Strong Businesses and Weak Politicians: The Domestic Political Economy of US-China Trade

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Abstract

How do business interests shape politicians' preferences on free trade? Past studies either focus on how the labor shock brought by globalization made politicians anti-trade, or how "Corporate America" pushed back against politicians' protectionist turn. Business interests are absent in the first case, too unified in the second. I argue that firms have different types of business concerns depending on their specific position in the market and interaction with the host state. They transmit their business concerns to politicians to shape the trade policy. Empirically, I focus on the U.S.-China trade relationship from 2017 to 2023. Adopting a text as data approach, I measure S&P 500 companies' various business assessments on China from their financial (10-K) reports and Congress Members' specific criticisms of China using Twitter data. I link firms' interests to politicians' preferences via lobbying expenses data. Results show that politicians who are lobbied by firms that discussed intellectual property rights violations in their reports are more likely to criticize China on trade and technology issues.

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1 Introduction

That there is a new, bipartisan consensus on China is a view widely held by U.S. foreign policymakers, journalists, and scholars (Carothers and Sun 2023). Central to this consensus is the idea that the free trade regime is no longer unconditionally beneficial to the U.S. and that trade with China should be made more conditional, whether on security or economic grounds. The purported unity in American interests behind the curtain of a consensus is perhaps least shared by the business community, some of which bear substantive economic losses when trading becomes more restrictive. But it is equally problematic to assume that "Corporate America" is fighting back against the policy turn in unison; firms face collective action problem, and some can benefit from trade being more encumbered. It is important to ask how the political consensus emerged in the first place, and what roles *different* business interests played in facilitating or resisting its emergence when interacting with the politicians.

In this paper, I study how firm interests shape politicians' preferences on free trade. I present a simple typology of business concerns, that could be driven by profit, protection, predation or patronage. When firms face favorable market conditions (thus seeking to maximize *profits*) or state actions (thus deriving benefits from *patronage*), they are likely to lobby politicians to be more supportive of free trade. When firms face unfavorable market conditions (thus seeking *protection* from competition) or ex-post opportunistic state action (thus subject to *predation*), they are likely to lobby politicians to be more critical of the current free trade regime.

Empirically, I study the recent trade tension between the U.S. and China from 2017 to 2023, spanning two administrations. I employ the recent advances in Natural Language Processing (NLP) and transformer-based models for text classification in measuring firms' and politicians' positions on China. On the one hand, I focus on S&P 500 companies and collect all their annual financial filings to the U.S. Securities and Exchange Commission (SEC) during the period. I label each instance of their discussion on China into six possible classes: whether it describes (1) having subsidiaries in China, (2) seeing China as an important market, (3) intense competition in the local market, (4) intellectual property rights (IPRs) violation, (5) industrial policies by the Chinese state, and (6) barriers to entry to the market. This classification scheme allows me to code firm-level business concerns from the rich textual data. On the other hand, I measure politicians' support or criticism on free trade with China using all tweets posted by Members of Congress (from 115th to 118th Congress) and adopting a similar text classification scheme. I further link up firms' interests to politicians' preferences using dyadic lobbying data.

Consistent with the predation-driven theory, regression results suggest IPRs violation is a positive and statistically significant predator for politicians' criticism on China about its trade and technology issues, at least during the Trump era. The results hold after controlling for the politicians' political party, ideology, or the total tweeting frequency, and are robust to alternative probability thresholds in the classification scheme.

This is one of the first few studies that explicitly connect firm-level interests to politicians' preferences and be able to juxtapose and test how different types of business concerns affect politicians simultaneously. It has implications on how we understand how firm heterogeneous preferences are shaped not just by market conditions but also the state actions in the trading country, how firm lobbying shapes trade policy, and how the U.S.-China trade tension might unfold in light of the role played by business.

2 Literature

What explains politicians' preferences on free trade? And how are those preferences shaped by firm interests? I situate my study in three strands of literature. The first focuses on how import competition and de-industrialization, particularly focusing on the episode of the "China shock," make politicians less pro-free trade, more protectionist, and more hostile towards the export-oriented countries (e.g., China). Autor, Dorn, and Hanson (2013) showed that import shocks from China cause higher unemployment, lower labor force participation, and reduced wages in U.S. labor markets. Voters who suffered from import competition are were more likely to vote for conservative, Republican candidates in the U.S. (Autor, Dorn, Hanson, and Majlesi 2020), or far right candidates in European countries (Milner 2021).

Examining politicians' preferences specifically, Feigenbaum and Hall (2015) found that U.S. legislators from regions most affected by Chinese import shocks voted in a more protectionist direction on trade-related bills. In terms of economic ideology, Meyerrose and Watson (2024) found that French legislators exhibited an ideological shift towards leftist economic views (e.g., supporting market regulation and welfare state) when they were from regions most hurt by China import shocks. In foreign relations, Kleinberg and Fordham (2013) found that legislators from districts whose sectors have lower export orientations and higher import sensitivity vis-à-vis China are more likely to vote for or sponsor bills that were hostile towards it. Similar results can be found in the Brazilian context, where Campello and Urdinez (2021) found that Brazilian citizens and legislators tend to hold negative views about economic ties with China when they are from localities that experienced import shocks.

My study critically engages with the China shock literature by highlighting two of its problems. First, it focuses on the influence of labor and implicitly assumes a Downsian median voter logic: labor constituents hurt by globalization used the ballot box to put pressure on their representatives, making them more protectionist and anti-free trade with China. However, American foreign policy-making tends to be heavily influenced by business leaders rather than labor (Jacobs and Page 2005). How business counteract or amplify labor's backlash against globalization and continue to shape the politicians' positions on U.S.-China trade is left unaddressed. Furthermore, import competition from China to the U.S. local labor markets might not be as exogenous as a shock as assumed by the literature; rather, it is an endogenous choice by American business and politicians to outsource labor-intensive manufacturing and prioritize corporate profitability and investment opportunities. Recent work in economic history emphasizes the role of business interest in shaping the U.S.-China trading relationship. Ingleson (2024) details how since the 1970s U.S. business and the Chinese government re-defined and co-created a trading relationship that was centered on access to cheap labor and offshoring production, rather than seeing China as an export market to absorb U.S. goods. Fast forward to 1990s: U.S. business further assumed the role of proxy lobbyists for Chinese government to put pressure on the Clinton administration, successfully de-linking the renewal of China's Most-Favored Nations (MFN) status to its human rights record and paving the way for its ascent to the World Trade Organization (WTO) (Hung 2021; Lichtenstein and Stein 2023). My study seeks to uncover how U.S. firm interests shape the recent episode of U.S.-China trade policy making.

