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Tariffs, Geoeconomics and Political Cleavages

Evidence from American High-Tech Firms

Phuong Pham
University of Rochester

Randall Stone
University of Rochester

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ABSTRACT

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Tariffs · Geoeconomics · American high-tech companies

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Phuong Pham, University of Rochester

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Abstract

Standard trade theories predicted that capital-intensive firms deeply integrated into global production networks would strongly oppose the Trump administration's announcement of sweeping global tariffs on the "Liberation Day" of April 2nd 2025. Why have American high-technology firms responded with puzzling heterogeneity? We argue that firms that play central roles in US geoeconomic influence strategies receive state compensation through subsidies, contracts, and exemptions, and in exchange exhibit rhetorical forbearance toward tariff policy. We test this argument using a new firm-quarter panel of 486 earnings call transcripts from 65 leading U.S. technology and defense firms (2024Q1–2026Q1), with firm-level measures of tariff negativity and upstreamness generated through a two-step GPT-5.4 pipeline. Incorporating these measures into a difference-in-differences design that leverages Liberation Day as an exogenous shock, we find strong evidence for our theory: hardware firms respond more negatively than digital firms, and more upstream hardware firms respond less negatively than their downstream counterparts. We find consistent results using lobbying disclosure data.

Keywords: Tariffs; Geoeconomics; American high-tech companies

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Introduction

President Donald Trump announced sweeping tariffs on imports from virtually every country in the world in April 2025, which triggered a range of responses from American companies. The American high-tech sector was among the most sensitive to tariffs due to its global value chains, but firms' attitudes within the industry were far from homogeneous. Apple, by contrast, the second largest high-tech company in the world by market capitalization, explicitly expressed its concern about the expected costs of tariffs after the Liberation Day. In May 2025 Tim Cook told analysts that tariffs could increase Apple's supply costs by $900 million in the June quarter (Business 2025). Qualcomm, having a strong supplier relationship with Apple and similarly exposed to the global market on the surface, while raising its voice about tariffs, was less negative about the impact of tariffs. In fact, in April 2025, Qualcomm said that it did not expect "any material impact from tariffs, and that it had not seen elevated buying of its products ahead of tariffs during the quarter" (Leswing 2025). This phenomenon reflects a broader pattern: high-tech companies are sharing a lot of characteristics - capital intensive and productive, highly exposed to foreign markets and generating high value-added products - but reacting differently to tariffs.

Such a divergence is puzzling to studies that anchor the dimensions above to predict trade policy preferences. Indeed, this literature has little to say about the within-sector variation of firms' responses to negative shocks (Hiscox 2002; Rogowski 1990; Zhang 2025; Osgood 2018). The expectations of these studies were that high-tech firms should have had a unified response to tariffs, as these firms are capital-intensive, skill-intensive, deeply integrated into global production networks, and highly reliant on the global market, either for importing intermediate inputs or exporting finished products. Why do some firms show ambiguity, or even support for tariffs? The leading firm-level theory of trade preferences is similarly stumped. According to the Melitz (2003) model, high-productivity firms thrive under free trade, while low-productivity firms survive in protected markets. US high-tech firms are globally competitive and are among the most productive firms in the world. They should staunchly defend free trade.

Recent developments in the study of economic statecraft offer the building blocks of an explanation for firms' puzzling acquiescence. Leading states may seek to exert influence by manipulating the behavior of firms, and leading high tech firms have technology, capital, expertise and market power, which are integral to power projection (Clayton, Maggiori, and Schreger 2023). State influence strategies depend on cooperation and information sharing by firms, so they rely on providing inducements more than overt coercion, particularly in democracies. Since firms vary in their assortment of products and positions in global value chains, they play different roles in state strategy. This variation leads to a range of inducements, leading to a variation in the firms' responses to any particular policy.

Based on the formal work of Clayton et al (2023), we propose a firm-level index of relevance to statecraft, which we call *geoeconomic centrality.* This concept combines what Clayton et al (2023) call *micro power*, which is the ability to coordinate the actions of firms, and *macro power*, which is the influence gained thereby over foreign entities. Firms that are relevant to statecraft are those that are relatively easy to coordinate, which generally means that they produce high-value, differentiated, tangible goods that are easy to track and control. In addition, they must occupy upstream positions in supply chains so that withholding their products disrupts production networks.[1] Our expectation is that firms that occupy positions of geoeconomic centrality moderate their criticism of government policies during episodes of economic statecraft because they are compensated for policies that affect them adversely.

We test our argument with a two-step empirical strategy. First, we construct a new firm-quarter panel dataset of 486 earnings call transcripts and quarterly lobbying disclosure reports from 65 Fortune 500 technology and defense firms, covering nine consecutive quarters from Q1 2024 through Q1 2026. Using a two-stage large language model pipeline, we generate firm-level measures of expressed tariff negativity and the degree of upstreamness from the substantive content of each earnings call transcript. The LLM-coded approach allows us to capture the nuance of corporate communication on trade policy at a scale beyond what manual coding or dictionary methods can achieve, and we validate the resulting measures through face validity checks and within-firm consistency tests across quarters. Second, we leverage the Liberation Day tariff announcement of April 2, 2025 as an exogenous shock to the trade policy environment to design a difference-in-differences setting to identify the causal effect of geoeconomic centrality on tariff negativity. We test our theoretical predictions through a triple interaction of hardware-product mix (micro power), upstreamness (macro power), and the post-treatment indicator, which isolates the differential response of geoeconomically central upstream hardware firms following the tariff shock. The results indicate that the hardware firms that are most directly affected by state influence strategies react most negatively to the tariff shock, but the upstream firms that provide the most influence moderate their opposition. The findings hold both

1. The Clayton et al (2023) model is an explicitly supply-side model of economic influence.

for statements in earnings calls and lobbying and are robust to various specifications and placebo tests.

Economic Tension, Tariffs and MNC Behavior

As competition between the United States and China has intensified, both sides have used economic tools to coerce other actors to follow their interests or to weaponize their centrality in the global economic network (Farrell and Newman 2019; Gertz and Evers 2020; Cha 2023; Norris 2016; Lee and Maher 2022). These measures include tariffs, trade sanctions, export controls, strategic subsidies or investment screening (Bauerle Danzman and Meunier 2024; Blackwill and Harris 2016; Mulder 2022; Eaton and Engers 1992; Mastanduno 2020; Hirschman 1980; Clayton, Maggiori, and Schreger 2024). The consequences have included reduced aggregate real income in both the United States and China (Fajgelbaum and Khandelwal 2022), divestment from China by multinational corporations (Vortherms and Zhang 2024) and shifting political coalitions in the United States (Mansfield and Solodoch 2024; Kim and Margalit 2021).

Firms are indispensable in great power competition, and states often mobilize their companies to achieve economic coercion goals. Clayton et al (2023) formalize how states weaponize firms in their geoeconomics framework. According to their model, the ability to control domestic firms that provide upstream inputs into global value chains is a key component of hegemonic power. Other studies show that firms do not internalize the foreign policy interests that motivate states to engage in geoeconomic influence, however, and they have incentives to resist policies that increase their input costs or restrict their international markets. Chen & Evans (2023) argue that firms support or oppose their home state's use of economic statecraft depending on whether they are high-value or low-value businesses. Other works show that firm responses to economic sanctions diverge: some over-comply, while others commit sanctions busting (Early and Peterson 2024; Pham 2025). Private actors actively influence policy-making processes. Firms originating from states targeted for economic reasons or sharing strategic traits with existing targets are more likely to engage in lobbying efforts to influence US sanctions (Peksen and Peterson 2023; Crescenzi 2018). Similarly, prominent chip producers including NVIDIA, Qualcomm and Intel have lobbied against export controls on China, leading the Trump administration to relax the regime[2].

One of the most salient issues for firms is tariffs. Apparently, when a state imposes tariffs on adversaries, its own domestic firms often suffer, especially in the short to medium term, due to higher input costs, disrupted supply chains, and potential retaliatory measures. Consequently, firms would act collectively to shape tariffs in their favor, conditional on their characteristic. Following that logic, recent work in political science has been examining more variation in firms' lobbying behavior on tariffs with more granular results. Kim (2017), offering a theory of trade liberalization, finds that productive exporting firms, especially with differentiated products, are more likely to lobby against tariffs, and that highly differentiated products have lower tariff rates. In the context of the U.S-China trade war, Eldes et al (2025) show that lobbying for tariff reductions by large firms is substantially more effective than for small firms, except for firms with foreign subsidiaries in China. The results above have emphasized the proactive role of firms in crafting tariff policy, and they have certain successes in driving tariffs towards

2. "Nvidia shares climb as White House relaxes export rules on China chip," *Financial Times*, July 14, 2025. https://www.ft.com/content/ba0929bd-5912-44fb-9048-c143aced4c8a?

their desired outcomes.

Notwithstanding their valuable contributions, previous research has yet to explain the puzzle we raise: the varying firm-level responses to tariffs under geopolitical tension. Existing studies have not established a direct link between geopolitics, tariffs, and firm behavior. Multinational corporations (MNCs), embedded in complex and interdependent production networks, are highly vulnerable to geopolitical disruptions. Consequently, their decision-making abroad reflects not only profit-maximization but also geopolitical calculations. To mitigate geopolitical risks—especially those arising from tariffs—firms adopt a variety of strategic responses (Caldara and Iacoviello 2022; Lubinski and Wadhwani 2020; Abdelal 2015; Bednarski et al. 2024). We propose that a firm's geoeconomic centrality helps explain the variation in firm responses to tariffs. Specifically, we highlight two mechanisms determining how geoeconomically central a firm is: its mobilizability - the likelihood of being mobilized/targeted for states' geopolitical purposes; and substitutability - the degree of indispensability to the state's geoeconomic capacity.

Theory & Hypotheses

Scope Conditions & Assumptions

Given the salience of economics in great power geopolitical competitions, firms are indispensable in state power, enabling their states to coerce opponents through market channels (Clayton, Maggiori, and Schreger 2024; Kalyanpur and Newman 2019; Clayton, Maggiori, and Schreger 2023). In this regard, we have three scope conditions for our theory. First and most importantly, we primarily look at high-tech sectors. In our modern world, technological innovation is mainly driven by firms, especially leading ones (Dosi 1982; Cantwell and Fai 1999; Malerba 2002; Gereffi, Humphrey, and Sturgeon 2005), and technology is the main battlefield of geopolitical rivalry (Ding 2024; Schmidt 2023), as high-tech firms occupy various positions in GVCs, and such chains are highly fragmented. With their occupation of different production stages, from upstream suppliers to downstream assemblers, these firms can complement state coercive power well when they are central in the network of production. We thus expect a high variation in firm-level exposure to foreign markets and their level of geopoliticization, conditional on their positions in the value chain. Second, we confine our theory to great power competition only. Great powers usually have influential firms in high-tech industries, and these powers have the ability and will to geopoliticize their firms to achieve their strategic goals (Farrell and Newman 2019). For middle and smaller powers, while having powerful companies, often lack the ambition and means to mobilize these entities for geopolitical ends. Therefore, by narrowing the scope to great-power competition, we ensure that the variation in our outcome variable truly stems from a firm's position in global value chains and their degree of state mobilization, rather than from confounders such as differences in states' structural capacity to use firms as geopolitical instruments. Additionally, we focus on private, multinational firms (MNCs) rather than firms under direct state control. This scope condition is crucial because the incentive structures that guide private MNCs are different across firms, and such differences are central for evaluating our theoretical expectations. Private firms must balance profit-maximization, shareholder pressures, and global market access against the political and regulatory constraints imposed by their home states so their support for tariffs or any instruments cannot be taken for granted.

In this way, private firms provide the clearest setting in which we can observe how our independent variables translate into the interested outcomes.

Our theory relies on three key assumptions. For analytical feasibility, we assume that in a relatively short to mid-term time horizon, firms are rational forward looking. This assumption is plausible, given our scope conditions above. High-tech industries are naturally fast-paced and disruptive, incentivizing companies to prioritize immediate foreseeable payoffs over uncertain long-term outcomes. Besides, under conditions of deep strategic uncertainty—where the duration of tariffs, the scope of retaliation, and the trajectory of great power rivalry are genuinely unpredictable—firms cannot reliably optimize over very long time horizons. As a result, they are more inclined to prioritize near-term payoffs and observable policy signals over speculative long-run returns (Knight 1921; Ellsberg 1961; Beckert 2016). Furthermore, we treat great power geopolitical rivalry and the timing of tariffs as exogenous. Great powers engaged in geopolitical competition, such as the United States and China, have structurally conflicting interests that cannot be altered abruptly, making rivalry a stable feature of the international system (Mearsheimer 2025; Pillsbury 2015). Although the tariffs themselves are not fully exogenous, their timing (when they are imposed) could be treated that way. While firms may anticipate tariff policy in general, the specific timing of announcements are driven by factors such as political scheduling, bureaucratic procedure, and negotiation dynamics, thus is plausibly unrelated to firm-level sentiment measured in the days and weeks following announcement. In addition, we assume that tariffs and geopolitical rivalry in high-tech sectors affect virtually every firm, albeit in various degree. This universal effect follows the exogeneity assumption, allowing us to both isolate our explanatory mechanisms from the macro landscape and ensure theoretical coherence, as we seek to explain why firm-specific characteristics cause differences in their support for tariffs, not to explain how firms shape the design of tariff policy under great power competition.

