American Firm Response to U.S.-China Technological Competition: the Case of U.S. Semiconductor Industry

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Abstract

The intensified competition between the United States and China over technology has renewed the scholarly interest in economic statecraft; that is what the state does. But scant attention has been paid to how domestic firms respond to state action and the worsening trade prospect. I argue that the industry segment that a firm occupies shapes its response when the state impedes international economic flows. I focus on the recent U.S. government's efforts to subsidize domestic semiconductor production and control the export of advanced chips to China since 2022. I compile an original dataset of top-30 U.S. semiconductor companies with various firm-level characteristics. Employing a word embedding approach, I model how firms discuss China and export control in their financial reports to shareholders. Results show that firms with domestic production capacity talk in a less pessimistic and alarmist fashion concerning China than fabrication-less (fabless) firms. Lower reliance on revenue from China, higher lobbying expenses, and higher investment commitment are particularly relevant in shaping the former's responses. This study highlights the importance of understanding the distributional conflicts in an industry and how they might condition the state's pursuit of national security.

1 Introduction

Over the past two decades, China has been re-orienting its developmental strategy to one that is driven by indigenous innovation and sought to "occupy the commanding heights" of numerous emerging technologies, including semiconductor and artificial intelligence (Naughton,

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2021). This set off a countermovement from the United States, declaring China as a competitor and employing a variety of domestic industrial policies and foreign economic tools to undermine China's quest for techno-economic supremacy. Two monumental events in the past year have set the tone for future U.S.-China competition. First, the Chips and Science Act was signed into law by President Biden on August 9, 2022, which offered $52 billion in subsidies and more than $24 billion in tax credit for semiconductor manufacturing and research and development (R&D). Second, the Commerce Department announced on 7 October, 2022 a new set of export controls on advanced semiconductors to China, restricting the latter's ability to obtain and manufacture cutting-edge chips.

The intensified competition between the U.S. and China has renewed the scholarly interest in "geoeconomics" and "economic statecraft" (Weiss, 2021; Weiss and Thurbon, 2021; Aggarwal and Reddie, 2021; Blackwill and Harris, 2016), which predominantly focus on what the state does to pursue national interest. But scant attention has been paid to how U.S. domestic firms respond to these state actions. This study examines how U.S. semiconductor firms respond to the U.S.-China geoeconomic competition and the worsening prospect of trade with China since 2022 to the present. Theoretically, I argue that firms have heterogeneous political preferences, which are shaped by the segment they occupy in a given supply chain. I offer a political account that focuses on the intersection of state interest, supply chain position, and firm preferences. Specifically, I argue that when the state places a premium on domestic manufacturing, this produces a distributional conflict within the industry among firms who have existing manufacturing capacities and those who do not. Firms that can capture this "security rent" by expanding domestic manufacturing have more aligned incentives with the state, hence being less concerned with the worsening trade prospect. Firms that are unable to capture this rent due to their previous specialization in the value chain are more likely to have misaligned incentives with the state, hence being more concerned with the worsening trade prospect amid geoeconomic competition.

Empirically, I compile an original dataset of top-30 U.S. semiconductor companies with various firm-level characteristics. I marshal data from firms' financial disclosure (Form 10-K and 10-Q filing to the U.S. Securities and Exchange Commission), lobbying expenditures

(Lobbying Disclosure Act (LDA) Reports) and other sources. I leverage techniques in natural language processing, particularly word embeddings, in measuring firms' response to the worsening trade prospect. And I perform regression analyses in testing how firms in various industry positions exhibit semantic differences in the way they discuss and assess risks regarding China. Results show that vertically integrated firms with manufacturing capacities, especially those that have pledged to make new domestic capital investment, show less pessimistic and alarmist assessment when it comes to China, when compared to firms that have outsourced manufacturing overseas.

This study seeks to make three contributions. First, this build on the firm-centric theories of trade in highlighting heterogeneous firm preferences (Melitz, 2003; Kim and Osgood, 2019; Kim, 2017; Osgood, 2016). It yields additional insights into how the segment that a firm occupies in a supply chain conditions its preferences, which has been previously understudied. Second, it challenges the state-centric literature of security study by highlighting how the intra-industry distributional conflicts might condition the state's pursuit of national security and foreign economic policy goals. Third, it demonstrates how advances in quantitative text analysis can be fruitfully applied to the study of firms' preferences, which have been hard to measure.

This paper proceeds as follows. Section 2 and 3 review the relevant literature (in trade politics, global value chain and international political economy) and develops my theoretical arguments. Section 4 gives an overview of my original dataset on the top-30 semiconductor firms in the U.S. and the collection of various firm-level covariates. Section 5 discusses the methodology of word embeddings and the empirical setup. Section 6 presents the results from word embeddings analyses and regression. Section 7 concludes by discussing future directions.

2 Literature

How would firms react to the worsening trade prospect when the geoeconomic competition among states intensifies? On the one hand, the literature on pressure group and rent seeking might lead one to expect that most firms would support trade restrictions. Trade protectionism is often a product of special economic interests capturing state institutions (Schattschneider, 1935), and the competition for export licenses can be a vehicle for rent seeking (Bates, 1981; Haber, Razo and Maurer, 2003). But one difficulty arising from this perspective is that many U.S. semiconductors benefited from exporting their products to China and have historically lobbied *against* export restrictions (Meijer, 2016). On the other hand, the standard trade model that emphasizes country-level comparative advantages and factor endowments might suggest that firms in advanced economies would oppose trade restrictions (Kim and Osgood, 2019). Since the U.S. semiconductor industry enjoys an advantage in capital availability and technological sophistication and that China is a net importer of semiconductors, most U.S. firms are expected to support free trade.

Both of these accounts are unsatisfactory because they assume firm preferences are homogeneous within a given industry. In contrast, a new wave of firm-centered theories of trade argues that firms exhibit heterogeneous preferences for free trade – larger and more productive firms have resources to engage in and derive more benefits from international trade, so they are more supportive of trade liberalization, which also drives less productive firms out (Kim and Osgood, 2019). The key insight is that there is always an intra-industry distributional conflict and resource reallocation in a given trade environment (Melitz, 2003).

This study takes firms' heterogeneous preferences and intra-industry distributional conflict seriously. But firm-level features that the current literature focuses on, such as firm size and productivity (Kim and Osgood, 2019) or product differentiation (Osgood, 2016; Kim, 2017), do not adequately capture the complexity of modern supply chains in which firms are situated. In the case of the semiconductor industry, for example, its supply chain consists of multiple segments, two of which are chip design and fabrication. Firms that specialize in chip design and outsource manufacturing to a third party (i.e., fabrication-less, or "fabless," firms) and firms that are vertically integrated and do both activities in-house (e.g., Integrated Device Manufacturers, or IDMs) likely have different policy preferences toward international trade or domestic industrial policy. The central argument of this study is that the supply chain position a firm occupies shapes how it responds to the worsening trade prospect due to the intensified

U.S.-China geoeconomic competition.

Why does the supply chain position of a firm affect its political preferences? The literature on global value chains (GVCs) highlights factors deriving from transaction cost economics and industrial organization. Firms who outsource labor-intensive activities to a decentralized network of oversea manufacturers (i.e., a "buyer-driven" supply chain) tend to prefer state policies that are facilitative, while vertically integrated firms who engage in capital- and technology-intensive industries (i.e., a "producer-driven" supply chain) and make asset-specific investments might demand more interventionist polices from the state (Gereffi, 1994; Gereffi, Humphrey and Sturgeon, 2005). These factors originating from firms' pursuit of economic interests fundamentally shape the structure of GVCs we see today. But states also have their own interests in reshaping the GVCs and influencing firms' political preferences, which are underemphasized by the GVC literature. This study offers a uniquely *political* account in explaining how the firm's supply chain position affects its political preferences, with the state's national security interest being the crucial intervening variable.

Drawing on insights in the literature of international relations and international political economy, I argue that state interests intersect with global supply chains and firm preferences in the following ways. First, states care about *relative gains* resulting from interactions in global economic networks (of trade, capital, or technology). Relative gains matter because states are concerned with security and survival; economic resources can be channeled into war-making capabilities (Kennedy, 1987) and technological advancements can confer military advantages on one's adversaries. In fact, the raison d'être of the U.S. export control regime has been denying rivals' (chiefly the Soviet Union and China) access to technologies that have military applications (or of "dual-use") and maintaining a technological gap with them (Meijer, 2016; Daniels and Krige, 2022). The recent U.S. export control on advanced chips to China is similarly justified on the ground of limiting their military applications (Bureau of Industry and Security (BIS), 2022)[1].