My study also extends the literature on firm politics and their heterogeneous preferences for free trade. The "new-new trade theory" goes beyond standard trade models that focus on country- or sector-level comparative advantage or factor endowments, and highlights the role of firms' export orientation (Milner 1988a), size, productivity and product differentiation (Kim 2017; Osgood 2016; Kim and Osgood 2019) in explaining their distributional gain from and preference for free trade. I build upon the insight from this literature by putting firms and their heterogeneous preferences for trade policy at the center of my study. But these studies often generalize from cross-country data that cover many free trade agreements or trading relationships, where the specificity of the Chinese political economic system and its evolving trading relationship with the U.S. is invariably lost. As discussed later, firms' business interests are powerfully shaped by not just market conditions but also the *state actions* in the trading country. This study situates firm heterogeneity back in the specific context of China's political economy by, for example, bringing in discussion of its historic use of quid pro quo policy (Jiang et al. 2018; Bai et al. 2023; Bian and Meier 2021) for technology absorption and its recent efforts in industrial policies (Naughton 2021).

My study further addresses a critical empirical gap, by linking firms' interests to politicians' preferences. On the one hand, studies have demonstrated that firms are important political actors who express their preferences on free trade. For example, Kim (2017) uses lobbying records to measure firms' lobbying for reduced tariffs; Osgood (2017) uses a variety of sources (e.g., trade coalition, congressional testimony, public submission or statements) to code firms' support for free trade agreements. In these studies, the firms' preferences are modeled as the outcome variable. On the other hand, studies have also shown that politicians' positions on free trade are influenced by business interests at district or state levels. For example, Milner and Tingley (2011) use district-level variables (e.g., percentage of people working in high skill jobs in the district as a measure for human capital) to measure factor endowments and to explain the politicians' voting for free trade; Hiscox (2002) uses state-level industrial characteristics (e.g., total production in the leading exporting and import-competing industries as a proportion of state income) to explain voting on trade bills. In these cases, politicians' pref-

Table 1: A typology on business concerns

		Conditions are...	
		Favorable	Unfavorable
Firms respond to...	Market conditions	Profit-driven	Protection-driven
	State actions	Patronage-driven	Predation-driven

erences are modeled as the outcome variables, while the authors can only rely on district- or state-level economic data as the explanatory variables. There is scant research that empirically links firms' preferences to politicians' preferences; my study is one of the first, to my knowledge, to fill this gap and conduct empirical tests on how firms interests affect politician's preferences.

3 Argument

Politicians' preferences on free trade are shaped by the specific types of business concerns raised by firms. A simple typology shown in Table 1 helps differentiate different concerns and specify the hypothesized directions of how they influence politicians' preferences on trade policy. Most importantly, it facilitates the juxtaposition and assessment of the relative importance of these hypothesis. In this typology, the first dimension is whether the firms are primarily responding to market conditions versus state actions in the foreign country; the second is whether those conditions are favourable or unfavourable to the firms' business.

When firms are responding to market conditions that are favourable in the foreign country, those concerns are primarily *profit-driven*; these concerns are likely to influence the politicians in a pro-free trade direction in order to not disrupt the benefits that can be derived from the free trade arrangement. Profit-driven concerns are widely considered by the literature that explains why some firms support free trade; their explanatory variables include firm's export dependence on overseas markets, multinational presence, and reliance on global intrafirm trade (Milner 1988a; Milner 1988b). In this study, I operationalize these profit-driven concerns in two ways: whether a firm sees China as an important market for revenue and growth, and whether a firm has any subsidiary, joint venture, or long-term fixed investment in China. I come up with two hypotheses:

Hypothesis 1a *If firms describe China as an important market for revenue and growth, those politicians lobbied by them are less likely to criticize China on trade.*

Hypothesis 1b *If firms have subsidiaries, joint ventures, or fixed investment in China, those politicians lobbied by them are less likely to criticize China on trade.*

The second type of business concerns is *protection-driven* ones, arising when firms trying to shield themselves from unfavorable market conditions. A primary form of protection that has historically dominated U.S. trade politics is import tariffs, where domestic producers who face intense import competition demand protection from politicians by restricting imports (Schattschneider 1935; Irwin 2019). But it is also possible that exporters in a comparative-disadvantage status who face fierce competition in foreign markets may support protectionism by the state (Mayda and Rodrik 2005), or even militarism (Chatagnier and Kavaklı 2017). I formulate the following hypothesis:

Hypothesis 2 *If firms describe China as an intense business competitor, those politicians lobbied by them are more likely to criticize China on trade.*

The third type of business concerns is when firms respond to state actions (by the government of the trading or hosting country) that are ex-post opportunistic and detrimental to their business; I call them *predation-driven* concerns. Here, I specifically focus on the dynamics of technology transfer and intellectual properties rights (IPRs). China has practiced the *quid pro quo* policy, where foreign firms that wish to enter the Chinese market are often required to set up a joint venture with a Chinese local partner to facilitate the transfer of technology; firms are essentially trading technology for market access. This policy has shown to contribute to substantive local knowledge spillover and industrial upgrading for China (Jiang et al. 2018; Bai et al. 2023). The welfare effects of this policy on U.S. firms and economy, however, remain debated. Menaldo and Wittstock (2021) argue that the overall benefits to the U.S. are positive in terms of patent royalties and access to China's labor and consumer markets. Bian and

Meier (2021), on the other hand, argue that technology transfer to China is driven by myopia, where CEOs with higher equity incentives transfer more technology to China in the short term, while leading to their firms to face more technological competition from China in the long run.

Regardless of its overall welfare effects to the U.S. economy, I argue that U.S. firms face the problem of ex-post opportunism when they transfer technology to China: Once they make a highly relational-specific investment by establishing a joint venture and transferring technology and tacit know-how to the Chinese partner, the Chinese firms and state can exercise ex-post opportunism (Williamson 1985) and undermine the U.S. firms' market access or presence in different ways.[1] First, the Chinese firms can use courts to sue U.S. firms for intellectual property rights violations or to shield themselves from infringement litigation.[2] Second, the Chinese state has started to use industrial policies circa 2010 to promote indigenous firms to take over the technological frontier, using instruments like subsidies, low-interest loans, and guidance funds (amounting to $1.6 trillion USD in 2018; Naughton (2021)). These policies particularly favor "strategic industries," such as semiconductor, which are IP intensive and often relied on earlier partnership with and technology absorption from Western firms, who are now being disadvantaged. Third, the Chinese state can erect further administrative and legal barriers to prevent U.S. firms from capturing the market share. I formulate these predation-driven concerns into three hypotheses:

Hypothesis 3a *If firms describe China violating their intellectual property rights or patents, those politicians lobbied by them are more likely to criticize China on trade.*

Hypothesis 3b *If firms describe China using industrial policies to promote its local competitors, those politicians lobbied by them are more likely to criticize China on trade.*

Hypothesis 3c *If firms describe China erecting barriers to entry to its market, those politicians lobbied by them are more likely to criticize China on trade.*

[1] Reports suggest that some of "coercive technology transfer" techniques, apart from joint venture, include "using local courts to invalidate American firms' patents and licensing arrangements, dispatching antitrust and other investigators, and filling regulatory panels with experts who may pass trade secrets to Chinese competitors" (Wei and Davis 2018).

[2] On Chinese courts using "anti-suit injunctions" to "block non-Chinese companies from enforcing IP rights in other jurisdictions," making "Chinese companies cannot be sued for alleged infringements" in "standard essential patents," see White (2022).