Geoeconomic Centrality: Microfoundations and Tariff Support

We attempt to apply the geoeconomic framework by Clayton et al (2023) into our paper. The key idea of this framework is, since the hegemonic countries, or more generally powerful ones, use their economic strength to extract economic and political surplus from other countries around the world, they need to utilize commercial channels like the threat to exclude targets from global supply chains, access to technology or services. In order to achieve these goals, the hegemons coordinate threats across disparate economic relationships as a means to exert their geoeconomic power over entities that they do not directly control. For example, they could impose export controls to prevent their firms (especially those which are in strategic sectors) from selling certain goods to the enemy, or they could demand these companies not use technologies or inputs from a rival. By this logic, firms are treated as passively following the flag. While there are reasons for companies to conform to state policy, we want to go beyond this framework by treating firms as active players that have "voice" in geoeconomic issues. We thus propose a crucial factor that determines how geoeconomically proactive firms are: geoeconomic centrality.

Building on the scope conditions outlined above, we theorize two mechanisms determining firms' geoeconomic centrality under great-power rivalry: how destructive it is to the economy of the opponent when that firm is absent (geoeconomic destruction) and how easily it is to mobilize a firm for geoeconomic purposes (mobilizability). These mechanisms capture how firms' structural positions and their likelihood of being mobilized or targeted for state purposes shape their strategic importance in the state geoeconomic strategy, eventually determining their attitude toward tariffs or similar instruments. In particular, variation in tariff support can be attributed to differences in firms' positions in global value chains and how likely they are subject to states' geopolitical measures, and these mechanisms are not fully seperable but usually interactive. By unpacking these firm-level mechanisms, we move beyond treating firms as passive recipients of state policy and instead highlight the ways in which their characteristics condition their geoeconomic centrality and, consequently, their willingness to support tariffs.

On the first mechanism, we expect that firms occupying more upstream positions in global value chains (GVCs) are less negative about tariffs than downstream ones. More upstream firms control critical inputs, technologies, or chokepoints that are unsubstitutable (Fishman 2025; Farrell and Newman 2019; Clayton, Maggiori, and Schreger 2024). Firms such as advanced semiconductor manufacturers, lithography toolmakers, or EDA software providers are the heart of production networks, where their outputs are essential for a wide range of downstream applications and their substitutes are rare. Because of that, these firms are highly valuable to states during geopolitical rivalry: when the state can successfully coordinate these firms for geoeconomic policy, it would be economically destructive for its adversaries, thanks to the ripple effect caused by upstream disruption (Acemoglu et al. 2012; Gabaix 2011; Ojha et al. 2018). In this regard, controlling upstream firms at the chokepoints magnifies a state's coercive capacity in international markets (Becko and O'Connor 2024; Clayton, Maggiori, and Schreger 2023), meaning these firms are geoeconomically central.

Additionally, upstream firms have different cost structure than lower-stream ones. Accordingly, these firms are less dependent on imported inputs or intermediate goods for their production, when there is a disruption in the supply chain, they are less vulnerable to such a shock (Baqaee and Rubbo 2023; Huneeus 2018) since they suffer less direct costs than downstream assemblers (Johnson 2018; Antràs et al. 2012). This distinct feature of upstream firms has two-fold implications. First, with their occupation of strategic nodes in the global supply chains, they enjoy a privileged position in the geoeconomic apparatus: state heavily depends on the cooperation of these firms to effectively project its geoeconomic power abroad. Subsequently, governments have strong incentives to offer those most upstream firms more benefits such as subsidies or preferential contracts to secure business alignment, eventually cementing the state power over strategic bottlenecks (Becko and O'Connor 2024). Second, thanks to their lower dependence on low-cost global sourcing, upstream firms are less vulnerable to tariffs or any geoeconomic tools that generate shocks to the supply of inputs and intermediates. This lower exposure to negative externalities caused by geoeconomic instruments means upstream companies are less likely to oppose tariffs or related measures. Even when they are bearing the brunt of heavy costs from tariffs, these costs could potentiall be offset by government support, as mentioned previously. Taken together, upstream firms have weaker incentives compared to mid or downstream ones to vehemently oppose tariffs.

Nevertheless, going beyond some part of the literature predicting collective support or indifference of tariffs from upstream firms, we expect that within the high-tech or strategic sectors, the effect of upstreamness varies greatly among upstream firms, compared to non-strategic or traditional ones. This pattern is well-documented in American trade history: American upstream producers in traditional industries during 19th and early 20th century, notably agriculture and steel manufacturers, collectively and staunchly supported protectionist measures (Schattschneider 1935; Gourevitch 1986; Irwin 2017). Their homogeneous behavior is well-explained by positional logic: upstream producers within a given sector shared the same competitive exposure and the same relationship with the state, making upstreamness a reliable predictor of protectionist tolerance. In high-tech or any strategic sectors, this homogeneity is less clear, as geoeconomic factors also govern their action, in parallel to their supply chain position: firms controlling genuine chokepoints attract state compensation and become neutral or even supportive of tariffs, while upstream firms that are less critical do not receive equivalent treatment so they remain more opposing. The result is that upstreamness alone is a weaker and noisier predictor of tariff attitudes in high-tech than in traditional industries, because geoeconomic heterogeneity among upstream firms might attenuate the average effect.

Hypothesis 1: More upstream firms are less negative towards tariffs than lower-stream ones.

From the geoeconomic perspective, depending on whether a firm is mobilizable or not, there would be a divergence in their tariff negativity. Importantly, mobilizability is not simply about how much a geoeconomic tool could hurt a firm. Instead, it is about whether such an instrument can effectively engage the firm in the first place and be sustainably enforced afterwards (Blackwill and Harris 2016; Luttwak 1990). As geopolitical/geoeconomic instruments, tariffs, export controls, and procurement incentives are designed to inflict as much damage to the target as possible, so they must be imposed on goods that are either tangible or strategically valuable, or both (Mulder 2022). Accordingly, these instruments usually target goods that are physically tangible and quantifiable, as they are more tractable through customs or cross-border monitoring, making it easier for agents to enforce punishment, grant exemptions, and direct compensation, which strengthens the state geoeconomic power. This is the case with high-tech companies: those selling hardware products are easier to be mobilized for economic coercion as well as having more exposure to tariffs (Osgood 2018), given the nature of their goods and their position in the global high-tech industries[3]. Granted, these firms could receive favorable treatment from the state, but the cost from sweeping tariffs could exceed its expected benefits when being mobilized. The logic is as follows. Hardware firms are, on average, more export-dependent, as they sell their products to all buyers across the world, and they earn a significant part of their revenue abroad so under growing protectionism, these companies could suffer from a huge loss. Digital or software-driven firms, on the other hand, while also export a lot, sell products that face less constraints under the same tariff regimes thanks to their intangibility and scalability. Consequently, we believe that hardware-intensive firms would be more negative towards tariffs than software ones. Moreover, due to physical and capital constraints as well as the extreme degree of specialization in the high-tech value chain, physical-linked providers usually have more product differentiation, or are less substitutable than digitally-driven ones. As shown by the recent work on the effect of differentiation on tariffs, highly differentiated goods usually have lower tariffs, productive exporting firms are more likely to lobby to reduce tariffs, especially when their products are sufficiently low-substitutable (Kim 2017; Osgood 2017, 2016; Baccini and Dür 2018).

3. As of 2026, most high-tech products subject to export controls or sanctions by the United States are physical or hardware-linked. See the Bureau of Industry and Security's Commerce Control List: https://www.bis.gov/regulations/ear/interactive-commerce-control-list?isExpanded=&category=&keyword=

Upstream hardware firms are different from down or midstream ones in their tolerance for tariffs. As argued previously, a successful mobilization upstream firms are usually more destructive to the enemy state or entities, and this is particularly true with big American hardware sellers. On the one hand, with their dominance in critical goods, they occupy chokepoints of global technology and defense so the mobilization of these firms against an enemy would be highly damaging to its economy (Farrell and Newman 2019). On the other hand, with their economic power, they are central in the making of economic policy, consistent with research showing that large firms exert disproportionate influence over trade policy outcomes (Gulotty 2022; Brock and Magee 1978; Ehrlich 2008). Additionally, these firms are extremely capital intensive so they cannot easily relocate from the targeted markets following tariffs, meaning tariff costs are real, but so is the collateral damage to the imposing state, given their upstreamness. Thanks to their occupation of economic chokepoints, upstream hardware firms would, therefore, be very likely to secure deals from the government, which could offset their losses incurred by tariffs.[4] The implication is, big upstream hardware firms have greater tolerance for tariffs, which makes them less opposed to tariffs compared to their downstream counterparts.

Hypothesis 2: Hardware firms are more negative towards tariffs than software ones.

Hypothesis 2a: Upstream hardware firms are less negative towards tariffs than downstream ones.

4. Indeed, some of the largest American chip-makers have received significant packages from the CHIPS & Science Act. For example, Intel was awarded $8.5 billion in grants and $11 billion in loans for projects in Arizona, New Mexico, Ohio, and Oregon; GlobalFoundries was awarded $ 1.5 billion to expand manufacturing in New York and Vermont, specifically for automotive and defense technologies.

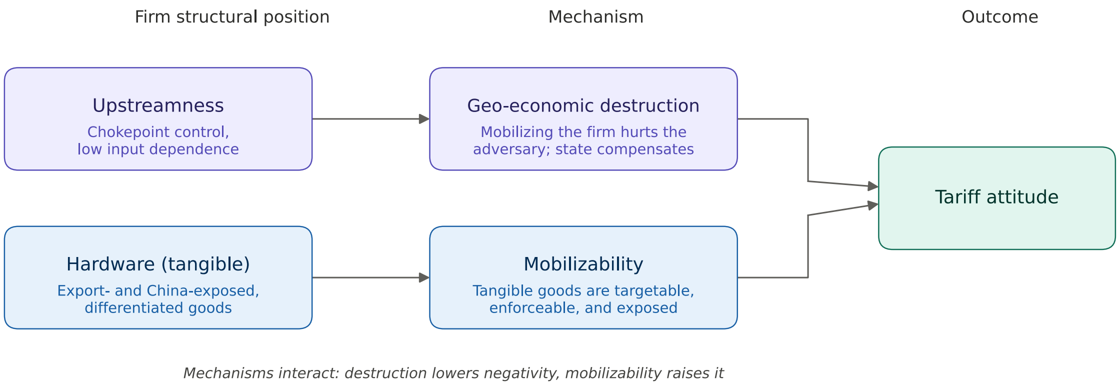

Figure 1: Theoretical Mechanisms

Research Design

Textual Data

In order to measure tariff negativity at the firm level, we need sources of firm-level text. Earnings calls are a valuable source of textual information because they allow market participants to ask firm leadership questions of their choosing. While the calls begin with a prepared presentation from management, this means that market participants have the opportunity to ask about the issues that they find most pressing, which is well-suited for our study of firm-level opinion about tariffs - a highly salient issue for firms. With the emergence of text analysis and large language models (LLMs), there is a proliferation of studies using earnings calls and other sources of corporate texts to examine firm-specific dynamics (Hassan et al. 2024; Clayton et al. 2025; Heinrichs, Park, and Soltes 2019; Bochkay, Hales, and Chava 2020). We take advantage of readily available sources of corporate text. Specifically, we use the Capital IQ Transcript data to acquire all earnings call transcripts of the 65 largest American high-tech firms by market capitalization (ranked by Fortune 500) from the first quarter of 2024 to the first quarter of 2026. This is a highly reliable source: the transcripts are well-structured and cover all firms that we need without any missing documents. The dataset is widely used by academic and industry research.

We focus only on American high-tech firms for several reasons. First, high tech sectors are at the forefront of great-power competition between the United States and China, meaning they are heavily exposed to coercive measures from both sides, including tariffs. American tech companies are heavily dependent on manufacturing and supply chains running through the European Union, China and Taiwan so they would be hit hard by tariffs, as warned by the head of the Consumer Technology Association that tariffs will "drive inflation" and "kill jobs," risking a recession in the United States (Shapero 2025). Secondly, the high-tech sector is a hard test for our theory. Thanks to their dominance role in the global supply chain of high technologies, American tech firms are likely to be mobilized by the state, following the geoeconomic logic, and constitute a critical role in American tariffs. Because of that, all high-tech firms enjoy some degree of state protection or compensation for potential losses from tariffs. If our results are significant even within this already-privileged sector, the effects of our proposed mechanisms must be substantively strong. Next, as American firms are globally dominant, studying how they respond to tariffs is foundational to understanding the microfoundations of American modern geoeconomics, given the intensification of US-China high-tech rivalry and the US weaponization of technological interdependence.