Second, states are concerned with *asymmetric dependence* arising from global economic

[1]In the Press Release, BIS says that the export control intends to restrict China's ability to obtain or manufacture advanced chips and supercomputers because they are used "to produce advanced military systems including weapons of mass destruction; improve the speed and accuracy of its military decision making, planning, and logistics, as well as of its autonomous military systems; and commit human rights abuses."

interactions (Hirschman, 1969). In particular, the new interdependence literature argues that some state can weaponize its asymmetric positions in international economic networks to coerce others. One mechanism is through the "chokepoint effect," which is denying other countries' access to the critical hubs in the networks which confer outsize efficiencies to the users (Farrell and Newman, 2019). For example, the global supply chain of semiconductors is highly asymmetric and exhibits multiple chokepoints: the U.S. captures 72% of the value-adding in the segment of software used in chip design,[2] while a single foundry in Taiwan – Taiwan Semiconductor Manufacturing Company (TSMC) – controls over 90% of the most advanced chips (10-5nm) fabrication market,[3] whose production relies on the Extreme Ultraviolet Lithography (EUV) machine that is manufactured by one (and the only one in the world) Dutch company, ASML. Part of the motivation of China's (and the U.S.) industrial policy to galvanize indigenous semiconductor manufacturing was to reduce these dependencies, fearing that their counterpart might one day cut off its access to these critical hubs or inputs.

To mitigate these concerns for relative gains and asymmetric dependence, I argue that states have incentives to reshape the configuration of the global value chain in multiple ways. One way is to employ export control to impede the flow of technology and prevent competitors from moving up the value chain. Another way is to place a political premium (through direct or indirect transfer of resources) on domestic manufacturing to reduce the asymmetry in the distribution of manufacturing capacities and the impact of being cut off from the networks. This premium placed on domestic manufacturing creates a new kind of rent, which I call *security rent* (based on national security), which is different from *monopoly rent* (based on market power) or *Ricardian rent* (based on outsized efficiency) (Galetovic, 2021). Crucially, this rent creates distributional conflicts within an industry, like the firm-centered theories of

[2]More technically, this segment is called Electronic Design Automation, or EDA. Modern chips consist of billions of transistors that are printed on a wafer on the scale of nanometers. This process necessitates the use of advanced software for chip design. Three American firms – Cadence, Synopsys, and Mentor – controlled around three-quarters of the market. "It was impossible to design a chip without using at least one of these firms' software... No other country came close" (Miller, 2022). Downstream players in the industry, whether they are fabless chip designers or foundries who help the former to fabricate the chip, are dependent on these U.S. software companies. This forms one of the bases of the U.S. export control on advanced chips, which applies *extraterritorially* to foreign persons who use American software during any stage of the chip design and production if the product is eventually re-exported to China.

[3]Hille, Kathrin. March 23, 2021. "TSMC: how a Taiwanese chipmaker became a linchpin of the global economy." *Financial Times*.

trade emphasize. But this is because only some firms have existing manufacturing capacities in the value chain and are thus able to capture this rent; firms specialized in segments with no manufacturing bases instead see resources being reallocated away from them.

Two clarifications are warranted here. First, the creation and chasing of security rent reduce economic efficiency in a Pareto-optimal sense, but efficiency is not the only relevant maximand in politics. Looking at China's recent industrial polices, studies find that the Chinese government did not "pick winners" by rewarding productive firms, nor did research & development (R&D) subsidies promote productivity growth (Branstetter, Li and Ren, 2022). Subsidies also created market distortion and inefficiency (Barwick, Kalouptsidi and Zahur, 2019), but did dramatically increased China's world market share (by 40% in the shipbuilding industry during 2006-13). The latter fact is important: to the extent that the state values market share in a strategic industry or a particular configuration of the supply chain that reduces asymmetric dependence, these efficiency-based criticisms might have missed the point.

Second, security rent is not reducible to "unproductive rent." The arguments I present above indeed resemble the classic import-substituting industrialization (ISI), which historically has degenerated into unproductive rent seeking and clientelism (Haber, Razo and Maurer, 2003). As Roberts, Choer Moraes and Ferguson (2019) remark, the line between protectionism and protection (of security) is always elusive. It is possible that the state's pursuit of national security can degenerate into rent seeking in some cases, or in other cases, this pursuit is merely a reflection of special interests capturing the state at its inception. But I maintain that there are instances where the state's pursuit of national security can be a causal variable not reducible to pressure group politics, particularly if there is a sufficient level of external threat. Woo-Cumings (1998) and Doner, Ritchie and Slater (2005) argue that state autonomy and developmental orientation of East Asian later industrializers stem from the enduring security threats they faced, which distinguished them from their populist Latin American counterparts. Taylor (2016) similarly explains cross-national innovation rates with a theory of "creative insecurity," which argues that external threat constrains domestic pork barrel politics and incentivizes the state to promote innovation. The key point is that during the state's pursuit of national security, external threat can limit rent seeking and prevent the state from being entirely hijacked by pressure groups.

3 Arguments

Below I briefly recapitulate my main theoretical arguments. I contend that semiconductor firms have heterogeneous political preferences towards trade, as firm-centered theories of trade emphasize. But their preferences are shaped by the industry position they occupy in a given supply chain. Instead of focusing on economic factors that shape the supply chain and firms' policy preferences, I offer a political account that focuses on the intersection of state interest, supply chain position, and firm preferences. States are concerned with relative gains and asymmetric dependence resulting from global economic interactions. To mitigate these concerns, states are incentivized to reshape the configuration of the supply chain, one way of which is to re-shore some manufacturing activities. By placing a premium on domestic manufacturing, the state creates security rent that can be captured by firms with some pre-existing manufacturing capacities. This produces a distributional conflict within the industry. On the one hand, firms who can capture this rent are more likely to have their incentives aligned with the state, hence being less concerned with the worsening trade prospect due to intense geoeconomic competition. On the other hand, firms that are unable to capture this rent due to their previous specialization along the value chain are more likely to have misaligned incentives with the state, hence being more concerned with the worsening trade prospect.

In the specific context of the U.S.-China competition over semiconductors, I argue that there is a distributional conflict among two segments of U.S. firms. Fabless firms who specialize in chip design and outsource their manufacturing process to third parties not only see their ability to export being impeded but also resources being reallocated away. Integrated Device Manufacturers (IDMs) who are vertically integrated and both design and fabricate chips are able to capitalize on the state's effort to reshore manufacturing and reap the security rent.

Some empirical implications follow. First, the difference between IDMs and fabless firms should be the most significant cleavage in shaping how firms respond to the worsening trade prospect. Second, IDMs that actually help fulfil the state's pursuit of increased domestic manufacturing (e.g. through expansion of existing production facilities, or building new ones) should be even more unfaced by the worsening trade prospect, because they have the most benefit to gain. And these patterns should hold even if we account for potential confounders such as firm size and lobbying expenses.

4 Data

4.1 Top semiconductor firms and their industry position

To test my arguments, I build an original dataset of top-30 semiconductor firms publicly traded in the U.S., ranked by their market capitalization.[4] I manually classify these 30 firms into six industry segments based on their main activities and products. The largest category is *fabless companies* (11 out of 30), which focus exclusively on chip design and outsource the fabrication to third-party foundries. Top fabless firms include NVIDIA (market cap: $604 billion), Broadcom ($261 B), and Advanced Micro Devices (AMD; $145 B). Another dominant category is *Integrated Device Manufacturers* (IDMs; 10 out of 30), which are firms that both design and manufacture chips with in-house fabrication plants ("fabs"). Top IDM firms include Texas Instruments ($158 B), Intel ($118 B), and Analog Devices ($93 B). The third category is *foundries*, which specialize in chip fabrication and receive orders from other chip designing customers. There are only 2 out of 30 U.S. firms in our datasets that are foundries, the largest being GlobalFoundries ($35 B). These patterns are consistent with the broader, cross-national analysis: while the U.S. is the largest player in the design segment (49% globally, followed by South Korea with 20%) by value adding, its domestic production capacity is much weaker, occupying only 11% of the fabrication segment (Semiconductor Industry Association (SIA), 2022).