The last type of concerns is what I call patronage-driven concerns, when firms respond to favourable state actions in the trading country. One illustrating example is Tesla and its operation in China. Tesla was able to secure substantial policy concessions and largess from China, including a change in China's national emissions regulations, and setting up a factory in Shanghai in an expedited fashion (168 working days) and without a local partner (a first for a foreign auto company), partly due to Elon Musk's close relationship with Li Qiang, a top Shanghai official and now the Premier (Hvistendahl, Ewing, and Liu 2024). I hypothesize that firms that benefit from these patronage-driven interests are likely to lobby politicians to not upset the current policy regime and trade relationship with China. Though not being the focus of and not subject to empirical test in this study, this kind of patronage-driven concerns might explain how Chinese industrial policies can create buy-in from U.S. business and pit certain firms against one another, creating another source of firm heterogeneity in trade policy preference.

4 Data and method

To assess how U.S. firm specific concerns affect politicians' preferences on free trade with China, I marshal three types of data: (1) firm-year level assessment on China, (2) firm-politician-year level of lobbying connection, and (3) politician-year level preference on China. I adopt a text-as-data approach and harness recent advances in Natural Language Processing (NLP) techniques to efficiently extract information and measure firm and politicians' preferences from textual data. In this paper, I focus on the period from 2017 to 2023 which spans the Trump and Biden administrations and the 115th to 118th Congress. I include as the relevant subjects of this study all S&P 500 firms – the top 500 publicly trading companies by market capitalization – and all Members of Congress – both the House and Senate at the federal level– in the said period.

4.1 Measuring firms' interests from 10-K filings

First, I rely on firms' financial filings, specifically their 10-K annual reports, to the U.S. Securities and Exchange Commission (SEC) to construct the firm-year level assessment on China. These filings contain rich textual information in their mandated sections such as Business Overview, Risk Factors, Selected Financial Data and, more importantly, Management's Discussion and Analysis ("MD&A"), which allows the company management to "tell its story in its own words" concerning its business performance (SEC 2011). Existing literature in finance and accounting has long used SEC filings for quantitative textual analyses, but most studies tend to employ a bag-of-words approach and develop manual dictionaries to measure positive or negative tones or sentiments (Loughran and Mcdonald 2016).

I measure six variables that relate to a U.S. firm assessment on or business experience in China: (1) whether it sees China as an important *market* for revenue and growth, (2) whether it has any *subsidiary*, joint venture or fixed investment in China, (3) whether it sees Chinese companies as intense *competitors*, (4) whether it experiences *violation* of intellectual property rights (IPR) or patents, (5) whether it sees the Chinese government using state *policy* to promote local industry, and (6) whether it sees *barriers* in entering the Chinese market. These specific political-economic concerns are not amenable to manual dictionaries or captured by word co-occurrence, but could be discerned with reasonable ease by a trained annotator.

My measurement strategy takes advantage of the recent advances in Large Language Models (LLMs) in text classification tasks.[3] I employ the BERT-NLI models developed and trained by Laurer, Atteveldt, et al. (2023) as the text classifier used throughout this paper. While the technical details of this family of models are discussed in Appendix A, its key advantages include its ability to generalize to unseen classification tasks (that its 435-million-parameter model was trained on 33 classification datasets with 389 classes) and its reproducibility (that it is non-proprietary and its results can be reliably validated and replicated).

[3] Gilardi, Alizadeh, and Kubli (2023), for example, show that ChatGPT outperforms MTurk crowd workers in several annotation tasks, such as identifying stance, topic, or framing from tweets and news articles, by about 25% on average in accuracy. But the main problem of using proprietary models like ChatGPT, apart from their cost, is that the model parameters and the underlying training data are frequently updated, rendering the classification results in a given time not necessarily reproducible later. Also, classification tasks do not really exploit the generative part of the *Generative* Pre-trained Transformer (GPT) models. Using ChatGPT for such tasks often produces extra tokens beyond the desired labels and requires additional prompts and queries to extract the label

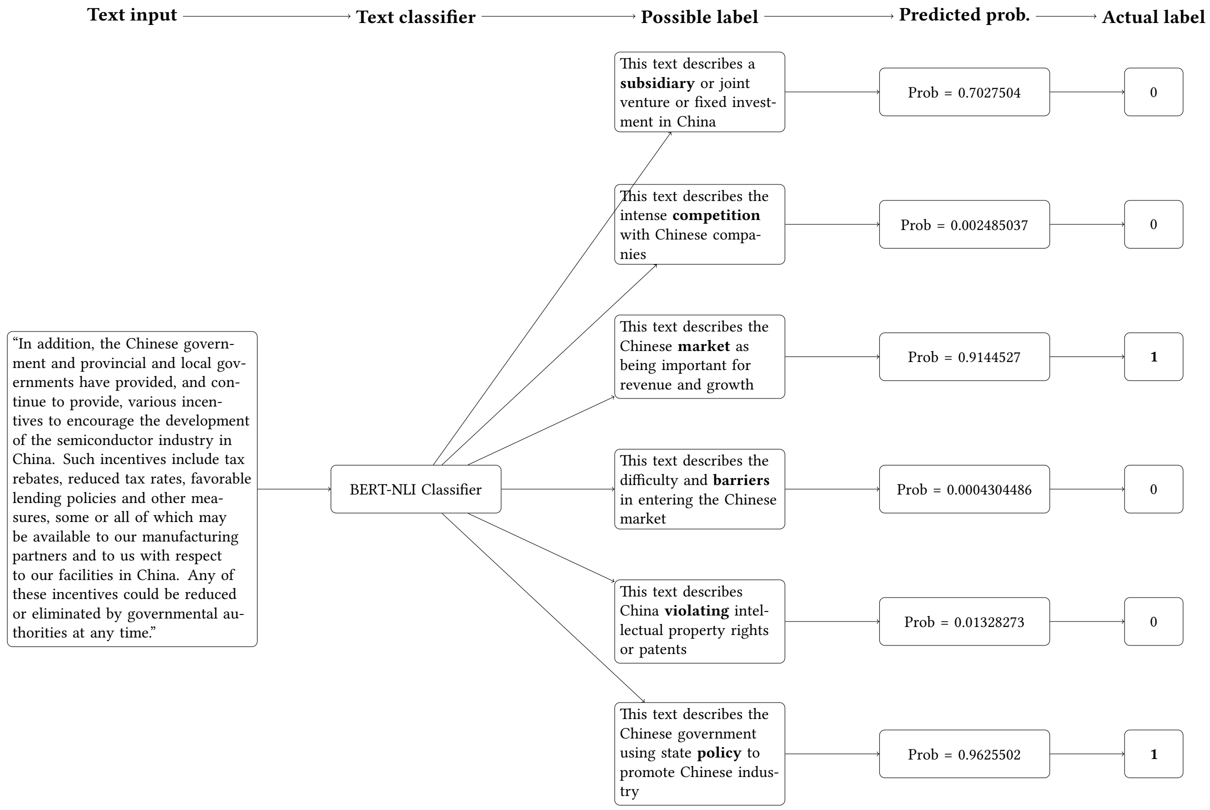

Figure 1: Workflow of classifying a text into 6 classes using a BERT-NLI classifier

Figure 1 demonstrates the workflow of classifying a sample text (excerpted from the 10-K report of Monolithic Power Systems Inc., a semiconductor firm, in 2017) into six possible classes: when a text, like a sentence or a short paragraph, is passed through the BERT-NLI Classifier, the model produces the predicted probability for each respective class verbalized in a statement. I allow multiple true classes, meaning that they are not mutually exclusive and their probabilities are independent, and use a probability threshold of 0.9 to code the label as 1 (or 0). For example, the sample text describes the policy instruments used by the Chinese government to promote the semiconductor industry, and that the U.S. firm's business can benefit from those incentives because it has facilities and manufacturing partners in China. The model assigns relatively high probabilities to the *policy* (prob = 0.96) and *market* (prob = 0.91) labels, while being a bit unsure about the *subsidiary* (prob = 0.70) label.[4]

from the original response, which adds to the computational and dollar costs.