Methodology

As LLMs have become more advanced, a number of studies have shown that these models can perform text-annotation, detection, classification and coding reliably (Gilardi, Alizadeh, and Kubli 2023; Le Mens and Gallego 2025; Umansky et al. 2026). We use LLMs to extract our key variables. We perform large-scale inference on a textual corpus of 486 earnings calls using frontier pre-trained, open-source LLMs. For our baseline results, we use the latest *GPT 5.4-mini* model of OpenAI released in 2026. Our approach has two steps. In our first step, we employ *GPT 5.4-nano* to read through all of the text (approximately 10000 words each) and extract all relevant information and passages, including trade policy quotes, trade-adjacent language, and business model descriptions. This compresses each transcript to around 1,000 words of relevant, informative excerpts. After that, we use GPT 5.4-mini to score them. GPT-5.4-mini reads the extracted passages and scores them on a firm's tariff negativity and upstreamness, as well as other latent trade environment measures. Instead of using 5.4-mini for both tasks, we only implement it in our second step, mainly for cost efficiency. Compared to 5.4-nano, 5.4-mini is more expensive, and extraction is a simple task that does not require nuanced judgment or sophisticated inference. The 5.4-nano handles this extraction task well because the instructions are clear and the output is straightforward (verbatim quotes from the text) [5]. Coding is much more complicated, as it requires nuanced interpretation of tone and context, followed by calibrating a scale across a rubric.

We adopt a two-step coding architecture rather than a single-pass approach for both computational and methodological reasons. On the computational side, earnings call

5. See Appendix for the snippets

transcripts average approximately 10,000 words, and submitting the full text of each transcript directly to the scoring model would impose substantial token costs across 486 observations while risking truncation at context window limits. More importantly, the two-step design offers a methodological advantage grounded in the structure of the underlying text. Earnings call transcripts are overwhelmingly composed of content unrelated to trade policy: quarterly revenue figures, product roadmaps, segment-level guidance, and analyst questions about margins, backlog, and capital allocation. Trade-relevant language, when present, typically constitutes fewer than 1000 words embedded within this larger corpus. Directing a scoring model to evaluate the full transcript risks diluting signal with noise, as the model must simultaneously identify relevant content and assess its valence and intensity. Separating these tasks allows each model to specialize: the extraction model identifies and isolates trade-relevant passages without evaluating their content, while the scoring model evaluates those passages without the distraction of irrelevant material. This procedure mirrors the standard practice in manual content analysis, in which a research assistant first identifies and excerpts relevant text segments before a trained coder applies the coding scheme to those segments (Krippendorff 2018). The decomposition reduces coder burden, minimizes context-dependent errors, and ensures that the scoring model's attention is concentrated on the substantively relevant portions of each document. We provide a full prompt in the Appendix.

Empirical Strategy

There are three clear, non-trivial identification threats to our causal inference. First and most importantly, firm-level GVC characteristics are endogenous and may correlate with unobservable determinants of expressed tariff attitudes. Firms do not randomly select into physical or digital value chains, and the characteristics that determine GVC position may independently shape how firms communicate about trade policy. In addition to that, there could be an anticipation effect that confound our results. Accordingly, Trump won the election in November 2024, and tariff threats were among his central campaign promises. Firms may have begun adjusting their rhetoric before the tariffs were effective, so if they started expressing more negativity in anticipation, our post-treatment effect might capture strategic repositioning rather than a response to the actual policy. Another issue is that earnings call rhetoric may reflect strategic communication rather than sincere attitudes. Firms communicate with multiple audiences simultaneously, investors, regulators, policymakers, and competitors, and may calibrate their expressed tariff attitudes accordingly.

To overcome these challenges, we employ a difference-in-differences (DD) design, leveraging the Liberation Day of April 2nd 2025 as our exogenous shock. The oldest and most commonly-used quasi-experimental design in causal inference (dating to the Snow (1855) research on the cholera outbreak in London), a DD estimate is the difference between the change in outcomes before and after a treatment (difference one) in a treatment versus control group (difference two). With this design, we employ an event-study to examine the causal effect of the two mechanisms above. Our equation is the following:

$$Y_{it} = \alpha_i + \gamma_t + \beta_1(H_i * P_t) + \beta_2(U_i * H_i * P_t) + \varepsilon_{it} \quad (1)$$

where Y_{it} is tariff negativity for firm i in quarter t, scaled from 0 (no mention or neutral framing) to 1 (severe negativity). α_i denotes firm fixed effects, which absorb all time-invariant firm characteristics including industry membership, business model, organizational culture, and baseline political orientation. γ_t denotes quarterly (year x quarter) fixed effects, which absorb common macroeconomic conditions and policy shocks affecting all firms in a given quarter. H_i is a binary indicator equal to 1 for firms whose products take physical form and cross customs borders (semiconductors, hardware systems, defense equipment, and networking hardware) and 0 for firms whose value creation is primarily digital (software, cloud services, internet platforms, and IT services). P_t is a binary indicator equal to 1 for quarters beginning in Q2 2025, immediately following the Liberation Day tariff announcement of April 2, 2025. U_i is the standardized pre-treatment mean of the LLM-coded upstreamness score, ranging from -1 (pure downstream, consumer-facing) to $+1$ (pure upstream, inputs supplier), averaged across pre-treatment quarters to construct a time-invariant firm characteristic[6]. We do not include additional time-varying firm-level controls such as quarterly revenue or stock returns, as these are plausibly affected by the tariff shock and would constitute post-treatment covariates on the causal path between tariff imposition and expressed attitudes (Angrist and Pischke 2009; Montgomery, Nyhan, and Torres 2018). Standard errors are clustered at the firm level to account for serial correlation within firms across quarters (Bertrand, Duflo, and Mullainathan 2004).

Several lower-order interaction terms are implied by the triple interaction in our specification: $Hardware_i$, $Upstream_i$, $Upstream_i \times Hardware_i$, and $Post_t$ (Brambor, Clark, and Golder 2006). The first three are time-invariant and therefore absorbed by firm fixed effects; the fourth is absorbed by calendar-quarter fixed effects. The remaining lower-

6. We include our verbatim LLM prompt in the Appendix

order term, $Upstream_i \times Post_t$, is omitted from our preferred specification on theoretical grounds: our framework predicts that upstreamness affects tariff attitudes primarily through customs exposure, which operates only on firms whose products take physical form and cross customs borders. A general upstreamness gradient extending to digital firms is not implied by our argument, and the within-digital point estimate is correspondingly small and not statistically distinguishable from zero (Table 2). Because $Upstream_i$ and $Hardware_i$ are correlated at $\rho = 0.53$ in our sample, including $Upstream_i \times Post_t$ partitions the same within-hardware gradient across two separately-underidentified pieces ($\hat{\beta}_{U\times P} = -0.036$, $p = 0.34$; $\hat{\beta}_{U\times H\times P} = -0.046$, $p = 0.31$); their sum, the within-hardware total gradient, equals -0.082 (SE $= 0.025$, $p = 0.001$), identical to our preferred specification.

Results

Before presenting the main findings, we will verify that the parallel trends assumption holds in our design. This is key to causal identification under the DiD, because the assumption justifies using the control group's pre-to-post change as the counterfactual trend for the treated group. If parallel trends hold, any additional post-treatment divergence between treated and control groups can be interpreted as the causal effect of the treatment. As a first cut, we conduct a Wald test, testing the joint null hypothesis that all pre-treatment event study coefficients equal zero, and we fail to reject the null, meaning that there is no evidence that contradicts the parallel trends assumption. We find further supporting evidence using an event study. As shown in Figure 1 and Figure 2, the pre-treatment coefficients are individually close to zero and statistically insignificant, as well as jointly indistinguishable from zero.

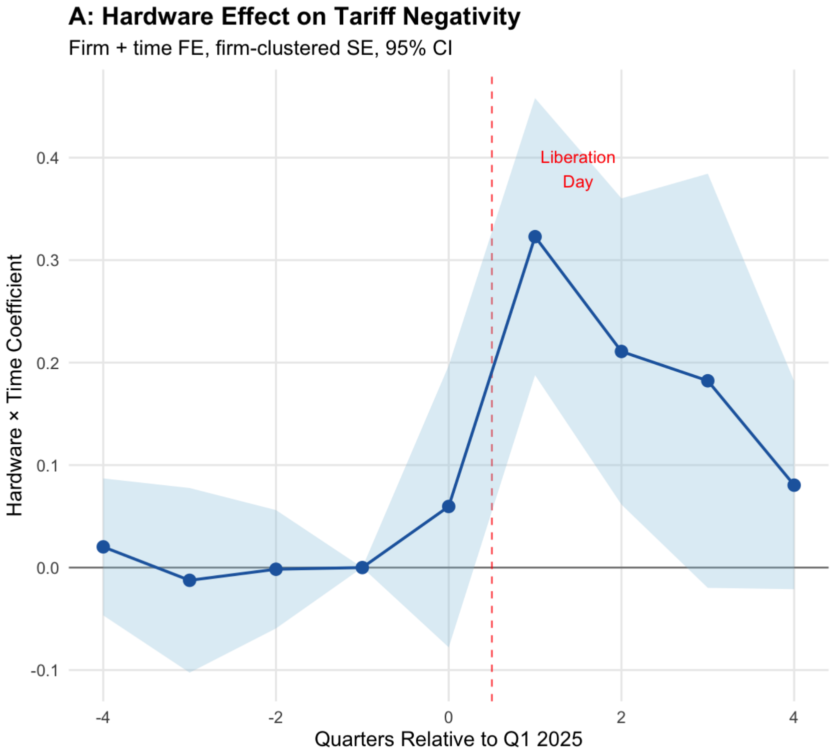

Figure 2: Tariff Negativity of Hardware Firms

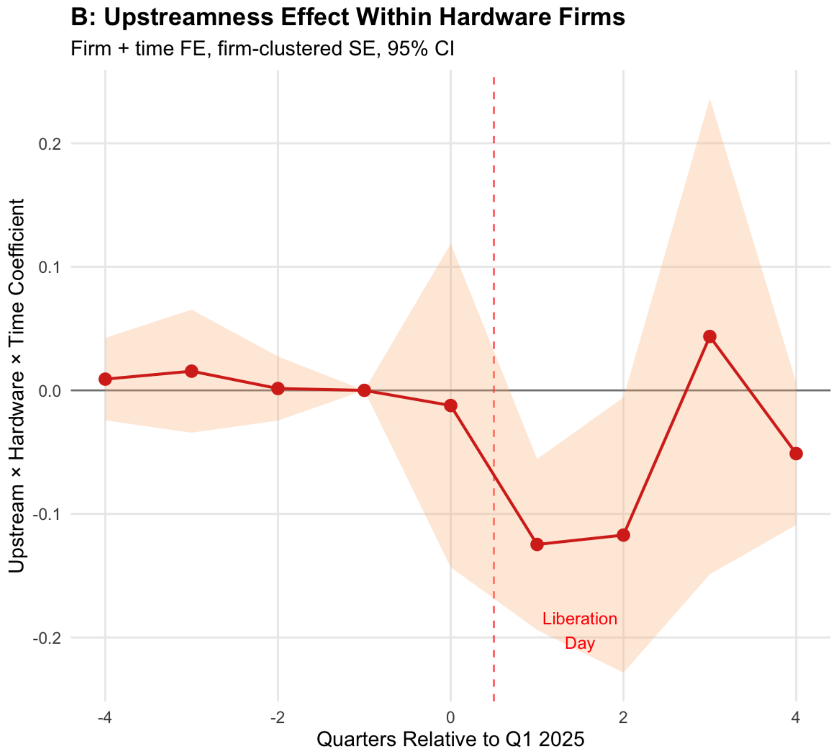

Figure 3: Effects of Upstreamness on Hardware Firms' Negativity

In addition, we have strong descriptive evidence that the Liberation Day tariffs dramatically altered the salience of trade policy in firm communications. Figure 3 plots the share of firm-quarter observations in which the LLM coding procedure detects any tariff-related discussion (i.e., observations with tariff negativity score more than zero) by calendar quarter. Throughout 2024, fewer than 5% of earnings call transcripts in our sample contain any tariff-related discussion. This share rises modestly to 22% in Q1 2025 as Trump's tariff agenda became increasingly central to the political conversation following his return to office. Following Liberation Day on April 2, 2025, tariff discussion appears in 75% of Q2 2025 transcripts — a 15-fold increase from the 2024 baseline. The share declines through Q3 and Q4 2025 as firms adapt to the new policy environment, then drops sharply to 25% in Q1 2026 following the Supreme Court's invalidation of the

IEEPA tariff regime.[7] The trajectory closely tracks specific policy events — pre-election baseline, anticipation, treatment onset, and treatment removal — providing strong descriptive evidence that the Liberation Day shock changed how firms communicate about trade policy. The close correspondence between our LLM-coded salience measure and the timeline of independently verifiable policy events further validates the construct validity of the coding procedure: the measure tracks the actual policy environment rather than picking up unrelated linguistic variation.

