political Tailoring*). The dependent variables in Panel B are two textual measures of tariff discussions: *Verbosity* (column 1) and *Fog Index* (column 2). All specifications include industry and year fixed effects. We winsorize all firm-level continuous variables at the 1% and 99% levels. To facilitate interpretation, all continuous independent variables are standardized to have a mean of zero and a standard deviation of one. Standard errors are clustered at the firm level. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. All variable definitions are provided in Appendix B.

Panel A: Determinants of Political Tailoring

	(1)	(2)
Dependent Variable	*Political Tailoring*	*Political Tailoring*
Import 10K	0.028**	0.028**
	(2.271)	(2.262)
Lobby	0.032**	0.031**
	(2.530)	(2.462)
PAC Donation	0.037***	
	(3.286)	
Donation to Republican		0.034**
		(1.984)
Donation to Democratic		0.001
		(0.051)
CEO Political Ideology	0.016	
	(1.448)	
Republican CEO		0.055**
		(2.220)
Democratic CEO		0.016
		(0.526)
Government Contractor	-0.107**	-0.109**
	(-2.215)	(-2.230)
Size	0.074***	0.071***
	(5.055)	(4.921)
BTM	0.020	0.019
	(1.601)	(1.530)
Sales Growth	0.011	0.011
	(1.184)	(1.199)
Leverage	0.034***	0.034***
	(2.712)	(2.713)
Institutional Ownership	-0.014	-0.015
	(-1.215)	(-1.302)
ROA	-0.024**	-0.023**
	(-2.079)	(-1.985)
Sentiment	0.112***	0.112***
	(13.811)	(13.814)
Length	0.383***	0.382***
	(35.129)	(35.070)
Observations	7,843	7,843
R^2 Adj.	0.344	0.344
Industry FE	Yes	Yes
Year FE	Yes	Yes

Table OA-4: Alternative Fixed Effects (Continued)

Panel B: Political Tailoring and Disclosure Quality

	(1)	(1)
Dependent Variable	*Verbosity*	*Fog Index*
Political Tailoring	0.058***	0.393***
	(17.727)	(5.869)
Import 10K	-0.004*	0.098*
	(-1.684)	(1.766)
Lobby	-0.002	-0.029
	(-0.861)	(-0.505)
Donation to Republican	-0.001	-0.122
	(-0.129)	(-1.287)
Donation to Democratic	0.003	0.180**
	(0.736)	(2.121)
Republican CEO	-0.002	-0.395***
	(-0.283)	(-3.340)
Democratic CEO	-0.004	-0.282**
	(-0.544)	(-2.029)
Government Contractor	-0.011	-0.122
	(-0.726)	(-0.499)
Size	0.032***	-0.472***
	(9.182)	(-5.960)
BTM	-0.011***	0.288***
	(-4.183)	(5.434)
Sales Growth	0.001	-0.057
	(0.501)	(-1.207)
Leverage	-0.006**	0.104*
	(-1.994)	(1.871)
Institutional Ownership	0.009***	-0.033
	(3.077)	(-0.587)
ROA	-0.008***	-0.002
	(-2.796)	(-0.037)
Sentiment	-0.001	-0.068
	(-0.246)	(-1.249)
Length	0.138***	-0.787***
	(41.302)	(-15.191)
Observations	7,843	7,843
R^2 Adj.	0.455	0.117
Industry FE	Yes	Yes
Year FE	Yes	Yes