[4]This example usefully illustrates both the flexibility and effectiveness of the classifier, but also highlight the potential pitfall of a blind reliance on the model (for example, that Chinese industrial policies are mentioned does not mean a U.S. firm is critical of them; in fact, they could be a beneficiary and demonstrate what I call patronage-drive concerns) and the inevitable trade-off between false positive and false negative rates (for example, the probability cutoff of 0.9 will fail to correctly classify the *subsidiary* label to be 1).

Building on this classification workflow, I annotated all relevant text from the S&P 500 companies' filings as follows. I collected 3,396 10-K reports from these companies that were submitted between 2017 and 2023.[5] I conducted minimal pre-processing on those reports[6] and tokenized each of them at the sentence level. In total, there are 10,540,875 sentences. I define as the relevant corpus those sentences that contain the words "China" or "Chinese"; this yields 43,107 sentences related to China. To make sure I sufficiently capture the context around the discussion on China, I pad each China-related sentence with its immediately preceding and following sentence; these padded sentences have an average token length of 111. These sentences were then fed into the BERT-NLI classifier for classification.[7] Table A1 in the Appendix shows sample text with the highest predicted probabilities for each of the 6 classes.[8]

Lastly, I aggregate these sentence-level labels and construct six firm-year level variables by summing up the total number of instances a firm mentioned a particular concern in their 10-K report. For an average firm in a given year, it mentioned China in 15.6 times (SD=18.0). For every 100 times they discussed China, 56.8 times they talked about subsidiaries or joint venture in China; 23.9 times they described China as an important market opportunity; 2.2 times they discussed intense competition in the market; 1.7 times they discussed China's industrial policy; 0.8 times they discussed barriers to entry; and 0.2 times they discussed intellectual property rights violations. I further break down the instances of discussing the 6 topics by industry sector over the years in FigureA1 in the Appendix.

[5] 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

[6] One advantage of using Transformer models is that they require minimal to no text pre-processing; in fact, they work well with natural sentences or paragraphs without the removal of stop words or stemming. Following Bill McDonald, I only remove markup tags (HTML, XBRL, XML), ASCII-encoded graphics, and tables from the 10-K filings.

[7] I used the open-source "deberta-v3-large-zeroshot-v2.0" model trained by Laurer, Atteveldt, et al. (2023) and publicly available on Hugging Face at https://huggingface.co/MoritzLaurer/deberta-v3-large-zeroshot-v2.0. For reference to readers who are interested in doing similar classification tasks, the inference was done using Jupyter Notebook and Google Colab's V100 GPU; the total inference time was around 90 minutes, averaging around 8 examples per second. This costed around $0.72 USD in total for 43,107 sentences as input and 6 labels as output. Using a A100 GPU should cut the inference time by half with some extra cost.

[8] The out-of-sample classification performance of the BERT-NLI classifier on financial filings cannot be timely incorporated in this version of the paper. In the next section, however, I provide the performance metrics of the classifier based on hand-coded Twitter data.

4.2 Measuring politicians' preferences from tweets

I measure politicians' preferences on trading with China using tweets as textual data. I rely on a dataset of all daily tweets posted by Members of Congress between June, 2017 to July, 2023.[9] I choose to focus on Twitter data instead of roll call data because there were very few bills that specifically focused on trading relationship with China; even if they did, Members of Congress often voted strategically along party lines or in an unanimous fashion.[10] Schwarz, Traber, and Benoit (2017) show that text-based (parliamentary speeches) scaling of ideal points exhibit more intra-party variation that those estimated from roll call. I similarly expect that U.S. legislators expressed discontents on Twitter about the current state of the U.S.-China trade relationship in a way that revealed more intra-party variation.

I operationalize politicians' preferences on free trade with China as the instances they criticized China on *trade* (e.g., unfair trade practices), on *technology* (e.g., "stealing" American technologies or intellectual properties), and on *job* (e.g., "taking away" American jobs). While these concerns do not constitute a blanket rejection of free trade per se, they communicate the intent to make trade more *encumbered*, more conditional, and hence less free.

I adopt a very similar text classification workflow I detailed above in annotating politician tweets. Out of 3,221,121 tweets made by all Members from the 115th to 118th Congress, 48,802 (1.5%) of them mentioned China[11] and are considered as the relevant corpus of this study. Each of these China-relevant tweet was minimally pre-processed[12] and fed into the BERT-NLI classifier for three non-mutually exclusive classes: criticizing China on trade, technology, and job.[13] To ensure the validity of our measurement strategy, I randomly selected a sample of 360

[9]The dataset, Tweets of Congress, is collected and maintained by Alex Litel (https://github.com/alexlitel/congresstweets).

[10]One example is the Uyghur Forced Labor Prevention Act (H.R.6256; S.65; P.L. 117-78), which was passed in the House with a 428–1 vote and, in the Senate, by unanimous consent in December, 2021. Though it doesn't overhaul US-China trading relationship in an overarching way, it is significant because it imposes limits on all imports from Xinjiang, China (in the form of a rebuttable presumption that puts the burden of proof on business to show that the goods were not produced with forced labor) and has widespread supply chain consequences.

[11]Or keywords in the following list: PRC, Beijing, Chinese, Hong Kong, HK, Taiwan, TW, Uyghur, and Tibet.

[12]Following the literature on fine-tuning BERT on Twitter data (Kawintiranon and Singh 2022), I replaced any URL with a special token HTTPURL, replaced any usernames with @USER, replaced "&" with "and," replaced emoji with their verbalized text equivalence.

[13]The exact hypotheses, or prompts, used in the classification model are: (1) The author of this text criticizes China for trade concerns; for example, China engaging in unfair trade practices, (2) The author of this text criticizes China for technology concerns; for example, China stealing American technologies or intellectual properties or IP, and (3) The author of this text criticizes China for job concerns; for example, China taking away

tweets and hand coded the values of the labels, comparing them to the predicted values out of the classifier who had not seen those tweets. The overall accuracy is 0.90 (precision=0.65; recall=0.75; balanced accuracy=0.84),[14] which gives me some confidence that the classification process is capturing the concepts of interest.