Our dataset also records 6 more U.S. firms in three other industry segments. One category is *Equipment manufacturers* (5 out of 30) who supplies equipment and related services in the production of semiconductors; top firms include Applied Materials ($100 B) and Lam Research

[4] Market capitalization data are retrieved from CompaniesMarketCap.com on March 15, 2023.

($66 B). The last two categories are least represented in our dataset with only one firm in each of them: *EDA & IP*[5] (Synopsys with $56 B) and *Materials* (Entegris with $ 12 B).

4.2 Financial disclosure as data: 10-K and 10-Q filings to SEC

To measure how semiconductor firms react to the worsening trade prospect amid the U.S.-China geoeconomic competition, I adopt a text-as-data approach and gather all Form 10-K (annual report) and 10-Q (quarterly report) filings by the top-30 firms to the U.S. Securities and Exchange Commission (SEC)[6]. Publicly traded companies in the U.S. are required to submit such reports periodically to disclose any relevant financial information to the shareholders. The requirement of transparency and accuracy is stringent: companies are prohibit by laws and regulations from "making materially false or misleading statements" and from "omitting material information that is needed to make the disclosure not misleading."[7] These filings mandate standard sections such as Business Overview, Risk Factors, Selected Financial Data (e.g., revenue and profit), and Management's Discussion and Analysis (MD&A; which allows company management to explain its business results and "tell its story in its own words"). Most relevant to our inquiry, Risk Factors is often the section where firms discuss the U.S.-China tension and U.S. foreign economic policies such as export control. Consider the Risk Factors section from the latest 10-K annual report by Nvidia (the largest fabless chip designer) filed on February 24, 2023, which discusses the impact of the U.S. export control at length:

> "[T]he U.S. government ... announced new **export restrictions** and **export licensing requirements** targeting **China**'s semiconductor and supercomputing industries. These restrictions ... specifically impact our A100 and H100 integrated circuits ... We are required to transition certain operations out of **China** ... which could be costly and time consuming, and adversely affect our research and development and supply and distribution operations, as well as our revenue ... We

[5] This is Electronic Design Automation and Intellectual Property, which predominantly refers to the tools (e.g., software) used to design chips. See footnote 2 for details.

[6] All SEC filings are publicly accessible on the U.S. Securities and Exchange Commission's EDGAR (Electronic Data Gathering, Analysis, and Retrieval) system: https://www.sec.gov/os/accessing-edgar-data

[7] U.S. Securities and Exchange Commission. "https://www.sec.gov/oiea/investor-alerts-and-bulletins/how-read-10-k10-q."

> have engaged with customers in **China** to provide alternative products not subject to the new **license requirements**, such as our new A800 offering ... The new requirements may have a disproportionate impact on NVIDIA and may disadvantage NVIDIA against certain of our competitors ..."

Discussion like the above allows us to systematically measure the firms' risk assessments and attitudes associated with the worsening trade prospect with China. A vast literature in finance and accounting has employed quantitative text analysis techniques using SEC filings as data (Loughran and Mcdonald, 2011). Few studies in political science, to my knowledge, have explored such a source of data. One recent exception is Hung (2022) in political sociology, which measures the number of mentions of "China" in the 10-K filings as a crude proxy for U.S. companies' exposure to China in sales or investment.

In total, I collected 145 Form 10-K or 10-Q filed between 2022 and 2023 by the top-30 semiconductor firms, which forms the *corpus* of the study. I use the entirety of the textual contents in each report as data (excluding numeric tables and after standard pre-processing, detailed below). Besides the textual content as data, I also extract relevant financial variables from the filings: total revenue and revenue from China in 2021 and 2022 respectively. These pieces of information allow us to construct a new variable – proportion of revenue derived from China in 21 and 22 – to assess how reliance on China for revenue might impact how firms respond to the worsening trade prospect.

4.3 Investment commitment and lobbying expenses

I collect information of whether firms have announced any capital investment plan since 2022, such as expanding existing facilities or building new plants, and compute their total investment pledge[8]. 8 out of 30 firms in our dataset have announced some investment plan, with Intel ($43 billion), Texas Instruments ($42 B), and Micron Technology ($35 B) making the largest pledge, all of which are IDMs.

These investment amounts are likely to correlate with firms' lobbying expenditures, specifically as the Chips and Science Act offers $52 billion in subsidies and more than $24 billion in

[8]Data are taken from "U.S. Semiconductor Ecosystem Map" by Semiconductor Industry Association.

tax credit for semiconductor manufacturing and research and development (R&D). This federal largesse spurred a lobbying frenzy in the semiconductor ecosystem, which saw their total expenditures increasing to $59 million in 2022 from $46 million in 2021 (a 28% increase) and $36 million in 2020 (a 64% increase).[9]

I collect lobbying expenditures of the top-30 firms using the Lobbying Disclosure Act (LDA) Reports. Under LDA, lobbying firms or organizations with in-house lobbyists are required to disclose their lobbying expenditures and reveal their client identities. I download all LDA reports filed during 2022 and 2023 that mentioned "Chips and Science Act," "Chips Act," or "semiconductor"[10] in their specific lobbying issues. [11] There are in total 1,063 of such records, of which 99 of them can be matched to the top 30 firms in our dataset. I then calculate their total lobbying expenditures during the period. 13 out of 30 firms record some lobbying expenditures during the period we cover, with Qualcomm ($7.1 million), Intel ($5.9 M), and AMD ($5.4 M) as the biggest contributors. See Figure A.1 in the Appendix for the visualization of the lobbying expenditures by top-30 clients overall and the top-30 semiconductor firms in our dataset.

4.4 Some descriptive patterns

Below I present some basic descriptive statistics and bivariate relationships to not only offer an overview of my firm-level dataset but also demonstrate three patterns about IDMs: 1) IDMs on average are less dependent on China for their revenues compared to fabless firms, 2) there is a positive relationship between lobbying expenses and new investment pledge, which is predominantly driven by IDMs, and 3) IDMs on average discuss China and export control less frequently in their financial disclosure.

Figure 1 visualizes the bivariate relationship between firms' total revenue in 2021 and

[9] Swanson, Ana and Don Clark. February 23, 2023. "Chip Makers Turn Cutthroat in Fight for Share of Federal Money." *The New York Times.*

[10] Nvidia, likely intentionally, misspelled semiconductor as "semi*n*conductor" in their latest LDA report. Nvidia is an interesting case where it is the largest semiconductor company by market capitalization but has historically spent little to no money in lobbying. The latest LDA report in the fourth quarter in 2022 is the *only* time in recent years that they disclose any lobbying-related expenditures. However, the total amount, $90,000, is meager comparatively.

[11] All LDA reports are accessible through the Senate Office of Public Records (OPR). They offer REST API for researchers to extract documents from their database efficiently: https://lda.senate.gov/system/public/