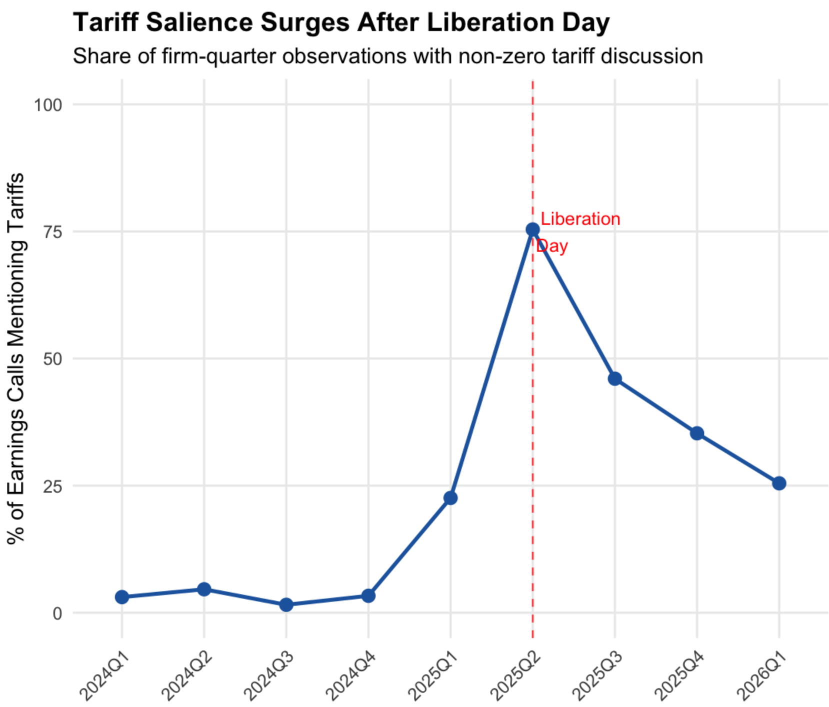

Figure 4: Tariff Salience Across Quarters

Our main results are in Table 1. Overall, they provide strong support for H2 and H2a. Hardware firms became more negative toward tariffs than software firms following

7. The International Emergency Economic Powers Act (IEEPA) is a 1977 Federal statute granting the President broad authority to regulate international commerce and financial transactions during a declared national emergency. President Trump relied on this authority to impose sweeping tariffs in April 2025, and On February 20, 2026, the U.S. Supreme Court overturned those tariffs in Learning Resources, Inc. v. Trump and Trump v. V.O.S. Selections, Inc., ruling that IEEPA does not grant the power to set tariffs.

Liberation Day by 0.139 points (Model 2), and within hardware firms, a one-standard-deviation increase in upstreamness reduces this effect by 0.082 points (Model 3). The level effect is robust under cluster-robust inference at the 1% level, and the within-hardware gradient remains significant at conventional levels under both CR2 cluster-robust standard errors with Satterthwaite degrees of freedom ($p = 0.034$) (Bell and McCaffrey 2002; Pustejovsky and Tipton 2018) and the restricted wild cluster bootstrap with Webb 6-point weights ($B = 9{,}999$, $p = 0.031$) (Cameron, Gelbach, and Miller 2008; MacKinnon and Webb 2018). Our result is also robust to leave-one-cluster-out validation: across all 32 specifications that drop each hardware firm in turn, the coefficient remains significant at the 1% level, with point estimates in $[-0.097, -0.064]$. In contrast, the coefficient of Upstream $\times$ Post in Model 1 is small and not statistically significant. This null result is consistent with our framework: our theory predicts that upstreamness affects tariff attitudes primarily through customs exposure, which operates only on firms whose products take physical form and cross customs borders. A general upstreamness gradient extending to digital firms is not implied by our argument, and the within-digital point estimate is correspondingly small (Table 2). The gradient should therefore be concentrated among customs-exposed firms, which is what Models 2 and 3 demonstrate directly.

To test this interpretation, we estimate the upstream effect separately within digital and hardware firms (Table 2). Among digital firms, upstreamness has no effect on tariff negativity, confirming that GVC position is irrelevant when products do not cross customs borders. Among hardware firms, the upstream effect is negative and significant. The split-sample analysis is inherently more sensitive than the full-sample interaction because

Table 1: Difference-in-Differences Estimates of Tariff Negativity

	(1) Baseline	(2) H2	(3) H2 + H2a
Upstream × Post	−0.002		
	(0.026)		
Hardware × Post		0.139***	0.184***
		(0.044)	(0.042)
Upstream × Hardware × Post			−0.082***
			(0.025)
Firm FEs	Yes	Yes	Yes
Quarter FEs	Yes	Yes	Yes
Observations	486	486	486

Notes: Standard errors clustered at the firm level in parentheses. Hypothesis labels follow the theory section: H2 = hardware firms more negative toward tariffs; H2a = upstream hardware firms less negative than downstream ones. The within-hardware gradient (H2a) remains significant at conventional levels under both CR2 cluster-robust standard errors with Satterthwaite degrees of freedom ($p = 0.034$) and the restricted wild cluster bootstrap with Webb weights ($B = 9{,}999$, $p = 0.031$).

$^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

it re-standardizes upstreamness within each subsample and operates on smaller N. The role of the split-sample analysis here is supplementary: it directly demonstrates that upstreamness has no effect among digital firms, and the effect still persists with hardware firms, validating our exclusion of the $Upstream_i \times Post_t$ interaction term.

Table 2: Split-Sample Analysis: Upstream Effect by Hardware Status

	(1) Digital Firms	(2) Hardware Firms
Upstream × Post	−0.029	−0.070***
	(0.032)	(0.022)
Firm FEs	Yes	Yes
Quarter FEs	Yes	Yes
Observations	243	243

Notes: Standard errors are clustered at the firm level in parentheses. Upstreamness is standardized within each subsample, so coefficients are on within-group scales and are not directly comparable in magnitude to the triple in Table 1.

$^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

To further probe our parallel trends assumption, we calculate the raw mean of tariff negativity through all of our time horizon. If there is no differentiation between hardware and software firms in the pre-treatment period, then the parallel trends assumption is not violated. Figure 5 illustrates this clearly: before Q1 2025, hardware and digital companies have mostly identical attitudes towards tariffs, and mostly insignificant and close to zero. Right after Q1 2025, though both types of firms are more pessimistic about tariffs, hardware firms become noticeably more negative afterwards, which can be explained by the anticipation effect. Accordingly, firms across both categories began discussing tariffs more frequently as Trump's hardline trade rhetoric intensified, and showed their uncertainty about the negative effects of tariffs on their business. The differential response emerges only at 2025 Q2, immediately following Liberation Day, when hardware firms diverge sharply upward while digital firms increase only modestly. Interestingly, we also see a steep decrease in negativity of hardware firms in Q1 2026, right after the Supreme Court struck down Trump's tariffs. This reconvergence of the two groups after the Supreme Court's invalidation ruling strengthens our causal finding: the cleavage in negativity disappears right after the treatment is removed.

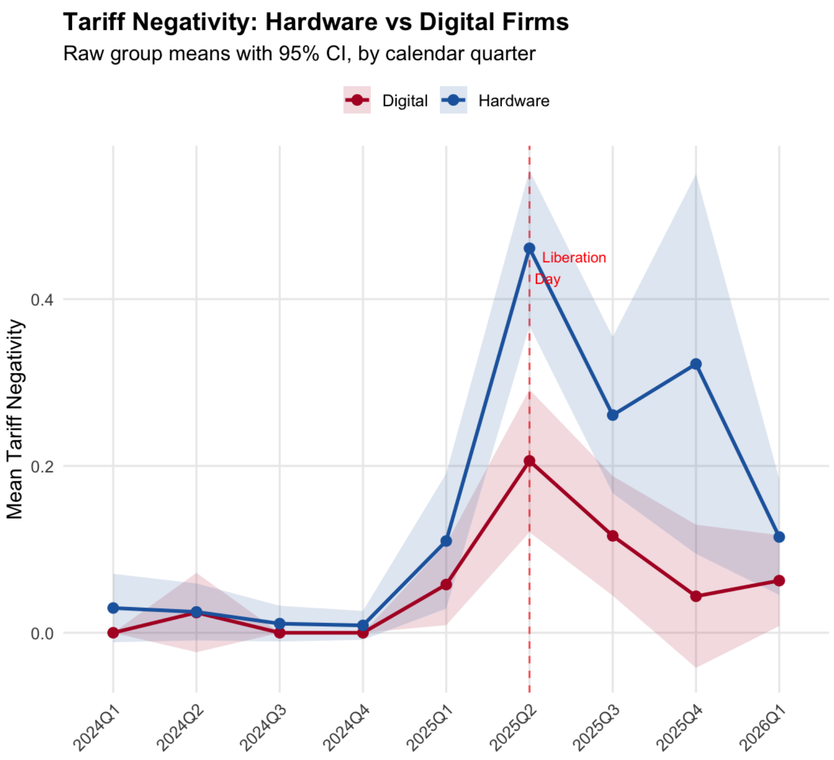

Figure 5: Mean Tariff Negativity

Preference Validation: Tariff-Related Lobbying Patterns

To examine whether the attitude towards tariffs extracted from earnings call scripts is consistent with business preferences, not just the artifact of strategic communication, we look at the pattern of how firms lobby for trade and tariff-related issues, and which agents they target. Lobbying is one of the most important political channels for firms to advocate for their preference (Grossman and Helpman 1994; Woll 2008; Kim 2017; Baumgartner et al. 2009; Schnakenberg 2017). Therefore, if the lobbying patterns are consistent with the tariff salience, it is plausible to say that firms reveal their true preference in their calls.

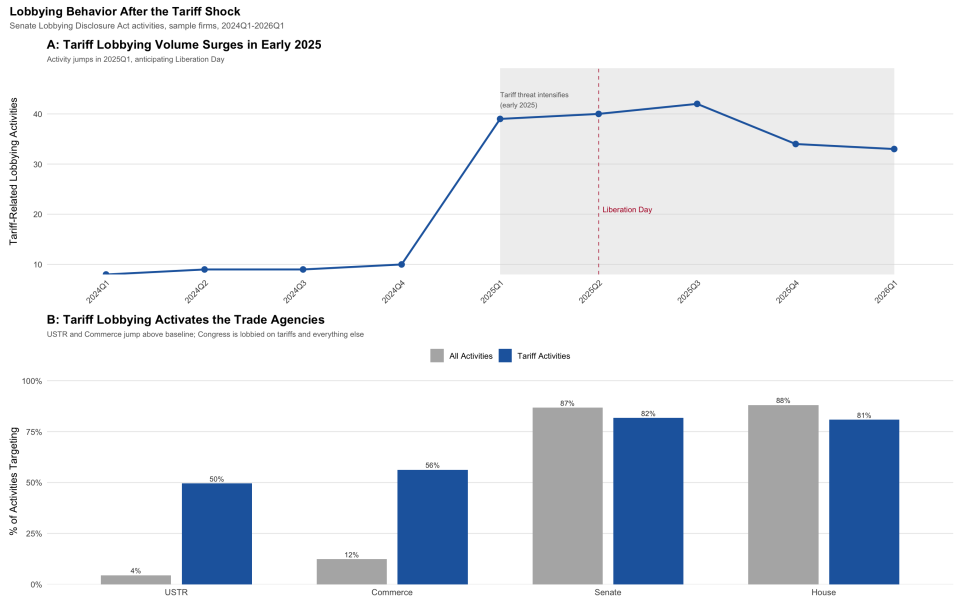

Figure 6: Tariff-Related Lobbying Behavior

Looking at Figure 6, we can see a consistent pattern of lobbying with a rising concern about tariffs in firms' earnings calls in Panel A. There is a surge in lobbying activities in the early of 2025, right after Trump took office, and the trend has been stable since then. Although firms could theoretically lobby for *more* tariffs, which goes against our story, we contend that under the context of tariffs proposed by Trump, this is not the case. This tariff regime is considered as the most sweeping one in U.S modern history, and it was expected to have devastating effect on the American economy and business activities, albeit at varying degrees (York and Durante 2026). It is thus unlikely that firms would lobby *for* such an economically destructive regime. In other words, we can be confident to say that the surging lobbying activities since Q1 2025 are *against* tariffs. Because of that, the intensification in tariff-related lobbying activities, combined with the shift of tariff salience and negativity, tells a coherent story: firms are not only showing unfavorable attitude towards tariffs but making effort to mitigate the cost to their business. Panel

B reinforces what we have so far. Compared to other activities/baseline, tariff-related lobbying is more clustered in the United States Trade Representative and the Department of Commerce. Obviously, this pattern is institutionally consistent: the 2025 tariffs were imposed and administered by executive agents, not legislative ones. As expected, when firms advocate for their interests, they would target towards the venues that are directly involved in the process. Taken together, our interpretation that earnings calls reflect genuine, costly political engagement and preference rather than cheap talk or strategic firm-to-firm communication are strongly supported.