I aggregate these tweet-level labels to politician-year measures by matching the tweets to the official Twitter handles of Congressional Members and their biographical details. I then summed up all instances where trade, technology, and job concerns were mentioned by each Member across the years. On average, a Member in a given year tweeted 870 times, in which 14 of them mentioned China; they criticized China for trade concerns 2.6 times, technology or intellectual properties concerns, 3.0 times, and, job concerns, 1.1 times. Republicans criticized China on these three economic issues combined more frequently than Democrats (an average of 9.9 times versus 3.0); Senators were more outspoken than Representatives (an average of 12.6 times versus 5.1). However, there are vocal critics on China *across* the aisle, most notably Sen. Marco Rubio (R-FL; 317 total tweets criticizing China across three economic issues in 2018), Sen. Josh Hawley (R-MO; 229 tweets in 2020), Rep. Jim Banks (R-IN; 175 tweets in 2020), Tim Ryan (D-OH; 94 tweets in 2022), Sen. Chuck Schumer (D-NY; 57 tweets in 2019), and Sen. Maggie Hassan (D-NH; 50 tweets in 2022).

4.3 Linking firms' and politicians' preferences via lobbying

After constructing firm-year and politician-year measures that capture their assessments on China, the crucial step is linking up the two, which requires some observable mechanism that transmits firms' interests to the politician's calculus. Lobbying activities can be such a conduit as firms *individually* lobby Congress on specific trade policies and express their heterogeneous preferences (Kim 2017). I rely on the dyadic data that link politicians to firms provided in LobbyView database (Kim 2018). A dyadic connection indicates that a firm lobbied on some

American workers' job.

[14] The classification performance can be substantively improved with fine-tuning, that is to adjust some weights of the pre-trained models to our specific data and classification tasks via supervised learning. Wang (2023) and Laurer, Van Atteveldt, et al. (2024) show that fine-tuning the BERT models on a small set of 300 to 500 examples can significantly improve their classification performance.

congressional bills that were sponsored by a politician in a given congressional session.[15] Based on LobbyView data from 2017 to 2020, a total of 13,539 dyadic records can be identified in which the S&P 500 companies were the clients and 597 legislators were involved. Some of most connected firm-politician dyads include Bank of America–Sen. Chuck Grassley (R-IA; 182 bills lobbied on by the former and sponsored by the latter over 4 years), Oracle–Sen. Lamar Alexander (R-TN; 113 bills) and Verizon–Sen. John Thune (R-SD; 112 bills).

I assume that when a firm has a lobbying linkage with a politician in this way, the former is likely to pass on their business concerns in China to the latter and influence their political rhetoric. As such, for a particular politician-year, I sum up all 6 business concerns from all firms that had any lobbying connection (regardless of intensity) with that politician; these business concerns are thus *inherited* from firms to legislators.

The setup of the regression analyses is as follows:

$$Y_{i,s,t} = \beta' \boldsymbol{X}_{i,t} + \theta' \boldsymbol{Z}_{i,t} + \gamma_s + \delta_t + \epsilon_{it} \tag{1}$$

where i denotes politician, s denotes state, and t denotes year. The dependent variable $Y_{i,s,t}$ is a measure of the total number of tweets posted by politician i from state s at year t which criticized China for trade (or technology, or job) concerns. $\boldsymbol{X}_{it}$ includes six business concerns that are "passed on" from firms to politician i if they have a lobbying connection in year t as defined above. $\boldsymbol{Z}_{it}$ is a set of control variables of politician i, including one's political party, chamber (Senate versus House), ideology from first dimension of DW-NOMINATE, and the total number of tweets in year t. I include two sets of fixed effects, γ_s for state fixed effects and δ_t for year fixed effects, absorbing state-specific or year-specific heterogeneities. I double cluster standard errors at the year level and politician level to account for the correlation in the error terms, $\epsilon_{i,t}$.

Unfortunately, LobbyView data are available only until 2020. Since I have complete, reliable dyadic information for the Trump era (2017 to 2020), the results in this period will be the main focus of this study. For the sake of completeness and exploratory analysis, I impute

[15]It is an indirect measure of the firm-politician connectivity, because while the lobbyists are legally required to file reports to disclose their lobbying activities, they are not required to reveal the individual politicians they contact.

the firm-politician connection for the Biden era (2021 to 2023) if a firm and a politician had a lobbying connection for at least 2 years out of the previous 4 years. These results are reported in the Appendix.

5 Results

The regression analyses results for the Trump era (from 2017 to 2020) are reported in Table 2, where the outcomes are politicians' criticism on China on trade (or technology or jobs). There is some support for the profit-driven concerns hypothesis. Model 1 and 2 (when the standard errors are clustered by year only) show that when firms have subsidiaries in China, those politicians lobbied by them are less likely to criticize China on trade and technology. However, the negative coefficients became statistically insignificant once the standard errors are double clustered at year and politician levels (in Model 4 and 5).

The most consistently supported hypothesis is the predation-driven concerns: when firms mentioned intellectual property rights violation, those politicians lobbied by them are more likely to criticize China on trade and technology issues. These correlations are robust to double clustering of standard errors. It is worth pointing out that the correlations persist even if we include political party and liberal-conservative ideology as the control variables. The turn towards being more critical on China trade and technology issues is not simply driven by partisanship or ideology. It is also interesting to note that no business concerns are able to consistently predict politicians' criticism on China on a jobs-related ground (Model 3 and 6); the firms in our sample are not really concerned about the employment ramifications of the U.S.-China trade relationship.

To ensure that the results are not merely driven by the probability threshold (0.9) I used during the text classification, I further change to the probability threshold to 0.8 and 0.7 when producing the labels. Results are reported in Table A2 in the Appendix; the IP violation variable is the only consistently statistically significant and positive predictor for politicians' criticism on trade and technology.

I also report the regression results for the Biden era (2021 to 2023) in Table A3 in the Ap-

Table 2: Correlations between business interests and politicians' criticism on China on Twitter from 2017 to 2020

Dependent Variables:	trade	technology	jobs	trade	technology	jobs
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
subsidiary	-0.042*	-0.069**	-0.007	-0.042	-0.069	-0.007
	(0.017)	(0.021)	(0.004)	(0.022)	(0.033)	(0.006)
marketOpp	0.052	0.137*	-0.003	0.052	0.137	-0.003
	(0.027)	(0.045)	(0.010)	(0.041)	(0.066)	(0.015)
competition	-0.116	-0.375	-0.029	-0.116	-0.375	-0.029
	(0.187)	(0.408)	(0.086)	(0.187)	(0.394)	(0.087)
violateIP	0.784***	1.56**	-0.010	0.784**	1.56**	-0.010
	(0.107)	(0.297)	(0.058)	(0.188)	(0.284)	(0.066)
statePolicy	-0.093	0.627	-0.108*	-0.093	0.627	-0.108
	(0.255)	(0.492)	(0.038)	(0.290)	(0.603)	(0.059)
barrierEntry	0.143	-0.295*	-0.012	0.143	-0.295	-0.012
	(0.206)	(0.125)	(0.068)	(0.245)	(0.188)	(0.066)
partyR	-1.56*	-1.79	-0.368*	-1.56	-1.79	-0.368
	(0.612)	(1.14)	(0.140)	(0.937)	(1.81)	(0.260)
chamberSenate	2.34*	3.07*	0.596*	2.34	3.07	0.596*
	(0.830)	(1.19)	(0.189)	(0.997)	(1.46)	(0.231)
nominate_dim1	4.95*	6.83*	1.46	4.95	6.83	1.46
	(1.81)	(2.51)	(0.904)	(2.18)	(3.32)	(0.961)
ntweet	0.002***	0.003**	0.0007**	0.002**	0.003*	0.0007*
	(0.0003)	(0.0005)	(0.0002)	(0.0006)	(0.0010)	(0.0002)
Fixed-effects						
year	Yes	Yes	Yes	Yes	Yes	Yes
state	Yes	Yes	Yes	Yes	Yes	Yes
Clustered standard errors						
year	Yes	Yes	Yes	Yes	Yes	Yes
politician ID	No	No	No	Yes	Yes	Yes
Fit statistics						
Observations	2,212	2,212	2,212	2,212	2,212	2,212
R^2	0.217	0.193	0.173	0.217	0.193	0.173
Within R^2	0.152	0.137	0.106	0.152	0.137	0.106