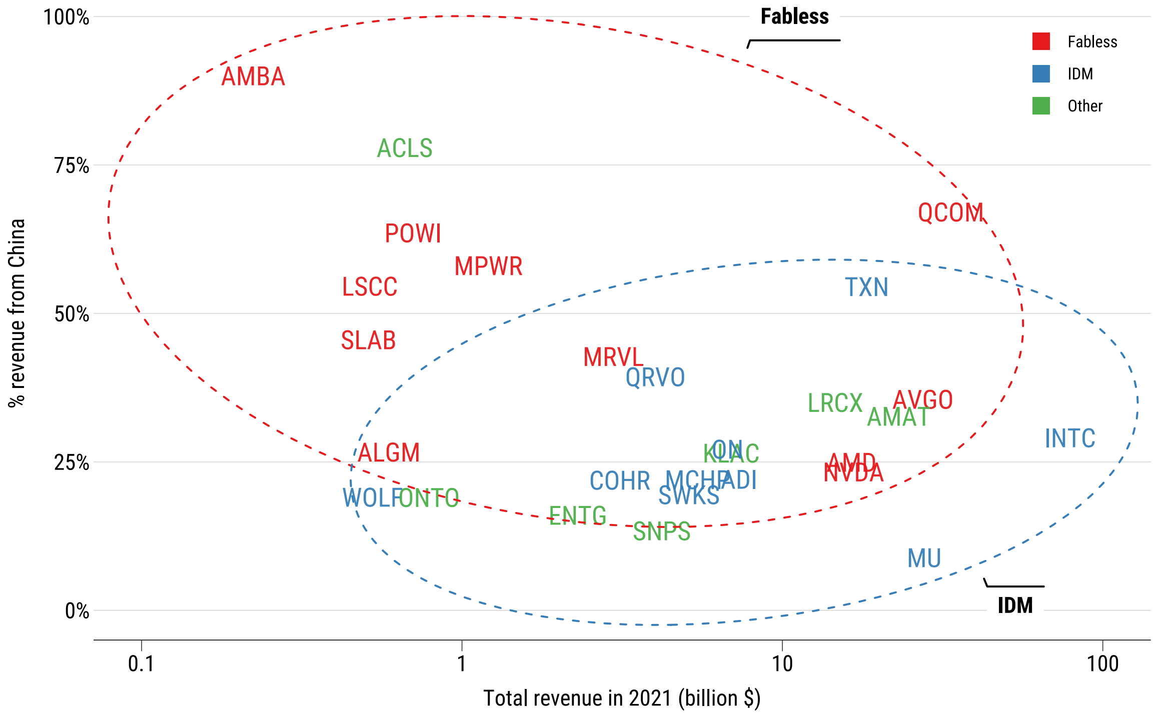

Figure 1: Bivariate relationship between firms' total revenue in 2021 and proportion of revenue from China. Labels are the stock symbols of the firms, colored by their industry positions. "Other" is the residual category that encompasses EDA & IP, Equipment, and Materials. All (two) foundries in our dataset, GlobalFoundries and Vishay Intertechnology, did not breakdown their revenues by regions, so they are dropped.

proportion of revenue from China, extracted from and calculated based on their financial disclosure (10-K annual reports). Two clusters emerge. Fabless firms are on average more reliant on China for their revenue (mean: 48.4%) compared to IDMs (mean: 26.3%). This makes sense since China is a net importer of semiconductors, importing $378 billion in chips in 2020, half of which were assembled into electronic products and then re-exported.[12] Fabless firms which design chips for various applications (e.g., Qualcomm's 4G mobile phone chips, which were later subject to U.S. export control vis-à-vis the Chinese tech giant Huawei) have long benefited from free trade between the U.S. and China. Some leading IDMs also have benefited substantively from exports to China (e.g., Texas Instruments' automotive chips, Intel's central processing unit (CPU) for supercomputing), but on average their revenue sources are more diversified than their fabless counterparts.

Figure 2 visualizes the bivariate relationship between firms' total lobbying expenditures

[12]Semiconductor Industry Association. July 13, 2021. "Taking Stock of China's Semiconductor Industry."

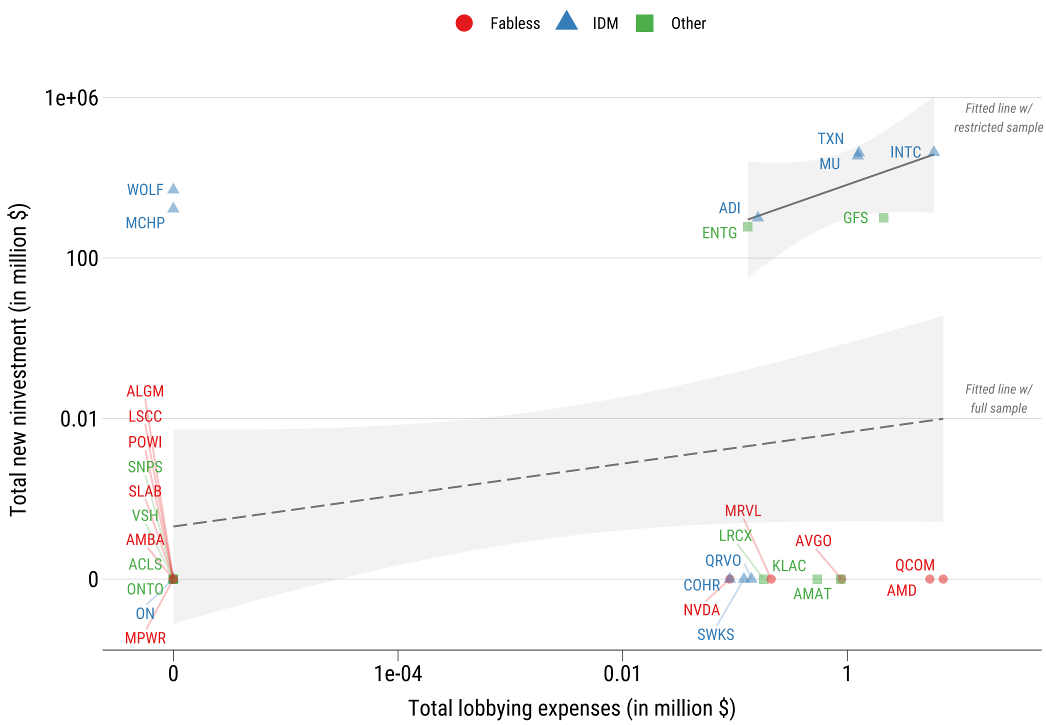

Figure 2: Bivariate relationship between firms' total lobbying expenditures in 2022 and 23 and newly announced investment. Labels are the stock symbols of the firms, colored by their industry positions. "Other" is the residual category that encompasses EDA & IP, Equipment, Foundry, and Materials.

in 2022 and 2023 and the amount of newly announced investment. There seems to be a positive relationship between the two: higher lobbying expenditures are associated with higher amount of investment pledges. But the relationships is predominantly driven by IDMs. None of the fabless firms has announced any new expansion or construction plan since 2022 (which makes sense since they do not have any fabrication facility), and more than half of them (6 out of 11) didn't engage in any lobbying activity. Notable exceptions are Qualcomm and AMD who are among top-3 firms in terms of lobbying expenditures, devoting $7 and $5 million respectively in lobbying since 2022. On the other hand, 6 out of 10 IDMs have announced some investment plan and 7 out of 10 have engaged in some level of lobbying activities. 4 IDMs – Intel, Texas Instruments, Micron Technology, and Analog Devices – lobbied and announced new investment plan, driving the positive correlation we observe between the two.

We now move into the textual contents in firms' financial disclosure documents. Here, the unit of observation is each Form 10-K or 10-Q by a firm and we count the number of instances where the keywords China or export control appeared in each document[13]. Figure 3 visualizes

[13]Throughout this study, we use regular expressions to capture variations in how firms discuss the same

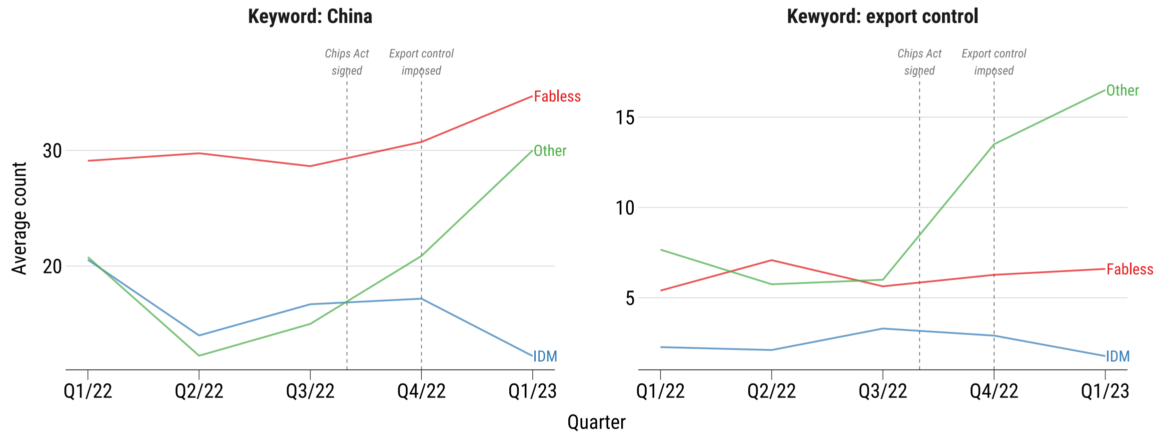

Figure 3: Average instances of "China" or "export control" being mentioned per document in firms' 10-Q and 10-K filings over time.

the average count of the keywords by industry positions over time. Two patterns appear. First, the average counts of China and export control increased after the third quarter in 2022. This is reassuring because the CHIPS and Science Act was signed into law by President Biden on August 9, 2022 and the Commerce Department announced the new round of export control on advanced chips to China on 7 October, 2022. We expect the discussion around China and export control to intensify after these two key events, and they do. Second, IDMs on average discuss China and export control less frequently than fabless or other types of semiconductor firms. But simply counting the instances of a keyword appearing is a poor measurement of the underlying sentiment and risk assessments associated with it. In other words, we need a systematic way to capture the *context* around which China or export control is discussed. We proceed to the methodological section where we employ advanced techniques from natural language processing (NLP), particularly word embeddings, to do so.