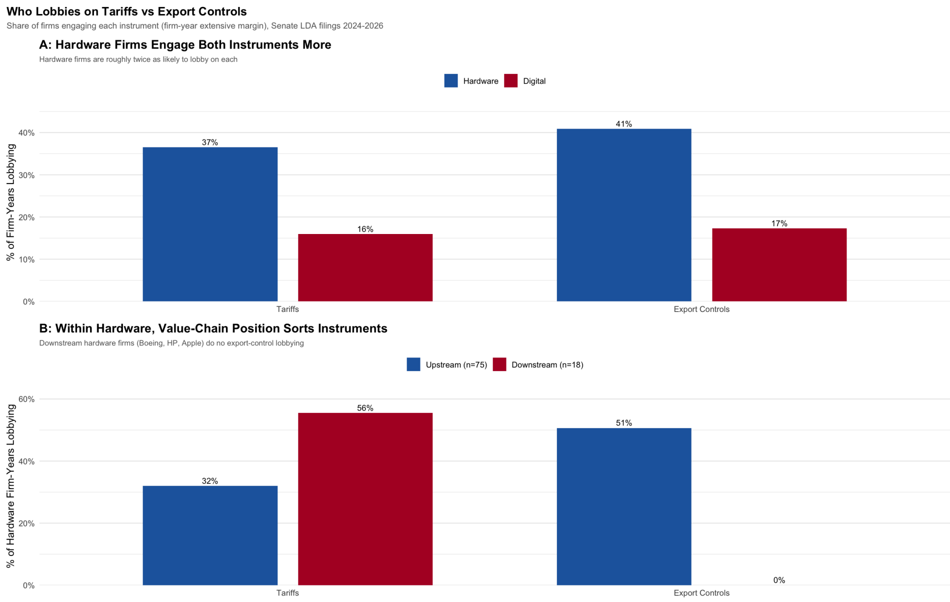

Figure 7: Tariff and Export-Control Lobbying by Firm Type

The lobbying evidence also recovers the heterogeneity organizing our main results. Figure 7 disaggregates lobbying by firm type, using the share of firms in each group that engage a given instrument. Hardware firms are roughly twice as likely as digital firms to lobby on both tariffs (37% versus 16%) and export controls (41% versus 17%), illustrating the rhetorical hardware-digital divide in their perception of tariffs and related instruments and confirming it is a feature of how firms act, not merely how they talk. Within hardware, value-chain position sorts firms across instruments: downstream producers such as Boeing, HP, and Apple concentrate on tariffs (56% of firm-years) and does not engage with export-control lobbying, while roughly half of upstream semiconductor firms lobby on export controls (51%). This reflects the structure of exposure: downstream firms bear tariff costs on imported goods, whereas upstream firms' principal vulnerability is restriction of their China sales. This divergence also provides a behavioral counterpart to the forbearance of upstream firms in our main analysis. That said, the within-hardware comparison rests on a modest number of clearly downstream hardware firms so we read it as descriptive corroboration rather than an estimated effect.

Discussion

Our results point to a coherent story: under the rising tension between the United States and China, American high-tech firms are divergent in their perception of tariffs, and such divergence depends on their key product and their position in the supply chain. Geoeconomically, the former determines how easy it is to mobilize a firm; the latter is about whether a firm is strategically substitutable, and they interact with each other in shaping the attitude and behavior of a company. Our theory is not only limited to high-tech firms, but also applies to those in other critical sectors. This is clearly demonstrated in the financial sector. The United States has been mobilizing the Society for Worldwide Interbank Financial Telecommunication (SWIFT) for decades against Iran and Russia [8]. Given its unsubstitutability in the financial system and the centrality of its product -

8. Some of SWIFT's key members, including The Goldman Sachs, JPMorgan, are ambiguous at best about tariffs. See: https://www.cnbc.com/2025/04/11/jpmorgan-chase-jpm-earnings-q1-2025.html; https://www.cnbc.com/2025/04/14/goldman-sachs-gs-earnings-q1-2025.html

financial infrastructure - it comes as no surprise that the organization and its members are integral in American geoeconomic apparatus (Fishman 2025; Cipriani, Goldberg, and La Spada 2023; Bapat et al. 2024).

The cleavage among American high-tech firms has profound implications for policymakers. First and most importantly, although tariffs are designed as an instrument to achieve foreign economic objectives, their effectiveness is questionable, as there is a potential resistance from firms that are expected to follow the flag. Accordingly, with the variation of negativity among American hardware firms, tariffs might not be fully imposed, because those that are heavily affected would attempt to stop or delay tariffs, either collectively or individually, as happened in the history of American international trade (Irwin 2017; Milner 1988; Woll 2008). This pushback could eventually undermine American geoeconomic power in general, given the dominance of American tech firms, especially in hardware, in the global economy. Additionally, tariffs might cause collateral damage to the American economy if hurting its tech companies. American high-tech firms have strong integration into Chinese market and industrial base, and they are indispensable to the American economy and the global economy (Hogg, Cimerman, and Johnson 2025; Wolf and Terrell 2016). If China keeps intensifying its retaliation against the American tariffs or geoeconomic pressure, these companies would lose revenue that is central to their research and development activities (Leahy, Hu, and Sevastopulo 2026). To the extent that these measures impose sustained revenue costs on American hardware firms, they create risk of cumulative erosion in competitive position and innovation capacity over the medium term. Paradoxically, the instrument intended to strengthen American economic security may, through retaliation and integration effects, weaken the firms that constitute the backbone of American economic power.

Conclusion

The divergence of American tech companies in their response to tariffs is both theoretically puzzling and empirically under-tested, as existing frameworks have not fully explained this phenomenon. Through the geoeconomic lens, we provide a new insight to explain the behavior of firms against the background of tariffs, and more broadly economic tension. Although we do not claim that this is the only factor accounting for the cleavage, we believe that our geoeconomic argument is valuable to the literature of IPE, and to some extent international security. Geoeconomics is an emerging line of research in IPE in the last decade, but there are very few studies looking at tariffs as a geoeconomic instrument, and how firms matter geoeconomically from that perspective. Therefore, our findings shed more light on the understanding of tariffs and the active role of firms as geoeconomic players, which questions part of the literature assuming that firms passively follow the flag and do not have geoeconomic preferences. Our findings are also relevant to the international security literature. Economics is now a critical dimension of national security, and the use of tariffs has been justified for national security purposes. As a result, big firms, in particular high-tech ones, are now playing a more significant role in the economic security apparatus, thanks to their resources and expertise as well as their technological dominance. Understanding how big tech companies differ in their perception of tariffs is thus necessary to examine their influence in the making and implementation of security policy.

Notwithstanding its contributions, this paper has some limitations. Due to data availability, we only focus on American companies, which makes our results less generalizable compared to cross-national analysis. Though leading high-tech companies are relatively homogeneous in their incentive structure and their supply chain characteristics, future studies can expand the analysis to non-American tech companies to stress-test the geoeconomic framework. Next, while the LLM-coded upstreamness works well for our design, we acknowledge that using existing firm-level supply chain data would be more standardized and allow us to capture more important features such as buyer-supplier relationships and input-output tables. Nevertheless, our research paves the way for other studies using the same LLM-based approach to extract more fine-grained firm-level supply chain information and triangulate with other established data sources to verify how good LLMs are in extracting firm-level features. In addition to that, our empirical setting is, to some extent, idiosyncratic to American trade policy: the tariffs applied unusually broad rates across many trading partners simultaneously, and reflected a distinctive administration's trade ideology. Granted, this setting offers several methodological advantages: sweeping scope and rate, disruptive, yet judicially invalidated later on, providing clean identification that more gradual tariff implementations would not afford. However, future research could improve on what we have by expanding to other tools, including but not limited to CHIPS Act allocation patterns, export controls, investment screening, or reciprocal foreign measures, which are all fruitful directions for further studies of the geoeconomic framework. In conclusion, tariffs are no longer purely economic instruments, and firms are no longer purely economic actors so the comprehension of geoeconomic logic that binds them together is a useful step toward making sense of the political economy of great-power rivalry.

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Appendix

Descriptive Statistics & Validation

A1. Summary Statistics

The estimation sample comprises 486 firm-call observations (286 pre-treatment, 200 post-treatment) across 65 firms (32 hardware, 33 digital). Table A1 reports mean tariff negativity by period, by sector and period, and by within-hardware upstreamness tercile; Table A2 lists the firms with the highest mean post-treatment tariff negativity.

Table A1: Descriptive Statistics: Tariff Negativity

Panel A. By period

Period	N	Mean	SD	Nonzero
Pre	286	0.0287	0.1170	21
Post	200	0.2080	0.2640	98

Panel B. By sector and period

Sector	N_{Pre}	N_{Post}	Pre	Post	Δ (Post−Pre)
Digital	143	100	0.0185	0.1250	0.1065
Hardware	143	100	0.0388	0.2910	0.2522
DiD (Hardware − Digital)					**0.1457**

Panel C. By upstreamness tercile (hardware firms)

Tercile	N_{Pre}	N_{Post}	Pre	Post	Δ (Post−Pre)
Low	46	35	0.0587	0.3870	0.3283
Mid	49	32	0.0214	0.2330	0.2116
High	48	33	0.0375	0.2460	0.2085

Notes: Unit of observation is the firm-call. "Nonzero" (Panel A) counts observations with strictly positive tariff negativity. Δ is the within-group post-minus-pre change in the mean; the DiD row in Panel B reports the raw (uncontrolled) 2×2 difference-in-differences. Panel C terciles are formed on fixed pre-treatment upstreamness within the 32 hardware firms; cell counts are small and the upstreamness gradient is estimated on continuous standardized upstreamness in the main regression (Model 3).

Table A2: Top 15 Firms by Post-Treatment Tariff Negativity

Rank	Firm	Tariff neg.	Upstreamness	Type
1	RTX	0.775	0.500	Hardware
2	QVCGA	0.700	−0.860	Digital
3	NVDA	0.662	0.520	Hardware
4	CNXC	0.633	0.067	Digital
5	AAPL	0.567	−0.600	Hardware
6	HPQ	0.550	−0.600	Hardware
7	AMAT	0.518	0.980	Hardware
8	EBAY	0.500	−0.720	Digital
9	GE	0.500	0.600	Hardware
10	SMCI	0.500	0.680	Hardware
11	MSI	0.467	0.075	Hardware
12	CDW	0.450	−0.200	Digital
13	ADI	0.438	0.750	Hardware
14	HWM	0.433	0.720	Hardware
15	AMZN	0.417	−0.120	Digital

Notes: Mean post-treatment tariff negativity by firm. Upstreamness is the fixed pre-treatment score.

A2. Sample Construction and Firm List

Our analysis uses 486 earnings call transcripts from 65 US-listed firms in the technology and defense sectors, covering nine consecutive quarters from Q1 2024 through Q1 2026. The sample comprises Fortune 500 firms in our target sectors with continuous quarterly reporting through the sample window. Transcripts were obtained from Capital IQ and parsed into a structured panel using custom Python preprocessing.

Firms are organized into the following sectoral tiers. The tier assignment is the primary input to the hardware indicator; the indicator itself is constructed at the firm level using the rule described below to handle within-tier heterogeneity.

- **Semiconductors (9):** ADI, AMD, AVGO, INTC, MCHP, MU, NVDA, QCOM, TXN
- **Semiconductor Equipment (3):** AMAT, KLAC, LRCX

- **Semiconductors/EMS (1):** SANM
- **Hardware/Systems (6):** AAPL, DELL, HPE, HPQ, SMCI, WDC
- **Networking/Cybersecurity (4):** APH, CSCO, MSI, PANW
- **Defense/Aerospace (10):** BA, GD, GE, HII, HWM, LHX, LMT, NOC, RTX, TDG
- **IT Services/Defense (5):** BAH, CACI, KBR, LDOS, SAIC
- **IT Services (7):** CDW, CNXC, CTSH, DXC, IBM, KD, NSIT
- **Software/Cloud (7):** ADBE, CRM, INTU, MSFT, NOW, ORCL, WDAY
- **Internet/E-Commerce (13):** ABNB, AMZN, BKNG, CHWY, CPNG, DASH, EBAY, EXPE, GOOGL, META, QVCGA, UBER, W

Hardware indicator construction. The hardware indicator equals 1 for firms whose primary revenue stream consists of physical goods that cross customs borders, and 0 otherwise. By tier, this includes all firms in Semiconductors, Semiconductor Equipment, Semiconductors/EMS, Hardware/Systems, and Defense/Aerospace. The Networking/Cybersecurity tier is split at the firm level by dominant product: Amphenol (APH), Cisco (CSCO), and Motorola Solutions (MSI) produce physical networking and electronic-component hardware and are coded as hardware; Palo Alto Networks (PANW) delivers primarily software and cloud-based cybersecurity and is coded as digital. The IT Services/Defense tier (BAH, CACI, KBR, LDOS, SAIC) is coded as digital, as these firms' revenue is predominantly from professional services and systems integration rather than physical goods crossing customs. The remaining digital tiers (IT Services, Software/-Cloud, Internet/E-Commerce) are coded as digital throughout. This procedure yields **32 hardware firms and 33 digital firms**.

The complete coded list:

- **Hardware (32):** AAPL, ADI, AMAT, AMD, APH, AVGO, BA, CSCO, DELL, GD, GE, HII, HPE, HPQ, HWM, INTC, KLAC, LHX, LMT, LRCX, MCHP, MSI, MU, NOC, NVDA, QCOM, RTX, SANM, SMCI, TDG, TXN, WDC
- **Digital (33):** ABNB, ADBE, AMZN, BAH, BKNG, CACI, CDW, CHWY, CNXC, CPNG, CRM, CTSH, DASH, DXC, EBAY, EXPE, GOOGL, IBM, INTU, KBR, KD, LDOS, META, MSFT, NOW, NSIT, NSIT, ORCL, PANW, QVCGA, SAIC, UBER, W

A3. Illustrative Tariff Discussion Excerpts

To validate the face validity of the LLM-coded tariff negativity measure, this section presents excerpts from earnings call transcripts with high LLM-assigned scores. The excerpts demonstrate that high-scoring observations correspond to substantive, interpretable discussion of tariff costs and policy uncertainty rather than superficial keyword matches.

NVIDIA (2025Q2): "On April 9, the U.S. government issued new export controls on H20, our data center GPU designed specifically for the China market.... We were unable to ship $2.5 billion in H20 revenue in the first quarter due to the new export controls.... Export controls should strengthen U.S. platforms, not drive half of the world's AI talent to rivals."

GE Aerospace (2025Q2): "The global aviation sector has long operated without tariffs on civil aircraft, engines and avionics. We'll continue to advocate for an approach that reestablishes zero-for-zero tariffs in the aviation sector.... The tariffs in aviation really aren't good for anybody."