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

pendix. Barriers to entry as a business concern positively predicts politicians' criticism on trade and technology, which lends some support for the predation-driven hypothesis. But these results are only suggestive because I rely on imputed dyadic lobbying connection due to data availability issues and that the results are not robust to alternative probability thresholds (reported in Table A4 in the Appendix). Whether there has been a shift in the business concerns after the transition from the Trump to the Biden era and whether it reflects actual changes in the Chinese political economic situation on the ground requires further research.

6 Conclusion & future direction

This study puts firms at the center of explaining U.S. politicians' preferences on U.S.-China trade relationship. Theoretically, it emphasizes that when formulating firms' specific types of business interests, it is important to bring in the state actions and the specific political economic context of the trading country. Empirically, it is one of the first studies that correlates firms' interests to politicians' preferences. Methodologically, it demonstrates the potentials of exploiting recent advances in LLMs and the rich textual data in financial filings to measure firms' preferences and concerns. The text classification workflow is highly flexible and can be applied to study topics other than U.S.-China trade.

There are many avenues to improve on the current work. On the sample of firms, I expect to move beyond S&P 500 companies (a very selected, perhaps unrepresentative, sample) and include all publicly trading companies in the U.S. listed on the SEC. On the firm-politician linkages, lobbying data can only reveal indirect relationship (whether a firm lobbied on a bill sponsored by a legislator); campaign contributions can be a more direct way to establish connection, though not without their problems. On the outcome, I intend to build a more comprehensive measure of politicians' positions on free trade with China by combining congressional record, roll call data, (co-)sponsorship data with social media data via a latent variable approach. Lastly, on the text classification, the text classifier can be fine-tuned to my specific data and tasks to enhance the classification performance; more rigorously out-of-sample tests should be done and more comprehensive accuracy metrics should be reported.

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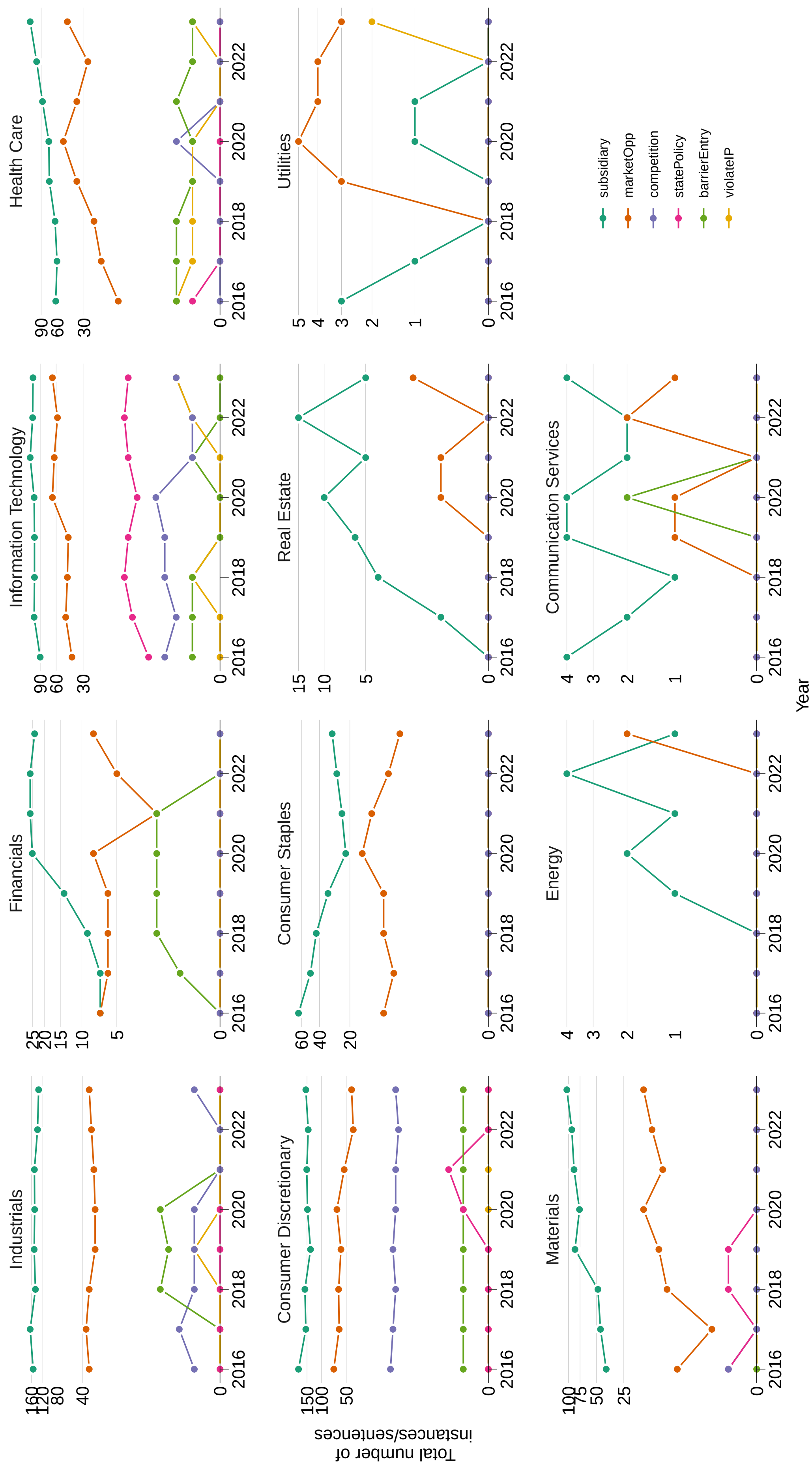
Appendix A NLI and zero shot classication

Table A1: Sample text from company 10-K reports with the highest predicted probabilities for 6 possible classes