5 Methodology

To test the arguments that semiconductor firms respond to the worsening trade prospect with China differently based on their industry positions, two methodological problems are present. First, we need a way to systematically measure *how* firms discuss concepts or phenomena of

underlying concept. For "China," we include any mentioning of either *China* or *Chinese*. For "export control," we include *export control, export require, export restrict, export licens, export regulat.* For simplicity, we discuss our results just in terms of "China" and "export control."

interest such as China and export control – what are the connotations, contexts, and associated words when they discuss them? Second, we need to relate the way they discuss concepts of interest to firm-level covariates such as industry position and perform hypothesis testing – does firms of a particular characteristic discuss some concepts of interest in a different way in a statistical and substantive sense, while controlling for other covariates? The first problem can be approached with the techniques of *word embeddings* developed in the field of natural language processing (NLP), the second with the recent method of *embedding regression* developed by Rodriguez, Spirling and Stewart (2023).

5.1 Word embeddings

The gist of word embeddings is based on the distributional hypothesis, the idea that we can learn the meaning of words from the *context* in which they are used. Specifically, we can represent words as dense vectors in a multi-dimensional space. Consider an example where we "embed" the word `king` in a K-dimensional space, where each dimension corresponds to some abstract characteristic of a word:

$$\texttt{king} = \underbrace{(.8, 1.5, ..., 2.1)}_{K} \tag{1}$$

The promise of word embeddings is that these word vectors should capture the context in which the words are used and hence the "meanings" of words, so that when we compare two semantically related words (e.g., `king` and `queen`), their word vectors would demonstrate a higher similarity than when we compare vectors of more distant words (e.g., `king` and `dog`). Furthermore, once we vectorize words in this way, we can directly compute on those vectors to perform analogical reasoning, so that $\texttt{king} - \texttt{male} + \texttt{female} = \texttt{queen}$. Word embeddings have been growingly popular in political science, especially in understanding how the semantic meanings of political concepts (e.g., equality) change over time (Rodman, 2020), or the partisan differences in discussing issues such as immigration (Rodriguez and Spirling, 2022).

Word embeddings are learned in an unsupervised manner – without any labelling of data

– over a very large corpus of text via neural network models; popular models include GloVe (Pennington, Socher and Manning, 2014) and Word2Vec (Mikolov, Chen, Corrado and Dean, 2013). One main advantage of this approach is that researchers can use the pre-trained embeddings estimated from these models directly without necessarily training their own models from scratch. For example, GloVe is trained using Wikipedia 2014 and Gigaword 5 to produce word vectors for 6 billion tokens, 400 thousand vocabularies in a 300-dimensional space, which can be readily downloaded and used for downstream analyses.[14]

5.2 Embedding regression

Furthermore, we can compare the word embeddings around a particular focal word given some context between groups (or covariate values) to assess whether there is a statistically significant difference in the ways they use that focal word. Rodriguez and Spirling (2022) develop a multivariate regression setup:

$$\underbrace{\mathbf{Y}}_{n\times K} = \underbrace{\mathbf{X}}_{n\times p+1} \times \underbrace{\beta}_{p+1\times K} + \underbrace{\mathbf{E}}_{n\times K} \tag{2}$$

where n is the number of instances when a focal word is observed in some particular context; the outcome $\mathbf{Y}$ is the stacking of all word embeddings (each of which is of length $1 \times K$) of the n instances where a focal word is observed; $\mathbf{X}$ is a matrix of p covariates plus a constant; β is a set of p coefficients plus an intercept (all of dimension K); and $\mathbf{E}$ is the error term.

The raw coefficients from the model are of $p + 1 \times K$ dimensions and can be used to calculate the estimated embeddings for the focal word, which allow us to obtain the estimated nearest neighbors (closest words in the vector space). In addition, if we turn these coefficients into their Euclidean norms, they become scalars that tell us the relative difference between groups in their word embeddings and whether this difference is statistically significant.

[14] https://nlp.stanford.edu/projects/glove/

5.3 Current study setup

Below I detail the empirical setup for this study. For all 145 Form 10-K or 10-Q filed between 2022 and 2023 by the top-30 semiconductor firms, we perform standard pre-processing of the textual contents[15] We then locate all instances where two focal words, China and export control, appear and record the context (defined as a window of 12 tokens) in which those focal words appear. Together, we record $n = 2,869$ instances where China is mentioned in some specific context, and $n = 935$ instances where export control is mentioned in some specific context. We then find the word embeddings of these context-specific instances based on the pre-trained GloVe embeddings (400K vocabularies; $K = 300$ dimensions). These context-specific word embeddings are the observations of our empirical analyses.

These word embeddings are then related to firm-level characteristics we collect. Specifically, the following covariates are used in the regression analyses:

- *Position IDM*: a dummy indicating if a firm is a Integrated Device Manufacturer (IDM)
- *Total revenue in 2021*: the total revenue of a firm in 2021; it is scaled by 2 standard deviations such that its regression coefficient is comparable to one from a dummy variable (Gelman, 2008)
- *Announced new investment*: a dummy indicating if a firm has announced any new investment
- *Low reliance on China*: a dummy of whether a firm's proportion of revenue from China in 2022 is lower than the median of all firms
- *High lobbying expenditures*: a dummy of whether a firm's lobbying expenditures are higher than the median of all firms
- *Three interaction terms*: the interaction terms (all dummies) between *Position IDM* and *Announced new investment*, *Low reliance on China*, and *High lobbying expenditures* respectively

6 Results

We first explore the group difference between the word embeddings of IDM and non-IDM (mostly fabless firms) when China or Export control is the focal word respectively. I pre-select

[15] Specifically, excess white spaces are cleared; each sentence that contains more than 15% numeric values are excluded. During the tokenization of the documents into words, all punctuation, numbers, symbols, separators, URL, HTML elements are removed. Common English stop words are removed. Tokens that appear less than 5 times are also removed.

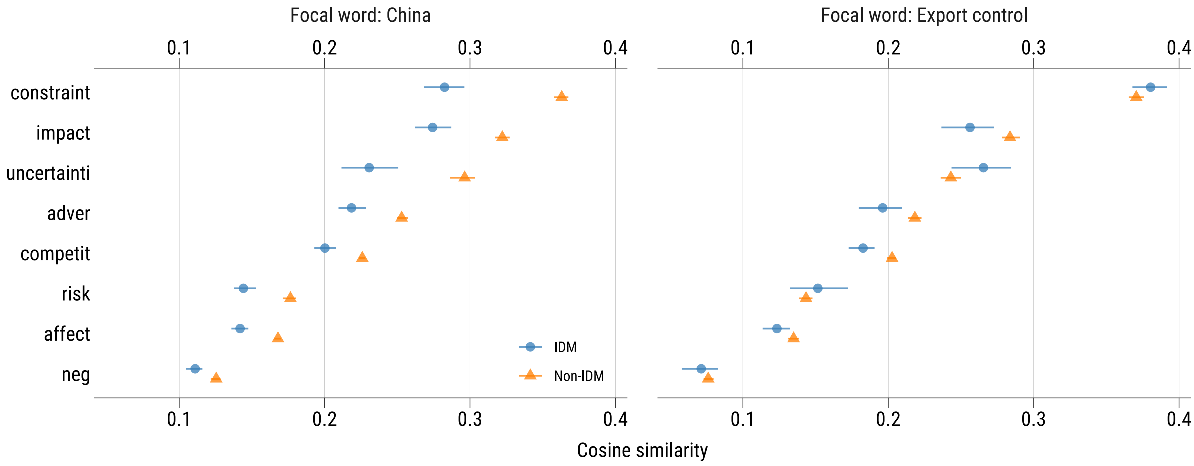

Figure 4: Cosine similarities between the embeddings of IDM (or non-IDM) and a set of selected negative features, when the focal word is China (or Export control).

a set of features that are commonly used in financial disclosure to convey a sense of negative financial assessments: *constraint, impact, uncertanti, adver, competit, risk, affect, neg*.[16] Figure 4 visualizes the cosine similarities between the word embeddings and the set of selected negative features, grouped by whether the firms are IDM or not. When the focal word is China, IDM firms' word embeddings exhibit lower cosine similarities with *all* selected negative features, when compared to non-IDM firms. In other words, IDM firms are less pessimistic and alarmist in the way they discuss China, while non-IDM firms are more likely to bring up unfavorable financial assessments. When the focal word is export control, however, the discrepancies between IDM and non-IDM firms are much less clear. One interpretation is that both IDM and non-IDM firms jointly share a concern for U.S. government's export control that can be potentially expansive and excessive, while they differ in the assessments of the impact of impeded access to the Chinese market.