Apple (2025Q3): "For the June quarter, we incurred approximately \$800 million of tariff-related costs. For the September quarter, assuming the current global tariff rates, policies and applications do not change... we estimate the impact to add about \$1.1 billion to our costs."

Raytheon (2025Q2): "The aerospace and defense sector has operated in a duty-free environment, and that has been instrumental to the industry maintaining one of the largest trade surpluses across American manufacturing industries for decades.... With respect to China, at current U.S. and China tariff rates, we estimate there would also be a cost impact of around \$250 million."

Boeing (2025Q2): "I would break this down into two categories: input tariffs that affect our cost to manufacture our products, and then the potential impact of retaliatory tariffs like those we are seeing in China.... The only region that we have an issue with aircraft delivery today is China, and due to the tariffs, many of our customers in China have indicated they will not take delivery."

HP Inc. (2025Q2): "Due to additional tariff costs that could not be fully mitigated in the quarter, our non-GAAP operating profit fell short of expectations.... Our operating margin was impacted by net tariff costs, mainly in Personal Systems."

Applied Materials (2025Q4): "The cost reductions were offset to some degree by tariff headwinds and by some of the inventory management."

A4. Illustrative Business Model Excerpts: Upstream vs. Downstream

To validate the face validity of the LLM-coded upstreamness measure, this section presents business model excerpts from firms at the upper and lower extremes of the upstreamness distribution. High-upstream firms describe themselves in terms of equipment, components, and manufacturing embedded within other firms' production processes. Low-upstream firms describe themselves in terms of users, guests, consumers, and customer experience.

Panel 1: High Upstream Firms (Inputs to Other Firms' Production)

Lam Research (0.99): "Our cobot technology offers an important and cost-effective solution to enable precise and repeatable maintenance beyond what human workers alone can achieve... inside the fab."

Applied Materials (0.98): "Our innovations are enabling the major device architecture inflections that are critical to advancing energy-efficient AI... We track many of your end customers in the semiconductor industry, both fabless and IDMs."

KLA Corp. (0.96): "We have to deal with some inefficiency as we've staffed up to support those fabs and now we have to move those folks to support other customers... Logic/Foundry chip makers at the leading edge."

Amphenol (0.84): "This revolution in AI continues to create a unique opportunity for Amphenol given our leading high-speed and power interconnect products... manufacturing presence around the world, new factories in Southeast Asia, North America, Mexico, Eastern Europe, North Africa."

Micron (0.80): "Manufacturing elements that we're integrating together on the front end to be able to really deliver that higher performance... new technologies in process flow for assembly and test, which will enable us to deliver the high volumes of integrated HBM cubes."

Panel 2: Low Upstream / Downstream Firms (Final Products to End Users)

Apple (−0.60)**:** "We love hearing from customers who are discovering for the first time the versatility of iPad, from the ultra-portable iPad mini built from the ground up for Apple Intelligence to the powerful M4 iPad Pro... iPad is there for our users whenever they need it."

Booking (−0.65)**:** "At Booking Holdings, we have always been driven by innovation... consumer adoption of mobile apps to using sophisticated machine learning models early in our business, we have consistently evolved to meet the needs of travelers and partners."

Airbnb (−0.68)**:** "We want to be very mindful of the guest journey and to be very thoughtful with regard to both personalization and timing around what type of products are we merchandising to the customer."

eBay (−0.72)**:** "As we look at our U.K. initiative... the changes we're making across key parts of the C2C experience will allow us to unlock the sizable market opportunity from the vast array of unique inventory sitting in U.K. consumers' homes."

Chewy (−0.85): "E-com has picked up a bigger share of that normalization and conversion relative to the other channels…there's a lot of innovation internally that is customer-facing."

The linguistic contrast between panels is consistent across the full sample: upstream firms describe themselves in terms of inputs, components, fabs, and integration into downstream production; downstream firms describe themselves in terms of users, guests, customer experience, and end-user satisfaction.

A5. Cross-Model Reliability: GPT vs. Claude

To assess robustness to LLM coder choice, we re-coded a random subsample of 50 transcripts ($N = 50$, ∼10% of the corpus) using Anthropic's Claude Sonnet, holding all prompts and scoring rubrics constant. The subsample was randomly drawn from the full corpus ($N = 486$) using a fixed seed for reproducibility, and both coders applied identical scoring prompts, response schemas, and temperature settings. Inter-coder reliability statistics are reported in Table A3.

Table A3: Inter-Coder Reliability: GPT-5.4-mini vs. Claude Sonnet

	Tariff Negativity	Upstreamness
Spearman ρ	0.961^{***}	0.891^{***}
Pearson r	0.978^{***}	0.875^{***}
Mean (GPT)	0.085	0.183
Mean (Claude)	0.052	0.010
SD (GPT)	0.191	0.606
SD (Claude)	0.119	0.628
N	50	50

$^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

We report two complementary measures of inter-coder agreement. Spearman's rank correlation (ρ) measures the strength of monotonic association between coders' scores, capturing whether the two models rank firms similarly regardless of the absolute magnitudes they assign. A Spearman ρ of 1.0 indicates that both coders produce identical orderings; values above 0.80 are conventionally interpreted as strong agreement (Schober, Boer, and Schwarte 2018). Pearson's r measures the strength of linear association and is more sensitive than Spearman to differences in absolute scoring level. Reporting both statistics allows us to distinguish agreement on ordering (Spearman) from agreement on magnitudes (Pearson). Agreement on either measure exceeds conventional thresholds for inter-coder reliability with continuous measures (Krippendorff 2018).

For our research design, Spearman ρ is the more substantively relevant statistic. Our main specification uses within-firm and within-quarter variation, captured by firm and calendar-quarter fixed effects, which absorb any systematic level differences between coders. What matters for identification is whether the two LLMs produce consistent *rankings* of firms on the tariff negativity and upstreamness dimensions — not whether they produce identical numerical scores. The Spearman correlations of 0.961 for tariff negativity and 0.891 for upstreamness indicate that the rank ordering of firms is highly stable across coders. The corresponding Pearson correlations (0.978 and 0.875) further indicate that, conditional on rank ordering, the two coders also produce scores that are linearly proportional to one another. Together, these statistics provide strong evidence that our measures capture genuine structural and rhetorical differences across firms rather than model-specific artifacts of language interpretation.

The modest downward shift in Claude's mean scores, particularly for upstreamness, where the gap is approximately 0.17, reflects differences in how the two models interpret the scoring rubric's anchors, not disagreement about substantive content. Claude appears to apply a somewhat more conservative threshold for assigning extreme scores at both ends of the scale, while GPT-5.4-mini extends more readily toward the boundaries. This produces a compression of Claude's distribution rather than reordering. Because our regression specification includes firm fixed effects, any constant difference in scoring level between coders is absorbed and does not affect the estimated treatment effects. The within-firm variation that drives our identification is preserved across coders, as evidenced by the high rank correlations.

We also examine agreement at the distribution extremes, where face validity considerations are sharpest. Among the ten firm-quarter observations with the highest GPT-coded upstreamness scores, nine receive Claude scores above 0.50, with Applied Materials (1.00), Lam Research (1.00), and Texas Instruments (0.80) achieving near-identical scores under both coders. The single exception is Dell, which scores 0.80 under GPT but 0.40 under Claude, reflecting a substantive ambiguity in classification, as Dell occupies an intermediate position selling both enterprise hardware (upstream-leaning) and consumer products (downstream-leaning). Among the ten firm-quarter observations with the lowest GPT-coded upstreamness scores, all ten receive Claude scores at or below 0.60, with consumer-facing platforms (Wayfair, Airbnb, Booking, Chewy, eBay) clustering at the bottom under both coders. This convergence at the distribution extremes, and particularly the strong agreement at the downstream end where consumer-facing firms cluster, is especially important for our identification strategy: the firms whose scores anchor the upstream and downstream ends of the distribution are precisely the firms whose contrast drives the within-hardware upstream effect documented in Model 3 of Table 1. These results provide strong evidence that our LLM coding procedure is robust to coder choice. While we use GPT-5.4-mini as the primary coder due to its lower cost and faster throughput across the full 486-transcript corpus, the substantive findings would be expected to hold under Claude-coded measures, given the high rank correlation and preserved ordering at the distribution extremes.

A6. LLM Prompts

We reproduce the full set of prompts used in the LLM coding pipeline (in Python) below. The extraction prompt (Stage 1) is applied to the full transcript; the three scoring prompts (Stage 2) are applied to the extracted passages. We use the same prompt for both our baseline OpenAI and our cross-validiation Claude coding schemes.

Extraction Prompt

```
You are extracting relevant passages from an earnings call transcript.

TASK: Find and extract VERBATIM quotes for THREE categories, plus a company summary.

CATEGORY 1: TRADE & POLICY ENVIRONMENT (DIRECT)
Extract ANY passage that EXPLICITLY touches on trade, tariffs, or policy by name:
- Tariffs, duties, Section 301/232, trade war, trade policy
- Import/export restrictions, customs, trade tensions
- Reshoring, nearshoring, onshoring
- CHIPS Act, IRA, government subsidies tied to domestic production
- Export controls, sanctions, entity lists
```

- Trade agreements, negotiations, deals

CATEGORY 2: TRADE-ADJACENT LANGUAGE (INDIRECT/LATENT)

Extract passages that DO NOT name tariffs but discuss phenomena PLAUSIBLY

CONNECTED to the trade environment. Cast an EXTREMELY WIDE net:

- Input cost increases, component cost volatility, margin pressure from sourcing
- Supply chain restructuring, diversification, dual-sourcing, shifting production
- China business: revenue, customers, competition, operations
- Manufacturing geography: where products are made, why certain locations
- Geopolitical risk or uncertainty
- Government incentives, subsidies, grants, tax credits
- Competitive framing against foreign firms
- Inventory strategy changes plausibly linked to supply uncertainty
- Pricing actions attributed to cost environment
- Capital expenditure shifts toward domestic capacity
- ANY mention of specific countries in supply chain context

CATEGORY 3: BUSINESS MODEL

- What products/services the company makes
- Who their customers are
- Revenue breakdown by segment/customer type
- Position in supply chain

COMPANY DESCRIPTION: Always provide a one-sentence description.

RULES:

- Extract VERBATIM quotes, 1-3 sentences each, max 100 words
- Up to 10 quotes per Category 1, up to 15 per Category 2

- When in doubt, INCLUDE IT

- ALWAYS provide company_description

Tariff Negativity Prompt

```
You are measuring how NEGATIVELY a firm frames tariffs and trade restrictions.

TARIFF_NEGATIVITY (0-1):
0.0 = no mention or positive/neutral framing
0.1-0.2 = passing mention with mild concern
0.3-0.4 = clear discussion of costs/challenges
0.5-0.6 = meaningful business problem, specific costs named
0.7-0.8 = serious threat, financial impact quantified
0.9-1.0 = severely damaging, explicit opposition

SILENCE = 0.0. Score OBSERVABLE TEXT only.

TARIFF_IMPACT (-1 to +1): Economic effect regardless of framing.
+1=strong beneficiary, -1=severely harmed, 0=neutral.

TARIFF_SALIENCE (0-1): How prominently tariffs feature.
0=not mentioned, 1=dominant topic.

EVIDENCE_TYPE: explicit | implied | contextual | no_signal
Use fine-grained scores.
```

Upstreamness Prompt

```
Determine firm’s position in the PRODUCTION VALUE CHAIN.
```

```
UPSTREAM (+1): Makes INPUTS for other companies' products
  (chips, components, cloud infrastructure, enterprise software platforms)
DOWNSTREAM (-1): Makes FINAL PRODUCTS for end users
  (consumer electronics, consumer software, retail, streaming)
MIDSTREAM (0): Mixed

SCORING:
+1.0 = Pure upstream (TSMC)
+0.8 = Heavily upstream (Qualcomm)
+0.6 = Mostly upstream (Intel)
+0.4 = Somewhat upstream (Nvidia)
+0.2 = Slight upstream lean (Microsoft)
 0.0 = Mixed
-0.2 = Slight downstream lean (Amazon)
-0.4 = Somewhat downstream (Meta)
-0.6 = Mostly downstream (Apple)
-0.8 = Heavily downstream (Netflix)
-1.0 = Pure downstream (Snap)

B2B  upstream. Key question: do products become INPUTS in other products?
CUSTOMER_TYPE: other_businesses | consumers | both | government
You MUST provide a score.
```

Latent Trade Environment Prompt

```
You are analyzing earnings call excerpts to measure how the TRADE POLICY
ENVIRONMENT manifests in a firm's communication. This is BROADER than
```

explicit tariff attitudes.

Score SEVEN dimensions:

1. TRADE_ENV_SALIENCE (0-1): How prominently does the firm discuss
trade-environment-adjacent topics? 0=none, 1=dominant theme.
Score based on PRESENCE, not valence.
0.0 = no trade-relevant discussion
0.05-0.15 = one or two brief mentions
0.2-0.3 = multiple references, some discussion
0.4-0.5 = clearly important topic
0.6-0.7 = major presence, shapes narrative
0.8-1.0 = dominant theme of the call

2. TRADE_NEGATIVITY_VALENCE (-1 to +1): Tone of trade-environment language.
-1=entirely negative, 0=neutral, +1=entirely positive.
If salience=0, set to 0.