Category	Sample text
barrierEntry	The Chinese government has also limited the flow of material into China by restricting the issuance of required import licenses, and the restriction on import licenses is expected to constrict further in 2020. In addition, changes to foreign trade policy and tariffs imposed by the current U.S. administration have resulted in China imposing new tariffs on the import of recyclables. It is currently anticipated that China will ban the import of recyclables completely in 2021. (prob = 0.993)
barrierEntry	Such regulations in China have the greatest impact, as only 34 foreign films, as selected by relevant authorities in China, may be distributed annually on a revenue share basis based on box office performance. In addition, in September 2018, China s film and television regulator, the National Administration of TV and Radio, published proposed regulations that would severely limit the streaming and broadcasting of foreign film and television content in China, further reducing foreign access to the Chinese market. UK Regulations Affecting Channel 5 Business. (prob = 0.977)
barrierEntry	Our failure or inability to obtain such licenses would substantially limit our markets and severely restrict our revenues. Many of the challenges noted above are applicable in China, which is a fast developing market for the semiconductor equipment industry and therefore an area of potential significant growth for our business. As the business volume between China and the rest of the world grows, there is inherent risk, based on the complex relationships among China, Japan, Korea, Taiwan, and the United States, that political and diplomatic influences might lead to trade disruptions. (prob = 0.973)
competition	The market for integrated circuit products in China is highly competitive, and both international and domestic competitors are aggressively seeking to increase their market share. Increased competition and, economic weakness in the China market has recently made it more difficult for us to achieve our desired sales volumes in China. In particular, the trade relationship between the U.S. and China has worsened, economic conditions in China remain uncertain, and we are unable to predict whether such uncertainty will continue or worsen in future periods. (prob = 0.976)
competition	Our business in China is subject to aggressive competition and is sensitive to economic and market conditions. Maintaining a strong position in the Chinese market is a key component of our global growth strategy. The automotive technology and components market in China is highly competitive, with competition from many of the largest global manufacturers and numerous smaller domestic manufacturers. (prob = 0.962)
competition	The market for integrated circuit products in China is highly competitive, and both international and domestic competitors are aggressively seeking to increase their market share. Increased competition or economic weakness in the China market may make it difficult for us to achieve our desired sales volumes in China. In particular, economic conditions in China remain uncertain and we are unable to predict whether such uncertainty will continue or worsen in future periods. (prob = 0.962)
marketOpp	Our sales to China-based customers represented 6.7 of total revenues in 2018, 6.3 of total revenue in 2017 and 5.7 of total revenue in 2016. In recent months, economic growth in China has moderated. Continued growth in many of our businesses, including those in the Environmental and Electronic Measurement Instrumentation group and our commercial aviation-related business units, could be negatively impacted if this trend proves to be long-lasting or systematic rather than cyclical in nature. (prob = 0.99)
marketOpp	We believe the decrease was due to business closures and restrictions associated with the COVID-19 pandemic, weaker end-market demand, a higher sales mix of mid-price products versus premium price products and further reductions to previously elevated channel inventory levels. We derive a substantial portion of our sales in China from premium-tier products. Changes in consumer preferences and purchasing behaviors including preferences for e-commerce, weakening consumer confidence and sentiment as well as economic uncertainty, socio-political risks, increased competition from Chinese based companies, and the potential future impact of the COVID-19 pandemic, may prompt Chinese consumers to postpone purchases, choose lower-priced products or different alternatives, or lengthen the cycle of replacement purchases. (prob = 0.975)
marketOpp	We believe that decrease was due to weaker end-market demand as a result of a weakening Chinese economy, elevated channel inventory levels, and a higher mix of mid-price products versus premium price products. We derive a substantial portion of our sales in China from premium-tier products. Changes in consumer preferences, weakening consumer confidence and sentiment as well as economic uncertainty, including the unknown impact from the coronavirus, may prompt consumers there to postpone purchases, choose lower-priced products or different alternatives, or lengthen the cycle of replacement purchases. (prob = 0.952)
statePolicy	Government initiatives are propelling China to expand its domestic manufacturing capacity. Although China is currently seen as an important long-term growth region for the semiconductor capital equipment sector, the U.S. Department of Commerce Commerce has added certain China-based entities to the U.S. (prob = 0.978)
statePolicy	In addition, some governments have provided and may continue to provide significant assistance, financial or otherwise, to some of our competitors or to new entrants and may intervene in support of national industries and/or competitors. In particular, we face the threat of increasing competition as a result of significant investment in the semiconductor industry by the Chinese government and various state-owned or affiliated entities that is intended to advance China's stated national policy objectives. In addition, the Chinese government may restrict us from participating in the China market or may prevent us from competing effectively with Chinese companies. (prob = 0.973)
statePolicy	For example, we may face increased competition as a result of China actively promoting and reshaping its domestic semiconductor industry through policy changes and investment. These actions, in conjunction with trade tensions, may restrict us from participating in the China market or may prevent us from competing effectively. Certain competitors possess sufficient financial, technical and management resources to develop and market products that may compete favorably against our products, and consolidation among our competitors may allow them to compete more effectively. (prob = 0.968)
subsidiary	Xi'an ("PTI Xi'an") is a wholly-owned subsidiary of Powertech Technology Inc. ("PTI") and was created to provide assembly services to us at our manufacturing site in Xi'an, China. In connection therewith, we had capital lease obligations of 80 million and net property, plant, and equipment of 76 million as of August 31, 2017. (prob = 0.991)
subsidiary	In October 2021, Deckers (Beijing) Trading Co., LTD (DBTC), a wholly owned subsidiary of the Company, entered into a credit agreement in China (as amended, the China Credit Facility) that provides for an uncommitted revolving line of credit of up to CNY , or , with an overdraft facility sublimit of CNY , or . The China Credit Facility is payable on demand and subject to annual review with a defined aggregate period of borrowing of up to months. The obligations under the China Credit Facility are guaranteed by the Company for of the facility amount in US dollars. (prob = 0.986)
subsidiary	(DCEC) is a joint venture in China with Dongfeng Automotive Co. Ltd., a subsidiary of Dongfeng Motor Corporation, one of the largest medium-duty and heavy-duty truck manufacturers in China. DCEC produces Cummins 3.9 to 13 -liter diesel engines, with a power range from 80 to 680 horsepower, and natural gas engines. (prob = 0.976)
violateIP	This contract is expected to supply the majority of our power consumption needs in Singapore with more favorable pricing than our previous supply arrangements. 73 — 2023 10-K Table of Contents Chinese patent by manufacturing and selling certain Crucial DDR4 DRAM modules. The complaint seeks an order requiring MXA and 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 million Chinese yuan plus court fees incurred. (prob = 0.988)
violateIP	Trade Representative s Priority Watch List for 2018. Further, the standards for patentability in China remain more restrictive than in other major markets, including the U.S., Europe and Japan. Also, while a framework exists for protecting patents for 20 years, enforcement mechanisms are often lacking or inconsistent. (prob = 0.965)
violateIP	This may increase our vulnerability to our technology being reverse engineered or our trade secrets being compromised. If we are unable to protect our intellectual property in China or other countries, it could have a material adverse effect on our business, results of operations, financial condition, and cash flows. Competitors also may harm our sales by designing products that substantially mirror the capabilities of our products or technology without infringing our intellectual property rights. (prob = 0.952)

Figure A1: Time-series of 6 classes of assessments on China by industry, from 2017 to 2023.