This interpretation is supported by discriminatory features analyses. Instead of arbitrarily selecting a set of features, we first find the nearest neighbors of the word embeddings in the vector space, then compute their cosine similarities with the group-specific embeddings, and finally calculate the ratio between the two sets of cosine similarities. In simple terms, this cosine similarity ratio reveals features that maximally discriminate one group over the other. Figure 5 visualizes the results. When the focal word is China, the most discriminatory words

[16]These words are "stemmed" so that different forms of the same base word – for example, *adversely* (adverb) and *adverse* (adjective) – are treated as the same.

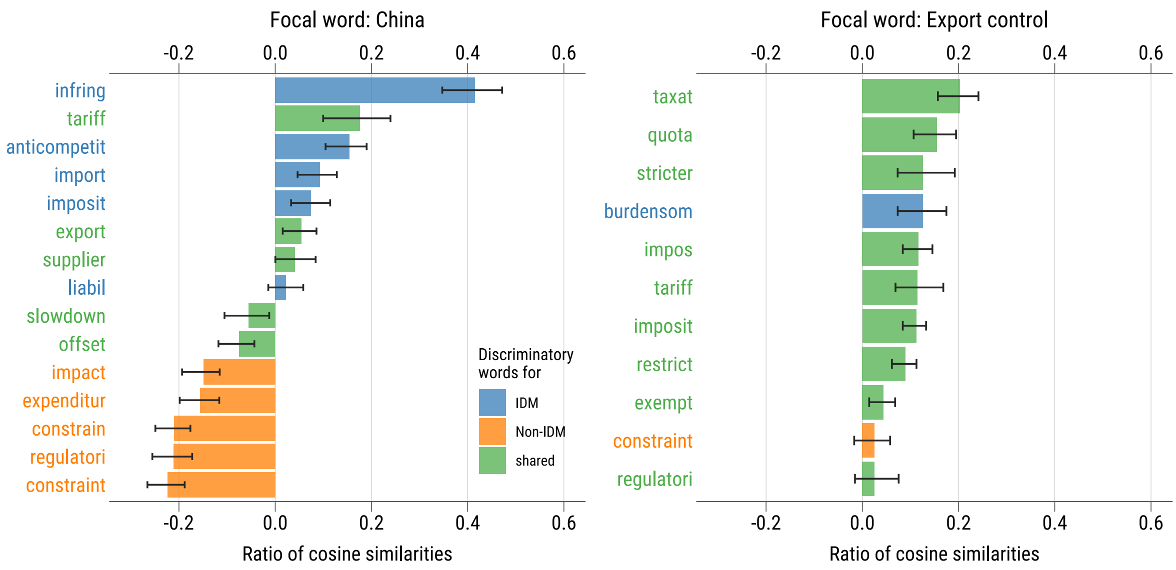

Figure 5: Discriminatory words for IDM and non-IDMs, selected by computing the nearest neighbors-cosine similarity ratios. Ratios are scaled such that positive values (in blue) generally denote discriminatory words for IDMs, negative values (in orange) generally denote discriminatory words for non-IDMs. Words in green are features shared by both groups.

that help us distinguish IDMs from non-IDM ones include *infring* and *anticompetit*. These show that IDMs exhibit substantive concerns other than impact on revenue (e.g., infringement of intellectual property rights or anti-competitive behaviors from Chinese firms; more below) that are less commonly discussed by non-IDMs. Meanwhile, words such as *constraint, regulatori, expenditur, impact* are more discriminatory of non-IDM firms, which are consistent with the results shown in Figure 4 above that non-IDM firms are more likely to be concerned about revenue impact or supply capacity constraints.

On the other hand, when the focal word is export control, IDMs and non-IDMs share many similar features (e.g., *taxat, quota, stricter, impos, tariff, imposit, restrict, exempt, regulatori*) in their word embeddings and there is no meaningful discriminatory feature that help us distinguish one group from the other. This shows that they discuss export control in very similar manners.

We move on to the embedding regression analyses to systematically relate a set of firm-level covariates to their semantic differences in discussing China and export control. Again, the outcome of the regression analyses is $n \times K$ word embeddings matrix, where n is the number of instances when a focal word ($n = 2,869$ for China and $n = 935$ for export control)

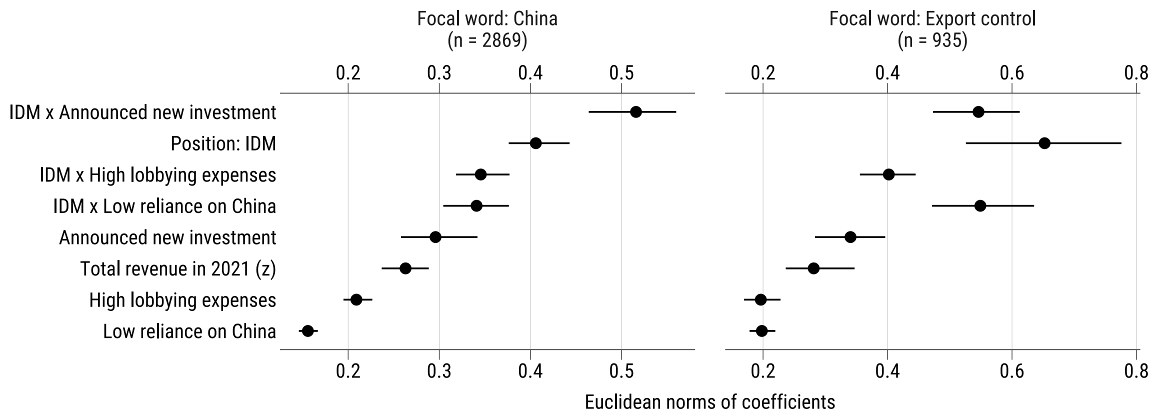

Figure 6: Embedding regression results. All covariates are dummies to facilitate comparison: *Announced new investment* is a dummy of whether a firm has announced any new investment; *low reliance on China* is a dummy of whether a firm's proportion of revenue from China in 2022 is lower than the median of all firms'; *high lobbying expenditures* is a dummy when a firm's lobbying expenditures are higher than the median of all firms'. All coefficients are statistically significant at 0.01 level.

is being observed given some context (window set to be 12 tokens), embedded in a $K = 300$ dimensional space from pre-trained GloVe embeddings. Figure 6 visualizes the (Euclidean norms of) coefficients from the regression which help us assess the relative importance of covariates in contributing to group difference in the word embeddings.

When the focal word is China, being in the industry segment of IDM (normed estimate: 0.41; standard error: 0.02) leads to significant difference in the word embeddings when compared to those of non-IDM firms. Furthermore, the interactions between IDM position and three other dummies produce notable differences. Most significantly, being an IDM *and* having announced a new investment produces the strongest difference (normed est: 0.52; se: 0.03) in the word embeddings. Similarly, being an IDM *and* having low reliance on China (normed est: 0.34; se: 0.02) *or* having high lobbying expenditures (normed est: 0.35; se: 0.02) are also strongly suggestive of differences in the word embeddings.

To more substantively interpret the regression results, we use the original estimated coefficients (vectors) to obtain the estimated embeddings for a hypothetical group and the associated nearest neighbors. We compare two ideal-typical cases that are maximally different from each other according to the model: a fabless firm with high reliance on China, no new investment, and low lobbying expenditures, and an IDM with low reliance on China low reliance on

	Predicted nearest neighbors for an ideal-typical:	
Focal word	Fabless firm	IDM
China (Model 1)	constraint, slowdown, regulatori, tariff, impact	lawsuit, infring, supplier, antitrust, anticompetit
Export control (Model 2)	tariff,stricter, regulatori, restrict, impos	tariff, stricter, imposit, regulatori, impos

Table 1: Predicted nearest neighbors for an ideal-typical fabless firm (high reliance on China, low lobby expense, no new investment) and IDM (low reliance on China, high lobby expense, and some new investment).