3. SUPPLY_CHAIN_SHIFT (0-1): Discussion of restructuring/relocating supply chain.
4. CHINA_DISCUSSION (0-1): ANY discussion of China business/risk/opportunity.
5. COST_ATTRIBUTION (0-1): Attribution of costs to external/macro/policy factors.
6. MANUFACTURING_LOCATION (0-1): Discussion of WHERE firm manufactures and why.
7. GOV_INCENTIVE_DISCUSSION (0-1): Discussion of government subsidies/incentives.

EVIDENCE_TYPE: explicit_trade | trade_adjacent | contextual | no_signal
CONFIDENCE: 0.8+ extensive, 0.5-0.8 moderate, 0.3-0.5 limited, 0.1-0.3 weak

Use fine-grained scores (0.12, 0.35, 0.57). Score ALL dimensions.

A7. Human Validation

To ensure that our LLM-coded DV is precise, we get an research assistant to classify the tariff negativity based on earnings call scripts. Specifically, our research assistant was assigned 50 randomly selected transcripts from our sample (similar to the number of observations in our cross-model check, for consistency). Then the assistant was given a guidance on the rubric to score the negativity in the scale of 0 to 1, similar to the LLM prompt. To ensure that the variable is free-of-bias and independently validated, the assistant did not have any information on the LLM-coded values, and she has to justify her scoring. We use the same metrics as our cross-model validation above, and compare the human-coded negativity with the GPT-coded value. Our results are presented in the Table A4 below.

Table A4: Human Validation of LLM-Coded Tariff Negativity

	Spearman ρ	Pearson r
Tariff negativity (overall)	0.64***	0.45***
Tariff presence (exact agreement)	94%	

Notes: "Tariff presence" is exact agreement on whether a transcript contains any negative tariff discussion.

Overall, the correlation between human and GPT-coded value is acceptable, though weaker than that in the cross-model test. Human and model agree strongly on transcripts that actually discussed tariffs (94%)). The agreement with the ordering of negativity is relatively decent with 0.64 of Spearman score, meaning the assistant and the LLM are reasonably in line with each other on how they rank firms' tariff negativity. The Pearson score, which is about the linearity between two sets of raw score, while positively significant, is weaker than the Spearman one. This weaker linear relationship means that there is some degree of disagreement between the research assistant and the LLM. Although a more moderate relationship is far from ideal in our validation, this does not pose a significant problem to our key results. As tariff negativity is originally a continuous, fine-grained score, a low Pearson score is expected: human could catch the nuance and language subtlety very well, but the exact scoring on a continuous scale could be subjective and less standardized than the LLM, which leads to some discrepancies in the coding. Because the sample size is small, the results are highly sensitive to outliers, which, combined with the human subjectivity, explains the moderately weak Pearson score. Additionally, the Pearson score is still positively significant, and being juxtaposed with the Spearman score, we could still safely conclude that the human assistant and our LLM is still relatively in agreement with each other, which validates our LLM-coded values.

B. Robustness Tests

B1. Binary Dependent Variable

We binarize our dependent variable, 1 if a firm has a negative attitute towards tariffs in a given transcript (tariffs_negativity > 0), and 0 otherwise. This is the *extensive margins* of how salient tariffs are to their business, albeit less precise than our baseline outcome, which emphasizes the *intensive margins*. We re-run all of our specifications in the main text with this new variable, and the results are below.

Overall, the results are well aligned with our main specifications, with one small

Table B1: Robustness: Binary Dependent Variable

	(1) H1	(2) H2	(3) H2 + H2a
Upstream × Post	0.024		
	(0.043)		
Hardware × Post		0.237^{***}	0.281^{***}
		(0.081)	(0.079)
Upstream × Hardware × Post			-0.079^{*}
			(0.046)
Firm FEs	Yes	Yes	Yes
Quarter FEs	Yes	Yes	Yes
Observations	486	486	486

Notes: Standard errors clustered at the firm level in parentheses.
$^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

caveat. The effect of upstreamness within hardware firms after Liberation Day, while still negative, are less significant than our baseline (only at 90 %). However, we contend that this is far from weakening our key findings. The drop in significance of upstreamness within hardware firms can be attributed to the coarser coding scheme for the outcome variable, because collapsing tariff negativity to an indicator discards the within-positive variation. Under this new operationalization, two hardware firms that differ in the intensity of their tariff negativity, which is what the variation H2a captures, are coded identically once the measure is binarized. The binary DV therefore tests the extensive margin (whether any negativity is expressed), on which the gradient is necessarily weaker, while the level effect, which also operates on the extensive margin, is fully preserved.

B2. Exclusion of Defense Firms

To verify that our results are not an artifact of the defense sector's distinctive relationship to trade policy, we re-estimate our specifications excluding all defense-related firms, both aerospace and military-hardware primes (Defense/Aerospace) and defense service contractors (IT Services/Defense). These two groups have tariff posture which is governed by forces largely orthogonal to the customs-exposure mechanism we identify. Aerospace and equipment primes operate in a near-monopsonic environment in which the U.S. government is the dominant customer; this relationship shapes their public stance on trade policy through fixed-price procurement and domestic-sourcing mandates such as the Buy American Act and specialty-metals provisions - channels unrelated to global value chain position (Sandler and Hartley 1995; Rogerson 1994; Moran 1990; Congressional Research Service 2024). Their tariff attitudes vary widely as a result of the commercial-versus-government distinction: firms with large civilian-aerospace businesses (Raytheon, General Electric) respond sharply to tariffs, while pure-play government primes remain near-silent[9]. Defense service contractors, by contrast, earn revenue from professional services rather than goods crossing customs, leaving them with negligible tariff exposure and a flatter distribution of tariff negativity[10].

The results, reported in Table B2, are unchanged in structure. The pooled baseline remains a precise null, while the hardware level effect and the within-hardware upstreamness effect are both significant and identical in sign to our main estimates. The pattern across the three specifications mirrors the full sample exactly: no pooled relationship between upstreamness and tariff negativity, a sharp hardware-versus-digital divergence, and an attenuating effect of upstream position within hardware firms. Notably, this holds on a substantially smaller sample — 50 firms rather than 65 — which only sharpens the inferential demands, yet the estimates remain well-identified. Because the two excluded

9. Within Defense/Aerospace, firm-level upstreamness and post-treatment tariff negativity are uncorrelated ($r = -0.07$, $n = 10$), and within the tier there is a high dispersion (SD = 0.24).

10. The two defense-related tiers occupy opposite extremes of within-tier dispersion in post-treatment tariff negativity: Defense/Aerospace exhibits the highest variation in the sample (SD =0.24= 0.24 =0.24), while the services-based IT Services/Defense tier is tightly clustered near zero (SD =0.08= 0.08 =0.08).

Table B2: Robustness: Difference-in-Differences Estimates Excluding Defense-Related Firms

	(1) Baseline	(2) H2	(3) H2 + H2a
Upstream × Post	−0.003		
	(0.029)		
Hardware × Post		0.122^{**}	0.197^{***}
		(0.052)	(0.048)
Upstream × Hardware × Post			-0.110^{***}
			(0.027)
Firm FEs	Yes	Yes	Yes
Quarter FEs	Yes	Yes	Yes
Observations	379	379	379
Firms	50	50	50

Notes: Sample excludes all defense-related firms (Defense/Aerospace and IT Services/Defense tiers), retaining 50 firms (22 hardware, 28 digital). Upstreamness is re-standardized within the restricted sample. Standard errors clustered at the firm level in parentheses.

$^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

tiers fall on opposite sides of the hardware/digital divide and are shaped by mechanisms distinct from the customs-exposure channel we propose, the persistence of these effects indicates that they are driven by the commercial hardware firms central to our argument rather than by the defense sector's idiosyncratic political economy.

B3. Placebo Test

We conduct two placebo tests to confirm that our estimates capture the effect of the Liberation Day tariffs rather than pre-existing differences between hardware and digital firms. We reassign the treatment to two earlier cutoffs, Q2 2024 and Q4 2024, and re-estimate Model 3 on the pre-treatment subsample. The two dates deal with different concerns. Q2 2024 was when the trajectory of trade policy remained uncertain so a genuine Liberation Day effect should leave no trace at this date. Q4 2024 is more demanding: by then Trump had won the election, and given the centrality of tariffs to his agenda, firms may have begun anticipating and responding to the coming policy before it took effect. A significant placebo effect at Q4 2024 would suggest that the hardware-digital divergence we attribute to Liberation Day in fact began with electoral anticipation. A null result, by contrast, indicates that any anticipation was not yet differential across firm types, and that the divergence is specific to the policy shock itself.

Table B3: Placebo Tests: Fake Treatment Dates in the Pre-Treatment Period

	(1) Real Treatment (Q2 2025)	(2) Placebo (Q2 2024)	(3) Placebo (Q4 2024)
Hardware × Post	0.184^{***}	-0.006	0.033
	(0.042)	(0.022)	(0.036)
Upstream × Hardware × Post	-0.082^{***}	-0.008	-0.017
	(0.025)	(0.022)	(0.032)
Firm FEs	Yes	Yes	Yes
Quarter FEs	Yes	Yes	Yes
Sample	Full	Pre-only	Pre-only
Observations	486	286	286

Notes: Column (1) reproduces our main estimate in the main text. Columns (2) and (3) replace the treatment with fake dates in the pre-treatment period (Q2 2024 and Q4 2024 respectively), estimated on the pre-treatment subsample only. Standard errors clustered at the firm level in parentheses.

$^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

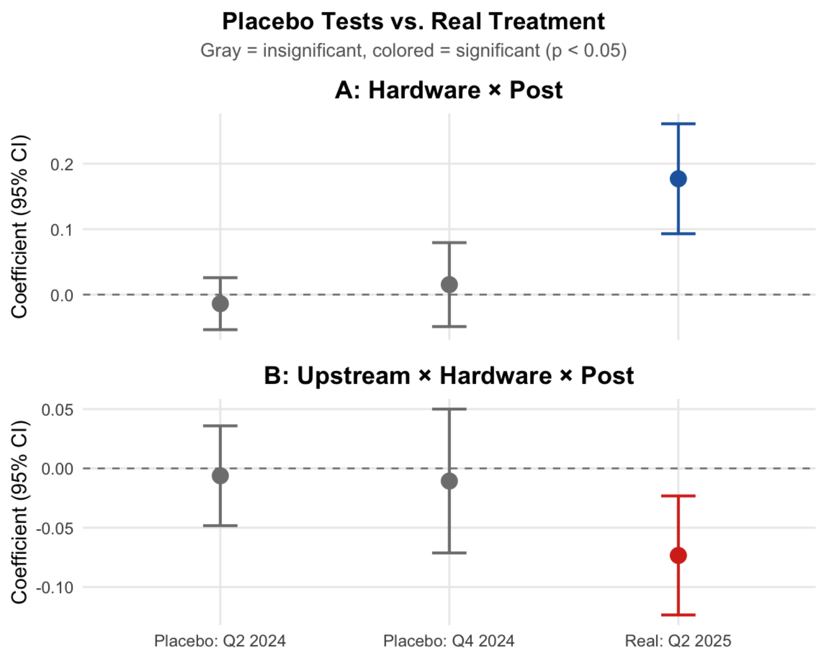

Figure B1: Placebo and Real Effects

Table B3 and Figure B1 report the results alongside the real estimate. At both placebo dates - Q2 2024 and Q4 2024 - neither the hardware level effect nor the within-hardware upstreamness effect is distinguishable from zero: the point estimates cluster tightly around the dashed zero line, and every confidence interval comfortably contains it. The contrast with the actual Liberation Day estimate is stark. The real hardware effect (Panel A) sits an order of magnitude above its placebo counterparts, and the real upstreamness effect (Panel B) is the only estimate whose confidence interval excludes zero, falling well below the placebo intervals that straddle it. The placebo treatments also explain almost none of the within-firm variation in tariff negativity. Together with the joint pre-trends test, these results indicate that the divergence in tariff attitudes is specific to the Liberation Day policy shock and not an artifact of trends already underway before treatment.

B4. Two-way Clustered Standard Errors: Firm and Calendar-Quarter

Our main specifications cluster standard errors at the firm level, allowing for arbitrary within-firm correlation across quarters. This may understate uncertainty if tariff negativity is also correlated across firms within a given quarter. For instance, if a macroeconomic announcement or a common news cycle moves many firms' earnings-call sentiment simultaneously. To tackle this issue, we cluster on both firm and calendar quarter, allowing correlation within firms over time and within quarters across firms. We note that the quarter dimension comprises only nine clusters, well below the threshold at which cluster-robust inference is reliable on its own. As such, we treat this specification as complementary to the firm-level small-sample corrections reported above (CR2 standard errors and the wild cluster bootstrap) rather than as a substitute for them. We expect that the results would align well with our main specification.

Table B4: Robustness: Two-Way Clustered Standard Errors (Firm and Quarter)

	(1) Firm-Clustered	(2) Two-Way Clustered
Hardware × Post	0.184^{***}	0.184^{*}
	(0.042)	(0.062)
Upstream × Hardware × Post	-0.082^{***}	-0.082^{**}
	(0.025)	(0.020)
Firm FEs	Yes	Yes
Quarter FEs	Yes	Yes
Clustering	Firm	Firm & Quarter
Observations	486	486

Notes: Column (1) clusters standard errors by firm (65 clusters); column (2) clusters by both firm and calendar quarter (65 and 9 clusters respectively). Standard errors in parentheses.