Appendix B Robustness checks

Table A2: Correlations between business interests and politicians' criticism on China on Twitter from 2017 to 2020, using probability threshold of 0.8 (Model 1 to 3) and 0.7 (Model 4 to 6) during the text classification

Dependent Variables:	trade	technology	jobs	trade	technology	jobs
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
subsidiary	-0.0187	-0.0395*	-0.0011	-0.0095	-0.0238	0.0003
	(0.0093)	(0.0166)	(0.0023)	(0.0063)	(0.0105)	(0.0021)
marketOpp	0.0455	0.1287	-0.0036	0.0184	0.0787	-0.0074
	(0.0443)	(0.0744)	(0.0144)	(0.0340)	(0.0654)	(0.0112)
competition	-0.1501	-0.3844	-0.0226	-0.0893	-0.3285	0.0075
	(0.1400)	(0.3881)	(0.0527)	(0.1135)	(0.3229)	(0.0466)
violateIP	0.9792**	2.072***	0.0258	0.8517*	1.893***	-0.0233
	(0.3015)	(0.2713)	(0.0787)	(0.2937)	(0.1730)	(0.0873)
statePolicy	-0.3784	-0.0723	-0.2219*	-0.1306	-0.0104	-0.1054
	(0.3026)	(0.6560)	(0.0823)	(0.2517)	(0.5571)	(0.0661)
barrierEntry	0.0864	-0.2341	0.0166	0.0186	-0.2229	-0.0033
	(0.1850)	(0.1629)	(0.0999)	(0.1738)	(0.1294)	(0.1007)
partyR	-1.600	-1.858	-0.3777	-1.618	-1.877	-0.4044
	(0.9505)	(1.849)	(0.2634)	(0.9579)	(1.857)	(0.2676)
chamberSenate	2.356*	3.099	0.6098*	2.371*	3.086	0.6134*
	(0.9979)	(1.464)	(0.2324)	(1.006)	(1.473)	(0.2360)
nominate_dim1	5.021	6.951	1.487	5.047	6.971	1.519
	(2.207)	(3.369)	(0.9843)	(2.225)	(3.389)	(0.9831)
ntweet	0.0023**	0.0031**	0.0007*	0.0023**	0.0031**	0.0007*
	(0.0006)	(0.0009)	(0.0002)	(0.0006)	(0.0010)	(0.0002)
Fixed-effects						
year	Yes	Yes	Yes	Yes	Yes	Yes
state_abbrev	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	2,212	2,212	2,212	2,212	2,212	2,212
R^2	0.21827	0.19254	0.17304	0.21812	0.19204	0.17412
Within R^2	0.15342	0.13683	0.10753	0.15315	0.13613	0.10861

Clustered (year & bioguide_id) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table A3: Correlations between business interests and politicians' criticism on China on Twitter from 2021 to 2023

Dependent Variables:	trade	technology	jobs
Model:	(1)	(2)	(3)
Variables			
subsidiary	-0.0235	-0.0604	-0.0024
	(0.0351)	(0.0296)	(0.0164)
marketOpp	0.0119	0.1487	-0.0078
	(0.0472)	(0.0725)	(0.0190)
competition	0.1111	-0.5500	0.2756
	(0.2757)	(0.4152)	(0.1945)
violateIP	0.0733	0.3808	-0.1315
	(0.3982)	(0.6067)	(0.1743)
statePolicy	0.3002	1.876	-0.0395
	(0.5564)	(1.088)	(0.2242)
barrierEntry	4.517***	4.813***	1.182
	(0.4125)	(0.2845)	(0.4534)
partyR	0.1805	-0.2937	-0.2636
	(1.030)	(1.206)	(0.6600)
chamberSenate	1.633*	3.180*	0.7801
	(0.5573)	(0.8693)	(0.3806)
nominate_dim1	3.019	5.099*	1.297
	(1.055)	(1.567)	(0.5821)
ntweet	0.0020*	0.0032**	0.0010*
	(0.0006)	(0.0006)	(0.0003)
Fixed-effects			
year	Yes	Yes	Yes
state_abbrev	Yes	Yes	Yes
Fit statistics			
Observations	1,658	1,658	1,658
R^2	0.30266	0.37983	0.20796
Within R^2	0.21543	0.30734	0.13636

Clustered (year & bioguide_id) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table A4: Correlations between business interests and politicians' criticism on China on Twitter from 2017 to 2020, using probability threshold of 0.8 (Model 1 to 3) and 0.7 (Model 4 to 6) during the text classification

Dependent Variables:	trade	technology	jobs	trade	technology	jobs
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
subsidiary	-0.0053	-0.0232	0.0005	-0.0036	-0.0214	0.0003
	(0.0165)	(0.0158)	(0.0094)	(0.0136)	(0.0129)	(0.0074)
marketOpp	0.0089	0.1247	-0.0054	0.0095	0.1026	-0.0003
	(0.0328)	(0.0618)	(0.0184)	(0.0244)	(0.0499)	(0.0128)
violateIP	0.6113	0.3175	0.0243	0.4586	0.0198	-0.1031
	(0.3838)	(0.5292)	(0.2073)	(0.3271)	(0.4332)	(0.3391)
competition	0.0582	-0.5422	0.2467	-0.0139	-0.7074	0.1891
	(0.2481)	(0.4167)	(0.1413)	(0.2440)	(0.4393)	(0.1160)
statePolicy	0.2435	1.050	-0.0152	0.2184	1.127	0.0054
	(0.4227)	(0.7604)	(0.0835)	(0.3609)	(0.7486)	(0.1113)
barrierEntry	-0.2406	-0.5338	-0.2459	0.0191	-0.3199	-0.1330
	(0.9916)	(1.476)	(0.4043)	(0.8972)	(1.433)	(0.3957)
partyR	0.2254	-0.2686	-0.2530	0.2022	-0.3292	-0.2334
	(1.040)	(1.242)	(0.6651)	(1.044)	(1.260)	(0.6566)
chamberSenate	1.683*	3.207*	0.8060	1.657*	3.118*	0.8102
	(0.5498)	(0.8585)	(0.3866)	(0.5426)	(0.8641)	(0.3851)
nominate_dim1	3.062	5.211*	1.304	3.122*	5.284*	1.311
	(1.062)	(1.605)	(0.5928)	(1.062)	(1.627)	(0.5880)
ntweet	0.0021*	0.0034**	0.0011*	0.0021*	0.0034**	0.0011*
	(0.0005)	(0.0006)	(0.0003)	(0.0005)	(0.0006)	(0.0003)
Fixed-effects						
year	Yes	Yes	Yes	Yes	Yes	Yes
state_abbrev	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics						
Observations	1,658	1,658	1,658	1,658	1,658	1,658
R^2	0.30139	0.37457	0.21193	0.30147	0.37814	0.21467
Within R^2	0.21424	0.30208	0.14048	0.21505	0.30580	0.14354

Clustered (year & bioguide_id) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*