China, some new investment, and high lobbying expenditures.[17] Table 1 shows the predicted nearest neighbors for the hypothetical fabless firm and IDM from the estimated embeddings. When talking about China, a hypothetical fabless firm is most likely to mention "*constraint, slowdown, regulatori, tariff, imapct*," which is consistent with the results we presented. For a hypothetical IDM, however, it is more likely to bring up "*lawsuit, infring, supplier, antitrust, anticompetit*."

To further understand the substantive concerns of a IDM, I use the estimated embeddings to obtain the nearest *context* that is most indicative of a IDM.[18] The top example comes from a series of filings by Micron Technology (the fourth largest IDM in our dataset), which discusses how the firm's manufacturing subsidiaries in China have been subject to allegations of patent infringement by Chinese firms and courts:

> On March 19, 2018, Micron Semiconductor (Xi'an) Co., Ltd. ("MXA") was served with a patent infringement complaint filed by Fujian Jinhua Integrated Circuit Co., Ltd. ("Jinhua") in the Fuzhou Intermediate People's Court in Fujian Province, China (the "Fuzhou Court"). On April 3, 2018, Micron Semiconductor (Shanghai) Co. Ltd. ("MSS") was served with the same complaint. The complaint alleges that MXA and MSS infringe a Chinese patent by manufacturing and selling certain Crucial DDR4 DRAM modules. The complaint seeks an order requiring MXA and

[17] Recall that all covariates in our models are dummies. The estimated embeddings for the ideal-typical fabless firm is simply the intercept of the model, which is the reference group. For the ideal-typical IDM, we simply combine four coefficients (*Position: IDM, IDM x Announced new investment, IDM x Low reliance on China, IDM x High Lobbying expenses*) together to obtain the estimated embeddings.

[18] The exact nearest context is "*stop manufacturing using selling offering sale accused products China pay damages million yuan plus court fees incurred March MXA served patent infringement complaint filed*," which is not highly readable because the texts are pre-processed and stopwords are removed.

> MSS to destroy inventory of the accused products and equipment for manufacturing the accused products in China; to stop manufacturing, using, selling, and offering for sale the accused products in China; and to pay damages of 98 million Chinese yuan plus court fees incurred.

Accusations of patent infringement are not limited to China; Micron Technology has been repeatedly sued by domestic competitors in the U.S. courts too. But it did list "complaints in Chinese courts alleging patent infringement" as a separate item in their Risk Factors section and said that "[t]he laws of some foreign countries may not protect our intellectual property to the same degree as do U.S. laws." (Form 10-Q, Micron Technology, Inc., for the quarterly period ended December 2, 2021.) In short, our word embeddings model is picking up substantive concerns and challenges faced by IDMs regarding China that are different from those of fabless firms, particularly patent infringement accusations. This might offer an additional reason in explaining why IDMs are less pessimistic (Figure 4) in their discussion about China.

The regression results when using export control as the focal word is more mixed. The right panel in Figure 6 shows that IDM position and its interaction with new investment, low reliance on China, and high lobbying expenses similarly produce significant differences in the word embeddings. But the predicted nearest neighbors shown in Table 1 across the hypothetical fabless firm and IDM are essentially equivalent. This is more consistent with the results shown in Figure 5 where we have difficulty finding discriminatory words for one group over the other, that IDMs and non-IDMs discuss export control in a highly similar fashion. This warrants further investigation and improvement of the word embeddings models.

In summary, the word embeddings analyses show that there are significant semantic differences in the ways that IDMs and non-IDMs discuss China (though less so in export control), after controlling for their firm size (total revenue), reliance on China for revenue, and lobbying expenditures. IDMs are less pessimistic when talking about China in the sense that they are less likely to bring up words such as "impact" and "constraint". More importantly, IDMs that have made some investment pledge in expanding their domestic manufacturing capacities produce the biggest semantic differences in how they discuss China. They are also more likely to bring up unique challenges such as patent infringement allegations by their Chinese counterparts. Non-IDMs, mostly fabless firms, are more likely to offer alarmist assessments when they discuss China.

7 Conclusion

This study explores how semiconductor firms respond to the worsening trade prospect amid the intensified geoeconomic competition between the U.S. and China. It specifically investigates the role of industry position in shaping firms' preferences and responses. There are several limitations to the study that represent room for future improvement. First, the analyses primarily focus on IDMs versus non-IDM firms (mostly fabless). Other important segments, such as EDA and equipments, are insufficiently represented in the dataset and are lumped together in the empirical analyses. Future studies should further disaggregate these segments and investigate their heterogeneous preferences. Second, this study uses off-the-shelf, pre-trained word embeddings to analyze financial documents that might be highly idiosyncratic in their use of the language. One future improvement is to use word embeddings that are specifically trained on a large corpus of financial documents (e.g., FinBERT (Araci, 2019)) and are more attuned to semantic nuances in this specialized domain. Third, the semantic differences in their financial disclosure might not translate into actual differences in firm strategies and action. Talk can be cheap and it represents an inherent limitation of textual analyses. Future studies should collect further data on firm action (e.g., lobbying for free trade, reallocation of investment and resources in/out of China) and to triangulate them with our text as data.

References

Aggarwal, Vinod K. and Andrew W. Reddie. 2021. "Economic Statecraft in the 21st Century: Implications for the Future of the Global Trade Regime." *World Trade Review* 20(2):137–151.
URL: *https://www.cambridge.org/core/product/identifier/S147474562000049X/type/journal*$_article$

Araci, Dogu. 2019. "FinBERT: Financial Sentiment Analysis with Pre-trained Language Models.". arXiv:1908.10063 [cs].
URL: *http://arxiv.org/abs/1908.10063*

Barwick, Panle Jia, Myrto Kalouptsidi and Nahim Bin Zahur. 2019. "China's Industrial Policy: an Empirical Evaluation." *NBER Working Papers* (No. 26075).

Bates, Robert. 1981. *Markets and States in Tropical Africa: The Political Basis of Agricultural Policies.* Berkeley and Los Angeles, California: University of California Press.

Blackwill, Robert D and Jennifer M Harris. 2016. *War by Other Means: Geoeconomics and Statecraft.* Harvard University Press. Publication Title: War by Other Means.

Branstetter, Lee G., Guangwei Li and Mengjia Ren. 2022. "Picking Winners? Government Subsidies and Firm Productivity in China." *NBER Working Papers* (No. 30699).

Bureau of Industry and Security (BIS). 2022. "Commerce Implements New Export Controls on Advanced Computing and Semiconductor Manufacturing Items to the People's Republic of China (PRC).".
URL: *https://www.bis.doc.gov/index.php/documents/about-bis/newsroom/press-releases/3158-2022-10-07-bis-press-release-advanced-computing-and-semiconductor-manufacturing-controls-final/file*

Daniels, Mario and John Krige. 2022. *Knowledge regulation and national security in postwar America.* The University of Chicago Press. Place: Chicago ; Publication Title: Knowledge regulation and national security in postwar America.

Doner, Richard F., Bryan K. Ritchie and Dan Slater. 2005. "Systemic Vulnerability and the Origins of Developmental States: Northeast and Southeast Asia in Comparative Perspective."

International Organization 59(02).
URL: *http://www.journals.cambridge.org/abstract*$_S$0020818305050113

Farrell, Henry and Abraham L Newman. 2019. "Weaponized Interdependence: How Global Economic Networks Shape State Coercion." *International Security* 44(1):42–79.

Galetovic, Alexander. 2021. Patents in the History of the Semiconductor Industry: The Ricardian Hypothesis. In *The Battle over Patents: History and Politics of Innovation*, ed. Stephen H. Haber and Naomi R. Lamoreaux. 1 ed. Oxford University Press.
URL: *https://academic.oup.com/book/39256*

Gelman, Andrew. 2008. "Scaling regression inputs by dividing by two standard deviations." *Statistics in Medicine* 27(15):2865–2873.
URL: *https://onlinelibrary.wiley.com/doi/10.1002/sim.3107*

Gereffi, Gary. 1994. The Organization of Buyer-Driven Global Commodity Chains: How U.S. Retailers Shape Overseas Production Networks. In *Commodity chains and global capitalism*, ed. Gary Gereffi and Miguel Korzeniewicz. Contributions in economics and economic history Praeger. Place: Westport, Conn Publication Title: Commodity chains and global capitalism.

Gereffi, Gary, John Humphrey and Timothy Sturgeon. 2005. "The governance of global value chains." *Review of International Political Economy* 12(1):78–104.
URL: *http://www.tandfonline.com/doi/abs/10.1080/09692290500049805*

Haber, Stephen, Armando Razo and Noel Maurer. 2003. *The Politics OF Property Rights: Political Instability, Credible Commitments, and Economic Growth in Mexico, 1876-1929.* Cambridge University Press.