$^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table B4 reports the result. Allowing for within-quarter correlation across firms leaves both estimates significant: the hardware level effect remains the same, so does the within-hardware upstreamness effect. The point estimates are unchanged, as clustering affects only the standard errors, and the standard error on the upstreamness effect in fact declines slightly under two-way clustering, indicating that within-quarter correlation is modest and contributes little additional uncertainty. The persistence of both effects under this less conservative error structure suggests that the results are not driven by common shocks affecting many firms in the same quarter, but reflect the genuinely differentiated response of hardware firms to the tariff regime.

B5. Alternative DV: Tariff-Related Lobbying

Our main analysis rests on a difference-in-differences design in which both the dependent variable (tariff negativity) and a key independent variable (upstreamness) are coded by a large language model from earnings-call transcripts. This approach raises two related concerns. First, both the outcome and the regressor originate from the same text-analysis pipeline, so any systematic measurement error in the model's coding, a tendency to associate certain rhetorical styles with both negativity and value-chain position, for instance, could induce a spurious correlation that the design would not detect. Second, and more broadly, expressed attitudes in earnings calls are a form of communication; a skeptic might argue that what we capture is strategic talk directed at investors rather than firms' underlying preferences, raising questions about whether our findings extend to consequential political behavior. A robustness analysis that replicates our results using an outcome that is both unambiguously behavioral and drawn from a independent data source of the LLM pipeline would address both concerns directly.

We construct a firm-quarter panel from Senate Lobbying Disclosure Act filings (57 firms, 513 firm-quarters, 2024Q1–2026Q1), where the outcome variable is the share of each firm's quarterly lobbying activities that mention tariffs, and we mirror our main specification with firm and calendar-quarter fixed effects and firm-clustered standard errors. Lobbying is a costly, legally disclosed action rather than cheap talk, and it is recorded in administrative filings that owe nothing to our text pipeline. If the same pattern appears in lobbying behavior, the concern that our main results are an artifact of LLM-based measurement is largely mitigated.

Estimating this design requires attention to treatment timing, because lobbying and expressed preferences respond to different moments. Our main analysis dates the treatment to Liberation Day (2025Q2), when the tariff regime was actually imposed. For lobbying, however, the relevant shock can arrive a quarter earlier, in 2025Q1, for two reasons. First, firms routinely intensify lobbying at the onset of a new administration in order to reestablish access to incoming officials; because this cannot occur until appointees are in place, it necessarily begins in the first quarter of the new term. Second, the incoming administration had signaled throughout the campaign that aggressive trade policy would be a centerpiece of its agenda, giving exposed firms clear incentive to lobby *before* the policy was finalized, while its design remained open to influence. The same logic explains why the two outcomes respond at different times. In 2025Q1 the eventual policy remained uncertain and, by historical precedent, was expected to prove less radical than campaign rhetoric implied; it would therefore have been premature for firms to voice dire assessments to investors in their earnings calls. Lobbying, which is forward-looking and aimed at shaping policy before enactment, responds to the *anticipated* shock; expressed preferences, which report realized conditions to investors, respond to the *actual* shock in 2025Q2, once Liberation Day made the consequences concrete. We therefore present both timings: Table B5 dates treatment to Liberation Day (2025Q2), matching our main analysis, and Table B6 dates it to the administration change (2025Q1).

Under both timings, the estimates are directionally consistent with our main results: hardware firms increase tariff lobbying relative to digital firms, and the within-hardware upstream interaction is negative, echoing the rhetorical forbearance of upstream firms. Under the Liberation Day timing (Table B5), the hardware effect is positive and significant and the triple interaction is negative but at threshold. Re-dating treatment to the administration change (Table B6) sharpens both estimates and improves model fit. That the pattern recovered from administrative lobbying records mirrors the pattern recovered from LLM-coded earnings calls is reassuring since the two designs share neither a dependent variable nor a data source, yet they point to the same structural divide.

The two timings differ in whether they satisfy the parallel-trends assumption, and in instructive ways. Under the Liberation Day timing, an event-study check reveals pre-treatment movement: the hardware leads are jointly marginally significant (Wald $p = 0.06$), reflecting that lobbying had already begun to rise in 2025Q1, before the formal imposition of tariffs. This is the anticipatory effect described above. Re-dating treatment to 2025Q1 absorbs this anticipation: the 2024 pre-treatment leads for the hardware interaction are then jointly indistinguishable from zero (Wald $p = 0.46$), and the hardware differential jumps sharply at 2025Q1 and remains elevated thereafter. For the hardware-digital distinction, then, the re-timed design satisfies parallel trends and supports a causal interpretation, in data wholly independent of our earnings-call measure.

We are more cautious about the within-hardware upstreamness interaction. Even under the re-timed specification, a joint test of its 2024 pre-treatment leads is marginally significant (Wald $p = 0.05$), indicating that parallel trends do not cleanly hold for this finer comparison. We therefore read the upstreamness component of the lobbying analysis as suggestive rather than causally identified, consistent with our broader finding that upstreamness operates principally on firms' expressed preferences and on their sorting across policy instruments, rather than on the dynamics of tariff-lobbying volume. To recapitulate, the lobbying analysis provides independent behavioral story of the divide between hardware and software for our argument: the result is robust to a shift from an LLM-coded attitudinal outcome to a disclosed behavioral one, drawn from an entirely separate data source. The upstreamness mechanism, by contrast, rests primarily on the expressed-preference evidence of our main analysis, where it is most cleanly identified.

Table B5: Lobbying Difference-in-Differences, Treatment at Liberation Day (2025Q2)

	(1) Baseline	(2) Hardware	(3) Triple
Upstream × Post	-0.007		
	(0.008)		
Hardware × Post		0.019	0.031^{**}
		(0.012)	(0.013)
Upstream × Hardware × Post			-0.026^{*}
			(0.014)
Firm FEs	Yes	Yes	Yes
Quarter FEs	Yes	Yes	Yes
Observations	513	513	513

Notes: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table B6: Lobbying Difference-in-Differences, Treatment at Administration Change (2025Q1)

	Tariff Lobbying Share
Hardware × Post	0.040**
	(0.017)
Upstream × Hardware × Post	−0.034*
	(0.020)
Firm FEs	Yes
Quarter FEs	Yes
Observations	513

Notes: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

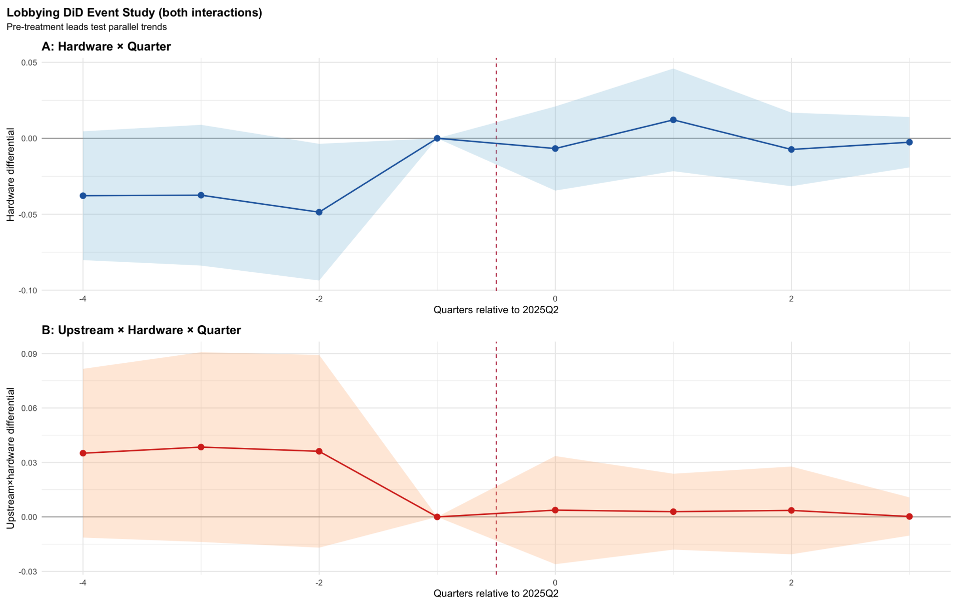

Figure B2: Event Study (Original Treatment)

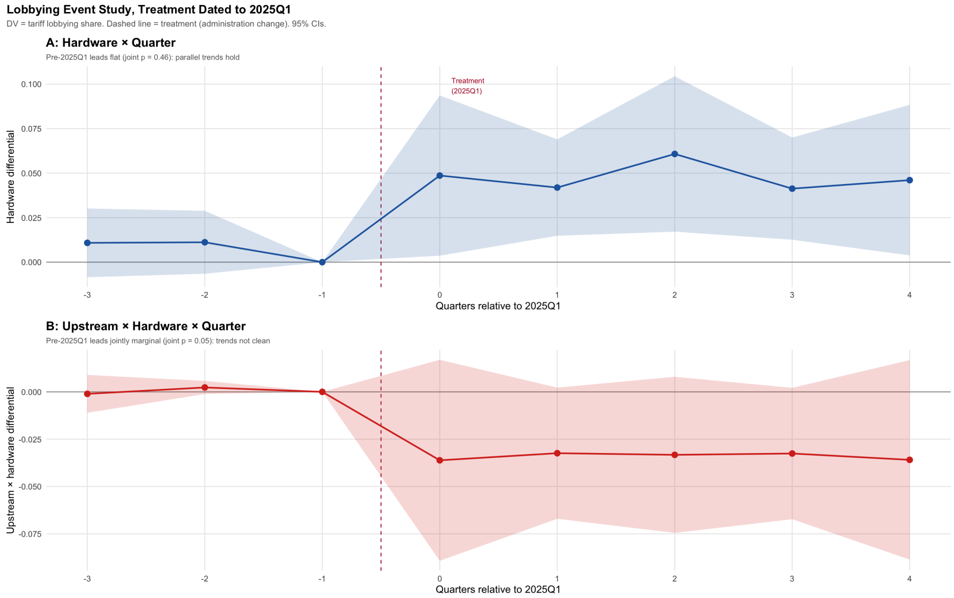

Figure B3: Event Study (Q1 2025 as a Treatment)

B6. Wild-Cluster Bootstrap, CR2 Standard Errors and Leave-One-Out Estimate

Table B7: Wild Cluster Bootstrap Inference for the Within-Hardware Interaction

	Upstream × Hardware × Post
Point estimate	-0.082
Cluster-robust t-statistic	-3.02
Bootstrap p-value	0.031
Reject H_0 at 5%	Yes
Bootstrap replications	9,999
Weights	Webb 6-point
Clusters (firms)	65

Notes: Wild cluster bootstrap-t for the triple-interaction coefficient from the preferred specification, imposing the null and resampling residuals at the firm level with Webb (2023) six-point weights over 9999 replications. The procedure provides finite-sample-valid inference with a moderate number of clusters, under which asymptotic cluster-robust standard errors can be unreliable.

Table B8: CR2 Bias-Corrected Cluster-Robust Inference

	Hardware × Post	Upstream × Hardware × Post
Point estimate	0.184	−0.082
CR2 standard error	0.060	0.028
t-statistic	3.07	−2.97
Satterthwaite d.f.	11.18	4.64
p-value	0.011	0.034
Significant at 5%	Yes	Yes

Notes: Bias-corrected cluster-robust (CR2) standard errors with Satterthwaite degrees-of-freedom corrections, clustered by firm (Bell and McCaffrey 2002; Pustejovsky and Tipton 2018). CR2 adjusts for the downward bias of conventional cluster-robust standard errors under a moderate number of clusters, and the Satterthwaite correction yields effective degrees of freedom reflecting the concentration of identifying variation. The low effective degrees of freedom for the triple interaction (4.64) indicate that it is identified from a limited number of high-leverage firms at the extremes of the value-chain distribution; the coefficient nonetheless remains significant at the 5% level. Estimates are from the preferred specification with firm and calendar-quarter fixed effects.

Table B9: Leave-One-Firm-Out Estimates of the Within-Hardware Interaction

	Upstream × Hardware × Post
Baseline estimate (all firms)	−0.082
Across 32 leave-one-firm-out fits:	
Estimate range	[−0.097, −0.064]
p-value range	[0.0005, 0.019]
Fits significant at 5%	32 of 32
Fits significant at 10%	32 of 32
Most attenuating exclusions (smallest $\lvert\hat{\beta}\rvert$*):*	
Drop Apple (AAPL)	−0.064 ($p = 0.009$)
Drop Micron (MU)	−0.076 ($p = 0.003$)
Drop Motorola Solutions (MSI)	−0.077 ($p = 0.004$)
Drop HP (HPQ)	−0.077 ($p = 0.019$)
Drop Broadcom (AVGO)	−0.078 ($p = 0.003$)

Notes: Each row drops one hardware firm and re-estimates the preferred specification. The coefficient remains negative and significant at the 5% level in all 32 fits. The exclusions that most attenuate the estimate are firms at the endpoints of the upstreamness distribution: downstream producers (Apple, HP) and upstream suppliers (Micron, Broadcom). This is consistent with an effect identified across the full range of value-chain positions rather than driven by any single firm. Firm and calendar-quarter fixed effects included throughout; standard errors clustered by firm.

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