Hirschman, Albert O. 1969. *National power and the structure of foreign trade.* Publications of the Bureau of business and economic research, University of California University of California Press. Place: Berkeley.

Hung, Ho-fung. 2022. *Clash of Empires: From 'Chimerica' to the 'New Cold War'.* Elements in Global China Cambridge University Press.

Kennedy, Paul M. 1987. *The rise and fall of the great powers : economic change and military conflict from 1500 to 2000.* Power and Morality Collection at Harvard Business School. Random House. Place: New York, NY Publication Title: The rise and fall of the great powers : economic change and military conflict from 1500 to 2000.

Kim, In Song. 2017. "Political Cleavages within Industry: Firm-level Lobbying for Trade Liberalization." *American Political Science Review* 111(1):1–20.
URL: *https://www.cambridge.org/core/product/identifier/S0003055416000654/type/journal*$_{a}rticle$

Kim, In Song and Iain Osgood. 2019. "Firms in Trade and Trade Politics." *Annual Review of Political Science* 22(1):399–417.
URL: *https://www.annualreviews.org/doi/10.1146/annurev-polisci-050317-063728*

Loughran, Tim and Bill Mcdonald. 2011. "When Is a Liability Not a Liability? Textual Analysis, Dictionaries, and 10-Ks." *The Journal of Finance* Vol. 66(No. 1):pp. 35–65.

Meijer, Hugo. 2016. *Trading with the enemy : the making of US export control policy toward the People's Republic of China.* First edition. ed. Oxford University Press. Place: Oxford ; Publication Title: Trading with the enemy : the making of US export control policy toward the People's Republic of China.

Melitz, Marc J. 2003. "The Impact of Trade on Intra-Industry Reallocations and Aggregate Industry Productivity." *Econometrica* 71(6):1695–1725. Place: Oxford, UK and Boston, USA Publisher: Blackwell Publishing Ltd.

Mikolov, Tomas, Kai Chen, Greg Corrado and Jeffrey Dean. 2013. "Efficient Estimation of Word Representations in Vector Space.". arXiv:1301.3781 [cs].
URL: *http://arxiv.org/abs/1301.3781*

Miller, Chris. 2022. *Chip War: The Fight for the World's Most Critical Technology.* New York: Scribner. Publication Title: Chip War.

Naughton, Barry. 2021. The Rise of China's Industrial Policy: 1978 to 2020. Technical report Universidad Nacional Autónoma de México.

Osgood, Iain. 2016. "Differentiated Products, Divided Industries: Firm Preferences over Trade Liberalization." *Economics & Politics* 28(2):161–180.
URL: *https://onlinelibrary.wiley.com/doi/10.1111/ecpo.12075*

Pennington, Jeffrey, Richard Socher and Christopher Manning. 2014. Glove: Global Vectors for Word Representation. In *Proceedings of the 2014 Conference on Empirical Methods in Natural Language Processing (EMNLP)*. Doha, Qatar: Association for Computational Linguistics pp. 1532–1543.
URL: *http://aclweb.org/anthology/D14-1162*

Roberts, Anthea, Henrique Choer Moraes and Victor Ferguson. 2019. "Toward a Geoeconomic Order in International Trade and Investment." *Journal of International Economic Law* 22(4):655–676.
URL: *https://academic.oup.com/jiel/article/22/4/655/5637576*

Rodman, Emma. 2020. "A Timely Intervention: Tracking the Changing Meanings of Political Concepts with Word Vectors." *Political Analysis* 28(1):87–111.
URL: *https://www.cambridge.org/core/product/identifier/S1047198719000238/type/journal_article*

Rodriguez, Pedro L. and Arthur Spirling. 2022. "Word Embeddings: What Works, What Doesn't, and How to Tell the Difference for Applied Research." *The Journal of Politics* 84(1):101–115.
URL: *https://www.journals.uchicago.edu/doi/10.1086/715162*

Rodriguez, Pedro L., Arthur Spirling and Brandon M. Stewart. 2023. "Embedding Regression: Models for Context-Specific Description and Inference." *American Political Science Review* pp. 1–20.
URL: *https://www.cambridge.org/core/product/identifier/S0003055422001228/type/journal_article*

Schattschneider, E. E. (Elmer Eric). 1935. *Politics, pressures and the tariff*. Prentice-Hall political science series Prentice-Hall. Place: New York.

Semiconductor Industry Association (SIA). 2022. State of the U.S. Semiconductor Industry. Technical report.

Taylor, Mark Zachary. 2016. *The Politics of Innovation: Why Some Countries Are Better Than Others at Science and Technology.* New York: Oxford University Press.

Weiss, Linda. 2021. "Re-emergence of Great Power Conflict and US Economic Statecraft." *World Trade Review* 20(2):152–168.
URL: *https://www.cambridge.org/core/product/identifier/S1474745620000567/type/journal*$_{a}rticle$

Weiss, Linda and Elizabeth Thurbon. 2021. "Developmental State or Economic Statecraft? Where, Why and How the Difference Matters." *New Political Economy* 26(3):472–489.
URL: *https://www.tandfonline.com/doi/full/10.1080/13563467.2020.1766431*

Woo-Cumings, Meredith Jung-En. 1998. National security and the developmental state. In *Behind East Asian Growth: the political and social fundations of prosperity*, ed. Henry S. Rowen. Routledge pp. 319–337.

A Additional figures

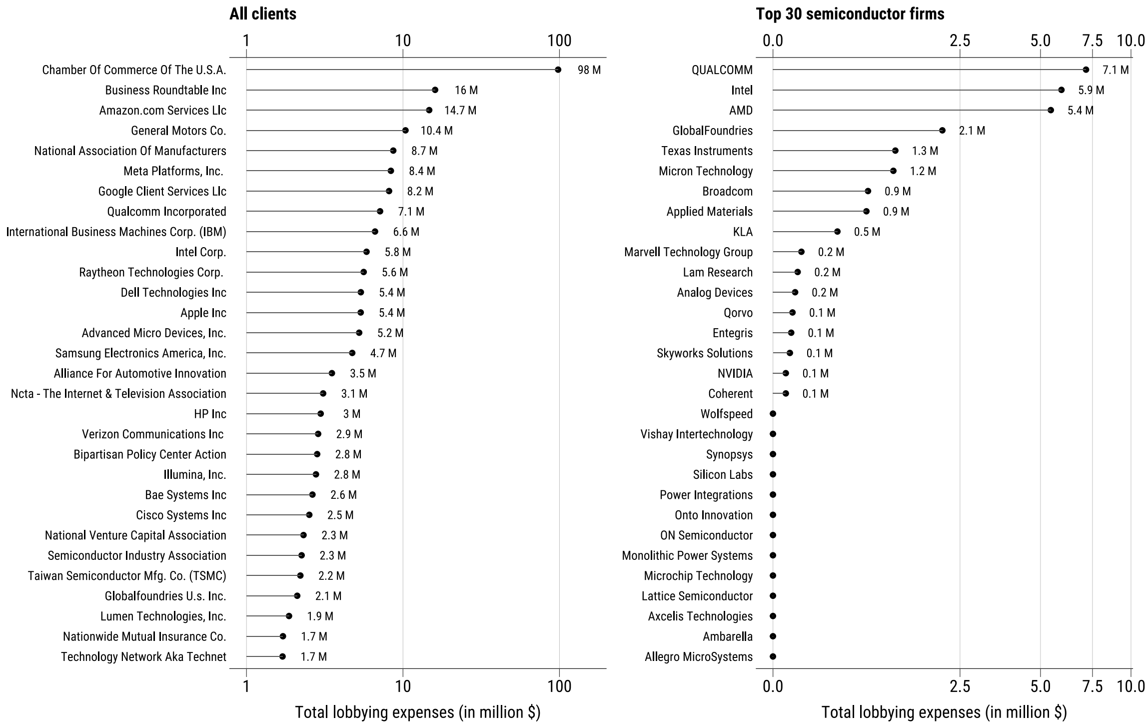

Figure A.1: Organizations with the most lobbying expenditures in 2022 and 2023, specifically on issues related to the Chips and Science Act and semiconductor. The left panel shows the top-30 clients out of the full sample. The right panel focuses on the 30 semiconductors in our dataset.